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ORIGINAL PAPER

From Credit Risk to Social Impact: On the Funding Determinants in Interest-Free Peer-to-Peer Lending

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Abstract
Based on a unique data set on US direct microloans, we study the funding determinants of interest-free peer-to-peer crowdlending aimed at borrowers in the US. By performing logistic regressions on funding success and Tobit regressions on the reversed funding time, the existence of a social underwriting by a third-party trustee and information in the description texts fostering the investors' trust are shown to be the main predictors of successful funding. Regarding social impact, the possibility to empower women and groups of borrowers appeals to the investors, whereas empowerment of the family or community beyond the borrowers themselves appears to remain unappreciated. When examining the vulnerability of the borrowers as a predictor, the results manifest differences amongst the attitudes of the investors towards social impact. In the subsample of non-endorsed loans, the investors appear to prefer to support borrowers with an immigration background. In contrast, this is not the case with endorsed loans.

Keywords Text analysis · Crowdlending · Microfinance · Funding probability · Funding time

Introduction

In this paper, we study the determinants of funding in interest-free peer-to-peer (P2P) lending. The interest rate is typically the most crucial parameter in P2P lending, as it usually reflects the repayment risk of a loan. Setting this parameter equal to zero changes the economic basis of the lending, as the investors who are willing to accept such conditions must derive some utility from sources other than the financial return. Therefore, the lenders in this context can be assumed to be socially oriented or ethical investors. We study the question of the funding determinants in this context with a novel data set stemming from the online microfinance platform Kiva.

While crowdfunding enjoys rapid growth in the past decade, its application in microfinance has just recently drawn attention from scholars and is relatively under-researched (Berns et al. 2018). Traditionally, microfinance institutions (MFIs) grant microcredit to the poor who are excluded from the normal financial market. With the emergence of crowdfunding technique, altruistic individuals from all over the world can support more directly the unbanked population (Ly and Mason 2012a). A few studies investigate the investors' investment behavior in prosocial crowdfunding and indicate the importance of both investors' financial and ethical considerations (e.g., Ly and Mason 2012b; Burtch et al. 2014) . Nevertheless, it is noteworthy that prior studies focus exclusively on a specific type of prosocial crowdfunding, in which MFIs act as an intermediary between borrowers and investors (see e.g., Allison et al. 2013; Burtch et al. 2014; Allison et al. 2015; Moss et al. 2015; Dorfleitner et al. 2019). In this intermediary-based crowdfunding model, MFIs play a significant role throughout the loan life cycle (e.g., screening loan applicants, preparing loan applications, monitor loan repayment). Therefore, this kind of prosocial crowdfunding cannot be seen as pure P2P lending and the investors' investment behavior is influenced by the presence of MFIs (Allison et al. 2015; Berns et al. 2018). As a result, the investors' real attitude and preferences regarding the properties that make an applicant supportable could be obscured and not be well understood. The question arises how the investors in interest-free P2P lending can make investment decisions without mediating MFIs. However, no study has yet

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been conducted to answer this question, and our knowledge regarding the complex motives of the prosocial investors is still very limited. This study seeks to fill this gap by investigating the investors' investment behavior, especially their ethical motives in a pure P2P setting.

Our investigation is related to business ethics in several ways. First, it touches on the question of the fair interest rate in microcredit (Hudon and Ashta 2013), which has been disputed for a long time. In our setting, the interest rate is zero and therefore can be regarded as fair to the borrower in any case. Second, as the lenders sacrifice the complete interest to let the borrowers profit, the transactions are also a matter of altruism and—more concretely—of philanthropic giving (Obaidullah and Shirazi 2014). Third, the responsibility of the lender for the borrower in microcredit is an important problem, as providing microcredit has led to cases of over-indebtedness (Schicks 2014). However, this issue is solved in our context because if the borrower is not able to repay the loan, the only penalty he or she faces is receiving no further loan. Thus, it is very unlikely that over-indebtedness emerges from a Kiva direct loan. Fourth, the honesty on the side of the borrower is a relevant ethical dimension in our setting, as no one verifies the authenticity of the information given in the self-written description texts.

Our study follows the framework of prior studies analyzing the investors' dual motives in prosocial crowdfunding (e.g., Allison et al. 2015; Dorfleitner et al. 2019; Berns et al. 2018). Under this framework, the investors' financial and non-financial considerations can be examined at the same time. In general, we apply signaling theory (Spence 1973, 2002) to understand the direct communication between borrowers and investors. In particular, special attention is paid to signals in the self-written description texts as recent studies show the informativeness of the unverified texts (see e.g., Allison et al. 2015; Berns et al. 2018).

To investigate the funding determinants of interest-free P2P lending, we examine more than 6,000 US direct loan applications on the online microfinance platform Kiva. Unlike prior studies that focus exclusively on Kiva's intermediary-based model in developing countries (e.g., Burtch et al. 2014; Moss et al. 2015), we utilize a unique data set of direct loans in the USA. The data set is unique as it includes not only the basic information about US direct loans from Kiva's official API but also other crucial information derived from original campaign web pages such as the description texts and endorsement details. The empirical examinations provide very interesting insights regarding the investors' investment behavior in interest-free P2P lending. First, a third-party endorsement is found to be crucial to funding success and funding speed, even if the so-called 'trustee' has no financial responsibility. Second, there is evidence that signals related to trust between investors and borrowers in the self-written description texts can influence the fundraising result. Third, the investors do appear to empower women and groups, but not others beyond the borrowers themselves. Last but not least, the investors appear to care about the borrowers' vulnerability, but to a varying extent.

With these findings, our study makes the following two contributions. First, to our knowledge, this is the first study that sheds some light on the financial and prosocial considerations of the investors funding interest-free P2P loans. While the two motivational dimensions that we investigate on the lenders' side, namely avoiding repayment risk and seeking social impact, are the same as in earlier research on the intermediary-based model, it should be noted that we do not expect to find the same well-known results now in a different setting. Rather one can say that while the two dimensions as such are canonical, we aim to study whether and how they are perceived and appreciated in a new and even purer ethical context. In the end, the details of the findings are important, as from these one can draw conclusions on the functionality of the platform and the real preferences of the investors involved in such interest-free P2P lending.

Second, our study contributes to the research of microfinance in developed countries as Kiva's direct loan model is only available in the USA. Despite growing interest in microfinance in developed countries, there is still limited research on this topic (Pedrini et al. 2016; Forcella and Hudon 2016). Most studies on microfinance in developed countries are surveys or qualitative analysis (e.g., Kraemer-Eis and Conforti 2009; Carboni et al. 2010; Bruhn-Leon et al. 2012; Diriker et al. 2018), and very few of them conduct empirical investigations (e.g., Cozarenco et al. 2014; Bourlès and Cozarenco 2018; Cozarenco and Szafarz 2018). We empirically investigate how altruistic investors make lending decisions to help the minority in developed countries who are less likely to attract attention from the public compared with their counterparts in developing countries, thus providing the opportunity to understand microfinance in different contexts.

The remainder of the paper is organized as follows: Kiva's funding model for direct loans is introduced in section "Kiva's Funding Model for Direct Loans". In section "Theory and Hypotheses Development", four hypotheses are derived from theoretical considerations and existing studies. Section "Data and Methodology" describes the data and the employed methodology. The results of regressions and robustness checks are displayed in section "Results". Section "Conclusion" concludes.

Kiva's Funding Model for Direct Loans

Kiva is well-known as an online crowdfunding platform that enables microlending to the poor by mobilizing debt capital from the worldwide crowd of altruistic investors. The

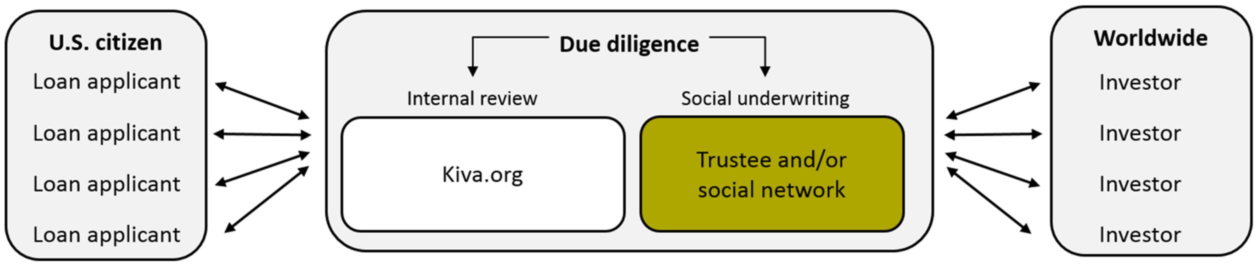

Fig. 1 Kiva's direct P2P model for direct loans in the United States

standard lending model on Kiva is devoted to the crowdfunding of loans that are mediated through MFIs in developing countries. Under this intermediary-based microfinancing model, the investors refinance microloans which have already been granted to applicants by MFIs.

Apart from the intermediary-based microfinancing model, Kiva also facilitates a direct P2P lending model in which micro-borrowers and socially oriented lenders interact directly without any financial intermediation. Kiva direct loans, focusing on US inhabitants who wish to develop a promising business idea but struggle with access to capital, provide interest-free debt capital of up to 10,000 USD. The borrowers do not pay and the investors do not receive any interest on the loan. The investors fully bear the credit default risk. To minimize the risk of fraud, Kiva carries out an internal due diligence process.[1] Additionally, Kiva requires the loan applicant to successfully pass the process of so-called 'social underwriting'. During a private fundraising period, the applicant's network (family, friends) is asked to fund the loan application to further affirm the applicant's creditworthiness. Therefore a small portion of the loan amount has always been collected before the application is posted online.[2] Moreover, the loan applicant can be endorsed by an entity (an organization or an individual) that is in a relationship with the loan applicant. Even though the entity does not have any financial liability (Kiva 2019a), Kiva calls it trustee and expects that the entity helps to strengthen the borrower's commitment to the repayment obligation. After the 3-stage screening process of the applicant's creditworthiness, the direct loan application is posted publicly and available to the crowd of socially oriented investors. After the loan is granted, Kiva monitors the repayment behavior of the borrower. When the borrower fails to repay the loan in time, Kiva will remind the borrower via phone call or email. Kiva adjusts the trustee's ability to further endorse borrowers based on the repayment rate of the loans endorsed by the trustee. When the borrower defaults, the borrower can no longer apply for loans on Kiva. According to the official statistics (Kiva 2019b), the repayment rate for US direct loans on Kiva is 78%, which is evidently lower than 97.5%, the repayment rate for MFIs facilitated loans. Kiva's direct P2P model is summarized in Fig. 1.

It should be noted that Kiva's direct model is, to a large degree, unique in the practice of microfinance as well as in the field of P2P lending. From the microfinance perspective, this model is special as there is no MFI involved. From the standpoint of classical P2P lending, the fact that the borrowers do not need to pay any interest and that the investors, therefore, do not receive any financial compensation for the credit risk they take is very unusual. Therefore, Kiva's direct loan model combines the concepts of microfinance and P2P lending.

Theory and Hypotheses Development

Theoretical Basics

Findings from Related Fields

While interest-free P2P lending is a relatively new phenomenon, its origin can be traced back to microfinance, as its underlying and fundamental objective is to help the poor population realize their economic potential (Kiva 2018a). To better understand the investors' behavior in interest-free P2P lending, we first discuss multiple motivations of MFIs and their funders in the field of microfinance.

Traditionally, MFIs rely mainly on governmental subsidies or philanthropic donations (Hudon and Traca 2011; Ghosh and Van Tassel 2013). Accordingly, many MFIs focus mainly on the social outreach and impact of their business. Studies find that microfinance programs in developing countries can reduce poverty (Robinson 2001; Khandker 2005;

[1] The internal due diligence process includes a review of the financial history, a verification of the identity and a validation of the business. Also, all applicants are screened through the Office of Foreign Assets Control terrorism database due to national security reasons.

