Online microfinance in Eastern Europe: Personal versus business loans funding

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Abstract

Across the European Union, the market size of crowdfunding totals €16.9 billion with 1,231 active platforms (Chervyakov and Rocholl, 2019). However, the shares of microcredit (MC) allocated to business and personal loans are difficult to compute (European Commission, 2007a), and accessing the availability of banking industry MC is equally hard to ascertain (European Commission, 2007b). Recent efforts by the European Microfinance Network (EMN) report that between 2012 and 2017 business loans were losing ground to personal loans both in the number (60% to 41%) and the value of disbursed loans (80% to 52%) as well as in terms of active borrowers (61% to 41%) (Bendig et al. 2014; Botti et al. 2016; Diriker et al. 2018). Personal loans are thus quickly catching up with business microloans and verged on €1 billion in 2017. Based on data about Eastern European countries sourced from the online peer-to-peer (P2P) crowdfunding platform Kiva, this paper examines the relation between soft information and prosocial P2P crowdfunding performance, in particular the funding speed, both for personal and for business loans. To the best of our knowledge, this paper represents the first to identify a relationship between soft information, measured by the text length describing the loan purpose on personal and business loans, and P2P crowdfunding performance.

In keeping with previous studies (e.g., Dorfleitner et al., 2019a; Dorfleitner and Oswald, 2016), we apply a censored *tobit* regression model to predict the speed of loan funding on Kiva, by controlling for field partner, loan, borrower, and socioeconomic-geopolitical characteristics respectively. We furthermore deployed two datasets: the Kiva P2P crowdfunding platform and the World Bank. The Kiva's dataset comprises 29,739 loans applied for between 2011 to 2018 from five European countries (two countries from the lower middle-income group: the Republic of Moldova and Ukraine, and three from the upper middle-income group: Albania, Armenia, and Georgia). This paper identifies how applying for personal loans increases the speed of funding time compared to business loans. Additionally, the results support the hypothesis of a *quasi*-U-shaped relationship between soft information and funding speed but applicable only to business loans.

We provide new evidence on the relationship between personal versus business loans and crowdfunding performance. The resulting policy recommendations suggest P2P crowdfunding may require a greater focus on personal loans which constitute the "weakest link" in P2P lending marketplaces such as Kiva and furthermore gain less support from lenders. The results provide insights about microentrepreneurs to lenders with investing in education, skills and entrepreneurial training therefore appearing as crucial to their business success in line with thematic objective 10 (FI-Compass, 2018, 2016).

Keywords: microfinance, peer-to-peer lending, soft information, funding time, personal and business loans.

1. Introduction

New entrepreneurial finance alternatives, including microcredit (MC), crowdfunding, and peer-to-peer (P2P) lending, have advanced rapidly in both developed and developing economies, and have combined with traditional finance to fund and grow new ventures (Bruton et al., 2015). Estimates of the global MC industry come in at $114 billion (Convergences, 2018). In the European Union (EU), these alternative financial options are expanding with a crowdfunding market size totalling €16.9 billion (Chervyakov and Rocholl, 2019) and a MC industry valued at €2.1 billion (Diriker et al., 2018). However, institutional research gaps nevertheless still remain. At the research level, besides MC "there is even less empirical evidence on the impact of crowdfunding and peer-to-peer lending" (Bruton et al. 2015:15). At the institutional level, the European Commission (2007a) stresses the difficulties in measuring the shares of MC in terms of business and personal loans, and with any assessment of the availability of MC in banking industry a difficult task (European Commission, 2007b). Recent efforts from the European Microfinance Network (Bendig et al., 2014; Botti et al., 2016; Diriker et al., 2018) reveal that business loans are losing pace to personal loans in number (60% to 41%), and the value of disbursed loans (80% to 52%), as well as in terms of active borrowers (61% to 41%). In addition, personal loans are quickly catching up with business loans and verged on €1 billion in 2017. Thus, our paper addresses this dual gap through studying the relationship between soft information (measured by the text length describing the loan purpose) and prosocial Peer-to-Peer (P2P) crowdfunding performance, in particular the funding speed both for personal and business loans. Our research approach is twofold. Firstly, we run a model to account for the speed of funding. Secondly, we perform a subsample analysis running the models for business and personal loans to study the relevance of soft information. Microentrepreneurs tradition finance their projects exclusively through debt in accordance with a fair overview of the project scale (Agier and Szafarz, 2013). However, information asymmetries generate moral hazard problems with these loans potentially serving for unproductive purposes (Godquin, 2004), such as personal loans in which the reduction in the information asymmetries might end up costly, and with soft information thus becoming less relevant to personal lenders.

This study applied two datasets. Microdata comprises 29,739 loans made between 2011 to 2018 from five European countries (two countries from the lower middle-income group: Moldova and Ukraine, and three from the upper middle-income group: Albania, Armenia, Georgia) collected from KIVA, the first and largest prosocial P2P platform (Allison et al., 2013; Chen et al., 2017), including field partner (FP), loan, and microentrepreneur (ME) characteristics. We then also collected information related to socioeconomic and geopolitical characteristics from the World Bank. In keeping with previous research (e.g., Dorfleitner et al., 2019), we employ censored *tobit* regression models to study the speed of loan funding on Kiva.

