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Liquidity risk in FinTech lending: Early impact of the COVID-19 pandemic on the P2P lending market

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ABSTRACT

This study empirically investigates the impact of the COVID-19 pandemic on the liquidity risk incurred by the peer-to-peer (P2P) lending market. As the pandemic adversely affects financial markets globally, a better understanding of the dynamics of successful P2P lending is necessary under the conditions of financial distress. By using the cross-country database of secondary market listing outcomes at Bondora (Estonia) and employing probit, ordered probit and tobit regression methods, we provide evidence of the pandemic-induced exposure to liquidity risk in the P2P lending market. Despite increased volatility in the financial markets, results show that COVID-19 risk increases the probability of successful listing during the pandemic. However, this outcome comes at significant liquidation costs for investors in the form of higher premiums. Further analysis based on listing outcomes and loan characteristics shows a negative association between COVID-19 risk and share of overdue loans and average overdue days in secondary market listings. Simultaneously, more experienced investors dominate the market as COVID-19 risk increases, a trend that is reflected in shorter listing times. The findings of this study imply certain early tendencies in financial markets during pandemic-induced turmoil and open new avenues for further research.

1. Introduction

Peer-to-peer (P2P) lending platforms offer attractive and predictable returns, enticing yield-hungry investors keen to diversify their portfolios with alternative investments. However, a key distinction between P2P lenders and banks is that the former neither accept deposits nor provide loans. Thus, P2P lending markets operate according to a different set of rules when screening borrowers. According to Weiss et al. (2010), evaluating the creditworthiness of borrowers is difficult for lenders because both sides meet anonymously through the Internet.

Risk evaluation is at its infancy in the P2P lending literature. The future of the industry is still bleak because it largely depends on complex and interrelated factors, most of which are at a macro level (Li et al., 2016). Potential risk factors resulting from variability of defaults, loan recovery, platform failure, fraud or cybercrime pose a threat to investors and platforms (Milne and Parboteeah, 2016). One of the early indications of vulnerability came in 2018 when the wave of defaults swept across the Chinese P2P lending market (Wildau and Jia, 2018). Consequently, investors withdrew funds, forcing the collapse of platforms that were unable to maintain

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liquidity. By 2020, the number of Chinese P2P lending platforms was down to only 29 from approximately 6000, leaving investors with a loss of more than US$115 billion (Bloomberg, 2020). Economic downturn due to the COVID-19 pandemic, consequent supply chain disruption, energy crisis and the war in Ukraine increased the likelihood of unsustainable losses by the industry.

The impact of COVID-19 uncertainties on liquidity risk and supply of funds among financial technologies, such as P2P lending, is far from conclusive. To this end, we examine the impact of the uncertainty related to the COVID-19 pandemic on the liquidity of the P2P lending market. The central question of this study is as follows: *How does COVID-19 risk affect the liquidity of the P2P lending market?* We examine the impact of COVID-19 risk on the probability of successfully selling the loan stake at Bondora Secondary Market (BSM) as well as their risk profile and liquidation cost. We examine the liquidity risk of the P2P lending market during the COVID-19 pandemic using the Bondora platform based in Estonia. We use COVID-19 risk in conjunction with the borrower- and country-specific factors in regression estimations.

Estonia is significant as a target research jurisdiction for several fundamental reasons. Firstly, the early adoption of digital technologies in the banking sector and wider economy led to the ICT's sector's high contribution of 7.8% to the gross value added of the economy in 2020 (Eurostat, 2022). Accordingly, the wide usage of digital services led to the high number of more than 200 FinTech companies (Laidroo et al., 2021), including internationally renowned companies such as Wise, Guardtime and Zego. The high penetration of FinTech solutions contributed to the modernisation of the traditional banking sector while alternative finance and investment platforms complemented capital markets (Divissenko and Eenmaa, 2019). Secondly, Estonia is well known for its high density of start-up companies and FinTech investments relative to the size of its economy and population. There were 10.9 start-up companies per 10,000 inhabitants in 2022, 7.7 unicorns per million population and over €225 billion FinTech investments (Atomico, 2023; Invest Estonia, 2022; Findexable, 2022). Thirdly, Estonia has a globally focused entrepreneurial-friendly environment where 25% of start-up founders are foreign citizens (Invest Estonia, 2022). This type of business ecosystem highlights the global angle of Estonia in terms of FinTech development. Finally, there is very limited regulation on crowdfunding in Estonia. The Estonian Financial Supervisory Authority (FSA) does not monitor the crowdfunding industry, whereas only investment crowdfunders are required to have authorisation from the Estonian FSA (Ellenoff et al., 2015). Therefore, the case of Estonia provides a unique institutional perspective for generalising and scaling the findings of this research globally, at least within the scope of Continental Europe.

The results of our empirical analysis can be summarised as follows. The probability of successful listing increased during the pandemic. Investors were more likely to liquidate their loan stakes successfully when COVID-19 risk increased during the pandemic. The increase in the number of daily COVID-19 cases and deaths also led to a higher probability of a successful listing outcome. This result remains consistent after the adjustment for resampling bias and robustness tests. We also find a significant shift in investor attitude towards the risk profiles of loans. The average loan overdue days and probability of overdue loans among successfully liquidated loans decreased during the pandemic period compared with the pre-pandemic period. We find the same negative relationship when COVID-19 risk is proxied by the number of daily cases and deaths. This finding indicates that investors withdrew from their stakes in less risky loans as COVID-19 risk increased. However, we find that with COVID-19 risk, the liquidation of loan stakes came at considerable cost for investors. The probability of 'cashing out' the loan stake for premium considerably decreased with an increase in COVID-19 pandemic risk. Finally, we find important changes in investor sentiment at different stages of the pandemic. The probability of successful listing increased as COVID-19 risk increased in the early stage of the pandemic from February to April 2020. However, during May and June 2020, the effect of COVID-19 risk was largely inconclusive in terms of determining the probability of successful listing. At the same time, overdue loans consistently decreased and more experienced investors dominated the market as COVID-19 risk increased.

This study offers several contributions to the existing literature in terms of its implications for risk management in P2P lending. Firstly, this study evaluates the early impact of the pandemic effect among FinTech lending practices. P2P lending markets have not yet experienced any economic downturn before 2020. The findings of this study reveal how investors and borrowers behave during the pandemic period. Secondly, the data on secondary market listings are unique because of the combination of multiple databases encompassing borrower- and country-specific characteristics of the listed loan stakes. Utilising such data allows us to develop a regression model covering a wide range of risk factors. P2P lending platforms and investors can use this modelling framework to manage liquidity risk. Specifically, our modelling provides elasticities of liquidity risk, as reflected in coefficient parameters with respect to a number of liquidity characteristics. These coefficients might serve as a benchmark for modelling the management of 'provision funds'. Thus, under the crisis conditions, this fund can be used to release or withhold investor models for managing the liquidity risk. Finally, our analysis provides a comprehensive view of the influence of COVID-19 risk on liquidity risk. We use three measures of pandemic risk and several macroeconomic variables that increase the credibility of the findings. This approach allows for a better understanding of the interactions of the FinTech industry with the economy and broader financial market during the period of economic distress.

The remainder of the paper proceeds as follows. Section 2 describes the methodology and data. Section 3 presents the results of empirical analysis. Section 4 discusses the results and concludes the paper by pointing out its limitations and the promising avenues for further research.

2. Methodology and data

2.1. Hypothesis development

For over a decade, P2P lending platforms benefited from favourable external conditions, but data were unavailable for observing the tendencies under financial distress. In fact, 2020 was the first year that the P2P lending market experienced a global economic downturn. An extensive amount of literature indicates that pandemics have an enormous economic cost that can impact financial markets (Haacker, 2004; Santaeulalia-Llopis, 2008; Yach et al., 2006). Specifically, pandemics are linked with the collapse of the banking sector, lower lending to the poor and higher deposit withdrawals (Lagoarde-Segot and Leoni, 2013; Leoni, 2013; Skoufias, 2003). Alternative lending markets, such as crowdfunding and P2P lending, mainly serve small and medium businesses and low-income individuals. Following the typical behaviour in traditional financial markets, pandemics trigger a 'herding behaviour' among P2P lending market investors, wherein they rush to turn their stakes into cash (Gonzalez, 2019; Lee and Lee, 2012; Zhang and Chen, 2017). Additionally, multidimensional interlinkages between economic agents create a multi-layered network where the exposure to credit risk transfers to the non-bank private financial sector (Avdjiev et al., 2019; Giudici et al., 2020).

On the contrary, several COVID-19 support programmes are implemented by governments to ease the financial hurdles of small enterprises and low-income households. Interventions took the form of COVID-19 moratoria and public guarantees to effectively bail out borrowers served by P2P lenders (European Banking Authority, 2020). Interventions are intended to mitigate the downturn of the economy and safeguard against borrower delinquencies (Civelek and Xiarewana, 2020). Gordon and Jones (2020) highlight that loan delinquency rates might be considerably less under the policy intervention measures, thereby significantly reducing the adverse impact of the COVID-19 pandemic. Kargar et al. (2020) also indicate that liquidity conditions improve in the corporate bond market during the pandemic because of the U.S. Federal Reserve's 'lending/purchase programme'.

Accordingly, we formulate the following main hypothesis for our study:

Hypothesis 1. COVID-19 risk increases the probability of successfully selling the loan stake at Bondora Secondary Market.

From the theoretical perspective, there is potential for a negative liquidity spiral when a sharp drop occurs in the funding liquidity of traders (Brunnermeier and Pedersen, 2009). In this regard, exchanges seek to reduce counterparty default risk between participants and increase funding liquidity. This will increase margin requirements and reduce market liquidity, eventually leading to a procyclical negative liquidity spiral. Brogaard et al. (2014) and Shkilko and Sokolov (2020) argue that high-frequency market makers are more likely to withdraw from the market following large increases in margin requirements.

Thus, we expect the impact of COVID-19 risk to be twofold. From one side, we expect that during the pandemic period, market turmoil will drive investors to liquidate and sell their risky assets (Gros, 2020; Wójcik and Ioannou, 2020). Since P2P loans are considered to be high risk, market turmoil pushes investors to change their risk appetite and withdraw their funds from low-risk loans as well as their high-risk loans. On the other hand, the costs related to the liquidation of loans increase as a result of the COVID-19 pandemic risk. In the case of BSM, investors sell more of the high rated (low risk) loans for a discount instead of a premium. This behaviour is comparable to an increase in bid-ask spreads, withdrawal spikes and selling pressure on illiquid assets observed in traditional financial markets (Foley et al., 2021; Mittal et al., 2020; Chebbi et al., 2021). Consequently, an increase in COVID-19 related deaths and cases tend to be associated with increased market illiquidity and volatility (Baig et al., 2020). We therefore formulate two additional hypotheses for our study:

Hypothesis 2. COVID-19 pandemic risk decreases the risk profile of loan stakes sold at the Bondora Secondary Market.

Hypothesis 3. COVID-19 pandemic risk decreases the probability of selling loan stakes for a premium at the Bondora Secondary Market.

