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Peer-to-Peer (P2P) Lending in Europe: Evaluating the Default Risk of Borrowers in the Context of Gender and Education

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Abstract

In recent years, the importance of social lending activities and their effects on consumers have been highlighted by the widespread use of peer-to-peer lending platforms and the global race in fintech. Our study focuses on factors that affect the likelihood that European borrowers on peer-to-peer lending platforms, which are currently based in Estonia, Finland, and Spain, will default on their loans. Starting with the publicly accessible Bondora database, we examine the different economic and social characteristics of the borrowers to analyze the factors that contributed to loan default between 2013 and 2021. We use a Logit model to calculate the ex-post probability of default for factors derived from Principal Component Analysis as well as the original variables supplied by the database. The results show how crucially important education is for borrowers in lowering the risk of default, along with loan characteristics like high debt levels, long loan terms, and high interest rates. In addition, gender plays an important role in determining loan default, with a particular focus on women's conditions within the family. Regarding financial inclusion and its social implications, our findings suggest different ways to

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improve financial literacy and promote peer-to-peer lending. Future research could develop on the findings by applying them to other lending platforms and countries.

Keywords: Peer-to-peer lending; education; gender gap; financial literacy

Introduction

Nowadays, financial technology is recognised as one of the most vital innovations in the financial industry. As supported by an internet-based platform, peer-to-peer (P2P) lending has been introduced as a new e-commerce phenomenon in the financial field. In this context, bringing more economical efficiencies has great potential according to Milne and Parboteeah (2016) and Bachmann et al. (2011). The P2P lending market offers the possibility to get a loan even for those borrowers who would often not be eligible on traditional lending channels. The P2P lending market might represent a substitute for the traditional bank lending market (De Roure et al. 2022). P2P lending offers a better rate of return to lenders and greater access to credit at affordable costs for borrowers. Therefore, this type of lending can outperform traditional lending in the retail sector (Wardrop et al., 2016).

From a borrower perspective, P2P lending platforms provide a lower access threshold than traditional lending. For instance, in P2P lending, the borrowers are mostly small and medium owners and some low-income carriers (Jiang et al., 2018). However, despite the rapid growth, P2P lending platforms face threats from higher levels of default rates due to their rules of making loans to customers who have a lower level of credit. One of the key requirements for inventors is to assess and manage the risk of default loans of borrowers to sustain the development of the P2P lending platforms. If the platform cannot help them manage the risk and obtain a reasonable rate of return on the investment in P2P lending, they will leave it. (Zhou et al., 2021) On one hand, P2P lending platforms are flexible when it comes to the availability of credit information through both soft and hard financial information to assess borrowers' creditworthiness (Wang et al., 2019). On the other hand, one of the main problems that arise in traditional lending and P2P lending is information asymmetry between lenders and borrowers.

Additionally, efficient data analysis techniques like big data can play an important role in mitigating information asymmetries in P2P lending platforms (Yan et al., 2015). Moreover, Chen et al. (2020) empirically studied the cash flow implications of P2P lending and found that the cash flow of P2P platforms is affected by reputation, capital, and operational structure. However, there is another way to mitigate information asymmetry through social networking. In this context, group leaders can effectively act as an effective way to monitor the liability. (Jin and Freedman, 2014). In this vein,

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Kgoroeadira et al. (2019) found that borrowers' due diligence plays a vital role in P2P lending and can target funding success to reduce information asymmetry and adverse selection.