To the best of our knowledge, our work is the first to identify a relationship between the loan type (personal versus business), soft information, and prosocial P2P crowdfunding performance. To classify personal and business loans, we extend the classification put forward by Kiva (Ly and Mason, 2012a).

Our results demonstrate how personal loans gain a higher funding speed in comparison to business loans. The results also highlight the relevance of soft information to the prosocial P2P crowdfunding performance, reflected in a *quasi*-U-shaped relationship between performance outcomes and the text length describing the loan purpose (soft information). Thus, our findings suggest that soft information is relevant to the funding speed for business loans whereas this is not relevant for personal loans. Policy recommendations on prosocial P2P crowdfunding may require more focus on personal loans that constitute the "weakest link" in P2P marketplaces such as Kiva, and also gain less support from lenders. Our study also addresses the investment priorities of the European Commission on three thematic objectives: i) enhancing the competitiveness of small and medium-sized enterprises, ii) promoting social inclusion, combating poverty and discrimination, and iii) investing in education, training and vocational training for skills and lifelong learning (FI-Compass, 2018, 2016). Furthermore, our results contribute to addressing the gap outlined by Lavopa and Szirmai (2018): further research is needed in order to understand the competitiveness and performance across sectors in business loans as well as the trajectories of economic development in both traditional and modern sectors.

The remainder of the paper is structured as follows. The next section briefly reviews the literature and state the research hypothesis. Section 3 presents the variables, data sources and methods. Section 4 discusses the results. Section 5 concludes.

2. Background and research hypothesis

Prosocial P2P crowdfunding

Crowdfunding emerged in the wake of the global financial crisis and broadly relies on the assumption of the "wisdom of the crowd" in order to screen new ventures (Bruton et al., 2015). There are several types of crowdfunding; ranging from donation-based to reward-based crowdfunding (for the spectrum of crowdfunding types, see Berns et al., 2020). This study focuses on a specific type of crowdfunding, the so-called prosocial P2P crowdfunding. This type of crowdfunding deploys no investment model and makes no returns to lenders as they are entitled to receive only the invested loan amount without any interest. In this particular context, neither the P2P crowdfunding platform nor its lenders receive interest even while microfinance institutions collect interest payments to cover operational expenses and profits (Galak et al., 2011). Thus, prosocial P2P crowdfunding stems from the crowd of social-oriented lenders (Jancenelle et al., 2019), with prosocial motivations and where the social performance of the microfinance institutions (MFIs) matters to gaining access to funding (Dorfleitner et al., 2020). This international phenomenon of Internet-based MC is relatively new, although there is growing interest in the topic (Allison et al., 2015). In addition, there is still scant research on the relationship between MC and the promotion of the EU's objectives around job creation and financial inclusion (Bendig et al., 2014, 2012).

The crowdfunding and microcredit industries in Europe

In 2017, the key figures on the volume and value of the microfinance industry in Europe stood at 635,330 microloans worth a total value of €2.1 billion. The industry is highly fragmented on the supply side with

65% of MFIs disbursing less than 100 loans per year. The average loan amount was €7,700 and with an average repayment rate of 92% according to the latest survey performed by the European Union (EU) and covering the 2016-2017 period (Diriker et al., 2018). This survey also highlights significant differences between personal and business microloans with the latter greater both in size (€8,913 versus €3,098 for personal microloans) and in loan maturity (45 months versus 31 months) but with lower annual percentage rates (11% versus 18%). Based on this survey, there were almost 1 million active borrowers even though the growth rate in the number of loans disbursed was only 1%. This modest growth may be partially explained by new entrepreneurial finance alternatives for starting up or developing new ventures (Bruton et al., 2015). In fact, this might reflect the case in Europe as the crowdfunding market size totals €16.9 billion (Chervyakov and Rocholl, 2019) against an MC industry market size amounting to €2.1 billion (Diriker et al., 2018), thus some eight times smaller in a situation partially explained by the global financial crisis (Botti et al., 2018).

The 2016/2017 survey report from the European Microfinance Network (EMN) details how individual entrepreneurs rather than microenterprises represent the dominant type of business client (Diriker et al., 2018). Indeed, over the last six years business loans have steadily lost pace to personal loans, recording only a 3% growth rate versus 282% for personal loans. Hence, the MC disbursed for business and personal loans reached 1,071 and 999 million euros, respectively. The global proportion of MC allocated to business loans thus fell back from 80% to 52% compared with the increase from 20% to 48% in personal loans between 2012 and 2017 according to data from EMN (Bendig et al., 2014; Botti et al., 2016; Diriker et al., 2018). These personal loans constitute a new development within the aim of financing personal projects such as professional integration in the marketplace, training, and mobility as well as assisting help poor families with their specific needs, such as rent, education or emergencies stemming from the global financial crisis (Jayo et al., 2010). This body of research and empirical data serve to reinforce the importance of this research topic. The European MC industry evolved in conjunction with support for entrepreneurial activities with both business and personal loans representing either side of the same coin. However, the distribution of loans is shifting towards the personal segment in overall terms (Botti et al., 2016), which has been growing faster than the business segment (Diriker et al., 2018). Nevertheless, the number of active borrowers of business loans increased from 263,000 to 407,000 (2012 to 2017), meaning a greater reach in the numbers of ME served but a lower average MC loan size. Drawing on this evidence, microenterprises display different financing patterns to Small and Medium Enterprises (SMEs) and are more likely to make recourse to internal financing instruments and short-term debt (e.g., credit cards, bank overdrafts) (Masiak et al., 2017). However, there is scant evidence on individuals or MEs in receipt of prosocial P2P crowdfunding in Europe.