2.2. Methods of regression modelling

We perform four sets of regression estimations in this study. The first empirical technique is probit regression analysis, which estimates the dependent variable as binary values. The key dependent variable in this empirical study is the binary variable representing the status of listings. We test liquidity risk at the platform in terms of which loan stakes are 'cashed out' in the secondary market. The model is based on Eq. (1), which uses a binary-dependent variable with the country- and borrower-specific variables. Probit regression tests Hypothesis (1) and estimates the determinants of the probability of success (θ_i) as follows:

$$\theta_t = Pr(S_i = 1|\text{Observed variables}) = Pr\left(\alpha + \beta_D D + \beta_E X_t^E + \beta_B X_t^B + \varepsilon_{it}\right) \tag{1}$$

S_t is a binary variable representing the status of listings (SUCC_LIST_DUMMY); it takes the value of 1 if the listing is successfully 'cashed out' and 0 otherwise. $\beta_D D$ is the variable representing the COVID-19 pandemic risk. We use three proxies to represent the pandemic: (1) a dummy variable that equals 1 for the dates later than March 11, 2020 when the World Health Organization (WHO) declared COVID-19 as a pandemic and 0 otherwise, (2) the number of country-level reported daily cases of COVID-19 per million population and (3) the number of country-level reported daily COVID-19 related deaths per million population. Unpredictable, dangerous disease outbreaks can generate intensive public concerns that exert a significant effect on market liquidity. During the COVID-19 pandemic, the daily case and death numbers were widely perceived as indicators of pandemic severity. Therefore, early studies of the COVID-19 pandemic extensively used these proxies to represent COVID-19 risk (Iyke, 2020; Bose et al., 2022; Chebbi et al., 2021; Nigmonov and Shams, 2021; Okorie and Lin, 2021).

$\beta_E X_t^E$ represents the vector of economy-specific control variables [e.g. Economic Sentiment Indicator (ESI)]. Existing literature provides robust evidence that general economic development significantly affects the liquidity risk of financial institutions (Dinger, 2009; Valla and Saes-Escorbiac, 2006). Evidence of the positive impact of economic development on alternative financial markets is also present in Khrawish et al. (2010) and Mollick (2014). Thus, we include ESI as a proxy variable for economic development. Change in stock market index (CH_ST_MAR_IND) is another economy-specific variable used in this study. Jagtiani and Lemieux (2018), Tanda

(2019), Fung et al. (2020) and Thakor (2020) indicate a direct relationship between traditional financial markets and alternative lending markets. We expect that increased stock market volatility (CH_ST_MAR_IND) during the pandemic directly impacts liquidity risk by decreasing the probability of successful listing. We also control for country individual effects using country-level population (POPULATION) as a proxy.

$\beta_B X_t^B$ represents the vector of borrower-specific control variables. Existing studies on P2P lending extensively use borrower and loan characteristics to estimate loan funding success and default (Cai et al., 2016; Galema, 2020; Nigmonov et al., 2022; Serrano-Cinca et al., 2015; Wei and Lin, 2017). The variable representing the restructuring of a loan (RESTRUC_DUMMY) denotes whether the original maturity date of the loan is increased. This proxy may signal to lenders the survival probabilities of individual loans. We expect that restructured loans have lower probabilities of success in the secondary market. Interest rates (INTEREST), which are expressed as a percentage, are likely to be positively related to selection because they increase the loans' attractiveness to lenders. Loan duration (LOAN_DUR) is expressed in months and provides lenders additional information about the default risk of the loan. Loans with shorter durations tend to signal quality by reducing asymmetric information problems and increasing the probability of selection (Menkhoff et al., 2012; Steijvers and Voordeckers, 2009). The debt-to-income score of the borrower (DTI) is an important indicator used in lending to signal borrower solvency. Loan amount (AMOUNT) is another important indicator of solvency risk, where larger loan amounts are riskier to the extent that they increase default incentives. We expect that the loan amount is negatively related to the probability of selection. Traditional forms of finance segregate offers of financing arrangements based on age and gender (Bellucci et al., 2011; Blanchflower et al., 2003). With their liberal approach and adherence to market mechanisms, P2P lending markets may be less prone to investor bias with respect to certain demographics such as age and gender (Cumming et al., 2019; Duan et al., 2020). Therefore, we include the age and gender (AGE, GENDER) of borrowers to control the individual demographic characteristics of borrowers.

We test Hypothesis (2) using Eqs. (2) and (3). Specifically, Eq. (2) empirically estimates the likelihood of late payments (ϑ) among listed loans by running the following probit regression estimation:

$$\vartheta_t = Pr(L_i = 1|\text{Observed variables}) = Pr\left(\alpha + \beta_D D + \beta_E X_t^E + \beta_B X_t^B + \varepsilon_{it}\right) \tag{2}$$

where L_t is a binary variable representing the status of the individual loan (OVERDUE_DUMMY); it takes the value of 1 if the listed loan is overdue and 0 otherwise. Variables defining COVID-19 risk and control variables are the same as in Eq. (1). Existing literature highlights that investors are searching for higher yields and invested in less risky liquid assets during the last decade (IMF, 2019). Early indications from the financial markets during the COVID-19 pandemic reveal that liquidity in the credit market simply evaporates when a crunch tightens due to an extended period of accommodative financial conditions (Baldwin and Mauro, 2020). As overdue payment is the primary indicator of risky loans, we expect that investors mostly abandon overdue loans under normal economic conditions. Under the conditions of financial distress, investors abandon their investments in P2P loans regardless of the risk profile. Thus, we expect that the probability of overdue loans' listing decreases as COVID-19 risk increases.

In the following, we empirically estimate the average overdue days of listed loans (y) to further support our findings based on Eqs. (1) and (2).

$$y_t = \alpha + \beta_D D + \beta_E X_t^E + \beta_B X_t^B + \varepsilon_{it} \tag{3}$$

The descriptive statistics for borrower demographic characteristics highlight that around 39% of the listings are overdue loans.[1] Our sample also reports that the length of these overdue loans creates skewed observations with the minimum value of 0. Therefore, we use tobit regression estimation based on Eq. (3) because observations for OVERDUE_DAYS are trimmed. Given the aforementioned reasons, we expect that average overdue days decrease as COVID-19 risk increases.

Finally, we empirically estimate how the pricing of the loan stakes in the secondary market changed as a result of COVID-19 risk. We use the model based on the multinomial probit model where the dependent variable is whether the investor lists a loan with a discount (0 base category), par (1) or premium (2). Eq. (4) aims to test Hypothesis (3) as follows:

$$\begin{aligned}\vartheta_t &= Pr(L_i = 0|\text{Obs.vars})Pr(L_i = 1|\text{Obs.vars})Pr\left(L_j = 2|\text{Obs.vars}\right)\\ &= Pr\left(\alpha + \beta_D D + \beta_E X_t^E + \beta_B X_t^B + \varepsilon_{it}\right)\end{aligned} \tag{4}$$

2.3. Description of data and sampling method

Bondora is one of the early and the largest cross-border P2P lending platforms in Europe, with borrowers from three E.U. countries (Estonia, Finland and Spain). Bondora investors are based in 88 countries, including all countries of the E.U., thus encompassing a broad cross-country sample. It is possible to automate investments and trade loans in a secondary market. The secondary market is the main liquidity tool available in the P2P lending market through automated investments and trades in loan stakes. This feature of the platform offers an opportunity to exit the investment early and is equivalent to liquidating or ‘cashing out’ the financial instrument in traditional financial markets. Therefore, transactions in the secondary market create a unique setting for analysing liquidity risk in the P2P lending market.

[1] Mean value of OVERDUE_DUMMY is equal to 0.3941 as per Table 1

In this study, we combine secondary market transactions of the Bondora P2P lending platform from January 2020 to June 2020. We combine each listing with the country-specific variables and corresponding loan details from the loan book dataset. The updated database consists of 19 variables with over five million observations. In P2P lending, investors only invest in a small portion of the loans. Accordingly, secondary market listings consist of the small stakes of loans listed by investors for 'cashing out'. Each observation represents a small stake of the loan invested by the investors, which mean each loan can be traded numerous times and repeatedly in the market. All loans are unsecured consumer loans with principal amounts of €500–€10,000 and repayment terms ranging from 3 to 60 months. The number of unique loans included in our database and traded in the market amounts to 114,873. The high number of observations indicates high trading volumes in the secondary market and its importance in understanding the liquidity risk of P2P loan investments.

In addition, each of the listings in the database contains observations for the starting and ending times of the listing. This information allows examination of the data using survival analysis, which facilitates estimating the timing of failure. We note that this study aims to assess an early impact of the COVID-19 pandemic risk; thus, it only considers the first six months of 2020. The later impact of the COVID-19 pandemic is better considered in a different setting than in one solely based on liquidity risk. This limitation of our study is highlighted in the last section of this paper along with the further avenues for future research. Table A1 in Appendix A describes all variables used in this study.

The P2P lending market in Continental Europe is experiencing high rapid growth. Countries in Continental Europe have similar regulations and represent an excellent opportunity for analysing the current tendencies in P2P lending markets. The database used in this study consists of loan stake listings that originated in Estonia, Finland and Spain. Our sample for the analysis comprises heterogeneously distributed observations across the time period and country of loan origination. For instance, listings are overrepresented by the loans issued in Estonia with 66% of all observations. The database also contains disproportionately large amounts of observations for the high volatility period of March–April 2020. This potentially creates an issue of sample selection which is addressed in the robustness test section of this paper.

3. Results

3.1. Descriptive analysis

Bondora publicly discloses its financial records, including the full loan-book and secondary market transactions. In this regard, the data available from Bondora are extremely suitable for analysing investor sentiments across Europe during the pandemic. Fig. 1 depicts the loan portfolio of Bondora from January 2019 to June 2020 with the share of overdue loans. Following the financial market turmoil as a result of the pandemic, Bondora experienced certain disruptions in the loan portfolio (Tomberg, 2020a). As depicted in Fig. 1, the volume of loans substantially dropped from April 2020. However, this was the result of reduced investor funding rather than the fall in loan applications (Tomberg, 2020b). Certain actions were also undertaken by the company to maintain steady returns for investors during these times. Loan originators based in Finland and Spain were suspended, the partial pay-out feature of 'Go & Grow' was automatically activated for most of the investor withdrawals and new loan applications were stringently reduced (Bondora, 2020). We also observe from Fig. 1 that the share of overdue loans increased from early 2020 throughout the pandemic period. However, the state of overdue loans might be misrepresented in their current form because of the restrictions placed on loan applications and various government subsidies for borrowers. We also note that despite the restrictions on new loan applications, loans were actively traded in the secondary market during the pandemic period.

Fig. 2 depicts the daily number of listings as a line chart with the date of the pandemic declaration highlighted in a dashed line. The line chart visually indicates contagion-type conditions in BSM around the dates of the declaration. This period is characterised by the tumultuous behaviour of investors as the pandemic scare unfolded and the WHO declared COVID-19 a pandemic. The changes in daily listings were extremely high in March, with relative stabilisation by April. However, Tomberg (2020b) noted that the reduction in secondary market activity was the result of restrictions imposed by Bondora rather than the changes in investor sentiment. Drastic changes in the BSM combined with the response measures undertaken by both governments and the platform led to important policy implications that are highlighted in the last section of this paper.

