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Crowdlending in Microfinance: A New Source of Debt Capital

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Dissertation zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft

eingereicht an der Fakultät für Wirtschaftswissenschaften an der Universität Regensburg

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Tag der Disputation: 19.12.2018

Acknowledgement

I would like to express my sincere thanks to Prof. Dr. Gregor Dorfleitner for his continuous and great support for my PhD study. I am grateful for giving me the opportunity to pursue the doctoral dissertation, sharing your knowledge and experience and providing valuable guidance for my empirical research and scientific writing.

My gratitude also goes to Prof. Dr. Klaus Röder for being my second advisor.

Furthermore, I would like to thank my family for the outstanding support which has made my PhD study possible. Special thanks to my parents for their generous encouragement and keeping me highly motivated throughout the last three years. Big thanks to my sister for welcoming me in her flat whenever I traveled to Regensburg. Moreover, I would like to say thank you to my partner for accompanying me through the ups and downs and being patient whenever I had to work during the weekend.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 A spotlight on classical microfinance

The microfinance industry is a financial sector which has risen sharply in the past years and which continues to grow in outreach, service offers and its mission. The global outreach of microfinance is clearly illustrated by the number of customers having increased from 13 million in 1997 towards 211 million customers in 2013 (Cull and Morduch, 2018). The microfinance movement has its foundations in the Grameen bank in Bangladesh, a pioneer in successfully granting microcredits to the poor without credit history or collateral. Microfinance institutions (MFIs), which aim to provide financial services to the unbanked poor have been established mostly in developing countries. The service offers have highly been extended by establishing saving possibilities through deposits, insurances and payment services for the poor part of the population (Bogan, 2012; Hoque et al., 2011). In line with the growth, the mission of microfinance has been broadened from poverty alleviation of the poorest in developing countries (Morduch, 1999) towards financial inclusion of the unbanked population, which is not served by the mainstream financial market (Helms, 2006).

This thesis focuses on microcredits, the core of the microfinance movement. Therefore, a spotlight on classical microfinance with regards to innovations in the contract, the mitigation of credit default risks and the rising demand for debt capital of MFIs is provided in the following.

Information asymmetry in credit markets resulting in adverse selection and moral hazard risks is very well known (e.g. Akerlof, 1970; Stiglitz and Weiss, 1981; Hoff and Stiglitz, 1990). In the microfinance sector, lenders, in particular MFIs, have to deal with the problem of imperfect information and imperfect enforcement due to lacking collateral of the poor (Hoff and Stiglitz, 1990). Apart from direct screening and monitoring activities, MFIs have the possibility to use indirect mechanisms in order to reduce the information asymmetry. Indirect mechanisms are e.g. introducing reasonable interest rates, the threat of terminated access to credit, instrumentalizing the risk of reputational loss and establishing an interlinkage of credit transactions with other markets (Stiglitz and Weiss, 1983; Hoff and Stiglitz, 1990). However, additional key innovations have been the main drivers that make lending to the poor without collateral possible and successful (Morduch, 1999; Armendáriz de Aghion and Morduch, 2010).

Group lending with joint liability: Loans are granted to a group of borrowers who is jointly responsible for the total loan amount and jointly burdens the credit default risk. Therefore, group members have an incentive to select appropriate peers of similar risk, monitor their peers' entrepreneurial activities and enforce successful loan repayment (Ghatak, 1999; Stiglitz, 1990; Besley and Coate, 1995).

Progressive lending: MFIs build up the borrowers' expectation to receive future loans of increasing size dependent on their repayment performance (Churchill, 1999). MFIs are able to test the borrowers' creditworthiness with small loans, to increase the opportunity cost of default and to enforce loan repayment in particular ex-post (Armendáriz de Aghion and Morduch, 2000).

Regular repayment schedule: Borrowers are required to repay small installments following a regular weekly or monthly schedule immediately after loan disbursement. Thus, MFIs steadily obtain information about the borrowers' repayment behavior and skim off the borrowers' outside income independently of the investment return (Armendáriz de Aghion and Morduch, 2000).