[2] Note that for our analysis the private fundraising does not play a significant role because every loan application fulfills this requirement (typically approximately 10% to 15% of the loan amount is prefunded).

Imai et al. 2010) and especially empower women (Cheston and Kuhn 2002; Swain and Wallentin 2009). As the microfinance industry has grown exponentially in the past few decades (Beatriz and Marc 2011), it attracts a much broader range of funders including different public and private investors. Many non-governmental organizations (NGOs) that provide funding to MFIs are often very active in areas such as health, women's empowerment, and children's issues (Ledgerwood et al. 2013). Institutional investors like pension funds or insurance companies also fund MFIs as they seek 'impact investing' (Ledgerwood et al. 2013). However, institutional investors could also be attracted to fund MFIs because investing in MFIs can be financially attractive (Krauss and Walter 2009; Galema et al. 2011). There is a tendency that more and more MFIs in developing countries become for-profit organizations (Battilana and Dorado 2010; Khavul 2010), despite some criticism that MFIs experience 'mission drift' (Dichter and Harper 2007). In addition, various funders or participants in the microfinance industry claim that MFIs should go beyond financial efficiency and social impact and be engaged in environmental issues as well (Hammill et al. 2008; Allet et al. 2011). Allet (2014) find that MFIs in developing countries for which social responsibility is the key motivation are more likely to promote an environmentally friendly practice.

In recent years, microfinance has also spread to Western economies. As the economic and social context in developed countries is different, microfinance in developed countries has slightly different focuses. According to Bendig et al. (2012, 2014) and Diriker et al. (2018), job creation, poverty reduction, and microenterprise development are the most important missions for MFIs in Western European countries. Although women's empowerment is also an objective of MFIs in developed countries, it plays a less prominent role (Bendig et al. 2012, 2014). MFIs in developed countries are niche institutions (Kraemer-Eis and Conforti 2009; Cozarenco et al. 2014) and still rely heavily on government subsidies and support (Kraemer-Eis and Conforti 2009; Bruhn-Leon et al. 2012). As a result, they focus particularly on encouraging entrepreneurial activities (Carboni et al. 2010; Cozarenco et al. 2014), as governments expect to create more employment opportunities and reduce the financial burden of social welfare (Underwood 2006; Barinaga 2014; Pedrini et al. 2016). Besides governments, an increasing number of commercial banks in developed countries fund or support MFIs to realize their socially responsible investment policies (Pedrini et al. 2016). However, while the microfinance sector in developing countries starts to experiment with a commercialization process, MFIs in developed countries are less profit-oriented (Kraemer-Eis and Conforti 2009; Jayo et al. 2010). Moreover, environmental responsibility is also a concern of MFIs in developed countries (Forcella and Hudon 2016). Forcella and Hudon (2016) find that investors' concern for environmental issues is an important determinant of MFI's environmental performance.

Despite the great achievement gained by microfinance in the past few decades, the problem of financial exclusion still prevails. According to a recent estimate of the World Bank (Demirguc-Kunt et al. 2018), 1.7 billion people do not have a bank account and can be defined as the unbanked population. Therefore, microfinance in developing and developed countries has a long way to go. Due to the development of internet technology in the recent decade, new financing alternatives, such as crowdfunding, provide the unbanked group new financing opportunity. P2P lending, sometimes also referred to as 'crowdlending', is the most important type of crowdfunding (Ziegler et al. 2017). Numerous studies (e.g., Freedman and Jin 2008; Yum et al. 2012; Lin et al. 2013) investigate the investment behavior of individual investors in P2P lending. Some of them suggest that individual investors have a quite different mindset and show several biases when making lending decisions (e.g., Pope and Sydnor 2011; Lee and Lee 2012; Duarte et al. 2012). For instance, Lee and Lee (2012) observe investors' herding behavior in P2P lending. Duarte et al. (2012) and Pope and Sydnor (2011) suggest that P2P lending investors respond to signals of characteristics in attached pictures. Recent studies pay more attention to soft facts in the descriptive texts of loan applications (e.g., Herzenstein et al. 2011; Dorfleitner et al. 2016).

As a crowdfunding platform dedicated to promoting microfinance, Kiva has achieved huge success via its intermediary-based lending model (Kiva 2018a). Many studies examine the behavior of individual investors under this model (see e.g., Burtch et al. 2014; Allison et al. 2015; Moss et al. 2015). Burtch et al. (2014) find that cultural differences and geography have a significant influence on the fundraising outcome of Kiva intermediated loans. Dorfleitner et al. (2019) observe that MFIs who have a better level of social performance in terms of lending to women, lending responsibly and charging low interest, are more likely to be refinanced through Kiva. Jenq et al. (2015) examine behavioral biases of the investors supporting Kiva's intermediated loans and find that the investors favor those borrowers who appear to be more attractive. Allison et al. (2015) assess the effect of linguistic cues on the funding result for Kiva intermediated loans and find evidence that the investors prefer to support loan applicants who position their ventures as an opportunity to help others.

Differences in the Considered Setting

While some of the above findings on Kiva's intermediary-based model are important to our considerations, we argue that the interest-rate free P2P lending setting is very different. As Johnson et al. (2010) point out, most so-called

P2P microlending models actually do not facilitate the direct interaction of borrowers and investors and thus can not be seen as real P2P lending. This fundamental difference between the intermediary-based model and real P2P model would probably lead to different investor behavior.

First, the repayment rate in the P2P setting is (with 78%) rather low when compared with that in Kiva's intermediary-based model (97.5%).[3] This implies that the investors in interest-free P2P lending assume much higher credit risk. The credit risk in Kiva's intermediary-based model is less of a problem, and the corresponding investors may spend less effort in identifying trustworthy borrowers as the expected loss rate is only 2.5%. The fact that the funding probability in the interest-free P2P lending is less than 67%[4], which is much lower than 99% in the intermediary-based model (Berns et al. 2018), also implies the investors' serious concern about the default risk in the new setting. Second, as there is no financial compensation for the considerably higher potential credit risk of direct loans, the investors may take non-financial considerations more seriously. One could argue that the money spent on financing direct loans is 'play money'. But even if this were the case, there still must be a reason that one loan application is preferred over another. Third, the participants of direct loans interact directly without any intermediation. The borrowers of direct loans have the chance to promote their campaigns by deciding what information they want to deliver to the investors as they write their description texts themselves. At the same time, direct loan investors have more autonomy and responsibility in screening loan applications as they can no longer utilize the information of credit profile and social performance of MFIs.[5] Taking the above together, we expect that the investors in the interest-free P2P lending are more likely to reveal their real attitude and preferences from both the financial and non-financial perspectives.

Signaling in Interest-Free P2P Lending

While the information asymmetry prevails in every lending situation, the problem is even more serious for P2P lending investors since they are not professionals like banks or other institutional investors (Yum et al. 2012; Lee and Lee 2012). In the case of Kiva direct loans, the investors only have very limited information to evaluate loan applications. A typical US direct loan application on the Kiva website only includes very basic personal, geographical information, a brief loan description, and trustee information, while the repayment history of the borrower is difficult to obtain due to Kiva's effort to protect the borrowers' privacy. What makes the situation worse is the fact that there is even no interest rate for these direct loans, which usually serves as a signal of the credit risk of the loan.[6] Therefore, the investors of Kiva direct loans have to overcome adverse selection and the risk of moral hazard (Bruton et al. 2011).

According to signaling theory (Spence 1973, 2002), high-quality insiders can intentionally send positive signals about themselves to influence the decision-making of outsiders (Connelly et al. 2011). Signaling theory is often applied in the entrepreneurship literature to explain how the entrepreneurs attract potential investors (Lester et al. 2006; Alsos and Ljunggren 2017). Moss et al. (2015) and Jancenelle et al. (2018) argue that signaling theory is also applicable in the case of crowdfunding as the entrepreneurs are insiders and signals in crowdfunding are observable and costly. Several studies in crowdfunding literature adopt explicitly or implicitly signaling theory to investigate the investor's investment behavior (Allison et al. 2013, 2015; Moss et al. 2015; Jancenelle et al. 2018; Berns et al. 2018). In the context of interest-free P2P lending, the borrowers can send signals indicating their worthiness of being supported to reduce the severe information asymmetry. At the same time, the investors respond to these signals based on their financial and non-financial assessment. Even though signals sent by the borrowers in crowdfunding cannot be verified, Moss et al. (2015) argue that dishonest signals may not be in the best interest of the borrowers and they should strategically choose what signals to send. Michels (2012) also demonstrate that unverified information on the P2P lending platform Prosper can influence individuals' decisions and reduce the cost of debt.

Theoretical Basis: A Special Type of Investor Reacting to Signals

From the fact that no interest rate is charged and therefore the expected financial return is negative, we conclude that the backers of campaigns in the direct loan model must have some other source of felicity when investing. As Ly and Mason (2012a) or Allison et al. (2013) show, the investors in the intermediary-based model appear to be socially

[3] See Kiva (2019b). It's even lower than that of usual P2P lending. As an example, the average repayment rates for the German P2P lending platforms, Auxmoney and Smava, are 88% and 86.2% (Dorfleitner et al. 2016).

[4] See descriptive statistics in Section "Data and methodology".

[5] In Kiva's intermediary-based model, the investors can see credit profiles of the MFIs, including default rate, delinquency rate, loans at risk rate, etc. Moreover, they can also see whether a special social performance badge is assigned to the MFI (Kiva 2019c).

[6] The interest rate a potential borrower is willing to accept can signal the creditworthiness of the borrower in the sense that high interest rates are only accepted by borrowers with low creditworthiness, which corresponds to the idea of lemon markets (Akerlof 1970).

oriented. There is no reason for the assumption that in the direct model totally different investors are active. However, due to the discussed differences, the investors surely are not identical either, especially because the expected repayment in the direct loan setting is much lower than in the intermediary case. Still, following Dorfleitner et al. (2019), we model an investor's utility as comprising the financial return r and the social return s weighted with the factor $\alpha > 0$:

$$r + \alpha \cdot s \tag{1}$$

Even if $E(r) < 0$, empirical evidence from the intermediary-based model shows that the investors still stress credit risk to be closest to zero (Dorfleitner and Oswald 2016; Jenq et al. 2015). In contrast to kinship groups, the investors are not acquainted with the borrower personally and face even greater information disadvantages due to the distance to the borrower and the limited information provided in the loan application. It is evident that the investors are willing to provide capital only under the condition of a positive personal utility. Consequently, the expected social return $E(s)$ should overcompensate for the expected negative financial return.

Combining signaling theory and the above theoretical considerations, we develop several concrete hypotheses to investigate where the investors might induce a positive $E(s)$ or an $E(r)$ close to zero.

Hypotheses Development

To help investors evaluate the credit risk of borrowers, P2P platforms usually adopt several identifiable or quantifiable mechanisms such as the assignment of credit ratings and cooperation with partners. Several studies show that borrowers' credit ratings assigned by P2P platforms or external agencies are important to the investors' investment decisions (Freedman and Jin 2008; Barasinska and Schäfer 2014). Risk ratings of the MFIs in the intermediary-based microfinancing model could also be informative for the investors (Berns et al. 2018). However, the Kiva direct loan applicants do not have such a credit rating which may facilitate the investors' decision-making. Instead, the direct loan applications on Kiva can have trustees who endorse the borrowers.