Table 1 reports descriptive statistics using the total values for the variables used in this study. The descriptive statistics in the breakdown of countries are provided in the Internet Appendix. The mean value of SUCC_LIST_DUMMY for the full sample is 0.7850, indicating that around 78.5% of listings were successful. The success of the listings is similar across the three countries under consideration. The mean value of SUCC_LIST_DUMMY for individual countries varies between 0.7712 and 0.7893. The mean value for the loan status (OVERDUE_DUMMY) in the sample is 0.3941, indicating that 39.41% of listed loans are late loans. The status of loans differs considerably across the countries. The mean values of loan status are 0.3061 for Estonia, 0.5499 for Finland and 0.6073 for Spain, reflecting the variability of listed loans across the countries. The difference in the values also indicates that loans issued in Spain and Finland are riskier compared with the loans issued in Estonia. Significant differences between the countries are addressed in the regression model by including the country-specific variable (POPULATION) and running the regression on specific subsamples based on countries.[2]

We report the descriptive statistics for variables that reflect borrower and loan characteristics in Table 2. Most borrowers in the

[2] Refer to the Internet Appendix for the country sample analysis

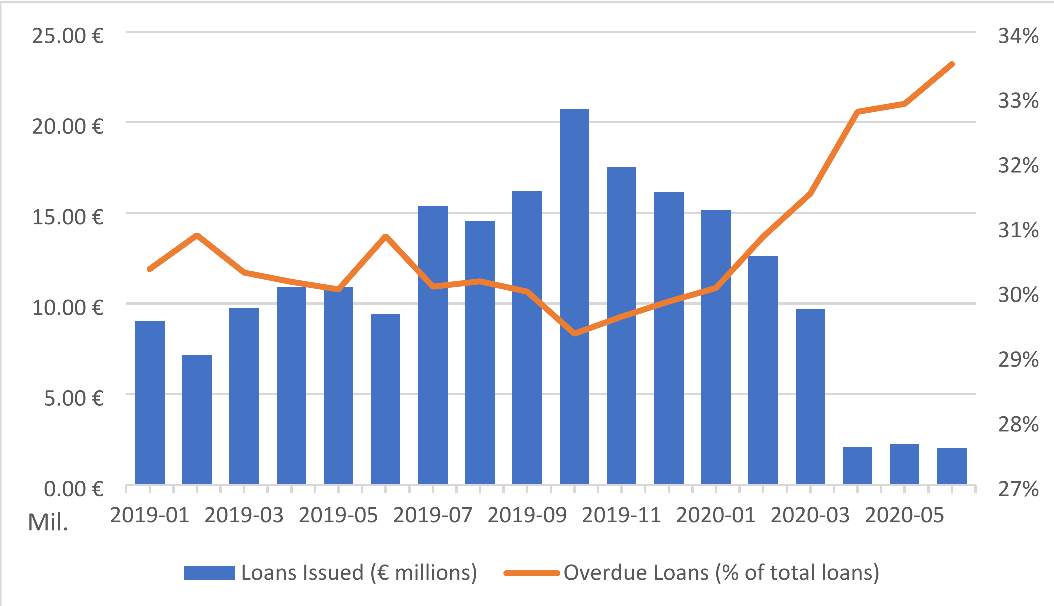

Fig. 1. Loan portfolio and overdue loans issued by Bondora (January 2019–June 2020).
Source: Bondora (2020)

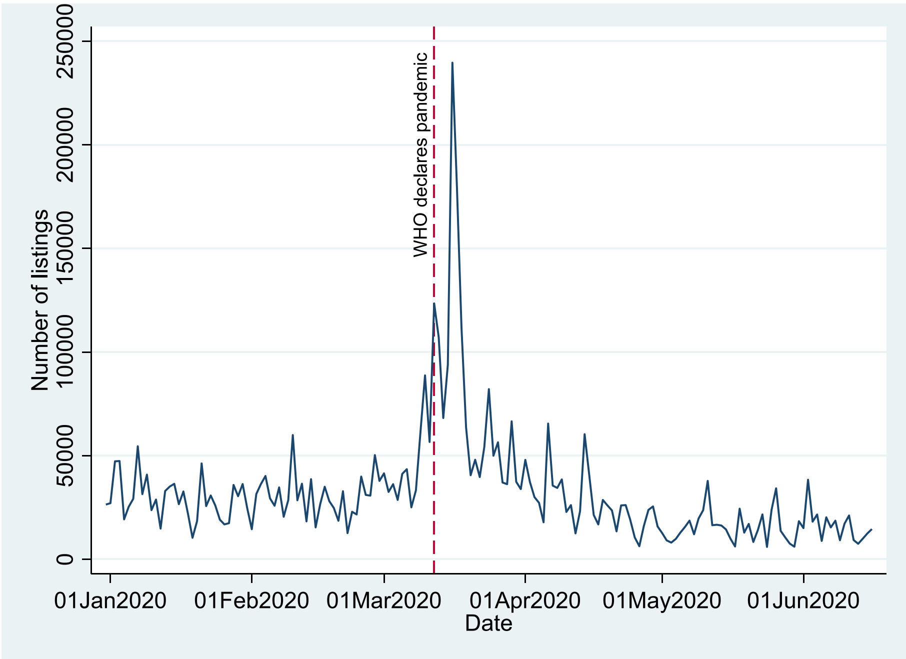

Fig. 2. Daily number of listings in the Bondora Secondary Market (January 1, 2020 – June 30, 2020).
Source: Bondora (2020)

database are male (66.48%), with the distribution of the ratings of borrowers concentrated around the lower-rated loans. Borrowers are also more likely to be employed in their jobs for more than 5 years (39.67%). The loan characteristics reveal that 'A' and 'AA' rated loans respectively contribute to 4.51% and 5.42% of the total loan portfolio in BSM during the period under consideration, whereas the largest share of listings (21.10%) are attributed to the loans rated as 'E'. We use borrower gender and employment duration in the baseline regression models as control variables. Loan ratings are used to build the subsamples of the database for additional analysis.

Table 3 reports the descriptive statistics for the listing outcome (SUCC_LIST_DUMMY), loan status (OVERDUE_DUMMY) and loan

Table 1
Descriptive statistics.

Variables	N (,000)	Mean	Median	St. dev.	Min	Max
Dependent variables						
SUCC_LIST_DUMMY	5386	0.7850	1.0000	0.4108	0.0000	1.0000
OVERDUE_DUMMY	5386	0.3941	0.0000	0.4887	−15.2599	196.4954
OVERDUE_DAYS	5386	147.2862	0.0000	306.5176	0.0000	20.3323
Independent variables, pandemic indicator variables						
PANDEMIC_DUMMY	5386	0.5787	1.0000	0.4938	0.0000	1.0000
DAILY_CASES	5386	205.9101	7.0000	953.3348	0.0000	1.0000
DAILY_DEATHS	5386	18.2620	0.0000	101.2723	0.0000	3942.0000
Independent variables, macroeconomic and country-specific variables						
CH_ ST_MAR_IND	5386	−0.0019	0.0000	0.0182	−0.1324	0.0883
ESI	4656	90.9912	96.5000	10.4580	61.9000	115.6000
POPULATION (,000,000)	5179	7.3312	1.3208	14.0000	1.3209	46.7000
Independent variables, borrower-specific variables						
AGE	5386	42.0721	41.0000	12.3555	18.0000	71.0000
DTI	5386	3.2735	0.0000	12.2091	0.0000	75.6100
INTEREST	5386	32.6437	29.2300	21.3615	7.2700	264.3100
AMOUNT (,000)	5386	3.0631	2.5500	2.3261	0.0831	10.6320
RESTRUC_DUMMY	5386	0.3624	0.0000	0.4807	0.0000	1.0000
LOAN_DUR	5386	46.6310	48.0000	13.0861	3.0000	60.0000

Note: Table 1 reports descriptive statistics for continuous and binary variables included in the regression analysis. The variable descriptions are provided in Appendix A.

Table 2
Descriptive statistics for borrower demographic characteristics.

Variables	N	%
Panel A: GENDER		
Male	3,581,050	66.48
Female	1,486,887	27.60
Other	318,991	5.92
Total	*5386,928*	*100*
Panel B: EMP_DUR		
Trial period	15,597	0.29
Up to 1 year	951,367	17.66
Up to 2 years	118,222	2.19
Up to 3 years	104,802	1.95
Up to 4 years	69,021	1.28
Up to 5 years	1,384,480	25.70
More than 5 years	2,136,681	39.67
Retiree	356,635	6.62
Other	249,248	4.63
Total	*5386,053*	*100*
Panel C: RATING		
A	292,102	5.42
AA	242,747	4.51
B	688,650	12.78
C	997,536	18.52
D	1,044,084	19.38
E	1,136,671	21.10
F	747,207	13.87
HR	237,789	4.41
Total	*5386,786*	*100*
Panel D: PREMIUM		
Discount	3,048,597	56.59
Par	1,288,127	23.91
Premium	1,050,204	19.50
Total	*5386,786*	*100*

Note: Table 2 reports descriptive statistics for discrete/ordinal variables included in the regression analysis. The variable descriptions are provided in Appendix A of the main paper.

overdue days (OVERDUE_DAYS) before and during the pandemic. The mean value of SUCC_LIST_DUMMY considerably increased from 0.6881 to 0.8555 during the pandemic period. The standard deviation of SUCC_LIST_DUMMY decreased from 0.4632 to 0.3516 during the pandemic period compared with the pre-pandemic period. The two-sample *t*-test yielded a significant value of chi-square statistic as reported in Table 3. This finding indicates significant differences between the pre- and post-pandemic values of listing outcomes.

The probability of listed loans being overdue (OVERDUE_DUMMY) decreased from 44.65% to 35.59% during the pandemic period compared with the pre-pandemic period (based on mean values). The standard deviation of OVERDUE_DUMMY decreased from 0.4971 to 0.4788 during the pandemic period compared with the pre-pandemic period. Overdue days (OVERDUE_DAYS) for listed loans also reduced during the pandemic period compared with the pre-pandemic period in terms of both mean values and standard deviation. More importantly, we observe that the probability of selling the loan stake in the secondary market for premium reduced from 0.2373 (pre-pandemic) to 0.1641 (post-pandemic). The two-sample *t*-test yielded significant values of chi-square statistics. These values indicate significant differences between the pre- and post-pandemic risk appetite of investors. We observe that investors also withdrew from their investments in less risky loans after the pandemic.

We report a correlation matrix in Appendix B (Table B1) for the variables employed in the regression analysis. Most of the variables have a low level of statistically significant correlation with one another, as reflected in the low levels of correlation coefficients. High correlation coefficients are observed between variables that are not used in the same model. For example, the correlation coefficient between DAILY_CASES and DAILY_DEATHS is 0.8920, indicating a strong positive correlation. However, we use these two variables as different proxies of the same indicator. The only concerning correlation observed in Table B1 is between INTEREST and RATING. The high correlation between these variables is predictable because lower-rated loans are assigned with higher interest rates. This study does not use RATING as an independent variable in regression analysis. Instead, we use RATING to draw subsamples of the dataset for regression estimations reported in Table 6 later (Section 3.4). The next section discusses the results that empirically estimate the listing outcomes and further explain the changes in investor sentiment over the pandemic period.

3.2. *Results of baseline regression analyses*

Table 4 provides the results of the regression models based on Eqs. (1)–(4) with four respective dependent variables. The goodness of fit for Model (1) of Panel A is 0.0663, represented by the pseudo-R-squared value. Models (2) and (3) of Panel A yield goodness of fit of around 0.0426 and 0.0366, respectively. The likelihood ratio chi-square values are significant, indicating that at least one of the predictors' regression coefficients is not equal to 0. The table reveals a significant impact of COVID-19 pandemic-related risk on the outcome of listings. All three proxies of the pandemic risk (PANDEMIC_DUMMY, DAILY_CASES and DAILY_DEATHS) generate significant positive coefficients that are consistent across Models (1), (2) and (3) of Panel A. Specifically, the increase in COVID-19 cases tends to significantly increase the likelihood of successful listing. The numbers of COVID-19-related deaths tend to have a greater impact on the likelihood of successful listing with a higher magnitude of coefficient (0.0302).