Business versus personal loans

There is scant evidence from the crowdfunding literature studies addressing the dichotomy between personal versus business loans, with the few exceptions including Ly and Mason (2012a) who test different sectors of activity before finding that activities falling under the category of "personal use" face the slowest funding times. "Personal use" accounts for one of their smallest subsamples (391 observations) with the authors arguing these loans are for purposes of consumption and lenders may therefore perceive these loans are less likely to be repaid.

Both business and personal loans have a maximum cap of €25,000 in the EU. However, they differ in their aims, whether supporting self-employment activities, microenterprises or SMEs or personal or consumption needs (e.g., expenses with rent, education or other personal expenses) (Diriker et al., 2018). However, prosocial lenders may differ from financial lenders with the primary interest of the former not necessarily repayment but rather acting according to a prosocial agenda with altruistic motives (Berns et al., 2020). Furthermore, these motives appear rather complex and there is still only a limited understanding (Dorfleitner et al., 2019). Extending the argument of the prosocial agenda of lenders put forward by Kiva, there is also relevance in testing whether personal loans receive a higher funding speed than business loans given that their primary purpose is "to help those in need" (Galak et al., 2011, p. 131). We may accordingly formulate our first hypotheses:

H1: Personal loans report high funding speeds than business loans.

Soft information

A comprehensive body of research in the prosocial P2P crowdfunding literature studies the impact of ME narratives on their funding performance (e.g., Allison et al., 2015, 2013; Jancenelle et al., 2019; Moss et al., 2018, 2015). On reward-based crowdfunding platform such as Kickstarter, linguistic styles may boost the rate of social entrepreneur funding success rather than that for commercial entrepreneurs (Parhankangas and Renko, 2017). Within the context of P2P crowdfunding, soft information, defined as "additional information about the borrower's individual situation" (Dorfleitner et al., 2016:169), is susceptive of influencing lending decisions. However, soft information related with the text length describing the loan's purpose has received little attention in the literature. One exception is Galak et al. (2011) who deploy this variable to determine the borrower's occupation.

Based on the literature, we do expect a non-linear relationship between soft information and the funding speed. This non-linear relationship stems from two main arguments: i) lenders value longer soft information text descriptions, which identify clear purposes (e.g., Cumming et al., 2017), and ii) longer descriptive texts may overload arguments with negative impacts on the funding performance (e.g., Moy et al., 2018). Based on the information overload argument, we thus hypothesise:

H2: There is a non-linear relationship between soft information and the funding speed.

3. Variables, data source, and methods

Variables

Table 1 summarises the dependent and independent variables deployed with funding speed serving as the dependent variable. We measured the funding speed according to the reversed funding time, hence the natural logarithm of 1000 divided by the funding time accounted for in days. This reversed funding time "can serve as a proxy for funding speed as it measures how fast a loan can be funded" (Dorfleitner et al., 2019:10). The "reversed funding time of non-funded loans is set to be zero as their funding time is infinite" (Dorfleitner et al., 2019b:8–10), which in our sample represents 4,101 observations of which

3,144 are business loans and 957 personal loans. For the reversed funding time, these values are set at zero.

As the main independent variables, we applied personal loans and soft information. The personal loans variable constitutes a binary variable that takes the value of 1 whenever the loan has a personal goal, and 0 when the loan is for a business goal. To measure the loan type, we reclassify the Kiva activity sectors that categorise personal expenses as personal loans. Business loans thus made up the remaining loan applications. This classification extended the concept of personal loans adopted by Ly and Mason (2012a) to account for the real purpose of the personal loans. In our understanding, the "personal use" activity put forward for Kiva (Ly and Mason, 2012a) constrains the perspective on all personal loans. Hence, we selected all the Kiva activities susceptible to classification as personal loans: for instance, we categorized activities such as personal housing expenses, higher education costs, home appliances, primary/secondary school costs, personal expenses or personal medical expenses in this broader concept of personal loans. In the case of business loans, we followed the Lavopa and Szirmai (2018) classification. This classification stratifies loans according to the International Standard Industrial Classification of All Economic Activities (ISIC rev3), which were further allocated to either business loans or personal loans. With this assumption in favour of a broader definition of personal loans, we do expect to account for real personal loan activities, and thereby minimising the potential bias from incorrectly categorising a personal loan as a business loan. We measured soft information by the number of words and squared the number of words in the text describing the purpose of the loan.

The control variables applied are FP, loan, and ME characteristics, as well as the socioeconomic-geopolitical variables.

[insert table 1]

Method

The dependent variable constitutes a continuous variable (funding speed) and, in keeping with previous studies (e.g., Dorfleitner et al., 2019), we deemed the censored *tobit* regression model suitable and applied this to analyse the dependent variable with a cluster of zeros corresponding to non-funded loans.