Finally, this study contributes to the growing literature on determinants of the probability of defaults by exploring the rapidly developing P2P lending sector. The assessment of default risk in P2P lending platforms has become increasingly prominent due to the unsecured nature of those loans, which makes the ability to predict default risk an essential criterion in identifying credit risk. Based on this, the goal of our study is to evaluate the default risk of borrowers using loan data from a European P2P lending platform, Bondora which is a leading P2P lending platform in Europe, established in 2009 and currently based in Estonia, Finland, and Spain. The assessment of default risk in P2P lending platforms has become increasingly prominent due to the unsecured nature of those loans, which makes the ability to predict default risk a essential criterion in identifying credit risk. Based on this, the goal of our article is to evaluate the default risk of borrowers using loan data from Bondora which is a leading P2P lending platform in Europe, established in 2009 and currently based in Estonia, Finland, and Spain. With one million customers, as of May 16, 2022, Bondora has issued P2P loans that total 605.429 million euros. Among determinants of the probability of defaults, we underline the key role of education coupled with a series of elements that can be reconnected to some features of the broad and not well-defined concept of financial literacy (see Houston, 2010, and Atkinson and Messy, 2012, among other studies), such as over-indebtedness behaviors and these represent contributions to the existing literature on financial literacy and financial inclusion. Moreover, by providing some clues on the gender gap in P2P lending, the analysis of the linkage between women's role in social structures and the probability of default, allows us to argue about different women's clusters' conditions in repaying debts and this could represent a topic of discussion both in financial and social literature.

This paper is structured as follows. In the next section, we will perform a short review of the most closely related work on default in the P2P lending market. Furthermore, we provide the data and discuss specific features of the data set. Then, we recall the statistical models exploited to obtain our empirical results, which are shown in the remaining part of the paper. Our conclusions and some policy implications are drawn in the final section.

Literature review

P2P lending can be defined as "financial exchange" that occurs between individuals without direct intermediation of a traditional financial institution (Omarini, 2018) so that it allows individuals to directly lend and borrow from each other on a common approach and on internet-based lending

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platforms (e.g., Lending Club, Bondora, Prosper). It can be questioned whether it will become a disruptive innovation as a so-called FinTech product (Ahelegbey et al., 2019). However, it is clear that P2P lending is quickly spreading globally. The P2P lending platform's primary role is to match the demand for and supply of funds (Nigmonov et al., 2022). Moreover, P2P lending practices are truly examples of how new technologies can transform the financial industry's future.

A part of the existing literature analyses the credit risk and default rate of loans. By using micro-credit data in Canada, Gomez and Santor (2003) found that the default rate of group lending is lower than traditional lending. Ravina (2008) investigated a more comprehensive empirical analysis of network lending by considering the perspective of lending success rate, interest rate, and default rate. Berger and Glesiner (2009) examined P2P lending by analyzing the role of financial intermediaries using data from a P2P lending platform, Prosper.com. In the same vein, Klafft (2008) conducted an empirical analysis and found that the transaction cost of the borrower's bank account authentication and the borrower's credit rating show a positive and significant impact on the transaction cost of P2P lending. Emekter et al., (2015) developed a model to evaluate loan default risk and performance. They used data from Lending Club. They found that, amongst others, credit grade, debt-to-income ratio, FICO score and revolving line utilization play an important role in loan default. Serrano-Cinca et al. (2015) examined P2P lending and the determinants that explain loan default by using the dataset from Lending Club. Their results suggest that loan characteristics, borrower indebtedness, annual income, and current housing situation were related to loan default. Moreover, Eid et al. (2016) studied the impact of income rounding on loan outcomes by using the dataset from Lending Club, they found that borrowers with a rounding tendency have a higher probability of default and are less likely to repay their loans. Carmichael (2014) used a discrete-time hazard function to predict the default in P2P loans and found that borrower's credit inquiries, income and loan purpose are statistically significant to evaluate credit scores.