We re-estimate OVERDUE_DUMMY based on Eq. (2), and the results are reported in Panel B of Table 4. According to Model (1) of Table 4 Panel B, the probability of the listed loan being overdue decreased during the pandemic period compared with the pre-pandemic period. Models (2) and (3) of Table 4 Panel B indicate that an increase in the number of daily reported COVID-19 cases and deaths decreases the probability of overdue loans being listed in the secondary market. This finding indicates that investors withdrew from their stakes in less risky loans during the pandemic.

We further support our findings related to overdue loans with the separate regression estimation of OVERDUE_DAYS as a dependent variable. The results of tobit regression with OVERDUE_DAYS as the dependent variable are reported in Panel C of Table 4. The results reported in Models (1)–(3) of Table 4 Panel C are consistent with the findings in Panel B. All three coefficients for pandemic variables are negative and significant, indicating the changed risk sentiment of investors during the pandemic. Investors fled the market chasing cash or low-risk markets. In doing so, they also departed from their stakes in relatively low-risk P2P loans.

Panel D of Table 4 reflects investors' decisions on the pricing of loans in the secondary market. As per Eq. (4), we split successful listing into three categories: loan stakes sold at a discount, par and premium. The coefficients for all three variables of COVID-19 pandemic risk are negative. This indicates that the COVID-19 pandemic risk significantly reduces the probability of 'cashing out' a loan stake for a premium. This finding shows the cost of liquidation for investors in the P2P lending market during the COVID-19 pandemic.

3.3. *Robustness tests*

Our sample for the analysis comprises of heterogeneously distributed observations across countries with overrepresentation of loans issued for borrowers in Estonia. The database also contains disproportionate amounts of observations for the pre- and post-pandemic periods. Another concern is that our sample includes both existing and new loans issued after January 2020. The pandemic may have affected the loan origination in the first place, while the results between the pandemic risk and liquidity could be driven by the difference in loan selection of the platform before and after January 2020. These features of the database potentially create complications related to sample selection bias, high dimensionality and multicollinearity.

To address these issues, we employ several procedures with robustness tests. Firstly, we run regressions with bootstrap samples that are drawn through stratified random sampling based on the country of loan origination and each month of 2020. This method reduces the sampling bias and warrants that our estimates are not affected by the under-weighting or over-weighting of a certain group of observations (Chernick and LaBudde, 2014; Tibshirani and Efron, 1993).

Secondly, we run robustness tests based on Heckman correction sampling method. Under the Heckman selection model (Heckman, 1979; Van de Ven and Van Praag, 1981), we complement the binary regression model with a selection equation based on COVID-19 cases and loan status (e.g. default or late loan). These tests are consistent with prior evidence in that the reporting of COVID-19 is

Table 3
Dependent variables before and after the pandemic.

Variable	N	Mean	Standard deviation	Chi-square statistic	
SUCC_LIST_DUMMY					
Pre-pandemic	2,269,693	0.6881	0.4632	−0.167***	(−456.90)
Post-pandemic	3,117,235	0.8555	0.3516		
OVEDRUE_DUMMY					
Pre-pandemic	2,269,693	0.4465	0.4971	0.0906***	(212.18)
Post-pandemic	3,117,235	0.3559	0.4788		
OVERDUE_DAYS					
Pre-pandemic	2,269,693	172.2157	336.2319	43.08***	(161.46)
Post-pandemic	3,117,235	129.1348	281.5404		
PREMIUM (DUMMY)					
Pre-pandemic	2,269,693	0.2373	0.4254	0.0732***	(212.58)
Post-pandemic	3,117,235	0.1641	0.3704		

Note: Table 3 reports the descriptive statistics for the listing outcome (SUCC_LIST_DUMMY), loan status (OVERDUE_DUMMY), loan overdue days (OVERDUE_DAYS) and premium paid (PREMIUM) in the pre- and post-pandemic period. Chi-square statistics are reported with t statistics in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). In this table, PREMIUM takes the value of 1 the loan stake is sold for a premium and 0 otherwise.

related to the country's management of the pandemic (Kobilov et al., 2021). We estimate the selection equation with reported COVID-19 tests and the COVID-19 Stringency Index (Hale et al., 2021). We also apply Heckman selection model to adjust for loan selection bias.

Thirdly, we implement the type of machine learning process, known as the least absolute shrinkage and selection operator (LASSO). This method provides a more robust analysis that allows us to find the important variables in a large set of potential determinants (Tibshirani, 1996; Belloni et al., 2014). It shrinks regression coefficients by penalising their magnitude and provides a narrow set of important variables, making the results easier to interpret and resolving the problem of multicollinearity (Meinshausen and Yu, 2009). The modified version of the LASSO model for inference (double-selection LASSO method) uses selected control variables in the inference model to estimate effects for variables of interest (Belloni et al., 2014).

Finally, we run the regression models with the sample that excludes the new loans issued during 2020 and with individual identifiers for each day. The results of the robustness tests are provided in Table 5. We observe that most of the COVID-19 risk variables reported in Table 5 are similar in terms of the coefficient signs to the baseline regression models reported in Table 4. Therefore, we can conclude that the selection of variables is well justified and does not significantly affect the impact of COVID-19 risk on the listing characteristics. Moreover, the detected impact of the COVID-19 pandemic on the outcome of listings is almost not affected by the selection mechanism used to construct our sample.

However, there are some exceptions in modified models of Panel E for OVERDUE_DAYS. We speculate that this discrepancy is the result of several government interventions during the period under consideration. Thus, the lending platforms continued serving late loans, adding to the reported late days. We also analyse the regression models based on four dependent variables for each country under consideration. The findings of country panels are provided and discussed as part of the Internet Appendix.

3.4. Additional analysis

We further estimate the regression using Eqs. (1)–(4) with four dependent variables on different subsamples of the database. We highlight that the loan quality significantly increased during the pandemic because of the government actions and the active role of the platform in managing the loans. For instance, the platform restricted Spain's loan requests as these are usually of lower quality and riskier. Governments likewise intervened with relief packages, effectively bailing out borrowers and adding an extra layer of safety for investors. Some can argue that the decreased overdue loan and average overdue days are mechanically caused by the decreased low-quality loans, which might not be relevant to liquidity risk.

To mitigate this potential shortcoming, we run regression estimations based on loan ratings of secondary market listings. We divide our database into three groups based on loan ratings and report the findings in Table 6. The results are generally consistent with the findings of baseline regressions. The probability of successful listing increased regardless of the loan rating as the severity of the pandemic increased. This outcome is observed in positive coefficients for pandemic proxies across Models (1)–(3) in Table 6. Thus, regardless of the loan quality, the likelihood of success increases with an increase in COVID-19 pandemic risk for the whole loan portfolio traded in BSM.

However, we observe inconsistent coefficients for Models (7)–(8) in Panel C (Table 6) that cover the loans with low ratings ('F' and 'HR' rated loans). We speculate that this is because of the platform's active role in reducing the low rated loans. However, further investigation of this issue requires a separate analysis of the loan book of Bondora and the consideration of both credit risk and liquidity risk. We leave this aspect of the study for future research as highlighted later in this paper.

Table 7 reports the results of the regression estimations based on two separate periods of the pandemic. The results of Models (1) and (2) in Table 7 reveal important implications regarding the impact of independent variables on the probability of successful listing at different stages of the pandemic. We observe that from February to April 2020, daily reported COVID-19 cases and deaths had a positive impact on the probability of successful listing. In May and June 2020, an increase in the daily reported cases and deaths decreased the probability of successful listing.

Table 4
COVID-19 risk and the listing characteristics.

Panel A: COVID-19 risk and the likelihood of successful listing			
Variables	DV=SUCC_LIST_DUMMY		
	(1)	(2)	(3)
PANDEMIC_DUMMY	0.5341***		
	(0.0013)		
DAILY_CASES		0.0051***	
		(0.0000)	
DAILY_DEATHS			0.0302***
			(0.0004)
Constant and controls	Yes	Yes	Yes
LR chi2	353,982.5696	49,086.8094	42,198.8485
Prob > chi2	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0663	0.0426	0.0366
N	5386,928	5386,928	5386,928
Panel B: COVID-19 risk and the likelihood of late payments in the loan listings			
Variables	**DV=OVERDUE_DUMMY**		
PANDEMIC_DUMMY	−0.0289***		
	(0.0015)		
DAILY_CASES		−0.0017***	
		(0.0000)	
DAILY_DEATHS			−0.0123***
			(0.0003)
Constant and controls	Yes	Yes	Yes
LR chi2	957,831.0377	961,068.4248	958,039.1806
Prob > chi2	0.0000	0.0000	0.0000
Pseudo-R-squared	0.1805	0.1811	0.1807
N	4,228,766	4,228,766	4,228,766
Panel C: COVID-19 risk and the loan overdue days for listed loans			
Variables	**DV=OVERDUE_DAYS**		
PANDEMIC_DUMMY	−0.3230***		
	(0.0101)		
DAILY_CASES		−0.0131***	
		(0.0013)	
DAILY_DEATHS			−0.0025***
			(0.0001)
Constant and controls	Yes	Yes	Yes
LR chi2	1,361,913.6284	1,351,254.0960	1,352,871.6543
Prob > chi2	0.0000	0.0000	0.0000
Pseudo-R-squared	0.1193	0.1184	0.1185
N	4,228,766	4,228,766	4,228,766
Panel D: COVID-19 risk and the premium for listed loans			
Variables	**DV=PREMIUM**		
PANDEMIC_DUMMY	−0.3261***		
	(0.0013)		
DAILY_CASES		−0.0022***	
		(0.0000)	
DAILY_DEATHS			−0.0141***
			(0.0003)
Constant and controls	Yes	Yes	Yes
LR chi2	254,717.9974	197,764.8427	175,242.0362
Prob > chi2	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0361	0.0368	0.0326
N	4,228,766	4,228,766	4,228,766

Note: Table 4 presents the results of probit and tobit regression analysis for the listing characteristics. Panel A reports the probit regression for COVID-19 pandemic risk for the likelihood of successful listings (SUCC_LIST_DUMMY). Panel B reports probit regression analysis for the likelihood of late payments (OVERDUE_DUMMY) among the listed loans. Panel C reports tobit regression analysis for the loan overdue days (OVERDUE_DAYS) for listed loans. Panel D reports ordered probit regression analysis for the premiums of listed loans (PREMIUM) for listed loans. Number of listings analysed: 5386,928. Failed: 1,158,162 (21.50%). Successful: 4,228,766 (78.50%). Number of unique loans: 114,873. Refer to Appendix A for the description of variables. All model specifications employ robust standard errors in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). Full regression results are available in the Internet Appendix.

The results for OVERDUE_DUMMY and OVERDUE_DAYS are inconsistent across Panels A and B in Table 7 when compared with the findings of the baseline regression. We can explain these inconsistencies with the varying impact of the pandemic on investor sentiment and borrower distress at different stages of the pandemic. In Models (7) and (8), which are based on PREMIUM as a dependent variable, we observe the different impacts of DAILY_CASES and DAILY_DEATHS at different stages of the pandemic. In the early stage of the pandemic (Panel A Table 7), COVID-19 pandemic risk decreased the premiums earned by investors for listed loans. In the later stage of

Table 5
COVID-19 risk and P2P market liquidity: Robustness tests.