Existence of an Endorsement

One of the most objective and obvious differences among direct loans is whether they are endorsed by a trustee. Mollick (2014) investigates the funding dynamics of the famous crowdfunding platform Kickstarter and suggests that a larger social network measured by the number of Facebook friends is associated with a more successful funding result. Studies in commercial P2P lending also show that borrowers' networks are very important in the reduction of information asymmetry (Liu et al. 2015; Lin et al. 2013; Freedman and Jin 2017). Likewise, personal networks of direct loan borrowers could play a role in the investors' decision-making. Kiva direct loans with an endorsement from trustees could be perceived as being safer because trustees have to evaluate the creditworthiness of borrowers beforehand and monitor borrowers' repayment behavior to minimize reputation risk. Indeed, Berger and Gleisner (2009) and Collier and Hampshire (2010) document that a community endorsement on the P2P platform Prosper leads to a favorable funding result, even though the endorsing lending-group leaders resume no financial responsibility. By considering the above, we expect that Kiva direct loans with a trustee endorsement are more likely to be funded.

H1 (Trustee endorsement) The existence of a trustee is positively related to funding success.

Apart from the potential existence of a trustee endorsement, the investors require more information to help them evaluate the borrowers' creditworthiness. Since the hard facts are limited in interest-free P2P lending, the investors' attention could be drawn to soft facts regarding the borrowers' creditworthiness in the description texts, which constitute the main part of the campaign web pages.

Creditworthiness Signals in the Description Texts

A significant amount of studies investigate soft factors in the description texts on P2P lending platforms (e.g., Allison et al. 2015; Moss et al. 2017; Jiang et al. 2018). For instance, the empirical fact that the descriptive texts can reduce information asymmetries and thus contribute to fundraising has been documented several times (e.g., Larrimore et al. 2011; Michels 2012). Although the description texts cannot be validated, they appear to contain some information (Michels 2012). However, generally the lenders should take into account that with a certain probability the information given in these texts is not completely correct, i.e., some applicants may cheat about their true motives and circumstances. Yet, this rationally only makes sense if the potential borrowers know which factors influence the funding probability.

As the description texts are written by different individual borrowers in Kiva's direct loan model, the text lengths differ. Several studies find that the length of the description text is a crucial driver of funding success in P2P lending (Larrimore et al. 2011; Michels 2012; Moss et al. 2017). Larrimore et al. (2011) argue that a lengthier text can provide more information about the borrower and thus build up trust between the borrower and investors in commercial P2P lending. Similarly, we expect that a longer and more detailed description text in interest-free P2P lending can also serve as a quality signal concerning the borrower's willingness to offer more information to the investors. However, as a very long description text could be troublesome for the non-professional investors to evaluate, we also expect that the positive effect of a longer description text to be dampened when the number of words exceeds a certain amount (e.g., Dorfleitner et al. 2016).

Besides the text length, linguistic signals in the description texts may indicate the project quality and could thus also affect the investors' decision-making. For instance, since microenterprise development is an important mission for microfinance in developed countries (Bendig et al. 2012, 2014; Diriker et al. 2018), the investors may pay special attention to the description of the loan usage. If there is little description related to business, the investors have no information to evaluate the feasibility of the underlying business and may be skeptical about the real intention of the borrower as Kiva direct loans are exclusively intended for entrepreneurial purposes (Kiva 2018b). Dorfleitner et al. (2016) also suggest that the mentioning of a business purpose in the loan application is related to a higher funding probability in P2P lending because business activities are more likely to create additional positive cash flows and help repay loans. Thus, we anticipate that a clear signal of the willingness to do business with the loan proceeds in the description texts contributes to funding success.

In addition, many studies in the entrepreneurship literature indicate that human capital is very important for the success of entrepreneurial activities (Robinson and Sexton 1994; Unger et al. 2011; Doms et al. 2010). A good education background has a strong and positive impact on entrepreneurship success, especially in a self-employment entrepreneurship setting (Robinson and Sexton 1994). With appropriate education, the borrowers are more likely to succeed in their entrepreneurial activities as they may gain the knowledge needed to manage the business. Indeed, Dorfleitner et al. (2016) find empirical evidence that the borrowers on a German P2P platform who mention their education background in the descriptive texts have a lower probability of default. Therefore, we anticipate that the investors may look for signals in the description texts which can indicate higher human capital, such as the borrowers' education background.

Based on the above considerations, we expect signals in the descriptive texts that build trust between direct loan investors and borrowers to play an important and positive role for funding success.

H2 (Trust) Signals in the descriptive texts that emphasize trustworthiness regarding the repayment are positively associated with funding success.

The theoretical considerations regarding the investors' utility imply that the investors are more likely to support loans with greater social impact to maximize their utility. The investors on prosocial P2P platforms are expected to help other people to alleviate impoverishment as they do not receive any interest from loans. Even return-oriented investors on commercial P2P lending platforms are occasionally motivated by social contributions (Pietraszkiewicz et al. 2017). Therefore, the concept of social impact is of large significance, especially for socially oriented investors, as Allison et al. (2013), Moss et al. (2017) and Jancenelle et al. (2018) prove for the intermediary-based model on Kiva. If we, therefore, assume an ethical dimension of philanthropy in the investors' perspective, the question of interest then is, which social aspects and corresponding signals they are appealed to.

To develop our hypotheses, we adhere to two major fields in which a social contribution can be made in microfinance, namely empowerment and vulnerability, following Gaiha and Thapa (2006). At the same time, we assume that the investors can perceive signals indicating the possibility of creating social impact in the description texts wherever applicable since there is no simple and quantifiable indicator of potential social impact like the social performance badge in the intermediary-based model on Kiva.

Empowerment

Empowerment is a process of change by which individuals or groups with little or no power (e.g., women, poor communities), gain in their power and ability to make choices that can change their lives (Cheston and Kuhn 2002). Based on the conceptual framework from Schulz et al. (1995), empowerment can be viewed at the individual, organizational and community levels. Accordingly, we discuss empowerment possibilities in interest-free P2P lending at these three levels.

Women's empowerment, particularly women's economic empowerment, is the core mission of the United Nations Industrial Development Organization (UNIDO 2018). It is intensively investigated in the microfinance literature and many studies agree that women's empowerment is a very important objective for microfinance (e.g., Kabeer 2001; Cheston and Kuhn 2002; Kabeer 2005; Swain and Wallentin 2009). Kiva offers a special loan category, exclusively to female borrowers, and prioritizes it on the loan requests list. As of October 2017, 81% of borrowers supported through Kiva have been female (Kiva 2018a). Heller and Badding (2012) find that female borrowers on Kiva in the intermediary-based model are funded 40% faster than their male counterparts. Ly and Mason (2012b) also find that it takes female borrowers of Kiva intermediated loans less time to gain funding. Therefore, we expect female borrowers of Kiva direct loans to receive more support from the investors.

Compared with individual direct loans, group direct loans are expected to attract more attention from direct loan investors as lending money to a group may increase the possibility of empowerment. As Thorp et al. (2005) argue, group formation can be an important way for the poor to be empowered. Stewart (2005) also agrees that the poor people within an organization can achieve more by taking collective actions since it is often too difficult for them to escape poverty through their own efforts. In Kiva's intermediary-based model, group loans are more likely to raise funds (Berns et al. 2018). Ly and Mason (2012b) argue that if the group size is relatively large, group loans are preferred because more beneficiaries profit from these loans.

Moreover, beyond the borrowers themselves, the investors could also empower others who have a close relationship with the borrowers such as their family members and communities. When the borrowers mention their family members and communities in the description texts, the investors may perceive this as an opportunity to empower more unprivileged people, rather than just the borrowers. Freedman and Jin (2008) find evidence that loan requests on Prosper that mention family members are more likely to be funded. Allison et al. (2015) also find that words related to family members in the description texts, written by MFIs, can reduce time to funding for Kiva intermediated loans. Calic and Mosakowski (2016) suggest that social entrepreneurs who focus on the preservation of nature, life support, and community are more likely to be funded on the donation-based crowdfunding platform Kickstarter. By supporting prosocial borrowers, the investors of direct loans do not only help the borrowers to fulfill their personal goals but also help more people indirectly. Therefore, we expect these prosocial loan applications to be preferred by direct loan investors.

H3 (Empowerment) A description text indicating empowerment possibilities is positively related to funding success.

Vulnerability

Besides empowerment possibility, direct loan investors can also look for the chance to help those who are in a very vulnerable position to make a social contribution. Vulnerability reduction is often seen as a desirable outcome of microfinance and closely examined in the microfinance literature (Zaman 1999; Tchouassi 2011; Swain and Floro 2012). Jenq et al. (2015) find that perceived neediness in the attached pictures is positively related to the funding speed of Kiva intermediated loans. According to Dorfleitner et al. (2016), P2P loan applications with negative keywords in the descriptive texts have a higher funding probability. Thus, we expect that the needy borrowers in the interest-free P2P lending can possibly attract more attention by expressing their misery in the descriptive texts.

Among the needy and vulnerable borrowers, the direct loan applicants with an immigration background are of special interest to us in this study as immigrants in developed countries often suffer from a lack of resources and financing support in the new environment. For instance, Aldén and Hammarstedt (2016) find that non-European immigrants in Sweden report upon more discrimination by traditional finance institutions. Pedrini et al. (2016) point out that the immigrant population is one of the most important targets for MFIs in developed countries. According to Jayo et al. (2010), more than 40% of MFIs in Europe identify the ethnic minorities and immigrants as their target clients. Therefore, the borrowers with an immigration background can be expected to be a target group of direct loan investors. In summary, we expect that direct loan applicants that appear to be vulnerable are more likely to be funded.

H4 (Vulnerability) If the description text indicates that a borrower is more vulnerable, the probability of funding is higher.

Data and Methodology

Data Description

Our analysis is based on interest-free direct loans which are requested by US inhabitants using the direct P2P model on Kiva. The data set is derived from Kiva's public API and includes loan applications posted on Kiva between 2011 and 2017 which can either be categorized as 'successfully funded' or 'unsuccessfully funded'. The data set is extended through additional information extracted from the original campaign web pages. Loan applications include information on loan conditions and the trustee endorsement if a trustee is provided. The applicant's personality and the purpose of the loan request are described in a descriptive text. The data set is cleared by removing 8 observations with unrealistic loan amounts of more than 10,000 USD (strict limit defined by Kiva) and 20 unsound loan applications without a description text and therefore lacking information both on the applicant and the purpose of the loan. The final data set comprises 6121 observations. Therein, 4077 loans are successfully funded and 2,044 loans have expired. All variables relevant to our analysis are explained in detail in Table 1.