Prior studies have reported the connection between individual risk and P2P lending default. Ma and Wang (2016) exploited the method of Interpretative Structural Modelling to investigate the factors that might influence credit risk in P2P lending under three aspects: i) the features of borrowers, ii) the characteristics of P2P lending platforms and iii) the environment. The results reveal that the audit mechanism of a P2P lending platform could affect the credit risk in P2P lending besides borrower's moral level, job stability and the policy environment. Polena and Regner (2018) examined the determinants of borrowers' default in P2P lending by using the dataset from Lending Club. The findings suggest that the debt-to-income ratio,

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inquiries in the past six months and a loan intended for small businesses are positively correlated with the default rate. While annual income and credit care are negatively correlated. Guo et al. (2016) conducted a study by proposing an instance-based credit risk assessment model in P2P lending to evaluate the return and risk of individual loans by using a dataset from Lending Club and Prosper. Lee and Kim (2017) used logistic regression on Survey of Consumer Finances (SCF) data for the time period 2007–2013, in order to estimate determinants of payday loans after the Great Recession. Zou et al. (2017) applied logistic regression to study determinants of Non-Performing Loans in P2P lending activities from a Chinese platform (i.e. PPDai).

Similarly, Lin et al. (2017) proposed a credit risk evaluation model to quantify the loan default risk by using a P2P lending platform in China. The empirical results suggest that gender, age, marital status, educational level, working years, company size, monthly payment, loan amount, debt-to-income ratio and borrower delinquency history play a significant role in loan defaults. Lee (2020) empirically tested a credit risk assessment model to understand P2P loan default risk. The results revealed that both the borrower characteristics and the conditions of the loan were significantly associated with loan default risk. Chen and Han (2015) conducted a comparative study between the US and China to study the differences in how soft and hard information is processed on P2P lending platforms. They found that both soft and hard have a profound impact on the lending outcomes. However, lenders in China rely more on soft credit information. In the same vein, Iyer et al. (2016) studied how lenders use soft and hard information to make investment decisions on borrowers; their conclusion was that lenders tend to use soft information for screening borrowers, especially for low-quality borrowers. More recently, Lyócsa et al. (2022) used data on loan and loan payments from both Bondora and Lending Club P2P lending platforms by comparing the out-of-sample and profitability of the credit and profit scoring using several statistical and machine learning models. They found that modelling the adjusted internal rate of return leads to much higher returns compared with modelling loan defaults. Tao et al. (2017) examined the borrower's personal financial information, and loan characteristics that might affect the P2P lending platform in China; the results revealed that among others, borrowers earning higher income are more likely to receive a loan and are less likely to default. Interestingly, the education dummy variable found positive indicates that borrowers with a higher education background may tend to take more risks. Thus, they have a higher default probability. However, given the lack of financial education in the general society, the lending marketplace may facilitate access to excessive amounts of debt due to oversupplying of credit to the financially distressed with a lower level of education (Demyanyk et al., 2017).

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An extensive amount of evidence has shown that females tend to be more risk-averse than males regarding making financial decisions (Eckel and Fullbrunn 2015). In this vein, Chen et al. (2020) examined the gender gap in the P2P lending platform Renrendai. They found that lending to females is associated with better loan performance, including a lower probability of default. Similarly, Barasinska and Schäfer (2014) focused on the success of female borrowers in a large German P2P lending platform. However, Santoso et al. (2020) studied the determinants of both loan rate and default status in P2P lending platforms in Indonesia over the period 2014-2018. They suggested three different names for P2P lending platforms (Alpha, Beta, and Gamma). The results pointed out that female borrowers have a higher probability of default than male borrowers in Beta and Gamma. However, regarding marital status, they found that female married borrowers significantly reduce the probability of default, especially for the beta. Furthermore, wives are less financially literate than husbands, which is consistent with a division of labor in which husbands manage finances (Hsu, 2016). Many initiatives exist to assist women borrowers, particularly in developing countries (for example, Women's Microfinance Initiative - http://www.wmionline.org).

Pengnate & Riggins (2020) analysed the role of sentiment in microfinance, starting from Kiva data. The authors highlighted the critical role of text mining in providing loans in microfinance, as well as the text of the loan description of the loan description.