Data and descriptive statistics

The data sources to measure the variables applied came from Kiva and the World Bank. Kiva started out in the United States in 2005 as an international and non-profit institution. Kiva is the largest prosocial P2P crowdfunding platform (Chen et al., 2017), serving 3.2 million borrowers in over 80 countries, of whom 81% are female. On this platform, borrowers can apply for a MC loan directly from the lenders or through a Field Partner (FP) that acts as a microfinance institution. Furthermore, FP administered loan applications benefit from a screening process and the build-up of trust with a third-party entity that raises the chances of funding success. In this case, FPs are entitled to charge operational fees and interest rates from applicants to cover their operational costs, with a small percentage of this revenue transferred to Kiva as service fees. The crowdfunding literature refers to this novel MC model as "pass-through microlending" (e.g., Allison et al., 2013)[1], in which Kiva acts as the marketplace while the FPs are intermediaries securing their refinancing from the crowd of lenders.

[insert table 2]

To implement our methodology, we excluded loan applications with information missing on either the dependent and covariate variables, reducing the selected sample from 32,200 to 29,739 observations corresponding to ten FPs from five countries for the 2011-2018 period. The three upper middle-income group countries (Albania, Armenia, Georgia) represent 88% of the observations and with the two lower middle-income group countries (Moldova and Ukraine) accounting for the remaining 12%. Table 2

[1] For further details, see the comprehensive analysis detailing the main steps to "pass-through microlending" in Allison et al. (2013).

presents the descriptive statistic summary in which the average funding speed is 3.8, corresponding to an average funding time of 18 days. The majority of the loans are business (76%), and the average text length is larger for personal loans than for business loans (12.9 versus 10.8 words). The pairwise correlation matrix in Table A1 (in the Appendix) reports no significant correlations of above 0.8 pointing to no multicollinearity issues.

4. Results

Baseline model

Table 3 reports the results for the *tobit* model according to three specifications. Specification I analyses the effect of personal loans on the funding speed. Specification II accounts for the effects of the soft information on the dependent variable. Finally, specification III analyses both these effects, i.e. personal loans and the soft information, on the funding speed. Due the similarity of the results returned by these three specifications, the discussion of the results incorporates the results from the full model.

[insert table 3]

The positive coefficient for the personal loans dummy variable, statistically significant at the 1% level, in specifications I and III supports H1 that maintains personal loans receive quicker funding than business loans. Several reasons might explain these results, such as the strategic and altruistic ethical motivations in the lending behaviours of lenders, as well as projects of a hybrid nature featuring both financial and social appeals (Berns et al., 2020). In addition, our findings also corroborate hypothesis H2, which states a non-linear effect between the number of words in the loan-purpose description on the funding speed. The relationship between funding speed and soft information displays a *quasi*-U-shape pattern with a minimum value of about 22 words. Up until this minimum number of 22 words, the funding speed decreases with the number of loan description words while the funding speed increases above this minimum. There are two main arguments to explain this. On the one hand, the lenders value longer text soft information descriptions, which points to clear purposes (e.g., Cumming et al., 2017). On the other hand, longer descriptive texts may overload arguments with a negative impact on funding performance (e.g., Moy et al., 2018). Short descriptions in loan-purpose texts may also reveal conciseness, that is, the smaller the number of words the better as this may contain hidden signals of entrepreneurial capabilities. For example, Karine is from Armenia and her loan-purpose description applies just use one word "livestock". While applying but a single word is certainly the most concise way to explain the loan's purpose, the lender may still be unclear about the detailed purpose due to a lack of information. This compares with Mesrop who also requested an MC loan in Armenia and for the same "livestock" activity but only applied six words to describe his loan purpose: "to purchase barley seeds and livestock". This text with six words stating two purposes, to buy seeds and livestock, may emerge as less clear than the one-word text. Thus, these examples support a *quasi*-U-shaped relationship between soft information and the funding speed. When the question becomes is it good to invest in Karine's loan, the lenders may want additional information before taking the decision on funding this loan. However, when we question whether lenders shall prefer loaning to Karine or to Mesrop, our model predicts that Karine gets a higher funding speed than Mesrop as her minimum of words and conciseness is better than less clear applications such as Mesrop's, who requests the loan for two different purposes instead of just one.

Regarding the control variables, the results identify how Kiva FPs with greater experience, and lower delinquency ratios, finance loans faster. Any positive variation in loan size and loan maturity leads to a decrease in funding speed in line with previous studies (e.g., Allison et al., 2015; Dorfleitner and Oswald, 2016; Ly and Mason, 2012b). The monthly repayment schedule dummy attains statistical significance at the 1% level for all specifications, indicating how the regular repayment schedule (monthly) decreases the funding speed versus the group of loans with irregular repayment schedules. As the irregular type of repayment schedule spans any frequency excluding the monthly basis, these irregular schedules may be preferable due both to their greater flexibility and to their more reasonable repayment schedules, adapted to microentrepreneur needs within the context of the prosocial P2P crowdfunding promoted by Kiva.

Regarding the characteristics of the entrepreneurs, our results show that female individual borrowers receive quicker funding than their male peers, and again in keeping with the prosocial P2P crowdfunding literature (Galak et al., 2011; Ly and Mason, 2012b). These results also align with Dorfleitner et al. (2019) and their study of direct loans. Finally, the socioeconomic and geopolitical variables highlight how the higher the variation in either GDP per capita or in the number of refugees, the lower the funding speed. Therefore, the potential reasons explaining these relationships stem from the motivations of lenders on prosocial P2P crowdfunding platforms such as Kiva, with a lack of interest over providing loans in countries with higher levels of GDP per capita but not to poor people elsewhere as the arguments behind MC identify its role as an effective tool against the vicious cycle of poverty in poor countries (Ang, 2004; Yunus, 2008, 1998).