Two dependent variables are observable. The first one is *Funding success*, being defined as a binary variable with a value of one if the loan request is successfully funded by the crowd of investors and zero otherwise. Additionally, the funding time for funded loans is observable. The funding time in days measures how long it has taken loan applicants to receive successful funding via the crowd. The second dependent variable, *Reversed funding time*, is calculated as 1000 divided by the funding time in days. Thereby, the reversed funding time of non-funded loans is set to be zero

Table 1 Definition of variables

Variable	Expected effect	Description
Dependent variables		
Funding success		Binary variable with a value of one if a loan application meets its funding goal, zero otherwise
Reversed funding time		Metric variable calculated as 1000 divided by the funding time (in days). The funding time indicates how long it takes loan applicants to meet funding goals. Values are logrithmized
Cox survival time		Metric variable measuring the survival time of loan applications. The original survival time is multiplied by 100 and logarithmized. For none-funded loans, the time until expiration is employed as the original survival time
H1 Trustee endorsement		
Trustee	+	Dummy variable with a value of one if the loan application has a trustee, zero otherwise
Type		Trustees are categorized into individuals, non-profit organizations, others, and no trustee endorsement. Reference category: individuals
Trustee's experience	+	Time period in days the trustee has had experience on Kiva
Trustee's proximity	+	Dummy variable with a value of one if the trustee and the applicant are located in the same US state, zero otherwise
H2 trust		
# of words	+	Length of the narrative description of the business idea and the applicant's background measured in 100 words
Keyword_Business	+	Dummy variable with a value of one if the applicant's planned entrepreneurship is explained, zero otherwise
Keyword_Education	+	Dummy variable with a value of one if the applicant's educational background is stated, zero otherwise
H3 empowerment		
Gender	+	Categorical variable for female individual/groups, male individual/group, and mixed group consisting of female and male borrowers. Reference category: male individual/groups
Individual	−	Dummy variable with a value of one if the loan is a individual loan, zero otherwise
Keyword_Family	+	Empowerment in terms of family members being positively affected by the loan. Dummy variable with a value of one if family empowerment is stated, zero otherwise
Keyword_Community	+	Empowerment in terms of the applicant's intention to benefit his or her community. Dummy variable with a value of one if community empowerment is stated, zero otherwise
H4 Vulnerability		
Immigration	+	Dummy variable with a value of one if an immigration background of the applicant is given, zero otherwise
Keyword_Negative	+	Dummy variable with a value of one if social dislocation of the loan applicant is mentioned, zero otherwise
Controls		
Principal per month		Metric variable calculated as loan amount (in USD) divided by loan length (in months, the duration between the disbursal date, and the due date of the last repayment obligation)
Keyword_Positive		Dummy variable with a value of one if the applicant's positivity experienced is stated, zero otherwise
Keyword_Purpose		Dummy variable with a value of one if the applicant's expectation with the help of loan proceeds is stated, zero otherwise
Video		Dummy variable with a value of one if a video is available, zero otherwise
Expiration		Metric variable (in months) calculated based on the duration between the posting date on Kiva and the planned expiration date
Year index		Index variable for each year in which the loan application is posted in an ascending order (e.g., 1 for 2011 and 7 for 2017)
Activity sector		Activity sectors are categorized into agriculture, arts, clothing, construction, education, entertainment, food, health, housing, manufacturing, retail, service, transportation, and wholesale. Reference category: agriculture
US state		US state in which the loan applicant is located

Table 2 Categorical variables depicting possible keywords in the description texts

Hypothesis	Variable	Keywords
H2 Trust	Keyword_Business	Business, career, client, company, customer, employment[a], entrepreneur[a], expand, financial stability, invest, job, network, profession[a], profitability[a], skills[a]
	Keyword_Education	Academic, Bachelor, college, degree, education, exam, graduation[a], Master, PhD, (high-/home-) school, student, study, undergraduate, university
H3 Empowerment	Keyword_Family	Aunt, boy, brother, (grand-) child, dad, (grand-) daughter, family, (grand-) father, husband, kid, marriage[a], mom, (grand-) mother, (grand-) parents, partner, pregnant, siblings, sister, (grand-) son, uncle, wife
	Keyword_Community	community, friend, help[a], serving others, support[a]
H4 Vulnerability	Keyword_Negative	Abuse, addiction[a], cancer, civil war, death, defeat me, destiny, difficulty[a], disruption[a] drug, enemy, hard work, incarceration, insane, pain[a], passed away, poverty, prison, sick, ups and downs, victim
Controls	Keyword_Positive	Enjoy, fun, happiness[a], greatness[a], love[a], pleasure, smile[a], thankful, thank you
	Keyword_Purpose	Believe, better future, better life, chance, dream, fascination[a], motivation, passion[a], purpose, vision

The keywords are obtained by analyzing the description text of loan applicants using the computerized text analysis software LIWC2015. All keywords are stated as being singular. The respective plural words are also taken into account

[a]indicates that all respective verbs, adjectives, and adverbs are also taken into account as keywords

as their funding time is infinite. This *Reversed funding time* can serve as a proxy for funding speed as it measures how fast a loan can be funded. Values are logarithmized.

All four hypotheses stated above are tested through several explanatory variables. Regarding H1, whether or not a trustee is given, is considered in the dummy variable *Trustee*. The variable *Type* distinguishes among different types of trustees: individuals, non-profit organizations and others. For loan applications with a trustee endorsement, we can calculate *Trustee's experience*, which indicates how long the trustee has been on Kiva in days at the point of time when the respective, new loan application is posted publicly. Furthermore, we include a dummy variable, *Trustee's proximity*, to indicate whether the trustee and the applicant are located in the same US state. The proximity of trustees and loan applicants located in the same US state is perceived as being higher.

Second, to test whether the applicant's effort to build trust helps to attract potential investors, signals within the description texts are considered. The extent of the description texts is often considered when examining the determinants of funding success in the crowdfunding literature (e.g., Parhankangas and Renko 2017; Pietraszkiewicz et al. 2017). The variable *# of words*, calculated by counting the number of words in the description texts, is a measure of trustworthiness and could reflect the applicant's willingness to share information with potential investors (Dorfleitner et al. 2016). To capture the possible u-shape relationship between the text length and the funding result, we also include the quadratic term of the text length *# of words*^{2} following Dorfleitner et al. (2016). In addition to the text length, we extract more signals from the description texts by searching for keywords that could provide more insights into the applicant's creditworthiness and the possibility of making a social contribution (see e.g., Berns et al. 2018; Jancenelle et al. 2018). All keywords are defined and reported in Table 2.

The dummy variable *Keyword_Business* indicates whether the applicant's intention of entrepreneurship can be detected in the text, while *Keyword_Education* clarifies whether the applicant mentions an appropriate educational background to enable the successful management of the entrepreneurial activity.

In the context of social lending, the empowerment attained through the granted credit is highly valuable to the investors, being the subject of H3. The dummy variable *Individual* indicates whether the loan supports only one individual borrower or more people, as is the case with a group of borrowers. The applicant's gender as one of the most discussed aspects of microfinance and crowdlending is considered in the categorical variable *Gender*. Female/male individuals or groups of only female/male borrowers are defined as being female/male, respectively. Groups consisting of male and female individuals are categorized as being mixed. Furthermore, empowerment of the applicant's family and community is measured by *Keyword_Family* and *Keyword_Community*, which indicate the mentioning of the family and the community to which the loan applicant belongs respectively.

Last but not least, the applicant's vulnerability is measured by the dummy variables *Immigration* and *Keyword_Negative*. The immigration background of the applicant and/or his family is considered if this aspect is explicitly mentioned in the loan application. Otherwise, the applicant is assumed to be a native US inhabitant with no immigration background. Furthermore, the description text usually includes information about the applicant's social and emotional constitution. Negative keywords are associated with the applicant's vulnerability as the applicant appears to have faced severe difficulties and social abuse, such as serious illness, drug addiction, and incarceration.

The following control variables are considered in the analysis. Loan conditions like the loan amount in USD and the loan length in months are included through the variable *Principal per month*. Furthermore, the intended usage of the loan is categorized into one of 14 activity sectors, such as services and food, represented by *Activity sector*. In contract to *Keyword_Negative*, *Keyword_Positive* indicates whether the applicant has a more balanced social constitution and expresses a positive emotion in the description texts. The applicant's expectation associated with the loan is represented by the dummy variable *Keyword_Purpose*. While all loan applicants are visualized in a photograph, only a few loan applicants use a video to further emphasize their personality (dummy variable *Video*). Additionally, *US state* and *Year index* indicate where the loan applicant is located and when the loan application was posted, respectively. As a last control variable, we include *Expiration* to measure how much time the loan applicant has for fundraising on Kiva. All loan applications have a defined period during which the loan must be fully funded; otherwise, the loan application is removed from Kiva's web pages.

Methodology

The main determinants of successful debt funding through Kiva by socially oriented investors are expected to be located in the areas of credit risk and social impact. All the variables related to H1 and H2 are summarized by the vector R_i in our models. The variables corresponding to H3 and H4 are represented by the vector S_i. The vector C_i represents the loan-specific controls and *Year index*. The loan-specific error term is ϵ_i. The latent variable Y_i^* is determined through

$$Y_i^* = \beta_0 + \beta_1 R_i + \beta_2 S_i + \beta_3 C_i + \epsilon_i ,$$

which is fed into respective link functions according to the logistic and Tobit estimations. Primarily, funding success, being defined as a binary variable, is subject to our research. We use logistic regression models with Eicker-Huber-White robust standard errors to estimate the probability of successful debt funding. Furthermore, we are interested in the funding time which is only observable as a positive time interval for successfully funded loans but not for non-funded loans. In order not to lose the observations of non-funded loans, we investigate the reversed funding time instead of the funding time. Thus, the total data sample consists of censored (reversed funding time = 0) and uncensored (reversed funding time > 0) observations. Due to the left-censoring of the data set, Tobit regression models are chosen to estimate the linear relationship between variables. Alternatively, the Cox proportional hazard model can be applied to estimate the time until the event of successful funding without losing the observations of non-funded loans. Therefore, the Cox proportional hazard model is run as a robustness check to verify the Tobit regression results.

Descriptive Statistics

Tables 3 and 4 present the descriptive statistics for metric and categorical variables that contribute to testing our hypotheses, while the descriptive statistics for our control variables are displayed in Table 5.

The requested loan amount ranges from 100 to 10,000 USD, which is set as the upper credit limit by Kiva. On average, the loan duration is 25.2 months. The calculated principal per month is defined with a minimum value of 10.4 USD/month and a maximum value of 1,333.3 USD/month. Both extreme scenarios appear in the subsample of non-funded loans. Less than 2% of the loans are requested by groups of at least two individuals. The majority of loan applicants is female, compromising 57% of the entire sample. More than 60% of the successfully funded loans are given to female borrowers.

A trustee is available for less than half of the loan applications on Kiva. In the subsample of funded loans, 55% of the loans are endorsed by a trustee, whereas in the subsample of non-funded loans, only 16% of the observations are endorsed by a trustee. On average, a trustee has experience of almost 15 months, which is a factor that does not differ greatly between the subsamples. The negative minimum value of − 119 days is reasonable in the case of a trustee being acquired after the public posting of a loan and the commencement of fundraising. Most of the trustees are categorized as being of the type 'others', followed by non-profit organizations and lastly by individuals. In more than 90% of the cases, the trustee and the loan applicant are located in the same US state.

The description text comprises an average of 545 individual words. The text description is more comprehensive in the subsample of successfully funded loans compared with the subsample of non-funded loans. Loan applications that do not state the entrepreneurial activity are seldom. The educational background is frequently stated. A share of 84% of the loan applicants provides insights into their family situation and 96% about their community. In 19% of the cases, an immigration background is explicitly mentioned in the description texts. The share of immigrants significantly differs by 7.5% between the subsamples of funded loans and non-funded loans. In less than 32% of all cases, the description texts include negative aspects.