Data and Methods

The Bondora database is publicly available and contains about 179.000 information about loans. As shown in Figure 1 and Table 1, its data cover the time period 2013-2021 and are mostly related to three countries. The whole database contains 112 variables, but we select only a few that are relevant to the following two criteria: i) only variables with almost 80% of correct values are taken into account; ii) a stepwise regression approach is employed to exclude someone not significant in determining the default condition (significant at least at 90% p-values). Table 2 resumes and describes the variables involved in the whole analysis.

Country	n.	%
Estonia	110714	61,9%
Spain	26270	14,7%
Finland	41955	23,4%
	178939	**100%**

Table 1. Borrowers country of origin

The table contains the borrowers' country of origin of loans recorded in Bondor's database.

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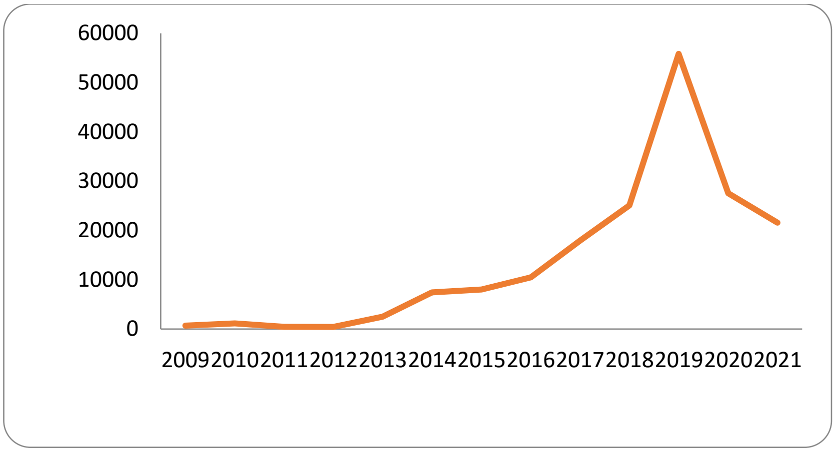

Figure 1. Number of loans by year in the sample

Variable	Description
Edu	1 Primary education 2 Basic education 3 Vocational education 4 Secondary education 5 Higher education
Amount	Amount the borrower received on the Primary Market. We apply log-function
loanduration	Current loan duration in months
debtttoincome	Ratio of borrower's monthly gross income that goes toward paying loans
Interest	Maximum interest rate accepted in the loan application
Age	The age of the borrower when signing the loan application
existingliabilities	Borrower's number of existing liabilities
Gender	1 Male 2 Woman
log(incometotal)	Borrower's total income. We apply log-function
maritalstatus	1 Married 2 Cohabitant 3 Single 4 Divorced 5 Widow
Woman	Dummy variables: 1 Woman 0 Male
married	Dummy variables:1 Married 0 other marital status
nomarried	Dummy variables:0 Married 1 other marital status
amountofpreviousloansbef	Value of previous loans
expectedloss	Expected Loss calculated by the current Rating model

Table 2 – Variables description

Loan default conditions could be an example of a binary response model for categorical data. In our approach, we define loan status as a dependent variable in a model where the variables available in the Bondora database are exploited as predictors. We employ the well known logistic regression, which is also used in a wide variety of applications, including social science research, marketing, and financial applications. Also, in credit risk, Logit models are applied to estimate the probability of default of exposures. As predictors, we include the variables contained in Table 2.

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Logistic regression is an application of a generalized linear model which is a useful tool to estimate the probability that an event occurs: in our case the event is a loan default. By using the logit link function, we apply a binary logistic model to the Bondora data.

The estimation is performed by Iterative Weighted Least Squares in the estimation, according to Davison (2003). The estimation function implies that the probability distribution is associated with an exponential family. The link function between dependent and independent variables is motivated by ease of interpretation of model parameters. Additionally, alternative models were fitted using the log-log and probit link functions and the consequential conclusions are similar.