Variables	DV=SUCC_LIST_DUMMY			DV=OVERDUE_DUMMY			DV=OVERDUE_DAYS			DV=PREMIUM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Bootstrap sampling												
PANDEMIC_	0.5424***			−0.1507***			−0.1987***			−0.3879***		
DUMMY	(0.0011)			(0.0006)			(0.0025)			(0.0005)		
DAILY_CASES		0.0111***			−0.0033***			−0.0118***			−0.0040***	
		(0.0000)			(0.0000)			(0.0000)			(0.0000)	
DAILY_DEATHS			0.0598***			−0.0282***			−0.0920***			−0.0184***
			(0.0002)			(0.0001)			(0.0008)			(0.0003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.0609	0.0493	0.0330	0.1734	0.1735	0.1726	0.1016	0.1023	0.1019	0.0224	0.0121	0.0099
N	5179,454	5,178,642	5,178,642	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766
Panel B: Heckman correction for COVID-19 reporting bias												
PANDEMIC_	0.4854***			−0.0955***			−0.3244***			−0.2978***		
DUMMY	(0.0024)			(0.0014)			(0.0057)			(0.0018)		
DAILY_CASES		0.0029***			−0.0009***			−0.0081***			−0.0010***	
		(0.0000)			(0.0000)			(0.0001)			(0.0000)	
DAILY_DEATHS			0.0032***			−0.0045***			−0.0230***			−0.0029***
			(0.0003)			(0.0003)			(0.0016)			(0.0002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,310,362	5,309,590	5,309,590	3,154,608	3,154,608	3,154,608	3,154,608	3,154,608	3,154,608	3,154,608	3,154,608	3,154,608
Panel C: Heckman correction for loan selection bias												
PANDEMIC_	0.2472***			−0.0003			−0.0078***			−0.1786***		
DUMMY	(0.0006)			(0.0007)			(0.0004)			(0.0007)		
DAILY_CASES		0.0031***			−0.0006***			−0.0024***			−0.0017***	
		(0.0000)			(0.0000)			(0.0001)			(0.0000)	
DAILY_DEATHS			0.0222***			−0.0049***			−0.0143***			−0.0084***
			(0.0001)			(0.0002)			(0.0012)			(0.0002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,310,362	5,309,590	5,309,590	3,248,491	3,248,491	3,248,491	3,248,491	3,248,491	3,248,491	3,248,491	3,248,491	3,248,491

COVID-19 and the likelihood of successful listing: Robustness tests

Variables	DV = SUCC_LIST_DUMMY			DV=OVERDUE_DUMMY			DV=OVERDUE_DAYS			DV=PREMIUM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)			
Panel D: Lasso inference models for model selection												
PANDEMIC_	0.9328***			−0.0503**			−0.5772***			−0.3684***		
DUMMY	(0.0000)			(0.0391)			(0.0156)			0.0032		
DAILY_CASES		0.0225***			−0.0014**			−0.0081***			−0.0112***	
		(0.0009)			(0.0008)			(0.0026)			0.0002	
DAILY_DEATHS			0.1173***			−0.0533***			−0. 0341***			−0.0419***
			(0.0045)			(0.0041)			(0.0023)			0.0012
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.0433	0.0473	0.0207	0.1135	0.1190	0.1162	0.0847	0.0849	0.0841			
N	5386,928	5386,928	5386,928	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766
Panel E: Excluding loans issued in 2020												
PANDEMIC_	0.5942***			−0.0943***			0.4115***			−0.1864***		

(*continued on next page*)

Table 5 (*continued*)

COVID-19 and the likelihood of successful listing: Robustness tests

Variables	DV = SUCC_LIST_DUMMY			DV=OVERDUE_DUMMY			DV=OVERDUE_DAYS			DV=PREMIUM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)			
DUMMY	(0.0014)			(0.0024)			(0.0066)			(0.0015)		
DAILY_CASES		0.0070***			−0.0010***			−0.0015***			−0.0025***	
		(0.0000)			(0.0000)			(0.0001)			(0.0000)	
DAILY_DEATHS			0.0334***			−0.0040***			0.0117***			−0.0118***
			(0.0004)			(0.0004)			(0.0015)			(0.0003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.0582	0.0268	0.0198	0.1772	0.1771	0.1783	0.0953	0.0950	0.0954	0.0251	0.0234	0.0225
N	4,292,286	4,292,286	4,292,286	3,275,510	3,275,510	3,275,510	3,275,510	3,275,510	3,275,510	3,275,510	3,275,510	3,275,510
Panel F: With date dummies												
PANDEMIC_	0.7246***			−0.0737***			−0.3627***			−0.2894***		
DUMMY	(0.0022)			(0.0023)			(0.0104)			(0.0021)		
DAILY_CASES		0.0044***			−0.0011***			−0.0049***			−0.0020***	
		(0.0000)			(0.0000)			(0.0001)			(0.0000)	
DAILY_DEATHS			0.0128***			−0.0037***			−0.0168***			−0.0059***
			(0.0003)			(0.0003)			(0.0015)			(0.0003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date (daily) dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.0630	0.0450	0.0420	0.1792	0.1793	0.1805	0.0953	0.1198	0.1202	0.0365	0.0345	0.0339
N	5386,928	5386,928	5386,928	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766	4,228,766

Note: Table 5 presents the results of robustness checks for sample selection based on six panels. Panel A reports the results after the application of bootstrap sampling with stratified sampling based on country, loan ID and each month of 2020. Panel B reports the results after the application of the Heckman selection model, where the selection in the sample is instrumentalised with COVID-19 cases as a function of COVID-19 tests and the COVID-19 stringency index. Panel C reports the results after the application of the Heckman selection model, where the selection in the sample is instrumentalised with loan amount and rating. Panel D provides the results for double selection lasso logistic regression. Panel E uses the sample that excludes observations for loans issued in 2020. Panel F controls for date (daily) dummies. Results are for probit regression analysis for the listing outcome (SUCC_LIST_DUMMY) and loan status (OVERDUE _DUMMY) of listed loans. Results for the loan overdue days (OVERDUE_DAYS) of listed loans are estimated with tobit regression method. Results for the premium earned on listed loans (PREMIUM) are estimated with the ordered probit regression method. All model specifications employ robust standard errors in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 6
COVID-19 and the likelihood of successful listing: borrower rating.

Variables	DV = SUCC_LIST_DUMMY			DV=OVERDUE_DUMMY			DV=OVERDUE_DAYS			DV=PREMIUM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Loans rated 'AA', 'A' & 'B'												
PANDEMIC_ DUMMY	0.4681***			−0.1854***			−0.6487***			−0.2822***		
	(0.0028)			(0.0028)			(0.0156)			(0.0024)		
DAILY_CASES		0.1537***			−0.0506***			−0.2177***			−0.0031***	
		(0.0009)			(0.0008)			(0.0046)			(0.0001)	
DAILY_DEATHS			0.2480***			−0.0533***			−0.2469***			−0.0211***
			(0.0045)			(0.0041)			(0.0223)			(0.0007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LR chi2	48,182.98	52,617.04	22,998.20	145,418.71	152,556.56	148,889.24	221,657.47	222,171.17	220,065.07	53,576.74	15,018.80	13,561.89
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0433	0.0473	0.0207	0.1135	0.1190	0.1162	0.0847	0.0849	0.0841	0.0271	0.0123	0.0111
N	1,170,046	1,170,046	1,170,046	1,083,536	1,083,536	1,083,536	1,083,536	1,083,536	1,083,536	1,083,536	1,083,536	1,083,536
Panel B: Loans rated 'C', 'D' & 'E'												
PANDEMIC_ DUMMY	0.4767***			−0.1549***			−0.2072***			−0.3813***		
	(0.0017)			(0.0016)			(0.0074)			(0.0014)		
DAILY_CASES		0.1353***			−0.0432***			−0.1033***			−0.0037***	
		(0.0005)			(0.0004)			(0.0020)			(0.0000)	
DAILY_DEATHS			0.1187***			−0.0571***			−0.1797***			−0.0168***
			(0.0013)			(0.0010)			(0.0050)			(0.0004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LR chi2	184,471.35	189,288.80	112,472.42	463,644.69	476,171.50	468,719.26	741,424.09	743,352.11	741,969.98	167,425.46	65,904.94	56,193.22
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0586	0.0601	0.0357	0.1166	0.1198	0.1179	0.0842	0.0844	0.0842	0.0291	0.0146	0.0124
N	3,040,825	3,040,825	3,040,825	2,941,112	2,941,112	2,941,112	2,941,112	2,941,112	2,941,112	2,941,112	2,941,112	2,941,112
Panel C: Loans rated 'F' & 'HR'												
PANDEMIC_ DUMMY	0.8039***			−0.1348***			0.0780***			−0.3703***		
	(0.0030)			(0.0029)			(0.0069)			(0.0027)		
DAILY_CASES		0.1150***			−0.0237***			0.0078***			−0.0058***	
		(0.0005)			(0.0005)			(0.0012)			(0.0001)	
DAILY_DEATHS			0.1488***			−0.0421***			−0.0339***			−0.0308***
			(0.0008)			(0.0007)			(0.0018)			(0.0007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LR chi2	99,907.01	75,348.40	58,142.57	196,761.34	196,884.42	197,908.40	440,971.65	440,885.91	441,185.09	83,403.90	50,687.03	44,991.61
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0933	0.0703	0.0543	0.1653	0.1654	0.1663	0.1046	0.1046	0.1047	0.0515	0.0336	0.0298
N	967,771	967,771	967,771	921,995	921,995	921,995	921,995	921,995	921,995	921,995	921,995	921,995

Note: Table 6 presents the results of regression analyses for panels of the dataset based on borrower rating. Results are for probit regression analysis for the listing outcome (SUCC_LIST_DUMMY) and loan status (OVERDUE _DUMMY) of listed loans. Results for the loan overdue days (OVERDUE_DAYS) of listed loans are estimated with tobit regression method. Results for the premium earned on listed loans (PREMIUM) are estimated with ordered probit regression method. All model specifications employ robust standard errors in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 7
COVID-19 risk and P2P market liquidity: Subsamples of pandemic periods.

Variables	DV = SUCC_LIST_DUMMY		DV=OVERDUE_DUMMY		DV=OVERDUE_DAYS		DV=PREMIUM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: February to April listings								
DAILY_CASES	0.0113***		−0.0016***		−0.0005***		−0.0039***	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
DAILY_DEATHS		0.0634***		−0.0109***		0.0010*		−0.0230***
		(0.0004)		(0.0003)		(0.0005)		(0.0003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes		
LR chi2	251,876.98	165,724.31	806,573.19	811,561.98	1,344,840.97	1,352,403.56	182,227.94	168,635.42
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0543	0.0357	0.1774	0.1785	0.0821	0.0825	0.0301	0.0278
N	3,449,514	3,449,514	3,449,514	3,449,514	3,449,514	3,449,514	3,449,514	3,449,514
Panel B: May – June listings								
DAILY_CASES	−0.0031***		−0.0065***		−0.0132***		0.0169***	
	(0.0003)		(0.0003)		(0.0004)		(0.0002)	
DAILY_DEATHS		−0.0328***		−0.0717***		−0.1729***		0.1110***
		(0.0019)		(0.0018)		(0.0028)		(0.0014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LR chi2	28,849.56	29,025.26	163,615.96	164,631.59	225,092.91	228,162.65	53,640.24	53,516.35
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0411	0.0414	0.2155	0.2178	0.0791	0.0805	0.0536	0.0535
N	729,940	729,940	729,940	729,940	729,940	729,940	729,940	729,940

Note: Table 7 presents the results of regression analyses using two panels based on pandemic periods. Panel A reports the results based on listings listed in the early period of the pandemic (February–April 2020). Panel B reports the results based on listings listed in the later period of the pandemic (May–June 2020). Results are for probit regression analysis for the listing outcome (SUCC_LIST_DUMMY) and loan status (OVERDUE _DUMMY) of listed loans. Results for the loan overdue days (OVERDUE_DAYS) of listed loans are estimated with tobit regression method. Results for the premium earned on listed loans (PREMIUM) are estimated with ordered probit regression method. All model specifications employ robust standard errors in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

the pandemic (Panel B Table 7), premiums earned for listed loans recovered with a positive impact of both reported daily cases and deaths on premiums. In this regard, we stipulate that by June, investor risk sentiments had adjusted to the new environment. By this time, investors started to hold on to their investments in P2P loans by only listing their high-risk loans in the secondary market and reducing the price paid for liquidation of their loan stakes.