Regarding our controls, more than 72% of the loan applications contain keywords indicating positive aspects. 80% of the loan applicants describe their expectations related to the loan. A video is not commonly available. The loans are

Table 3 Descriptive statistics for metric variables

Variable	Obs.	Mean	S.D.	Min	Median	Max
Total sample						
Loan amount	6121	4914.41	3036.05	100.00	5000.00	10,000.00
Loan duration (in months)	6121	25.24	8.14	1.00	24.00	51.00
Principal per month	6121	183.80	86.74	10.42	208.33	1333.33
# of words (in 100 words)	6121	5.45	2.27	0.66	5.25	26.25
Trustee's experience (in days)	2588	442.34	472.86	-119.00	280.00	2073.00
Expiration (in days)	6121	67.74	125.63	15.00	52.50	1682.01
Year index	6121	5.66	1.30	1.00	6.00	7.00
Funded loans						
Funding time (in days)	4077	44.15	30.09	0.10	39.04	300.55
Loan amount	4077	5206.48	2994.86	100.00	5000.00	10,000.00
Loan duration (in months)	4077	25.87	8.10	1.00	24.00	51.00
Principal per month	4077	191.92	82.07	12.50	208.33	1111.11
# of words (in 100 words)	4077	5.70	2.22	0.84	5.56	26.25
Trustee's experience (in days)	2255	440.50	472.36	-119.00	273.00	1986.00
Expiration (in days)	4077	79.89	150.76	15.01	58.05	1682.01
Year index	4077	5.52	1.40	1.00	6.00	7.00
Non-funded loans						
Loan amount	2044	4331.85	3034.47	125.00	5000.00	10,000.00
Loan duration (in months)	2044	23.98	8.09	6.00	24.00	42.00
Principal per month	2044	167.62	93.30	10.42	166.67	1333.33
# of words (in 100 words)	2044	4.95	2.28	0.66	4.65	21.39
Trustee's experience (in days)	333	454.76	476.72	-62.00	336.00	2073.00
Expiration (in days)	2044	43.52	32.48	15.00	34.59	462.76
Year index	2044	5.93	1.01	2.00	6.00	7.00

The entire data sample contains 6121 observations. The variables are defined in Table 1

widely distributed among the activity sectors with an emphasis on services, followed by food and retail.

Bravais–Pearson correlation coefficients for dependent and all explanatory variables are shown in Table 6. We do not expect any multicollinearity issues as all pairwise correlations for explanatory variables are far below 0.8, which is the critical value according to Kennedy (2008). The correlation between the two dependent variables *Funding success* and *Reversed funding time* is as high as 0.8566 which encourages us to examine both variables in separate regressions and an additional joint regression.

Results

Results Regarding Funding Success

To commence, we focus on the empirical results of the estimated logistic models regarding the probability of funding success on Kiva. The respective logistic regression models are presented in Table 7. Model I is the basic model consisting of details that are obvious in the loan applications. It is extended by adding information on trustee types in model II. Model III is the main model, including visible and less-visible details on credit risk indicators and social performance indicators of loan applications as determinants of funding success.

The dummy variable clarifying whether or not a loan application is endorsed by a trustee provides a clear picture as it is positive and significant at the 1% level (coeff.: 1.5398, st.err.: 0.0886.[7]) Loans that are endorsed by a trustee are more likely to be funded than loans without a trustee endorsement. The result is further strengthened by the dummy variables depicting the type of trustee in model II. While loans without an endorsement are less likely to be funded compared with loans endorsed by an individual, loans promoted by a non-profit organization are even more likely to be funded.

Furthermore, the foundation of trust between investors and the borrower is expected to play a role. The length of the description text is used as a measurement for the borrower's willingness to share information. The coefficient of

[7] If not otherwise specified, the coeff. and st.err. in parentheses are from model III.

Table 4 Descriptive statistics for main categorical variables

Variable	Total sample		Funded loans		Non-funded loans	
	N = 6121		*N* = 4077		*N* = 2044	
	Obs.	Relative	Obs.	Relative	Obs.	Relative
Funding success						
Yes	4077	66.61	4077	100.00	0	0.00
No	2044	33.39	0	0.00	2044	100.00
Trustee						
Yes	2588	42.28	2255	55.31	333	16.29
No	3533	57.72	1822	44.69	1711	83.71
Type						
Individual	478	7.81	405	9.93	73	3.57
Non-Profit	899	14.69	804	19.72	95	4.65
Others	1211	19.78	1046	25.66	165	8.07
No endorsement	3533	57.72	1822	44.69	1711	83.71
Trustee's proximity						
Yes	2358	91.15	2070	91.84	288	86.49
No	229	8.85	184	8.16	45	13.51
Keyword_Business						
Yes	6053	98.89	4031	98.87	2022	98.92
No	68	1.11	46	1.13	22	1.08
Keyword_Education						
Yes	3873	63.27	2638	64.70	1235	60.42
No	2248	36.73	1439	35.30	809	39.58
Individual						
Yes	6020	98.35	3993	97.94	2027	99.17
No	101	1.65	84	2.06	17	0.83
Gender						
Male	2521	41.19	1532	37.58	989	48.39
Female	3530	57.67	2488	61.03	1402	50.98
Mixed	70	1.14	57	1.40	13	0.64
Keyword_Family						
Yes	5180	84.63	3500	85.85	1680	82.19
No	941	15.37	577	14.15	364	17.81
Keyword_Community						
Yes	5897	96.34	3937	96.57	1960	95.89
No	224	3.66	140	3.43	84	4.11
Immigration						
Yes	1183	19.33	889	21.81	294	14.38
No	4938	80.67	3188	78.19	1750	85.62
Keyword_Negative						
Yes	1954	31.92	1334	32.72	620	30.33
No	4167	68.08	2743	67.28	1424	69.67

The entire data sample contains 6121 observations. Absolute values and relative values of the categorical variables are displayed. The variables are defined in Table 1

# of words is positive and significant (coeff.: 0.2465, st.err.: 0.0468). Therefore, the longer the text description, the higher the probability of successful funding. However, *# of words*^{2} has a significant and negative coefficient indicating an overall inverse u-shaped relation (coeff.: – 0.0096, st.err.: 0.0032). Regarding the coefficients of *Keyword_Business* and *Keyword_Education*, we are unable to find any evidence as both of them are not significant.

Concerning H3 and H4, we observe the following. The dummy variable demonstrating female borrowers is positive and significant in all model specifications (coeff.: 0.5298, st.err.: 0.0698). Female borrowers are more likely to receive

Table 5 Descriptive statistics for categorical variables–controls

Variable	Total sample		Funded loans		Non-funded loans	
	$N = 6121$		$N = 4077$		N=2044	
	Obs.	Relative	Obs.	Relative	Obs.	Relative
Keyword_Positive						
Yes	4450	72.70	2992	73.39	1458	71.33
No	1671	27.30	1085	26.61	586	28.67
Keyword_Purpose						
Yes	5018	81.98	3416	83.79	1602	78.38
No	1103	18.02	661	16.21	442	21.62
Video						
Yes	69	1.13	44	1.08	25	1.22
No	6052	98.87	4033	98.92	2019	98.78
Activity sector						
Agriculture	439	7.17	377	9.25	62	3.03
Arts	326	5.33	236	5.79	90	4.40
Clothing	445	7.27	288	7.06	157	7.68
Construction	95	1.55	56	1.37	39	1.91
Education	181	2.96	109	2.67	72	3.52
Entertainment	199	3.25	96	2.35	103	5.04
Food	1361	22.23	1071	26.27	290	14.19
Health	67	1.09	40	0.98	27	1.32
Housing	42	0.69	20	0.49	22	1.08
Manufacturing	26	0.42	20	0.49	6	0.29
Retail	974	15.91	611	14.99	363	17.76
Services	1862	30.42	1103	27.05	759	37.13
Transportation	92	1.50	41	1.01	51	2.50
Wholesale	12	0.20	9	0.22	3	0.15

The entire data sample contains 6121 observations. Absolute values and relative values of the categorical variables are displayed. The variables are defined in Table 1

funding than their male counterparts. Regarding the question of whether group loans are preferred over individual loans, we can ascertain that individual applicants have more difficulties receiving funding than groups of borrowers (coeff.: –0.9528, st.err.: 0.5608). The variable *Keyword_Family* proves to be negatively related to funding success (coeff.: – 0.1965, st.err.: 0.0915). The result is significant and contradictory to our expectations. One possible reason could be that the borrower's responsibility for his or her family members appears to be obstructive in terms of entrepreneurship as opposed to being positively perceived in terms of empowerment. The second variable representing community empowerment is positive but not significant (coeff.: 0.0729, st.err.: 0.1642).

Furthermore, the coefficient of the immigration dummy variable is positive and significant at the 1% level (coeff.: 0.5991, st.err.: 0.0969), providing evidence that immigrants are more likely to be successfully funded through the crowd of socially oriented investors. One reason behind this finding may be that the investors perceive immigrants as being needier and more vulnerable as they often suffer from exclusion in the United States. In contrast, the borrower's previous social dislocation stated by negative words does not appear to be a significant determinant.

The considered control variable for the time until the expiration of the loan application shows a positive and significant coefficient (coeff.: 0.0335, st.err.: 0.0035). Loans without a strict time limit for fundraising are more likely to be funded. It is interesting that *Year index* is positive and significant (coeff.: 0.3196, st.err.: 0.0419), which could be considered as an indication for the investor's learning curve in terms of supporting more US direct loans over time. Taking into account that the volume of US direct loans on Kiva has increased significantly over the last years (see Table 5) as well as the positive development of funding success, it appears promising that the investors are becoming more confident when providing capital directly to US inhabitants in need. None of the other controls such as *Keyword_Positive*, *Principal per month*, and *Video* provides any further insights.

Additionally, we divide the data sample into two subsamples with and without a trustee endorsement and run

Table 6 Bravais–Pearson correlation coefficients between all pairs of variables

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
1.	Funding success	1.000															
2.	Reversed funding time	0.8566*	1.000														
3.	Trustee endorsement	0.3725*	0.2377*	1.000													
4.	Type_Individual	0.1118*	0.0718*	0.3401*	1.000												
5.	Type_Non_Profit	0.2008*	0.1362*	0.4848*	−0.1117*	1.000											
6.	Type_Others	0.2082*	0.1253*	0.5803*	−0.1334*	−0.1896*	1.000										
7.	Type_No endorsement	−0.3725*	−0.2377*	−1.000	−0.3029*	−0.4305*	−0.5140*	1.000									
8.	Trustee's experience	0.2120*	0.1894*	0.5794*	0.0102	0.3172*	0.4297*	−0.5794*	1.000								
9.	Trustee's proximity	−0.3426*	−0.2147*	−0.9455*	−0.3407*	−0.4663*	−0.5286*	0.9455*	−0.5381*	1.000							
10.	# of words	0.1538*	0.0928*	0.1936*	0.0442*	0.0787*	0.1404*	−0.1936*	0.0799*	−0.1896*	1.000						
11.	Keyword_Business	−0.0023	0.0044	−0.0292*	−0.0331*	−0.0001	−0.0139	0.0292*	0.0060	0.0266*	0.0659*	1.000					
12.	Keyword_Education	0.0419*	−0.0034	0.1053*	0.0323*	0.0279*	0.0840*	−0.1053*	0.0365*	−0.1050*	0.2803*	0.0130	1.000				
13.	Gender_male	−0.1036*	−0.1386*	0.0303*	0.0293*	0.0570*	0.0239	0.0329*	−0.0233	−0.0346*	−0.0717*	−0.0348*	−0.0173	1.000			
14.	Gender_female	0.0959*	0.1339*	−0.0358*	0.0103	−0.0042	0.0334*	0.1165*	0.0223	0.0407*	0.0632*	0.0354*	0.0147	−0.8527*	1.000		
15.	Gender_mixed	0.0338*	0.0190	0.0261*	−0.0063	0.0104	0.0347*	−0.0170	0.0040	−0.0292*	0.0383*	−0.0033	0.0118	−0.0820*	−0.1121*	1.000	
16.	Individual	−0.0455*	−0.0316*	−0.0319*	0.0042	−0.0042	−0.0387*	0.0319*	−0.0063	0.0396*	−0.0434*	−0.0015	−0.0162	0.0719*	0.1071*	−0.8304*	1.000
17.	Keyword_Family	0.0478*	0.0461*	0.0173	−0.0009	0.0143	0.0093	−0.0173	0.0142	−0.0143	0.1570*	0.0283*	0.0793*	−0.1311*	0.1262*	0.0203	−0.0161
18.	Keyword_Community	0.0170	0.0301*	−0.0164	−0.0179	−0.0125	0.0029	0.0164	0.0329*	0.0213	0.0966*	0.0541*	0.0230	−0.0278*	0.0267*	0.0046	−0.0048
19.	Immigration	0.0886*	0.1353*	−0.0755*	−0.0268*	−0.0102	−0.0665*	0.0755*	−0.0166	0.0802*	−0.1665*	0.0242	−0.0760*	−0.0632*	0.0701*	−0.0332*	0.0277*
20.	Keyword_Negative	0.0242	0.0248	0.0013	−0.0086	0.0069	0.0012	−0.0013	0.0151	−0.0068	0.1731*	−0.0177	0.0390*	−0.0454*	0.0497*	−0.0209	0.0144
21.	Principal per month	0.1321*	0.0427*	0.2830*	0.0853*	0.1276*	0.1801*	−0.2830*	0.1640*	−0.2708*	0.1706*	0.0046	0.0659*	0.0789*	−0.0901*	0.0535*	−0.0651*
22.	Keyword_Positive	0.0218	−0.0018	0.0323*	0.0007	0.0139	0.0272*	−0.0323*	−0.0101	−0.0327*	0.2327*	0.0470*	0.0253*	−0.0773*	0.0747*	0.0107	−0.0132
23.	Keyword_Purpose	0.0664*	0.0512*	0.0640*	0.0145	0.0240	0.0483*	−0.0640*	0.0444*	−0.0564*	0.1878*	0.0274*	0.0537*	−0.0723*	0.0741*	−0.0095	−0.0007
24.	Video	−0.0064	−0.0052	−0.0131	0.0035	−0.0006	−0.0181	0.0131	0.0232	0.0129	0.0001	−0.0034	−0.0085	0.0081	−0.0087	0.0031	0.0017
25.	Expiration	0.1365*	0.0374*	0.1838*	0.0781*	0.1196*	0.0690*	−0.1838*	−0.0221	−0.1808*	0.0613*	0.0037	0.0408*	0.0204	−0.0197	−0.0033	0.0044