Subsample analysis

In order to test for differences across the loan types, we ran subsamples of personal and business loans, including a random business loan sample to control for different subsample sizes. This calibration allows us to achieve comparable results in order to test the soft information through recourse to a random sample of business loans (7,418 observations), including one third of all business loans (22,479 observations). The soft information relationship with funding speed across the loan types features in Table 4.

[insert table 4]

Overall, the results are similar across the variables with statistically significant coefficients and signs between the total and the random sample (specification models II and III). The comparison of results between personal loans (model I) versus business loans (model II) provides support to H2 only in the case of business loans. This thus confirms the *quasi*-U-shaped relationship between soft information and funding speed for business loans but not for personal loans. This result corroborates the dual nature of prosocial P2P crowdfunding in which, as Galak et al. (2011) describe, "lenders donate any interest earned on the loan to the field partner, and the stated purpose of the loan is to help those in need" (p. 131).

Hence, soft information may lose relevance whenever individuals describe personal loans as social-oriented lenders downplay the specific text description, and focus on the general personal purpose of the loan in accordance with their prosocial nature. To the best of our knowledge, our paper is the first to highlight how the type of loan affects lender decision making, and correspondingly arguing that investments in business loans are driven by a financial nature while investments in personal loans are driven by a prosocial nature. Thus, social-oriented lenders reveal an interest in soft information primarily when funding business loans rather than personal loans.

Lenders appear to display an awareness that the former hold primarily a financial aim while the latter generate a direct social impact on individuals and their households. In this vein, FP characteristics such as term of activity are not statistically significant for personal loans as the mindset of lenders may be prosocial when making investment decisions over funding personal loans. Additionally, the coefficients for the socioeconomic and macroeconomic characteristics change from the positive (in the personal loan subsample) to negative (in the business loan subsample), in terms of both GDP per capita and the number of refugees. This reinforces the social orientation argument in countries both with higher GDP per capita levels and with higher levels of refugees. In a nutshell, for business loans, lenders are clearly interested in understanding the purpose attributed to the lent money whereas for personal loans, lenders are interested in the prosocial orientation of the loan and may leave the actual purpose of the loan to one side.

5. Conclusions

Personal loans gain higher funding speeds than business loans. This might arise from several factors, such as the complex motives of prosocial lenders (Dorfleitner et al., 2019), the strategic and altruistic ethical motivations of the lending behaviour of lenders, as well as projects of a hybrid nature with both high financial and social appeals (Berns et al., 2020). The study of these factors fell beyond the scope of this paper while certainly constituting an avenue for future research. These social-oriented lenders appear to consider soft information about the loan's purpose only in the case of business loans as for personal loans lenders appear driven by a prosocial nature probably aiming at helping those in need. In this vein, the *quasi*-U-shape relationship reported between the soft information and funding speed reveals that soft information may hold relevance only for business loans.

Studying prosocial P2P crowdfunding platforms is essential to enhancing the microfinance ecosystem and nurturing its sustainability. To the best of our knowledge, this study contributes the first building block for understanding the differences across personal and business loans in P2P crowdfunding and identifying gaps for improving the entrepreneurial and writing skills of individuals and MEs when promoting their purpose in loan applications. This aligns with the European Commission (EC) thematic objective 10 of investing in education and training (FI-Compass, 2018, 2016). Although personal loans are gaining traction, policy-makers should acknowledge the relevance of maintaining the right funding balance between personal and business loans. Personal loans generally go into non-productive investments, even while generating relevant impacts on low-income groups in the long-run, thus contributing to EC thematic objective 9 of reducing social exclusion, poverty and discrimination. However, business loans are typically invested in productive investments to support individuals and MEs experiencing difficulties accessing funding and thereby supporting EC thematic objective 3 on the enhancement of SME competitiveness.

Personal loans make up the "weakest link" in P2P marketplaces such as Kiva. Policy recommendations on prosocial P2P crowdfunding might support the personal loans that gain the least support from lenders as well as business loans for sectors that receive the least funding and report lower funding speeds. Our contributions correspondingly align with thematic EC thematic objectives 3 (Enhancing the competitiveness of SMEs), 9 (Promoting social inclusion, combating poverty and any discrimination), and 10 (Investing in education, training and vocational training for skills and lifelong learning) (FI-Compass, 2018, 2016). However, this still requires further research in order to understand competitiveness and performance across sectors in business loans as well as the trajectories of economic development for the traditional and modern sectors in line with the work by Lavopa and Szirmai (2018). Additional research avenues might also extend our study on the supply and demand sides of prosocial P2P crowdfunding marketplaces. The supply-side studies might focus on the strategic and altruistic ethical motivations expressed in the lending behaviours of lenders (Berns et al., 2020). Demand-side studies might then analyse the impact of the different linguistic styles prevailing among social and commercial entrepreneurs as applied to reward-based crowdfunding, such as Kickstarter (e.g., Parhankangas and Renko, 2017), which might be useful for fostering a better understanding of prosocial P2P crowdfunding, its performance as well as boosting its financial-social impact on borrower livelihoods.