The last empirical technique of this study involves regressions with four different alternative measures of liquidity. The first is the survival analysis, which facilitates estimating not only whether the event occurs but also when it occurs. In the survival analysis based on Eq. (1), the dependent variable is the time until the occurrence of an event of interest (unsuccessful listing). Secondly, we estimate the liquidity of the market using the amount invested in each bid (INVEST_AMNT) and the percentage of the bid invested by each investor (PERC_INVEST). According to the network-based statistical models (Ahelegbey et al., 2019; Giudici et al., 2020), these two variables indicate the risk preference behaviour of investors. Larger values indicate that the lender follows a herding behaviour because of the preference for a well-funded listing (Zhang and Liu, 2012). Finally, following our survival analysis, we estimate the liquidity using the time between the posting of the investment and the actual bid (TIME_INVEST). This variable highlights the confidence level of investors through better connections, richer knowledge of the market and investment experience (Chen et al., 2022).

Table 8 provides the results of regression analysis using four alternative variables, which reveal significant practical findings. Panel A of Table 8 indicates a lower risk of failed listings for the period after the declaration of the pandemic.[3] Moreover, each percentage increase in the number of reported daily COVID-19 cases reduces the risk, 'ceteris paribus' [Model (2) Panel A, Table 8]. We also observe that the amount invested into each listing is significantly lower during the pandemic than during the pre-pandemic period (Panels B and C, Table 8). At the same time, waiting time for the listings decreases with an increase in COVID-19 risk (Panel D, Table 8).

4. Discussion and conclusion

Empirical analyses of our study indicate that the probability of successfully listing a loan stake increased during the pandemic period. However, this outcome was accompanied by a significant change in the risk profile of liquidated loans and costs for investors associated with liquidation. This result largely falls in line with the mixed evidence reported in latest studies on the impact of COVID-19 pandemic risk on financial markets (Baig et al., 2020; Chebbi et al., 2021). We can explain this tendency with the fact that the impact of the pandemic on the financial sector and the P2P lending market has not been fully realised during the early stages of the pandemic. This also explains why withdrawals dropped by April 2020 without a significant impact on borrower insolvency.

Our findings related to overdue loans indicate that the share of overdue loans and average overdue days of loan listing decreased as COVID-19 risk increased. Unlike under normal economic conditions, investors abandoned their investments in P2P loans regardless of

[3] The Internet Appendix provides further detailed description of the survival analysis.

Table 8
COVID-19 risk and P2P market liquidity with alternative variables.

Panel A: COVID-19 risk and the survival time of the listing						
Variables	DV = TIME_TO_FAIL		DV = TIME_TO_FAIL		DV = TIME_TO_FAIL	
	(1)		(2)		(3)	
	Parameter estimate	Hazard ratio	Parameter estimate	Hazard ratio	Parameter estimate	Hazard ratio
PANDEMIC_DUMMY	−1.9793***	0.1382***				
	(0.0072)	(0.0010)				
DAILY_CASES			−0.3778***	0.6854***		
			(0.0011)	(0.0008)		
DAILY_DEATHS					−0.2873***	0.7503***
					(0.0019)	(0.0015)
Controls	Yes		Yes		Yes	
Constant	Yes		Yes		Yes	
LR chi2	248,201.1066		271,000.4306		164,087.4244	
Prob > chi2	0.0000		0.0000		0.0000	
Pseudo-R-squared	0.0300		0.0328		0.0399	
N	5386,928		5386,928		5386,928	
Panel B: COVID-19 risk and the invested amount						
Variables			**DV=INVEST_AMNT**			
	(1)		**(2)**		**(3)**	
PANDEMIC_DUMMY	−0.0670***					
	(0.0009)					
DAILY_CASES			−0.0004***			
			(0.0000)			
DAILY_DEATHS					−0.0028***	
					(0.0002)	
Controls	Yes		Yes		Yes	
Constant	Yes		Yes		Yes	
R-squared	0.1269		0.1260		0.1260	
N	5386,928		5386,928		5386,928	
Panel C: COVID-19 risk and the percentage of invested bid						
Variables			**DV=PERC_INVEST**			
PANDEMIC_DUMMY	−0.0414***					
	(0.0010)					
DAILY_CASES			0.0001***			
			(0.0000)			
DAILY_DEATHS					0.0080***	
					(0.0002)	
Controls	Yes		Yes		Yes	
Constant	Yes		Yes		Yes	
R-squared	0.0865		0.0863		0.0864	
N	5386,928		5386,928		5386,928	
Panel D: COVID-19 risk and the time to investment						
Variables			**DV = TIME_INVEST**			
PANDEMIC_DUMMY	−3.9983***					
	(0.0080)					
DAILY_CASES			−0.0540***			
			(0.0002)			
DAILY_DEATHS					−0.2751***	
					(0.0019)	
Controls	Yes		Yes		Yes	
Constant	Yes		Yes		Yes	
R-squared	0.0639		0.0380		0.0230	
N	5386,928		5386,928		5386,928	

Note: Table 8 presents the results of regressions with alternative variables for P2P market liquidity. Panel A provides the results with Cox regression analysis for survival time of listings (TIME_TO_FAIL). Panel B provides the regression with the amount invested in each bid (INVEST_AMNT). Panel C provides the regression with the percentage of the bid invested by each investor (PERC_INVEST). Panel D provides the regression with the time between the posting of the investment and the bid as dependent variable (TIME_INVEST). Refer to Appendix A for the variable description. Number of listings analysed: 5386,928. Failed: 1,158,162 (21.50%). Successful: 4,228,766 (78.50%). Number of unique loans: 114,873. All model specifications employ robust standard errors in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). Full regression results for survival analysis (Panel A) are available in the Internet Appendix.

whether the loan was overdue or not. This finding falls in line with our expectations based on earlier literature (Baldwin and Mauro, 2020; IMF, 2019) and highlights the shift in investor sentiment during a pandemic. At the same time, liquidation of loans was a significant strain on investors, with COVID-19 risk significantly reducing the probability of successful selling for a premium. The liquidity risk actually behaved in a similar manner as in traditional financial markets with an increase in bid-ask spreads (Ben-Rephael, 2017; Mittal et al., 2020; Foley et al., 2021).

Another similarity with the typical behaviour in traditional financial markets was the rush to turn their stakes into cash, documented in the studies of Gonzalez (2019), Lee and Lee (2012) and Zhang and Chen (2017). Combined with government interventions, the rush to cash leads to a unique set of outcomes in BSM. The risk profile of loans changed significantly during the pandemic when investors abandoned their stakes in both high- and low-risk loans. This shift in risk appetite was reflected in the cost of liquidation reflected in premiums for loan stakes. Consequently, loan applications surpassed investments by June 2020. We argue that this tendency is equivalent to a negative liquidity spiral and a higher likelihood of withdrawal from the market reported for traditional financial markets (Brunnermeier & Pedersen, 2009; Brogaard et al., 2014; Shkilko and Sokolov, 2020).

We also observe different tendencies in investor sentiment at different stages of the pandemic. For instance, a spike in withdrawals mainly occurred during March 2020 in the Bondora P2P lending platform, but by April 2020, cash withdrawals mostly dropped to pre-crisis levels (Bondora, 2020). Throughout March and June 2020, the loan applications largely surpassed available investments. This finding is also confirmed in regression analyses on separate panels based on different stages of the pandemic. Thus, the findings of the present study represent the tendency that is specific to yield-hungry investors rather than the distress faced by borrowers. Additionally, our analysis with alternative indicators of liquidity suggests that COVID-19 risk increased risk aversion of investors, in that they reduced their stakes invested in each loan. At the same time, the lower risk of failed listings combined with shorter listing lifetime indicates the reduced herding behaviour of investors with an increased prevalence of experienced investors.

The findings of our study lead to a better understanding of the investor sentiment and the development of liquidity management tools employed by P2P platforms. During the market turmoil of 2020, P2P platforms withheld up to 50% of investor interest income as a contribution to their main tool of security against the financial hardship, namely 'provision fund' (RateSetter, 2020). As a consequence, these measures drove away yield-hungry investors in the long term even though they were effective in the short term. On the contrary, our study reveals that borrower distress was not the main issue for liquidity risk. Instead, we observe a significant increase in cost for investors during the liquidation of their loan stakes in the secondary market. In this regard, platforms can use the findings and modelling of this study to adjust the safeguard mechanisms. Elasticities of liquidity risk, reflected in coefficient parameters, might serve as a benchmark for 'provision funds', which are used under crisis conditions.

As the current pandemic moves into the later stage (probably transferring into an endemic), liquidity problems experienced by households, businesses and public sector organisations may also enter a more severe stage. Global turbulence related to supply chain disruptions, geopolitics and high inflation period may further exacerbate the problems related to borrower distress. As one of the risky sectors of financing, P2P lending may experience a wave of defaults in the coming years. This stream of defaults tends to seriously test the resilience of the industry and forces platforms to reconsider their risk management models.

Accordingly, future studies may use an extended time period throughout 2020 and beyond to analyse the risk patterns experienced during the subsequent waves of the pandemic. Hence, future studies will require a different set of conceptual framework and modelling. Specifically, with the introduction of vaccines, emergence of new COVID-19 variants and gradual shift from the pandemic to endemic, the COVID-19 proxies used in this study might prove to be irrelevant. With a shift of the emphasis from case and death numbers to vaccinations, hospitalisation rates and various 'back to normalcy' indices, future models will require more dimensions than did our study.

The focus of our study on a single P2P platform (Mintos) based in Estonia might also raise questions about scaling or extending the findings elsewhere. The unique institutional perspective of Estonia as a target jurisdiction has been highlighted in Section 1 of this paper. Thus, the findings of our study can be extended and generalised for multiple countries of Continental Europe. However, other types of FinTech lending platforms might practice different selection mechanisms or loan risk assessment methods. Therefore, future research could test whether our findings are generalisable to other types of FinTech lending or other non-bank lending markets.

P2P lending markets as part of 'shadow banking' are characterised by a high interdependence between various market players. Therefore, the analysis of both liquidity and default risks from the perspective of contagion risk should be the focus of future studies. In this regard, theoretical considerations of the full network contagion model (Avdjiev et al., 2019) or network-based credit risk models (Giudici et al., 2020) can be used for further extension of the modelling of this study. By focusing on liquidity and default risks, subsequent studies can improve current risk management models used by P2P lending platforms. P2P lending platforms, in turn, can improve their security mechanisms, such as contributions to the 'provision fund'.