		17.	18.	19.	20.	21.	22.	23.	24.	25.
17.	Keyword_Family	1.000								
18.	Keyword_Community	0.0448*	1.000							
19.	Immigration	0.1306*	0.0139	1.000						
20.	Keyword_Negative	0.1073*	0.0420*	0.0438*	1.000					
21.	Principal per month	−0.0390*	−0.0167	−0.1089*	−0.0202	1.000				
22.	Keyword_Positive	0.0987*	0.0368*	−0.0771*	0.0208	0.0573*	1.000			
23.	Keyword_Purpose	0.0783*	0.0739*	0.0293*	0.0758*	−0.0033	0.0905*	1.000		
24.	Video	−0.0060	0.0126	−0.0209	0.0165	0.0075	−0.0284*	−0.0023	1.000	
25.	Expiration	−0.0086	−0.0028	−0.0181	0.0128	0.1638*	0.0213	0.0092	−0.0183	1.000

The variables Activity sector and US state are not explicitly reported due to the number of categories and minor explanatory power. Values labeled with the symbol * are significant at the 5% level. The variables are defined in Table 1

Table 7 Coefficients of logistic models on funding success

	All observations			with trustee		w/o trustee
	(I)	(II)	(III)	(IV)	(V)	(VI)
Trustee endorsement						
Trustee	1.5852***		1.5398***			
	(0.0881)		(0.0886)			
Type_Non_Profit		0.3114*		− 0.0535	0.0455	
		(0.1828)		(0.1903)	(0.1920)	
Type_Others		− 0.0463		− 0.3274*	− 0.2496	
		(0.1661)		(0.1783)	(0.1798)	
Type_No_End.		− 1.5132***				
		(0.1510)				
Trustee's experience				0.0004***	0.0002	
				(0.0002)	(0.0002)	
Trustee's proximity				0.6564***	0.6614***	
				(0.2168)	(0.2150)	
Trust						
# of words			0.2465***	0.2647***	0.2645***	0.2683***
			(0.0468)	(0.0872)	(0.0873)	(0.0587)
# of words^2			− 0.0096***	− 0.0093	− 0.0089	− 0.0109***
			(0.0032)	(0.0063)	(0.0063)	(0.0041)
Keyword_Business			0.0294	0.3369	0.3248	− 0.1019
			(0.2981)	(0.4354)	(0.4378)	(0.3940)
Keyword_Education			− 0.0226	0.1292	0.1525	− 0.0332
			(0.0696)	(0.1344)	(0.1336)	(0.0839)
Empowerment						
Individual	− 1.0796*	− 1.0952**	− 0.9528*	− 1.3781	− 1.4042	− 0.8295
	(0.5519)	(0.5507)	(0.5608)	(1.1968)	(1.1501)	(0.7150)
Gender_female	0.5735***	0.5769***	0.5298***	0.2388*	0.2280*	0.6389***
	(0.0683)	(0.0683)	(0.0698)	(0.1369)	(0.1365)	(0.0849)
Gender_mixed	− 0.3578	− 0.3598	− 0.2615			− 0.4520
	(0.6348)	(0.6339)	(0.6404)			(0.8156)
Keyword_Family			− 0.1965**	− 0.0707	− 0.1169	− 0.2381**
			(0.0915)	(0.1710)	(0.1706)	(0.1116)
Keyword_Community			0.0729	− 0.1594	− 0.2733	0.1845
			(0.1642)	(0.3191)	(0.3264)	(0.2048)
Vulnerability						
Immigration			0.5991***	− 0.1029	− 0.1323	0.7473***
			(0.0969)	(0.1803)	(0.1801)	(0.1095)
Keyword_Negative			− 0.0162	− 0.1147	− 0.1093	0.0261
			(0.0715)	(0.1378)	(0.1375)	(0.0854)
Controls						
Keyword_Positive			− 0.1092	− 0.1465	− 0.1414	− 0.1024
			(0.0751)	(0.1461)	(0.1452)	(0.0909)
Keyword_Purpose			0.1307	0.1193	0.1520	0.1046
			(0.0838)	(0.1709)	(0.1692)	(0.1007)
Principal per month	0.0002	0.0002	− 0.0001	− 0.0003	− 0.0001	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0008)	(0.0008)	(0.0005)
Video	− 0.1297	− 0.1395	− 0.1438	− 0.6957	− 0.8832*	0.2408
	(0.3123)	(0.3142)	(0.3107)	(0.4658)	(0.4799)	(0.3371)
Expiration	0.0342***	0.0341***	0.0335***	0.0213***	0.0262***	0.0372***

Table 7 (continued)

	All observations			with trustee		w/o trustee
	(I)	(II)	(III)	(IV)	(V)	(VI)
	(0.0035)	(0.0035)	(0.0035)	(0.0046)	(0.0059)	(0.0046)
Year index	0.3287***	0.3309***	0.3196***		0.2132**	0.3169***
	(0.0407)	(0.0408)	(0.0419)		(0.0844)	(0.0526)
Activity sector	Yes	Yes	Yes	Yes	Yes	Yes
US state	Yes	Yes	Yes	Yes	Yes	Yes
_cons	– 1.5408*	– 0.0480	– 2.7005***	1.3975	0.2327	– 3.0215***
	(0.8953)	(0.9101)	(1.0089)	(1.4965)	(1.6047)	(1.0334)
N	6,121	6,121	6,121	2,550	2,550	3,533
Pseudo R^2	0.260	0.261	0.273	0.135	0.140	0.213

Models I–III include all observations. Models IV–VI consider the subsamples of loans with and without a trustee endorsement separately. Model I is extended by including the different types of trustees, resulting in Model II. Model III is the main model including several social performance indicators that have been extracted through keywords from the description text. Models IV–VI follow the main model

Eicker-Huber-White heteroskedastic-consistent errors are used. Values labeled with the symbols *, **, and *** are significant at the 10% level, the 5% level, and the 1% level. The variables are defined in Table 1

subsample regressions. In the subsample of endorsed loans, 38 observations are lost as all loans requested by a mixed group of female and male individuals are successfully funded. The focus on the subsample of loans with a trustee endorsement in models IV and V allows us to include further variables that provide details about the trustees. *Trustee's experience* is positive and significant in model IV, but not in model V, which also includes *Year index*. Consequently, as the trustee's experience in days increases over the years, the result appears to be time-dependent and should not be overvalued. A noteworthy observation is the positive and significant coefficient of *Trustee's proximity* (Model V: coeff.: 0.6614, st.err.: 0.2150). The fact that the trustee and the borrower are located in the same US state is positively related to funding success. One reason behind this finding could be that the endorsement from a trustee who is geographically closer to the borrower is more recognized and valued by the investors.

Regarding the borrower's willingness to share information in the description texts, the results are similar to those in the total data set. The coefficient of *# of words* is positive and significant (Model V: coeff.: 0.2645, st.err.: 0.0873 / Model VI: coeff.: 0.2683, st.err.: 0.0587). The inverse u-shaped relation is only significant for the subsample of loans without a trustee endorsement in column VI (Model VI: coeff.: – 0.0109, st.err.: 0.0041). *Keyword_Business* and *Keyword_Education* remain insignificant. Regarding empowerment, in contrast to the main models, the individual dummy is not significant for either of the subsamples, but female borrowers still appear to be targeted by the investors (Model V: coeff.: 0.2280, st.err.: 0.1365 / Model VI: coeff.: 0.6389, st.err.: 0.0849). *Keyword_Family* remains negative and significant in the subsample of non-endorsed loans (Model VI: coeff.: – 0.2381, st.err.: 0.1116). This may signal the investors' doubt that the explicitly mentioned care of family members may not be in line with successful entrepreneurship, especially without a trustee endorsement. *Keyword_Community* remains insignificant.

Interestingly, the vulnerability of borrowers emphasized by the immigration background does not appear to have any impact on the funding probability in the subsample of endorsed loans. In contrast, the immigration dummy is positive and significant in the subsample of loans without a trustee endorsement (Model VI: coeff.: 0.7473, st.err.: 0.1095). One possible explanation could be that direct loan investors are not a homogeneous group. One group of investors that support non-endorsed loans could have a higher weighting factor α for the social return in their utility function. These more socially oriented investors would still choose to support an immigrant without a trustee endorsement if the contribution of the social return to the personal utility is enough to compensate for a more negative financial return, indicated by the lack of a trustee endorsement. On the contrary, another group of less socially oriented investors could focus more on the credit profile of the borrowers and pay less attention to the social impact of lending. However, an alternative explanation could be that all of direct loan investors simply apply different selection criteria for endorsed and non-endorsed loan applications. It is possible that the investors would emphasize more on the possibility of making a social contribution for non-endorsed applications as they are riskier. But if the loan application is endorsed by a trustee, the investors may worry less about associated credit risk and not ask for further evidence indicating possible social impact. The above two possible explanations could also explain why the coefficient of the female dummy is smaller and less significant in the subsample of endorsed loans (Model V: coeff.: 0.2280, st.err.: 0.1365) than in the subsample of non-endorsed loans (Model V: coeff.: 0.6389, st.err.: 0.0849). In addition, the coefficients of *Keyword_Negative* have contrary signs in the subsample analysis, though they are insignificant (Model V: coeff.: – 0.1093, st.err.: 0.1375 / Model VI: coeff.: 0.0261, st.err.: 0.0854).

The results of all included control variables remain fairly unchanged compared with the models on the total data set.

Results Regarding the Funding Time

In addition to funding success, we can also observe the funding time of loan applications. We use the reversed funding time as a dependent variable, thereby measuring the funding speed. The model set up is analogous to the logistic models. The results are displayed in Table 8. Models I to III include the entire 6121 observations for funded and non-funded loans independently of whether the loan has a trustee endorsement.