We approach the multicollinearity problem by applying the Principal Component Analysis (PCA) to estimate new variables (the so-called "factor"). Following the approach by Lattin et. al (2003), with the aim of interpreting the Principal Components, we construct the factor loading matrix whose entries describe the correlation between the original variables and the new factors. In this framework, we use PCA to reduce the number of the variables and capture important features of loans.

Discussion

We have emphasized the key findings from our elaboration in this section. We categorize our results by loan characteristics, the role that education plays in defaulting, and the impact that borrowers' social status has. At the end of the section, we add the factorial analysis for the robustness check.

Features of loans

The role of the loan purpose is captured in Table 3, where % represents the ratio between defaulted loans and total loans. Looking at columns 6 and 10 in Panel A, we find that Education and Health are more likely to default, especially among people with low education levels. Probabilities of default related to Vocational education are at the same level as the ones related to primary education. In general, higher education reduces the probability of default (Panel A). When we combine the loan purpose and the gender status, Health is correlated with a high probability of default (Panel B). However, from these findings we capture the gender effect, even if we consider each use of the loan: it means that women borrowers reduce loan default (Table 3 - Panel B). On the other hand, the defaulted loan analysis concerning the marital status and use of loans contained in Panel C, is less clear than the data collected in other panels.

The role of the education

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Education is an ordinal variable, according to Table 2, with values: 1 Primary education; 2 Basic education; 3 Vocational education; 4 Secondary education; 5 Higher education. These values also can be ordered from the lowest to the highest; however, it needs to be clarified that the difference between categories is not equally spaced. A high degree of education reduces both ex-ante and ex-post probability of default (Tables 5 and 4). As reported in Table 4, Education could improve credit quality also if we disentangle the sample according to country of origin, except for Finland, where the negative coefficient is not significant. In providing P2P loans, the platform considers a high degree of study as a positive condition that improves the probability of default. In Table 5 the dependent variable refers to probability of default within a one-year horizon; it is a continuous bounded variable and not a categorical one. Therefore, we apply an Ordinary Least Square method for estimating coefficients. Bondora provides this variable, and we call it "ex-ante probability of default".

As expected, the amount of the borrowed debt determines an increase in default, as well as the loan duration, and the effect of the interest rate. These variables coupled with the number of existing liabilities could describe an over-indebtedness condition of borrowers. In addition, the role of debt-to-income ratio, as an independent variable, supports the hypothesis of over-indebtedness.

In Tables 4 and 5, we use a dummy variable to capture the gender effect on the probability of default. Ceteris paribus, a female condition reduces the ex-post probability of default; even, when the platform estimates the ex-ante probability of default, the effect is positive, i.e., the gender gap produces positive effects when females borrow a loan.

Social and marital status

When we consider the interaction effect between marital and female status, by using dummy variables, it emerges as a better interpretation of the results (Table 6). If we consider the two different statuses, "married women" (Model 1) and "no married women" (Model 2), we find two contrary signs. Married women's condition determines a positive effect on the probability of default, while on the contrary, no-married women reduce the ex-post probability of default. Also, in Model 3, by excluding the gender variable, the interaction between women and married marital status determines a positive effect on the probability of default. In Model 5, we evaluate the interaction between education and women by considering married women, and we found that education coupled with female gender reduces the probability of default.

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PCA results

We exclude from PCA dummy and multinomial variables. New variables represented by Principal Components (PCs) are resumed by v-variables. From communality analysis, we attribute the meaning to each PC. By using this approach, we solve the multicollinearity issue, by considering the orthogonality among PCs. Our findings from the PCA procedure confirm the results already described in the previous Section.

Eigenvectors in Table 7 suggest the PC's characteristics. V1 represents the perceived loan risk, since expected loss and interest are present in the positive and highest values. In Table 7, V1 shows a positive relationship with an ex-post probability of default, according to what we found in Table 5. V2 considers the borrower's indebtedness because it considers previous financial exposures: debt-to-income and the number of existing liabilities. Financial indebtedness (V2) is positively related to the probability of default, as shown in Table 8. The amount of loans and their duration, which are loan features (financial unsustainability), are characterized by V3, which is positively related to the probability of default. Borrowers' features are contained in V4, which is positively related to the probability of default. V5 is negatively related to the probability of default, as well as represents the financial soundness of the debtor. According to Panel B –Table 7, we choose only five PCs, which are those with eigenvalues bigger than 1.