CRediT authorship contribution statement

Asror Nigmonov: Conceptualization, Methodology, Data curation, Writing – original draft, Visualization, Formal analysis, Software. **Syed Shams:** Supervision, Validation, Writing – review & editing. **Khorshed Alam:** Supervision, Validation, Writing – review & editing.

Data availability

Nigmonov, Asror (2023), "Liquidity Risk in FinTech Lending", Mendeley Data, V1, doi: 10.17632/h4ndhvbdjt.1

Appendix A

Table A1
Description of variables.

Variable	Description of variable	Source
Dependent variables		
SUCC_LIST_DUMMY	Reason why the listing was sold or removed from the Bondora Secondary Market. Dummy variable equal to 1 if the listing is 'successful' and 0 otherwise (cancelled or failed).	*Bondora*
OVERDUE_DUMMY	Current status of individual loan. Dummy variable equal to 1 if the loans is overdue and 0 otherwise (current or repaid).	*Bondora*
OVERDUE_DAYS	The number of days the loan had been in debt at the date of the listing (log values).	*Bondora*
PREMIUM	Indicates whether the investor lists a loan with discount (0 base category), par (1) or premium (2).	*Bondora*
Independent variables, pandemic indicator variables		
PANDEMIC_DUMMY	Dummy variable equal to 1 for the dates later than March 11, 2020 (The date WHO declared COVID-19 a pandemic) and 0 otherwise.	*World Health Organization (2020)*
DAILY_CASES	Number of reported daily cases of COVID-19 in country *i* at time *t* (daily observations, log values).	*World Health Organization (2020), Johns Hopkins University & Medicine (2020)*
DAILY_DEATHS	Number of reported daily COVID-19 related deaths in country *i* at time *t* (daily observations, log values).	*World Health Organization (2020), Johns Hopkins University & Medicine (2020)*
Independent variables, macroeconomic and country-specific variables		
ESI	The E.U. Economic Sentiment Indicator (composite measure, average = 100, log values)	*Full business and consumer survey results, European Commission* https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en
CH_ST_MAR_IND	Change in average monthly stock market index values of country i at time t (monthly, percentage points).	Yahoo Finance, https://finance.yahoo.com/world-indices/
POPULATION	Population of country i in year 2018 (log values).	*OECD (2020), Population (indicator). doi:* https://doi.org/10.1787/d434f82b-en
Independent variables, borrower-specific variables		
RESTRUC_DUMMY	Dummy variable representing the restructuring of a loan. Equal to 1 if the original maturity date of the loan has been increased by more than 60 days, 0 otherwise.	*Bondora*
INTEREST	Maximum interest rate accepted in the loan application (%, log values).	*Bondora*
LOAN_DUR	Duration of loan (in months, log values).	*Bondora*
DTI	Debt-to-income (DTI) score of borrower (%, log values).	*Bondora*
AMOUNT	Value of individual loan (log values).	
AGE	Age of the borrower when signing the loan application.	*Bondora*
GENDER	Gender of borrower: 0-Male, 1-Woman, 2-Undefined.	*Bondora*
EMP_DUR	Employment time of borrower with the current employer: 0-Trial period, 1-Up to 1 year, 2-Up to 2 years, 3-Up to 3 years, 4-Up to 4 years, 5-Up to 5 years, 6-More than 5 years, 7-Retiree.	*Bondora*
Additional variables		
RATING	'Bondora Rating' issued by the rating model ranging between AA (1) and HR (8).	*Bondora*
TIME_TO_FAIL	Difference between the 'StartDate' and 'EndDate' of the listing if the listing is failed.	*Bondora*
INVEST_AMNT	Amount invested in each bid	*Bondora*
PERC_INVEST	Percentage of the bid invested by each investor	*Bondora*
TIME_INVEST	Time between the posting of the investment and the bid	*Bondora*

Appendix B

Table B1
Correlation matrix.

Variables	SUCC_LIST_DUMMY	OVERDUE_DUMMY	OVERDUE_DAYS	PANDEMIC_DUMMY	DAILY_CASES	DAILY_DEATHS	CH_ST_MAR_IND	ESI
SUCC_LIST_DUMMY	1.0000							
OVERDUE_DUMMY	−0.1680	1.0000						
OVERDUE_DAYS	−0.1823***	0.0497	1.0000					
PANDEMIC_DUMMY	0.2012***	0.0807	−0.0694***	1.0000				
DAILY_CASES	0.0555***	0.0612	0.0338***	0.1761***	1.0000			
DAILY_DEATHS	0.0513***	−0.0916	0.0325***	0.1529***	**0.8924*****	1.0000		
CH_ ST_MAR_IND	0.0167***	0.0612	−0.0167***	0.0189***	0.0407***	0.0110***	1.0000	
ESI	−0.0908***	0.0513	0.2827***	−0.1086***	0.1362***	0.1216***	−0.0299***	1.0000
POPULATION	−0.0162***	0.0470	0.1481***	−0.0556***	0.5530***	0.5014***	−0.0814***	0.2760***
AMOUNT	−0.0483***	−0.0275***	−0.0650***	−0.0590***	−0.0110***	−0.0064***	−0.0991***	0.2827***
AGE	0.0021***	−0.1200***	−0.0441***	0.0067***	0.0030***	0.0010*	−0.0319***	0.0821***
DTI	−0.1296***	−0.0191***	0.4274***	−0.0522***	−0.0043***	−0.0005	0.0060***	0.0547***
INTEREST	−0.0182***	−0.0201***	0.2326***	−0.0386***	0.2802***	0.2531***	−0.0796***	0.1759***
RESTRUC_DUMMY	−0.0123***	0.2510***	−0.1051***	0.0094***	−0.0624***	−0.0554***	0.0159***	0.1149***
LOAN_DUR	−0.0085***	0.0710	0.0294***	−0.0045***	0.0298***	0.0271***	−0.0064***	0.0074***
GENDER	0.0252***	0.0215	−0.0225***	−0.0079***	0.2496***	0.2271***	−0.0355***	−0.0765***
EMP_DUR	−0.0364***	0.2820	0.1517***	−0.0165***	−0.0071***	−0.0056***	0.0045***	0.0562***
RATING	−0.0474***	0.1740***	0.2205***	−0.0403***	0.2205***	0.1985***	−0.0886***	0.1543***

Variables	POPULATION	AMOUNT	AGE	DTI	INTEREST	RESTRUC_ DUMMY	LOAN_DUR	GENDER	EMP_DUR
AMOUNT	0.1481***	1.0000							
AGE	0.0191***	0.0514***	1.0000						
DTI	0.0342***	0.1919***	0.4274***	1.0000					
INTEREST	0.5834***	−0.0377***	0.2326***	0.0104***	1.0000				
RESTRUC_DUMMY	−0.1272***	0.0405***	−0.1051***	0.0708***	−0.1525***	1.0000			
LOAN_DUR	0.0553***	0.1967***	0.0294***	0.0817***	0.0600***	−0.0707***	1.0000		
GENDER	0.4421***	−0.0262***	−0.0225***	0.1088***	0.2493***	−0.0839***	0.0894***	1.0000	
EMP_DUR	−0.0015***	0.0172***	0.1517***	0.2004***	−0.0032***	0.0352***	0.0080***	−0.0023***	1.0000
RATING	0.4683***	0.0917***	0.2205***	0.0500***	**0.7682*****	−0.1159***	0.1959***	0.2154***	0.0063***

Note: Table B1 reports Pearson's correlation coefficients between the variables employed in the regression analyses of this chapter. Significant correlations are in bold. See Appendix A for variable definitions.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ememar.2023.101084.