All variables reveal a similar significance pattern as compared to the funding success analysis, implying that the same variables can explain funding success and speed. When inspecting the controls, the coefficient of *Keyword_Purpose* is positive and significant (coeff.: 0.1030, st.err.: 0.0545), which marks a first indication that the investors are attracted by the borrower's expectations related to receiving the loan. The coefficient of *Principal per month* is negatively related to the reversed funding time (coeff.: – 0.0008, st.err.: 0.0003). This could be due to the investor's distrust in the borrower's ability to repay a proportionally high loan amount after a short loan period. Loan applications including positive keywords appear to experience a slower funding process (coeff.: – 0.0854, st.err.: 0.0473).

All the other control variables demonstrate the same significant relations as those in the funding success analysis.

Implication Regarding the Hypotheses

All in all, H1, which states that the existence of a trustee is positively related to funding success, is supported. Moreover, the borrower's willingness to share information is positively related to funding success and the reversed funding time as it appears to build trust and attracts the investors, which supports our expectation in H2. However, text descriptions that are too long tend to deter the investors. Signals of entrepreneurship and education in the text description do not appear to influence the investors' behavior.

Evidence in favor of H3 is observed in terms of empowering women as female borrowers are favored by the investors. Groups of borrowers are more likely to be funded and receive funding faster when considering the total sample, but this is not apparent in the subsample regressions. Empowerment beyond the borrowers themselves does not appear to attract the investors. In the subsample of loans without a trustee endorsement, the investors are even reluctant to provide capital to applicants who explicitly mention their responsibility towards family members.

H4 on the vulnerability of the borrowers is partly confirmed for the complete sample and the subsample of loans without a trustee endorsement. The financial needs of immigrants are recognized and the investors strive to support these applicants. But this is not the case for those borrowers with a trustee endorsement. This is preliminary evidence that direct loan investors do react to the vulnerability of the borrowers, but—dependently on an endorsement—to a different extent.

Robustness Checks

To assess the robustness of our main findings, Cox proportional hazard models, which analyze the 'survival time' of the loan application, are carried out. There, both funding success and the funding time, are jointly considered as the time interval until the event of being successfully funded is estimated. For non-funded loans, the time until expiration is employed as the survival time. The survival time is multiplied by 100 and logarithmized to derive the variable *Cox survival time*.[8] The regression results are shown in Table 9.

Considering all observations in the columns I, II, and III, the majority of variables reveals itself to be consistent with our main results. A difference arises regarding the signals that build trust. The inverse u-shaped relation between the dependent variable and the text length is not confirmed anymore. However, the tendency remains unchanged (coeff.: – 0.0024, st.err.: 0.0017). *Keyword_Education* turns out to be negative and slightly significant (coeff.: – 0.0662, st.err.: 0.0353). Furthermore, the coefficient of *Keword_Family* becomes significant (coeff.: –0. 1028, st.err.: 0.0470). In summary, the overall picture is robust as our hypotheses are supported by the main indicators.

The results of Cox models for the subsamples of loans both with and without a trustee endorsement are presented in columns IV - VI. Most of the results remain stable with the same values and slightly changed confidence levels. A considerable gain in insight can be derived from the fact that the borrower's vulnerability can attract the investors in the subsample of non-endorsed loans but outfaces the investors in the subsample of endorsed loans. Both variables—*Immigration* (Model V: coeff.: –0.1513, st.err.: 0.0613 / Model VI: coeff.: 0.4527, st.err.: 0.0589) and *Keyword_Negative* (Model V: coeff.: – 0.0950, st.err.: 0.0465 / Model VI: coeff.:

[8] As 7 loan applications are funded within one day, the survival time is multiplied by 100 to avoid negative logarithmic values.

Table 8 Coefficients of Tobit models on reversed funding time

	All observations			With trustee		w/o trustee
	(I)	(II)	(III)	(IV)	(V)	(VI)
Trustee endorsement						
Trustee	1.0305***		0.9765***			
	(0.0483)		(0.0484)			
Type_Non_Profit		0.1144		− 0.0708	− 0.0015	
		(0.0883)		(0.0626)	(0.0634)	
Type_Others		− 0.0537		− 0.1754***	− 0.1236**	
		(0.0841)		(0.0599)	(0.0602)	
Type_No_End.		− 1.0187***				
		(0.0798)				
Trustee's experience				0.0003***	0.0001***	
				(0.0000)	(0.0001)	
Trustee's proximity				0.2308***	0.2315***	
				(0.0790)	(0.0784)	
Trust						
# of words			0.1671***	0.0819**	0.0832**	0.2569***
			(0.0289)	(0.0351)	(0.0348)	(0.0476)
# of words^2			− 0.0070***	− 0.0030	− 0.0028	− 0.0106***
			(0.0019)	(0.0024)	(0.0023)	(0.0030)
Keyword_Business			− 0.0240	0.0843	0.0684	− 0.0396
			(0.1942)	(0.1717)	(0.1704)	(0.4057)
Keyword_Education			− 0.0497	0.0022	0.0097	− 0.0458
			(0.0443)	(0.0455)	(0.0452)	(0.0797)
Empowerment						
Individual	− 0.6085**	− 0.6186**	− 0.5539**	− 0.2963	− 0.3212	− 0.7161
	(0.2753)	(0.2752)	(0.2727)	(0.2497)	(0.2479)	(0.5373)
Gender_female	0.4591***	0.4606***	0.4209***	0.1370***	0.1291***	0.6938***
	(0.0432)	(0.0432)	(0.0434)	(0.0434)	(0.0431)	(0.0805)
Gender_mixed	− 0.2460	− 0.2450	− 0.2003	− 0.0741	− 0.0932	− 0.2567
	(0.3317)	(0.3314)	(0.3285)	(0.2985)	(0.2964)	(0.6573)
Keyword_Family			− 0.0887	− 0.0152	− 0.0308	− 0.2404**
			(0.0590)	(0.0591)	(0.0587)	(0.1081)
Keyword_Community			0.0653	0.0341	− 0.0232	0.1597
			(0.1111)	(0.1046)	(0.1043)	(0.2169)
Vulnerability						
Immigration			0.4342***	− 0.0694	− 0.0749	0.7463***
			(0.0553)	(0.0581)	(0.0577)	(0.0988)
Keyword_Negative			0.0121	− 0.0643	− 0.0621	0.0642
			(0.0441)	(0.0445)	(0.0442)	(0.0801)
Controls						
Keyword_Positive			− 0.0854*	− 0.0717	− 0.0667	− 0.0945
			(0.0473)	(0.0481)	(0.0477)	(0.0855)
Keyword_Purpose			0.1030*	0.0250	0.0446	0.1095
			(0.0545)	(0.0578)	(0.0575)	(0.0957)
Principal per month	− 0.0007***	− 0.0007***	− 0.0008***	− 0.0004	− 0.0004	− 0.0008*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0005)
Video	− 0.1104	− 0.1180	− 0.0970	− 0.4076*	− 0.5013**	0.1679
	(0.1956)	(0.1956)	(0.1940)	(0.2143)	(0.2132)	(0.3242)

Table 8 (continued)

	All observations			With trustee		w/o trustee
	(I)	(II)	(III)	(IV)	(V)	(VI)
Expiration	0.0008***	0.0008***	0.0007***	0.0001	0.0003***	0.0156***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0014)
Year index	0.1702***	0.1724***	0.1660***		0.1032***	0.3287***
	(0.0189)	(0.0190)	(0.0191)		(0.0189)	(0.0476)
Activity sector	Yes	Yes	Yes	Yes	Yes	Yes
US state	Yes	Yes	Yes	Yes	Yes	Yes
_cons	2.0411***	3.0306***	1.3009**	3.1608***	2.8117***	– 0.3850
	(0.4986)	(0.5013)	(0.5417)	(0.3698)	(0.3726)	(0.8794)
N	6,121	6,121	6,121	2,588	2,588	3,533
Pseudo R^2	0.072	0.072	0.078	0.040	0.044	0.087

Models I–III include all observations. Models IV–VI consider the subsamples of loans with and without a trustee endorsement separately. Model I is extended by including different types of trustees, resulting in Model II. Model III is the main model including several social performance indicators, which have been extracted through keywords from the description text. Models IV - VI follow the main model. Eicker-Huber-White heteroskedastic-consistent errors are used. Values labeled with the symbols *, **, and *** are significant at the 10% level, the 5% level, and the 1% level. The variables are defined in Table 1

0.0971, st.err.: 0.0523)—demonstrate significant and opposite coefficients in the subsamples. The control variable *Keywords_Positive* is negative and significant in the subsample of endorsed loans, indicating that these investors do not appreciate positive emotions (Model V: coeff.: – 0.0991, st.err.: 0.0508).

Furthermore, we run additional logistic regressions and probit regressions on funding success, which are shown in Table 10. First, we include an interaction term of *Trustee* and *Immigration* in the main logistic model to further investigate how various investors of endorsed and non-endorsed loans behave in regards to loan applicants with an immigration background. The interaction term is negative and significant at the 1% level (Model I: coeff.: – 1.0468, st.err.: 0.1982). This implies that in the subsample of endorsed loans the immigration background indeed is not appreciated and lowers the probability of funding, while it increases the funding probability in the subsample of non-endorsed loans.

Second, all loan applications with an amount of less than 1,000 USD are excluded as these are less likely to properly support or enable entrepreneurship. The majority of variables does not change. The negative coefficient of *Keyword_Family* is not significant anymore. *Keyword_Purpose* turns out to be significant, indicating that the borrower's expectation increases in importance for higher volume loans (Model II: coeff.: 0.1432, st.err.: 0.0849).

Third, probit models analogous to the logistic models on all observations and the subsamples of endorsed and non-endorsed loans are run. The results are shown in columns III to VI. All variables employed to test the hypotheses on credit risk and social impact remain stable and are consistent with our main results.

Conclusion

In this paper, we study the funding determinants of interest-free P2P lending by utilizing a unique data set of direct loans requested by US inhabitants on the microfinancing platform Kiva during the observation interval from 2011 to 2017. The data set is unique as it represents social financing without interest compensation for credit risk to a borrower group from a developed country and utilizes textual information from original loan application texts.

The underlying Kiva model enables direct P2P lending between microentrepreneurs and investors. Although the investors bear the full credit risk, they are willing to grant interest-free loans to the borrowers, who are US inhabitants facing financial exclusion from the formal capital market.