References

Agier, I., Szafarz, A., 2013. Microfinance and gender: Is there a glass ceiling on loan size? World Development 42, 165–181.

Allison, T.H., Davis, B.C., Short, J.C., Webb, J.W., 2015. Crowdfunding in a prosocial microlending environment: Examining the role of intrinsic versus extrinsic cues. Entrepreneurship Theory and Practice 39, 53–73.

Allison, T.H., McKenny, A.F., Short, J.C., 2013. The effect of entrepreneurial rhetoric on microlending investment: An examination of the warm-glow effect. Journal of Business Venturing 28, 690–707.

Ang, M.H., 2004. Empowering the poor through microcredit. International Journal of Entrepreneurship and Innovation Management 4, 485–494.

Bendig, M., Unterberg, M., Sarpong, B., 2014. Overview of the Microcredit Sector in the European Union for the Period 2012–2013. European Microfinance Network, Brussels.

Bendig, M., Unterberg, M., Sarpong, B., 2012. Overview of the Microcredit Sector in the European Union for the Period 2010–2011. European Microfinance Network, Brussels.

Berns, J.P., Figueroa-Armijos, M., da Motta Veiga, S.P., Dunne, T.C., 2020. Dynamics of lending-based prosocial crowdfunding: Using a social responsibility lens. Journal of Business Ethics 161, 169–185.

Botti, F., Corsi, M., Zacchia, G., 2018. A new European microfinance panel data set: The European Microfinance Network survey 2006-2015. European Microfinance Network, Brussels.

Botti, F., Dagradi, D.L., Torre, L.M., 2016. Microfinance In Europe: A Survey Of Emn-Mfc Members. Report 2014/2015. European Microfinance Network, Brussels.

Bruton, G., Khavul, S., Siegel, D., Wright, M., 2015. New financial alternatives in seeding entrepreneurship: Microfinance, crowdfunding, and peer-to-peer innovations. Entrepreneurship Theory and Practice 39, 9–26.

Chen, R., Chen, Y., Liu, Y., Mei, Q., 2017. Does team competition increase pro-social lending? Evidence from online microfinance. Games and Economic Behavior 101, 311–333.

Chervyakov, D., Rocholl, J., 2019. How to make crowdfunding work in Europe. Bruegel Policy Contribution Issue n˚ 6| March 2019.

Convergences, 2018. Microfinance Barometer 2018. Convergences, Paris.

Cumming, D.J., Leboeuf, G., Schwienbacher, A., 2017. Crowdfunding cleantech. Energy Economics 65, 292–303.

Diriker, D., Landoni, P., Benaglio, N., 2018. Microfinance in Europe: Survey Report 2016-2017.

Dorfleitner, G., Oswald, E.-M., 2016. Repayment behavior in peer-to-peer microfinancing: Empirical evidence from Kiva. Review of Financial Economics 30, 45–59.

Dorfleitner, G., Oswald, E.-M., Röhe, M., 2020. The access of microfinance institutions to financing via the worldwide crowd. The Quarterly Review of Economics and Finance 75, 133–146.

Dorfleitner, G., Oswald, E.-M., Zhang, R., 2019. From credit risk to social impact: On the funding determinants in interest-free peer-to-peer lending. Journal of Business Ethics (in press). https://doi.org/10.1007/s10551-019-04311-8

Dorfleitner, G., Priberny, C., Schuster, S., Stoiber, J., Weber, M., de Castro, I., Kammler, J., 2016. Description-text related soft information in peer-to-peer lending–Evidence from two leading European platforms. Journal of Banking & Finance 64, 169–187.

European Commission, 2007a. The Regulation of Microcredit in Europe. European Commission, Brussels.

European Commission, 2007b. A European Initiative for the Development of Microcredit in support of Growth and Employment. European Commission, Brussels.

FI-Compass, 2018. Setting up a microfinance financial instrument. European Commission and European Investment Bank, Belgium and Luxembourg.

FI-Compass, 2016. Financial instruments working with microfinance. European Commission and European Investment Bank, Belgium and Luxembourg.

Galak, J., Small, D., Stephen, A.T., 2011. Microfinance decision making: A field study of prosocial lending. Journal of Marketing Research 48, S130–S137.

Godquin, M., 2004. Microfinance repayment performance in Bangladesh: How to improve the allocation of loans by MFIs. World development 32, 1909–1926.

Jancenelle, V.E., Javalgi, R.R.G., Cavusgil, E., 2019. Cultural entrepreneurship and legitimate distinctiveness in international prosocial crowdfunding. International Business Review 28, 802–810.

Jayo, B., González, A., Conzett, C., 2010. Overview of the microcredit sector in the European Union 2008-2009. European Microfinance Network (EMN) Working Paper nº6.

Lavopa, A., Szirmai, A., 2018. Structural modernisation and development traps. An empirical approach. World Development 112, 59–73.

Ly, P., Mason, G., 2012a. Individual preferences over development projects: Evidence from microlending on Kiva. Voluntas: International Journal of Voluntary and Nonprofit Organizations 23, 1036–1055.

Ly, P., Mason, G., 2012b. Competition between microfinance NGOs: evidence from Kiva. World Development 40, 643–655.