References

Ahelegbey, D.F., Giudici, P., Hadji-Misheva, B., 2019. Latent factor models for credit scoring in P2P systems. Physica A 522, 112–121.
Atomico, 2023. State of European Tech 2022. Retrieved from: https://stateofeuropeantech.com/1.european-teach-a-new-reality.
Avdjiev, S., Giudici, P., Spelta, A., 2019. Measuring contagion risk in international banking. J. Financ. Stab. 42, 36–51.
Baig, A., Butt, H.A., Haroon, O., Rizvi, S.A.R., 2020. Deaths, Panic, Lockdowns and U.S. Equity Markets: The Case of COVID-19 Pandemic. Available at SSRN 3584947.
Baldwin, R., Mauro, B.W.D., 2020. Economics in the Time of COVID-19. Centre for Economic Policy Research, London, UK.
Belloni, A., Chernozhukov, V., Hansen, C., 2014. High-dimensional methods and inference on structural and treatment effects. J. Econ. Perspect. 28 (2), 29–50.
Bellucci, A., Borisov, A., Zazzaro, A., 2011. Do male and female loan officers differ in small business lending? A review of the literature. In: The Economics of Small Businesses. Springer, pp. 195–219.
Ben-Rephael, A., 2017. Flight-to-liquidity, market uncertainty, and the actions of mutual fund investors. J. Financ. Intermed. 31, 30–44.
Blanchflower, D.G., Levine, P.B., Zimmerman, D.J., 2003. Discrimination in the small-business credit market. Rev. Econ. Stat. 85 (4), 930–943. Retrieved from: https://doi.org/10.1162/003465303772815835.
Bloomberg, 2020. China's Peer-to-Peer Lending Purge Leaves $115 Billion in Losses. Bloomberg News. August 14, 2020. Retrieved from: https://www.bloomberg.com/amp/news/articles/2020-08-14/china-s-peer-to-peer-lending-purge-leaves-115-billion-in-losses.
Bondora, 2020. June has most verified Estonian originations of 2020. Retrieved from: https://www.bondora.com/blog/june-has-most-verified-estonian-originations-of-2020/.
Bose, S., Shams, S., Ali, M.J., Mihret, D., 2022. COVID-19 impact, sustainability performance and firm value: international evidence. Account. Finance 62 (1), 597–643.
Brogaard, J., Hendershott, T., Riordan, R., 2014. High-frequency trading and price discovery. Rev. Financ. Stud. 27, 2267–2306. https://doi.org/10.1093/rfs/hhu032.
Brunnermeier, M.K., Pedersen, L.H., 2009. Market Liquidity and Funding Liquidity. The Rev. of Fin. Stud. 22 (6), 2201–2238. https://doi.org/10.1093/rfs/hhn098.
Cai, S., Lin, X., Xu, D., Fu, X., 2016. Judging online peer-to-peer lending behavior: a comparison of first-time and repeated borrowing requests. Inf. Manag. 53 (7), 857–867. https://doi.org/10.1016/j.im.2016.07.006.
Chebbi, K., Ammer, M.A., Hameed, A., 2021. The COVID-19 pandemic and stock liquidity: evidence from S&P 500. Q. Rev. Econ. Financ. 81, 134–142. https://doi.org/10.1016/j.qref.2021.05.008.
Chen, X., Chong, Z., Giudici, P., Huang, B., 2022. Network centrality effects in peer to peer lending. Phys. A Stat. Mech. Appl. 600, 127546.
Chernick, M.R., LaBudde, R.A., 2014. An Introduction to Bootstrap Methods with Applications to R. John Wiley & Sons.
Civelek, M.E., Xiarewana, B., 2020. Effects of Covid-19 on China and the world economy: birth pains of the post-digital ecosystem. J. Int. Trade Logist. Law 6 (1), 147–157.
Cumming, D., Meoli, M., Vismara, S., 2019. Does equity crowdfunding democratise entrepreneurial finance? Small Bus. Econ. 1–20.
Dinger, V., 2009. Do foreign-owned banks affect banking system liquidity risk? J. Comp. Econ. 37 (4), 647–657.
Divissenko, N., Eenmaa, H., 2019. Fintech regulation in Estonia (December 12, 2019). In: Cian, Marco, Sandei, Claudia (Eds.), Diritto del Fintech, Wolters Kluwer Italia 2020, pp. 623–643. Available at SSRN. https://ssrn.com/abstract=3575435.
Duan, Y., Hsieh, T.-S., Wang, R.R., Wang, Z., 2020. Entrepreneurs' facial trustworthiness, gender, and crowdfunding success. Finance 64, 101693. Retrieved from. http://www.sciencedirect.com/science/article/pii/S0929119920301371.
Ellenoff, D., Adler, J., DeDenato, M., Selengut, D., 2015. Review of Crowdfunding Regulation: Interpretations of Existing Regulation Concerning Crowdfunding in Europe, North America and Israel. Eurocrowd. European Crowdfunding Network, 2014. 18 Mar. 2015.
European Banking Authority, 2020. Banks report a significant use of COVID-19 moratoria and public guarantees. European Banking Authority. Accessed from: https://www.eba.europa.eu/banks-report-significant-use-covid-19-moratoria-and-public-guarantees.
Eurostat, 2022. Gross value added and income by A*10 industry breakdowns. http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a10.
Findexable, 2022. Global Fintech Rankings Report 2021. Findexable Limited & The Global Fintech Index. Retrieved from: www.findexable.com.
Foley, S., Kwan, A., Philip, R., Ødegaard, B.A., 2021. Contagious margin calls: how COVID-19 threatened global stock market liquidity. J. Financ. Mark. https://doi.org/10.1016/j.finmar.2021.100689.
Fung, D.W.H., Lee, W.Y., Yeh, J.J.H., Yuen, F.L., 2020. Friend or foe: the divergent effects of FinTech on financial stability. Emerg. Mark. Rev. 45, 100727 https://doi.org/10.1016/j.ememar.2020.100727.
Galema, R., 2020. Credit rationing in P2P lending to SMEs: Do lender-borrower relationships matter? J. Corp. Finan. 65, 101742. Retrieved from: http://www.sciencedirect.com/science/article/pii/S0929119920301863.
Giudici, P., Hadji-Misheva, B., Spelta, A., 2020. Network based credit risk models. Qual. Eng. 32 (2), 199–211.
Gonzalez, L., 2019. Blockchain, herding and trust in peer-to-peer lending. Manag. Financ. https://doi.org/10.1108/MF-09-2018-0423 ahead-of-print(ahead-of-print). Retrieved from.
Gordon, G., Jones, J.B., 2020. Loan Delinquency Projections for COVID-19. Federal Reserve Bank of Richmond, Richmond, USA. Retrieved from. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3650562.
Gros, D., 2020. The West's COVID-19 Learning Curve. Project Syndicate. March 30, 2020. Retrieved from: https://www.project-syndicate.org/commentary/covid19-learning-curve-slow-western-responseby-daniel-gros-2020-03.
Haacker, M., 2004. The impact of HIV/AIDS on government finance and public services. In: Haacker, M. (Ed.), The Macroeconomics of HIV/AIDS. International Monetary Fund, Washington, D.C.
Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., Tatlow, H., 2021. A global panel database of pandemic policies (Oxford COVID-19 government response tracker). Nat. Hum. Behav. https://doi.org/10.1038/s41562-021-01079-8.
Heckman, J.J., 1979. Sample selection Bias as a specification error. Econometrica 47 (1), 153–161.
IMF, 2019. Global Financial Stability Report. Lower for Longer. International Monetary Fund, Washington, DC.
Invest Estonia, 2022. Estonia leads Europe in startups, unicorns and investments per capita. Retrieved from: https://investinestonia.com/estonia-leads-europe-in-startups-unicorns-and-investments-per-capita/.
Iyke, B.N., 2020. COVID-19: the reaction of US oil and gas producers to the pandemic. Energy Res. Lett. 1 (2), 13912.
Jagtiani, J., Lemieux, C., 2018. Do fintech lenders penetrate areas that are underserved by traditional banks? J. Econ. Bus. 100, 43–54. https://doi.org/10.1016/j.jeconbus.2018.03.001.
Kargar, M., Lester, B., Lindsay, D., Liu, S., Weill, P.-O., Zúñiga, D., 2020. Corporate Bond Liquidity During the COVID-19 Crisis. National Bureau of Economic Research Working Paper Series, No. 27355.
Khrawish, H.A., Siam, W.Z., Jaradat, M., 2010. The relationships between stock market capitalisation rate and interest rate: Evidence from Jordan. In: Business and Economic Horizons (BEH), 2(1232-2016-101136), pp. 60–66.

Kobilov, B., Rouen, E., Serafeim, G., 2021. Predictable country-level bias in the reporting of COVID-19 deaths. J. Govern. Econ. 2, 100012 https://doi.org/10.1016/j.jge.2021.100012.
Lagoarde-Segot, T., Leoni, P.L., 2013. Pandemics of the poor and banking stability. J. Bank. Financ. 37 (11), 4574–4583.
Laidroo, L., Tamre, A., Kukk, M.-L., Tasa, E., Avarmaa, M., 2021. Fintech Report Estonia 2021. Finance Estonia & Tal Tech School of Business and Finance. Retrieved from. http://www.financeestonia.eu/wp-content/uploads/2021/06/FinTech-report-2021-final.pdf.
Lee, E., Lee, B., 2012. Herding behavior in online P2P lending: an empirical investigation. Electron. Commer. Res. Appl. 11 (5), 495–503. https://doi.org/10.1016/j.elerap.2012.02.001.
Leoni, P.L., 2013. HIV/AIDS and banking stability in developing countries. Bull. Econ. Res. 65 (3), 225–237.
Li, J., Hsu, S., Chen, Z., Chen, Y., 2016. Risks of P2P lending platforms in China: modeling failure using a Cox Hazard model. Chin. Econ. 49 (3), 161–172.
Meinshausen, N., Yu, B., 2009. Lasso-type recovery of sparse representations for high-dimensional data. Ann. Stat. 37 (1), 246–270.
Menkhoff, L., Neuberger, D., Rungruxsirivorn, O., 2012. Collateral and its substitutes in emerging markets' lending. J. Bank. Financ. 36 (3), 817–834. Retrieved from. http://www.sciencedirect.com/science/article/pii/S0378426611002640.
Milne, A., Parboteeah, P., 2016. The Business Models and Economics of Peer-to-Peer Lending (17). Brussels, Belgium. Retrieved from. https://ssrn.com/abstract=2763682.
Mittal, H., Saraiya, N., & Berkow, K., (2020, April 08). US Equity Liquidity in the Covid-19 Crisis. Retrieved from: https://www.marketsmedia.com/u-s-equity-liquidity-in-the-covid-19-crisis.
Mollick, E., 2014. The dynamics of crowdfunding: an exploratory study. J. Bus. Ventur. 29 (1), 1–16. Retrieved from. https://doi.org/10.1016/j.jbusvent.2013.06.005.
Nigmonov, A., Shams, S., 2021. COVID-19 pandemic risk and probability of loan default: evidence from marketplace lending market. Financ. Innov. 7 (1), 83. https://doi.org/10.1186/s40854-021-00300-x.
Nigmonov, A., Shams, S., Alam, K., 2022. Macroeconomic determinants of loan defaults: evidence from the U.S. peer-to-peer lending market. Res. Int. Bus. Financ. 59, 101516 https://doi.org/10.1016/j.ribaf.2021.101516.
Okorie, D.I., Lin, B., 2021. Stock markets and the COVID-19 fractal contagion effects. Financ. Res. Lett. 38, 101640 https://doi.org/10.1016/j.frl.2020.101640.
RateSetter, 2020. RateSetter increases provision and temporarily reduces interest rates. Retrieved from: https://www.ratesetter.com/blog/sp_announcement.
Santaeulalia-Llopis, R., 2008. Aggregate Effects of AIDS on Development. Washington University in St. Louis. Unpublished Manuscript.
Serrano-Cinca, C., Gutierrez-Nieto, B., Lopez-Palacios, L., 2015. Determinants of default in P2P lending. PLoS One 10 (10), e0139427. Retrieved from. https://www.ncbi.nlm.nih.gov/pubmed/26425854.
Shkilko, A., Sokolov, K., 2020. Every cloud has a silver lining: fast trading, microwave connectivity, and trading costs. J. Financ. 75, 2899–2927. https://doi.org/10.1111/jofi. 12969.
Skoufias, E., 2003. Economic crises and natural disasters: coping strategies and policy implications. World Dev. 31 (7), 1087–1102.
Steijvers, T., Voordeckers, W., 2009. Collateral and credit rationing: a review of recent empirical studies as a guide for future research. J. Econ. Surv. 23 (5), 924–946. Retrieved from. https://doi.org/10.1111/j.1467-6419.2009.00587.x.
Tanda, A., 2019. FinTech, BigTech and Banks: Digitalisation and its Impact on Banking Business Models (1st ed. 2019. ed.). Springer International Publishing, Cham.
Thakor, A.V., 2020. Fintech and banking: what do we know? J. Financ. Intermed. 41, 100833 https://doi.org/10.1016/j.jfi.2019.100833.
Tibshirani, R., 1996. Regression shrinkage and selection via the lasso. J. Royal Stat. Soc. Ser B: Stat. Methodol. 58 (1), 267–288.
Tibshirani, R.J., Efron, B., 1993. An introduction to the bootstrap. Monographs on statistics and applied probability, 57, pp. 1–436.
Tomberg, P., 2020a. Ask me Anything with Bondora CEO. Ask Me Anything session, Bondora. April 29, 2020.
Tomberg, P., 2020b. Live Q&A with Pärtel Tomberg, CEO of Bondora/Interviewer: M. Clannachan. Bondora. April 8, 2020.
Valla, N., Saes-Escorbiac, B., 2006. Bank Liquidity and Financial Stability. Banque de France, Direction de la communication, pp. 89–104.
Van de Ven, W.P.M.M., Van Praag, B.M.S., 1981. The demand for deductibles in private health insurance: a probit model with sample selection. J. Econ. 17 (2), 229–252.
Wei, Z., Lin, M., 2017. Market mechanisms in online peer-to-peer lending. Manag. Sci. 63, 4236–4257.
Weiss, G.N., Pelger, K., Horsch, A., 2010. Mitigating adverse selection in p2p lending–Empirical evidence from prosper.com. Available at SSRN 1650774.
Wildau, G., Jia, Y., 2018. Collapse of Chinese P2P lenders sparks investor flight. Financial Times. July 22 2018.
Wójcik, D., Ioannou, S., 2020. COVID-19 and finance: market developments so far and potential impacts on the financial sector and centres. Tijdschr. Econ. Soc. Geogr. 111 (3), 387–400.
Yach, D., Stuckler, D., Brownell, K.D., 2006. Epidemiologic and economic consequences of the global epidemics of obesity and diabetes. Nat. Med. 12 (1), 62–66.
Zhang, K., Chen, X., 2017. Herding in a P2P lending market: rational inference OR irrational trust? Electron. Commer. Res. Appl. 23, 45–53.
Zhang, J., Liu, P., 2012. Rational herding in microloan markets. Manag. Sci. 58 (5), 892–912.