Logistic regressions on funding success and Tobit regressions on the reversed funding time provide interesting insights into the investors' behavior regarding investment decision-making. The existence of social underwriting through a trustee endorsement appears to have a highly positive impact on funding success and the reversed funding time. Furthermore, the description length as a measurement to share information and generate the investor's trust is highly related to the probability of funding success as well as the funding time. Empowerment representing the investment's social impact appears to be a crucial predictor. Female borrowers are clearly preferred by all investors. Furthermore, groups of borrowers are more likely to be both funded and funded faster in the total sample. However, we do not find evidence that the investors appreciate empowerment of other people beyond the borrowers. At first glance, the borrower's vulnerability measured by the immigration

Table 9 Coefficients of Cox proportional hazard models

	Cox proportional hazard models					
	All observations			With trustee		w/o trustee
	(I)	(II)	(III)	(IV)	(V)	(VI)
Trustee endorsement						
Trustee	0.3727***		0.3525***			
	(0.0386)		(0.0385)			
Type_Non_Profit		0.0270		− 0.2021***	− 0.0680	
		(0.0655)		(0.0693)	(0.0697)	
Type_Others		− 0.0695		− 0.2387***	− 0.1499**	
		(0.0611)		(0.0654)	(0.0644)	
Type_No_End.		− 0.3966***				
		(0.0608)				
Trustee's experience				0.0006***	0.0002***	
				(0.0001)	(0.0001)	
Trustee's proximity				0.2757***	0.2432***	
				(0.0936)	(0.0908)	
Trust						
# of words			0.0739***	0.0706**	0.0800**	0.1609***
			(0.0247)	(0.0346)	(0.0370)	(0.0427)
# of words^2			− 0.0024	− 0.0030	− 0.0032	− 0.0071**
			(0.0017)	(0.0024)	(0.0027)	(0.0030)
Keyword_Business			0.0181	− 0.0990	− 0.0675	0.1496
			(0.1458)	(0.1589)	(0.1850)	(0.2435)
Keyword_Education			− 0.0662*	− 0.0266	− 0.0260	− 0.0521
			(0.0353)	(0.0484)	(0.0494)	(0.0517)
Empowerment						
Individual	− 0.5542***	− 0.5560***	− 0.5333***	− 0.3673	− 0.4348*	− 0.6644*
	(0.1683)	(0.1701)	(0.1737)	(0.2673)	(0.2423)	(0.3895)
Gender_female	0.2716***	0.2726***	0.2642***	0.1411***	0.1444***	0.4054***
	(0.0339)	(0.0339)	(0.0345)	(0.0463)	(0.0471)	(0.0533)
Gender_mixed	− 0.3459*	− 0.3372	− 0.3364	− 0.2237	− 0.2741	− 0.4695
	(0.2066)	(0.2080)	(0.2135)	(0.3050)	(0.2881)	(0.4505)
Keyword_Family			− 0.1028**	− 0.0105	− 0.0359	− 0.2186***
			(0.0470)	(0.0638)	(0.0655)	(0.0724)
Keyword_Community			0.0160	0.1690	0.0707	0.0542
			(0.0849)	(0.1056)	(0.1055)	(0.1400)
Vulnerability						
Immigration			0.1873***	− 0.1366**	− 0.1513**	0.4527***
			(0.0437)	(0.0603)	(0.0613)	(0.0589)
Keyword_Negative			− 0.0012	− 0.1017**	− 0.0950**	0.0971*
			(0.0353)	(0.0465)	(0.0465)	(0.0523)
Controls						
Keyword_Positive			− 0.0941**	− 0.0881*	− 0.0991*	− 0.0309
			(0.0376)	(0.0505)	(0.0508)	(0.0554)
Keyword_Purpose			0.0599	− 0.0106	0.0180	0.0577
			(0.0445)	(0.0620)	(0.0621)	(0.0637)
Principal per month	− 0.0006***	− 0.0006***	− 0.0007***	− 0.0002	0.0000	− 0.0018***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Video	− 0.0519	− 0.0564	− 0.0440	− 0.0692	− 0.2775	0.1088
	(0.1258)	(0.1255)	(0.1240)	(0.1910)	(0.1948)	(0.1889)

Table 9 (continued)

	Cox proportional hazard models					
	All observations			With trustee		w/o trustee
	(I)	(II)	(III)	(IV)	(V)	(VI)
Expiration	− 0.0020	− 0.0020	− 0.0020	− 0.0007**	− 0.0002	− 0.0385***
	(0.0017)	(0.0017)	(0.0017)	(0.0003)	(0.0002)	(0.0015)
Year index	0.2647***	0.2651***	0.2687***		0.2365***	0.1755***
	(0.0201)	(0.0202)	(0.0206)		(0.0220)	(0.0306)
Activity sector	Yes	Yes	Yes	Yes	Yes	Yes
US state	Yes	Yes	Yes	Yes	Yes	Yes
N	6121	6121	6121	2588	2588	3533
Pseudo R^2	0.017	0.017	0.017	0.013	0.018	0.054

Robustness analysis through Cox proportional hazard models for the total data sample and exclusively for the subsamples of loans with a trustee endorsement as well as loans without a trustee endorsement. Eicker-Huber-White heteroskedastic-consistent errors are used

Values labeled with the symbols *, **, and *** are significant at the 10% level, the 5% level, and the 1% level. The variables are defined in Table 1

background is positively related to funding success and the reverse funding time in the total sample. Further subsample analysis indicates that the investors respond to the borrower's vulnerability to a varying extent.

In summary, our findings lead to the conclusion that the investment decisions of the involved interest-free P2P investors take into account the credit risk as well as the social impact of the respective investment. There are no indications that they only use 'play money' to generate some amusement for themselves, as they appear to invest very seriously and goal-oriented. Our research provides insights into the investors' financial and ethical considerations in the context of online P2P microfinancing in developed countries such as the United States. As a practical implication for potential borrowers, it can be stated that for them it is advantageous to be able to acquire a trustee endorsement. If this is not possible, then the applicants can be advised to at least write a comprehensive text in which they reveal their need for empowerment and/or their vulnerability. For the observation period, it is arguable that the borrowers could not know exactly which features of their texts would boost the probability of being funded so that we regard the bias through purposeful dishonesty as negligible for this study. However, in the future it cannot be excluded that applicants use the findings revealed herein.

Last, this research also has some limitations: First, the data set does not contain information about the repayment of the granted loans, which would be essential to investigate the drivers of credit risk. Thus we cannot evaluate to which extent those variables that we used to test the credit risk hypothesis are really correlated with defaults. Second, as Kiva not only hosts the P2P lending platform subject to this research, but also the much larger intermediary-based model, the investors active there may be influenced by the latter model. Therefore, investors on a different interest-free P2P platform may behave differently. Due to this and the possibly different institutional features on other platforms, our results should only be generalized with caution. Third, the way we use keywords in the description texts as proxies for different financial and ethical aspects may still be connected with some inaccuracy. In addition, the proxy for trustee's proximity is not optimal as it cannot take into account the varying size of the US states and thus may cause some interpretation difficulties.

This leaves room for further research. For instance, with our data set we cannot finally clarify why the investors respond differently to the signals of vulnerability when screening endorsed and non-endorsed loans. Moreover, more precise proxies such as deeper linguistic features and better measurement of trustee's proximity, or surveys among active investors are needed to better understand the investors' behavior in such a prosocial P2P context. Summarizing, further research on the innovative interest-free P2P model appears to have a promising potential.

Table 10 Robustness analysis through further logistic and probit models on funding success

	All observations			With trustee		w/o trustee
	(I)	(II)	(III)	(IV)	(V)	(VI)
Trustee endorsement						
Trustee	1.6851***	1.5450***	0.9357***			
	(0.0933)	(0.0896)	(0.0516)			
Type_Non_Profit				− 0.0116	0.0203	
				(0.1025)	(0.1038)	
Type_Others				− 0.1623*	− 0.1373	
				(0.0966)	(0.0973)	
Trustee's experience				0.0002**	0.0001	
				(0.0001)	(0.0001)	
Trustee's proximity				0.3744***	0.3769***	
				(0.1197)	(0.1197)	
Trust						
# of words	0.2555***	0.2351***	0.1521***	0.1531***	0.1528***	0.1690***
	(0.0479)	(0.0475)	(0.0272)	(0.0522)	(0.0525)	(0.0339)
# of words^2	− 0.0101***	− 0.0089***	− 0.0063***	− 0.0059	− 0.0058	− 0.0073***
	(0.0033)	(0.0033)	(0.0019)	(0.0038)	(0.0038)	(0.0023)
Keyword_Business	0.0660	0.1604	− 0.0262	0.1390	0.1375	− 0.0891
	(0.3021)	(0.2849)	(0.1725)	(0.2454)	(0.2474)	(0.2303)
Keyword_Education	− 0.0118	− 0.0431	− 0.0028	0.0725	0.0788	− 0.0051
	(0.0699)	(0.0710)	(0.0411)	(0.0735)	(0.0735)	(0.0503)
Empowerment						
Individual	− 0.9245	− 0.9519*	− 0.5706*	− 0.6569	− 0.6827	− 0.4851
	(0.5678)	(0.5609)	(0.3065)	(0.5611)	(0.5499)	(0.4119)
Gender_female	0.5145***	0.5297***	0.3051***	0.1331*	0.1315*	0.3754***
	(0.0704)	(0.0710)	(0.0406)	(0.0724)	(0.0724)	(0.0498)
Gender_mixed	− 0.2172	− 0.2475	− 0.1154			− 0.2196
	(0.6495)	(0.6398)	(0.3534)			(0.4718)
Keyword_Family	− 0.2099**	− 0.1521	− 0.1032*	− 0.0597	− 0.0734	− 0.1252*
	(0.0927)	(0.0925)	(0.0533)	(0.0936)	(0.0938)	(0.0663)
Keyword_Community	0.0683	0.0956	0.0574	− 0.0516	− 0.0823	0.0892
	(0.1650)	(0.1662)	(0.1029)	(0.1704)	(0.1738)	(0.1229)
Vulnerability						
Immigration	0.8397***	0.5919***	0.3340***	− 0.0688	− 0.0726	0.4254***
	(0.1033)	(0.0987)	(0.0566)	(0.0957)	(0.0957)	(0.0662)
Keyword_Negative	− 0.0162	− 0.0113	− 0.0039	− 0.0609	− 0.0591	0.0209
	(0.0718)	(0.0728)	(0.0423)	(0.0741)	(0.0742)	(0.0521)
Interaction						
Trustee * Immigration	− 1.0468***					
	(0.1982)					
Controls						
Keyword_Positive	− 0.1057	− 0.1257	− 0.0683	− 0.0693	− 0.0688	− 0.0629
	(0.0754)	(0.0768)	(0.0439)	(0.0788)	(0.0787)	(0.0535)
Keyword_Purpose	0.1171	0.1432*	0.0798	0.0785	0.0902	0.0620
	(0.0845)	(0.0849)	(0.0490)	(0.0924)	(0.0923)	(0.0591)
Principal per month	0.0000	0.0000	− 0.0001	− 0.0001	− 0.0001	0.0001
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0004)	(0.0003)
Video	− 0.1572	− 0.1880	− 0.0848	− 0.3969	− 0.4572	0.1377
	(0.3164)	(0.3130)	(0.1803)	(0.2793)	(0.2829)	(0.2031)

Table 10 (continued)

	All observations			With trustee		w/o trustee
	(I)	(II)	(III)	(IV)	(V)	(VI)
Expiration	0.0338***	0.0332***	0.0129***	0.0090***	0.0101***	0.0140***
	(0.0035)	(0.0036)	(0.0018)	(0.0020)	(0.0024)	(0.0026)
Year index	0.3151***	0.3271***	0.1492***		0.0668	0.1788***
	(0.0418)	(0.0433)	(0.0237)		(0.0411)	(0.0301)
Activity sector	Yes	Yes	Yes	Yes	Yes	Yes
US state	Yes	Yes	Yes	Yes	Yes	Yes
_cons	− 2.8633***	− 2.6913**	− 0.9911*	0.8583	0.5497	− 1.3529**
	(1.0358)	(1.0850)	(0.5492)	(0.7242)	(0.7653)	(0.6039)
N	6121	5927	6121	2550	2550	3533
Pseudo R^2	0.276	0.269	0.256	0.128	0.130	0.192

Logit Model I includes an additional interaction term of trustee endorsement and immigration background. Logit Model II is based on loan applications with a loan amount > 1000 USD. Models III–VI are probit models analogous to the main Logit models for the total data sample and exclusively for the subsamples of loans with and without a trustee endorsement

Eicker–Huber–White heteroskedastic-consistent errors are used. Values labeled with the symbols *, **, and *** are significant at the 10% level, the 5% level, and the 1% level. The variables are defined in Table 1

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