First, the key role of education in determining the ex-post probability of default is confirmed by the three models. In addition, gender role is captured in Table 8, which confirms our previous results, even if we disentangle results for marital status (both Model 2 and 3).

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***Panel A** – Education and Use of loan*

	Undefined	Loan consolidation	Real Estate	Home improvement	Business	Education	Travel	Vehicle	Other	Health
Primary education	37.83%	58.54%	70.00%	66.67%	63.64%	77.78%	72.73%	52.94%	75.66%	78.95%
Basic education	57.51%	62.89%	60.17%	60.93%	59.38%	55.88%	53.94%	53.25%	64.58%	58.51%
Vocational education	36.40%	66.42%	62.59%	67.76%	67.48%	73.13%	66.67%	60.15%	69.10%	74.75%
Secondary education	34.10%	48.45%	43.58%	50.67%	46.43%	52.93%	47.83%	42.61%	50.78%	50.64%
Higher education	37.46%	45.71%	43.11%	50.09%	48.78%	55.66%	45.73%	44.10%	52.26%	54.48%

***Panel B**– Gender and Use of loan*

	Undefined	Loan consolidation	Real Estate	Home improvement	Business	Education	Travel	Vehicle	Other	Health
Male	38.29%	53.17%	46.34%	56.55%	49.34%	56.70%	50.06%	47.60%	56.75%	64.05%
Female	23.95%	51.74%	45.55%	50.93%	50.48%	53.50%	47.21%	44.46%	53.90%	49.16%
Undefined	69.39%	77.43%	96.08%	85.61%	83.56%	82.27%	84.38%	84.68%	83.20%	84.44%

***Panel C** – Marital status and Use of loan*

	Loan consolidation	Real Estate	Home improvement	Business	Education	Travel	Vehicle	Other	Health
Married	53.85%	48.89%	55.54%	52.36%	58.70%	51.88%	46.21%	57.65%	54.50%
Cohabitant	49.11%	48.25%	49.85%	42.38%	42.75%	42.24%	41.75%	47.64%	55.31%
Single	55.83%	47.46%	60.97%	53.72%	61.70%	57.05%	55.56%	62.12%	61.65%
Divorced	56.28%	54.05%	56.12%	59.01%	68.82%	49.67%	46.61%	63.04%	58.06%
Widow	53.66%	52.63%	49.08%	72.22%	66.67%	73.91%	31.25%	62.69%	57.14%

Table 3 Loan’s characteristics

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	All countries	EE	ES	FI
c	-1.62***	0.516***	0.441***	-0.87***
Education	-0.02***	-0.04***	-0.07***	-0.00
log(amount)	0.091***	0.016***	0.119***	0.109***
Loanduration	0.005***	0.004***	0.004***	0.002***
Debttoincome	0.001***	0.005***	-0.00	-0.00***
Interest	0.020***	0.008***	0.004***	0.030***
Age	0.004***	-0.00***	0.002***	0.006***
Existingliabilities	0.021***	0.012***	-0.01***	0.062***
Gender	-0.21***	-0.36***	-0.03*	-0.20***
log(incometotal)	-0.00	-0.12***	-0.13***	-0.16***
Maritalstatus	0.145***	0.115***	0.091***	0.245***

Table 4 Determinants of probability of default

*The table contains determinants of loan default. Dependent variable: dummy 1 defaulted 0 otherwise. Method: ML - Binary Logit (Quadratic hill climbing). Columns consider borrowers' countries of origin. All countries: Estonia, Spain, Finland. EE: Estonia. ES: Spain. FI: Finland. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent. Number of observations: 166991, 110635, 14106, 41954.*