Masiak, C., Block, J.H., Moritz, A., Lang, F., Kraemer-Eis, H., 2017. Financing micro firms in Europe: An empirical analysis. EIF Working Paper.

Moss, T.W., Neubaum, D.O., Meyskens, M., 2015. The effect of virtuous and entrepreneurial orientations on microfinance lending and repayment: A signaling theory perspective. Entrepreneurship Theory and Practice 39, 27–52.

Moss, T.W., Renko, M., Block, E., Meyskens, M., 2018. Funding the story of hybrid ventures: Crowdfunder lending preferences and linguistic hybridity. Journal of Business Venturing 33, 643–659.

Moy, N., Chan, H.F., Torgler, B., 2018. How much is too much? The effects of information quantity on crowdfunding performance. PloS one 13.

Parhankangas, A., Renko, M., 2017. Linguistic style and crowdfunding success among social and commercial entrepreneurs. Journal of Business Venturing 32, 215–236.

Yunus, M., 2008. Creating a world without poverty: Social business and the future of capitalism. Global Urban Development Magazine 16–41.

Yunus, M., 1998. Poverty alleviation: Is economics any help? Lessons from the Grameen Bank experience. Journal of International Affairs 52, 47–65.

Table 1: Definition of variables

Variable	Type	Definition	Source
Dependent variables			
Speed	Continuous (units)	The logarithm of 1000 divided by the funding time measured in days	Kiva
Covariate variables			
Independent variables			
H1: Personal versus business loans			
Personal loans	Binary (0/1)	Dummy variable which takes the value 1 when a loan has a personal use, and 0 when the loan has a business purpose	Kiva
H2: Soft information			
#words	Continuous (units)	Number of words used to describe the loans' purpose	Kiva
$(\#words)^2$	Continuous	Squared variable of number of words	Kiva
Control variables			
Field Partner Characteristics			
Activity	Continuous (years)	FP activity from starting date to present or closed date (last posted loan) with KIVA	Kiva
Delinquency	Continuous (%)	Ratio of value of delinquent paying back loans divided by value of all paying back loans	Kiva
Loan characteristics			
Size	Continuous	Loan amount requested on Kiva by the borrowers (US dollars)	Kiva
Maturity	Discrete (months)	Loan maturity in months.	Kiva
Repayment	Binary (0/1)	Dummy variable which takes the value 1 when monthly repayment, 0 otherwise	Kiva
Micro-Entrepreneurs characteristics			
Gender	Binary (0/1)	Dummy variable which takes the value 1 when female individual borrower, 0 otherwise	Kiva
Socioeconomic and geopolitical characteristics			
GDPpc	Continuous (US dollars)	Gross Domestic Product (GDP) per capita, Purchasing Power Parity - PPP	World Bank
Refugees	Discrete (units)	Number of refugees by country or territory of asylum	World Bank

Table 2: Descriptive statistics

	N	Mean	Median	S.D.	Min	Max	p25	p75
Full sample								
Speed	29,739	3.80	3.92	1.80	0.00	9.95	3.39	4.95
Personal loans	29,739	0.24	0.00	0.43	0.00	1.00	0.00	0.00
#words	29,739	11.29	10.00	5.80	1.00	41.00	7.00	14.00
Activity	29,739	8.49	8.60	1.65	1.97	12.04	7.94	9.41
Delinquency	29,739	24.27	3.38	38.86	0.00	98.93	0.64	20.94
Size	29,739	1,555.61	1,425.00	867.76	25.00	5,000.00	900.00	2,075.00
Maturity	29,739	24.42	26.00	10.58	2.00	99.00	16.00	27.00
Repayment	29,739	0.81	1.00	0.39	0.00	1.00	1.00	1.00
Gender	29,739	0.57	1.00	0.50	0.00	1.00	0.00	1.00
GDPpc	29,739	10,759.84	10,324.94	1,148.60	7,300.94	12,930.07	10,324.94	11,420.63
Refugees	29,739	9,766.58	17,970.00	8,234.29	131.00	17,970.00	1,991.00	17,970.00
Personal loans								
Speed	7,260	4.06	4.40	1.84	0.00	9.68	3.48	5.23
#words	7,260	12.92	12.00	6.03	3.00	36.00	8.00	17.00
Activity	7,260	8.50	8.60	1.65	1.97	12.04	7.94	9.41
Delinquency	7,260	37.56	3.38	45.13	0.00	98.93	3.25	98.93
Size	7,260	1,259.33	1,050.00	756.45	125.00	5,000.00	750.00	1,650.00
Maturity	7,260	27.71	26.00	15.62	5.00	99.00	19.00	27.00
Repayment	7,260	0.87	1.00	0.33	0.00	1.00	1.00	1.00
Gender	7,260	0.62	1.00	0.49	0.00	1.00	0.00	1.00
GDPpc	7,260	10,975.10	10,324.94	1,284.61	7,300.94	12,930.07	10,324.94	11,420.63
Refugees	7,260	9,090.44	2,620.00	8,386.79	131.00	17,970.00	1,991.00	17,970.00
Business loans								
Speed	22,479	3.72	3.79	1.78	0.00	9.95	3.37	4.83
#words	22,479	10.77	10.00	5.62	1.00	41.00	7.00	13.00
Activity	22,479	8.48	8.60	1.65	1.97	12.04	7.94	9.41
Delinquency	22,479	19.98	3.38	35.56	0.00	98.93	0.64	20.94
Size	22,479	1,651.30	1,500.00	879.72	25.00	5,000.00	975.00	2,175.00
Maturity	22,479	23.36	26.00	8.05	2.00	62.00	15.00	27.00
Repayment	22,479	0.79	1.00	0.40	0.00	1.00	1.00	1.00
Gender	22,479	0.55	1.00	0.50	0.00	1.00	0.00	1.00
GDPpc	22,479	10,690.32	10,324.94	1,092.10	7,300.94	12,930.07	10,324.94	11,420.63
Refugees	22,479	9,984.95	17,970.00	8,172.68	131.00	17,970.00	1,991.00	17,970.00