Table 5 Determinants of ex-ante probability of default

	All countries	EE	ES	FI
c	0.044***	0.134***	0.433***	0.039***
Education	-0.00***	0.001***	-0.00***	0.003***
log(amount)	0.003***	0.001***	-0.02***	-0.00
Loanduration	0.000***	0.000***	-0.00***	0.000***
debttoincome	-0.00***	-0.00***	0.000***	-0.00***
Interest	0.004***	0.007***	0.002***	0.006***
Age	-0.00***	-0.00***	-0.00*	-0.00***
existingliabilities	0.002***	0.002***	0.001***	0.008***
Gender	-0.02***	-0.03***	-0.01***	-0.02***
log(incometotal)	0.005***	-0.01***	0.001	-0.00***
maritalstatus	0.001***	-0.00***	0.014***	-0.01***

*Table contains determinants of Probability of Default, refers to a loan's probability of default within one-year horizon as a dependent variable. Method: ordinary least square. Columns consider borrowers' countries of origin. All countries: Estonia, Spain, Finland. EE: Estonia. ES: Spain. FI: Finland. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent. Number of observations: 166991, 110635, 1*

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	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
C	-1.54***	-1.81***	-1.81***	-1.76***	-1.71***
Education	-0.02***	-0.02***	-0.02***	-0.02***	
log(amount)	0.074***	0.074***	0.078***	0.074***	0.073***
Loanduration	0.003***	0.003***	0.003***	0.003***	0.004***
Debttoincome	0.011***	0.011***	0.010***	0.011***	0.011***
interest	0.019***	0.019***	0.019***	0.019***	0.019***
Age	0.003***	0.003***	0.003***	0.003***	0.003***
Existingliabilities	0.016***	0.016***	0.018***	0.016***	0.015***
Gender	-0.22***	0.048*			-0.13***
*woman*married*	0.273***		0.136***		0.275***
*woman*nomarried*		-0.27***		-0.22***	
*education*woman*					-0.02***

Table 6 Determinants of default. Dummy interactions model.

*The table contains determinants of loan default. Dependent variable: dummy 1 defaulted 0 otherwise. Method: ML - Binary Logit (Quadratic hill climbing). * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent. Number of observations: 166991, 110635, 14106, 41954.*

***Panel A** - Eigenvectors*

	V1	V2	V3	V4	V5
Age	-0.10221	-0.10928	0.184489	0.536572	0.261091
Amount	0.037283	-0.27965	0.662354	-0.01668	-0.21631
Amountofpreviousloansbef	-0.42665	0.119556	-0.08765	0.4624	0.097224
Debttoincome	0.078064	0.581849	0.368909	-0.1172	-0.28374
Existingliabilities	-0.32292	0.545979	0.149736	0.300873	-0.10321
Expectedloss	0.590227	0.200225	0.000846	0.290499	0.013096
Freecash	0.06474	0.26206	0.339797	-0.34297	0.380822
Incometotal	0.017181	-0.00247	0.234474	-0.03503	0.774158
Interest	0.582313	0.118249	-0.13044	0.331133	0.053682
Loanduration	0.061808	-0.369	0.416653	0.284333	-0.19243

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Panel B *- Eigenvalues*

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	2.095819	0.604932	0.2096	2.095819	0.2096
2	1.490887	0.264248	0.1491	3.586706	0.3587
3	1.226639	0.12935	0.1227	4.813345	0.4813
4	1.097289	0.047571	0.1097	5.910633	0.5911
5	1.049718	0.118975	0.105	6.960351	0.696
6	0.930743	0.078424	0.0931	7.891094	0.7891
7	0.852318	0.185204	0.0852	8.743412	0.8743
8	0.667114	0.279501	0.0667	9.410526	0.9411
9	0.387613	0.185752	0.0388	9.798139	0.9798
10	0.201861	---	0.0202	10	1

7 PCA Eigenvectors and eigenvalues.

The table contains both Eigenvectors (Panel A) and Eigenvalues (Panel) of PCA. In estimating PC, we use ordinary correlation

	Model 1	Model 2	Model 3
C	0.204***	0.224***	-0.05
V1	0.820***	0.820***	0.820***
V2	0.365***	0.355***	0.355***
V3	0.207***	0.199***	0.199***
V4	0.308***	0.312***	0.312***
V5	-0.04***	-0.04***	-0.04***
GENDER	-0.36***	-0.38***	-0.10***
EDUCATION	-0.02***	-0.03***	-0.03***
*MARRIED*WOMAN*		0.280***	
*NOMARRIED*WOMAN*			-0.28***

Table 8 Determinants of the probability of default with PC.

*The table contains determinants of loan default. Dependent variable: dummy 1 defaulted 0 otherwise. Method: ML - Binary Logit (Quadratic hill climbing). Columns consider borrowers' countries of origin. All countries: Estonia, Spain, Finland. EE: Estonia. ES: Spain. FI: Finland. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent. Number of observations: 166991, 110635, 14106, 41954.*

Conclusion

Access to financial services is one of fintech's effects that promotes and allows financial inclusion across the world. However, the access and the usage of financial services are only two of many features that must be analysed, especially in a context where increasing speed and accessibility coexist so that, permitting more tailored financial services can be scaled. One

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of the most important aspects, coupled with access and usage, is the quality of financial services. Measures to protect consumers to prevent over-indebtedness are often insufficient, and financial education plays a key role. Financial inclusion, as well as other fintech effects, can democratize access to finance, but they must consider social aspects, such as gender conditions, that are different among countries.

The amount of excess debt, the length and interest rate of the loan, and consequently the loan's financial characteristics are some of the factors that determine the debtor's risk of bankruptcy. Even the reason for taking out a loan, such as the need for medical care, can be used to predict its likelihood of default.

In our study, we also take into account the roles that gender and educational attainment play in predicting loan default circumstances.

Borrowers benefit from education not only in loan selection, but also in avoiding choosing too high an interest rate or accumulating debt that makes their financial situation unsustainable. In our study, the role of education is closely linked to some aspects of financial literacy, because we consider not only the borrower's level of education but also the ability to understand the role of financial variables and their effects on the household budget.

These last aspects are captured by the rate of interest, the amount of previous debt, and the destination of loans. Not only in the OECD (Organisation for Economic Co-operation & Development), but also at national levels, there are many initiatives to promote financial literacy. The large diffusion of P2P, and the possibility for people to quickly borrow money, need robust programs to enhance financial literacy and favourite inclusion.

From gender results, we show that female gender plays an important and positive contribution in reducing the ex-post probability of default. In terms of policy implications, there is room for improvement of financial literacy and inclusion in considering married women. In these cases, there are different possible explanations. First, often married women can delegate financial matters to their partner or other family members. Therefore, when they apply for a loan, there is both a lack of experience and financial awareness. Second, married women, in some cases, are used as formal loan applicants due to the financial unreliability of partners. These explanations could be corroborated by results obtained with no married women. The reduction in default probability is strictly connected with the absence of partners. For these reasons, programs aimed at financial literacy must operate better within families, inside which women often live in a condition of less financial knowledge.

For these reasons, P2P lending platforms and other forms of social lending must consider not only women's condition but also marital status and promote financial literacy among female borrowers. There are several

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limitations to our studies. First, we study only the Bondora database that analyses three countries and does not cover all pandemic outbreak periods. As a future purpose, we aim at extending our analysis to other platforms, studying other countries and economic areas. Second, a more detailed analysis of women's conditions is needed, to support our explanation of the opposite effect of the marital status variable. With specific surveys, one could better analyse the condition of women in the social structures they live in.

Conflicts of Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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