Table 3: Estimates of censored *tobit* models on funding speed

	(I)	(II)	(III)
H1: Personal versus business loans			
Personal loans	0.115***		0.155***
	(0.027)		(0.028)
H2: Soft information			
#words		-0.081***	-0.082***
		(0.007)	(0.007)
$(\#words)^2$		0.002***	0.002***
		(0.000)	(0.000)
Controls			
FP characteristics			
Activity	0.067***	0.073***	0.069***
	(0.007)	(0.007)	(0.007)
Delinquency	-0.003***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)
Loan characteristics			
ln(Size)	-1.071***	-1.096***	-1.062***
	(0.019)	(0.018)	(0.019)
Maturity	-0.024***	-0.019***	-0.021***
	(0.001)	(0.001)	(0.001)
Repayment	-0.226***	-0.279***	-0.284***
	(0.030)	(0.030)	(0.030)
Entrepreneur characteristics			
Gender	0.898***	0.910***	0.901***
	(0.022)	(0.022)	(0.022)
Socioeconomic-geopolitical characteristics			
ln(GDPpc)	-1.929***	-1.721***	-1.717***
	(0.105)	(0.104)	(0.105)
ln(Refugees)	-0.197***	-0.205***	-0.192***
	(0.009)	(0.009)	(0.009)
Constant	30.677***	29.462***	29.154***
	(1.033)	(1.026)	(1.033)
Observations	29,739	29,739	29,739
F-test	900.1	833.9	763.3
p-value	0	0	0
Pseudo- R^2	0.062	0.064	0.064
AIC	113,462	113,240	113,211
BIC	113,553	113,340	113,319

Notes: The variable definitions feature in Table 1. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Estimates of censored *tobit* models on funding speed by loan type

	(I) Personal Loans	(II) Business Loans	(III) Business Loans (random sample)
H2: Soft information			
#words	0.012	-0.091***	-0.110***
	(0.016)	(0.008)	(0.013)
$(\#words)^2$	-0.001	0.002***	0.003***
	(0.001)	(0.000)	(0.000)
Controls			
FP characteristics			
Activity	-0.008	0.038***	0.041***
	(0.018)	(0.007)	(0.013)
Delinquency	-0.013***	-0.001	-0.001*
	(0.001)	(0.000)	(0.001)
Loan characteristics			
ln(Size)	-1.215***	-0.784***	-0.769***
	(0.044)	(0.021)	(0.038)
Maturity	-0.012***	-0.052***	-0.050***
	(0.002)	(0.002)	(0.003)
Repayment	-0.314***	-0.141***	-0.056
	(0.072)	(0.033)	(0.058)
Entrepreneur characteristics			
Gender	1.176***	0.855***	0.871***
	(0.045)	(0.025)	(0.043)
Socioeconomic-geopolitical characteristics			
ln(GDPpc)	1.697***	-2.222***	-2.229***
	(0.291)	(0.098)	(0.163)
ln(Refugees)	0.305***	-0.252***	-0.249***
	(0.019)	(0.010)	(0.017)
Constant	-5.410*	33.195***	3.098***
	(2.889)	(0.971)	(0.077)
Observations	7,260	22,479	7,418
F-test	271.6	729.3	236.1
p-value	0	0	0
Pseudo-R^2	0.090	0.072	0.070
AIC	27,177	84,447	27,959
BIC	27,260	84,543	28,042

Notes: The variable definitions feature in Table 1. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix

Table A1: Pairwise correlations of explanatory variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Speed	1.000										
(2) #words	-0.136*	1.000									
(3) Activity	0.009	0.060*	1.000								
(4) Delinquency	-0.095*	0.227*	0.375*	1.000							
(5) Size	-0.327*	0.011	0.007	-0.111*	1.000						
(6) Maturity	-0.264*	0.205*	-0.097*	0.020*	0.342*	1.000					
(7) Repayment	0.002	-0.095*	-0.092*	0.214*	-0.102*	-0.207*	1.000				
(8) Gender	0.234*	0.002	0.030*	-0.067*	-0.023*	0.032*	-0.056*	1.000			
(9) Personal loans	0.080*	0.160*	0.005	0.194*	-0.194*	0.176*	0.088*	0.058*	1.000		
(10) GDPpc	0.014*	0.033*	-0.403*	-0.253*	-0.129*	-0.052*	0.166*	-0.045*	0.107*	1.000	
(11) Refugees	-0.230*	0.255*	0.290*	0.488*	0.074*	0.326*	-0.169*	0.032*	-0.047*	-0.418*	1.000

* shows significance at the .05 level