Targeting women: Several studies have identified female borrowers to be better credit risks than their male peers (e.g. D'Espallier et al., 2011; Kevane and Wydick, 2001). Women's limited mobility, the severe risk of damage by social sanctions, missing alternative sources of credit and the non-existence of a female labor market are proven to be reasons for the lower moral hazard risk of female borrowers (Goetz and Gupta, 1996; Morduch, 1999; Demirgüç-Kunt et al., 2008; Emran et al., 2011).

The classical microfinance movement has experienced widespread success around the globe accompanied by the development of a huge number of MFIs (Bruton et al., 2011). Thus the MFIs' demand for capital resources rises. Applying life cycle theory in the context of microfinance, the MFIs' need for capital differs in the distinct phases of institutional development. In the initial youth phase, MFIs have a high demand for risk-tolerant capital and quite often, donor funds are the main source (de Sousa-Shields and Frankiewicz, 2004; Bogan, 2012). In the growth phase, MFIs attempt to realize the transformation into a regulated institution. As this process is costly, the majority of MFIs remains dependent on external subsidized capital (Helms, 2006; Bogan, 2012). Donations and subsidies from international donors are one of the main sources for debt capital. However, donor funds are limited (Bogan, 2012). The transformation also provides new opportunities for an MFI. First, the MFI's access to commercial funding sources is enhanced (Mersland and Urgeghe, 2013). However, for the majority of MFIs the access to mainstream capital markets remains a challenge and is not used to its full extent (Helms, 2006; Hoque et al., 2011). Second, MFIs obtain the possibility to mobilize deposits. Deposit taking is known to be a stable and sustainable source of debt capital which helps MFIs to become less dependent on subsidized external capital (Caudill et al., 2009; Helms, 2006;

Bogan, 2012). But, in general, only regulated MFIs are allowed to mobilize deposits, which limits the use of this funding source (Bogan, 2012). Also in the phase of maturity, debt capital sources increase in importance, even though equity financing becomes available (de Sousa-Shields and Frankiewicz, 2004; Fehr and Hishigsuren, 2006; Bogan, 2012; Mersland and Urgeghe, 2013). Despite the increasing openness towards mainstream capital markets, the majority of external capital still comes from non-commercial investors which does not fulfill the MFIs' demand for funding and therefore, results in an increasing funding gap (de Sousa-Shields and Frankiewicz, 2004; Mersland and Urgeghe, 2013). The debt capital demand of MFIs in developing countries is not expected to fade.

Classical microfinance, in general, is mainly associated with poverty alleviation and financial progress in developing countries. Apart from this, the microfinance movement has also been present in developed countries with the aim to serve the poor (Conlin, 1999). In recent years, some researchers have taken interest in investigating microfinance programs in developed countries such as Canada, the United States, and the European Union. But one can say that the various patterns of microfinance in developed economies are still under-researched (Pedrini et al., 2016).

1.2 Introductory aspects on commercial peer-to-peer crowdlending

Crowdlending is an innovative approach which connects a crowd of private investors who are willing to fund loans requested by a private borrower without financial intermediation (Lin et al., 2013). Apart from crowdlending, several types of crowdfunding such as donation-based, equity-based and reward-based funding have emerged and are mainly accessible online to the public (Berns et al., 2018; Mollick, 2014). However, for this thesis the only relevant strand is peer-to-peer (p2p) crowdlending which implies that investors employ capital by granting loans and in exchange receive interest rates and the repayment of the loan principal. Commercial crowdlending as a source of debt capital through loans has emerged in the internet since 2005. The concept is realized by several commercial peer-to-peer lending platforms such as Zopa or Prosper.com which have grown impressively in recent years (Gonzalez and McAleer, 2011). To date (Sep.18), the first launched platform Zopa has transferred loans of more than 3.63 billion British pound in the UK and the leading platform Prosper.com has accompanied loan transactions valued 13 billion USD (Zopa.com, 2018; Prosper.com, 2018).

Commercial P2P platforms have intensively been researched. Analogous to the traditional credit market, the actors on online peer-to-peer lending marketplaces face the problem of information asymmetry. Adverse selection and moral hazard risk might be even more severe due to the anonymity of lenders and borrowers, the limited information mainly provided by borrowers themselves and missing monitoring and enforcing possibilities for lenders (Herzenstein et al., 2011;

Bachmann et al., 2011; Lin et al., 2013; Emekter et al., 2015). Despite the obstacles of information asymmetry, investors and borrowers engage with each other using the online debt capital marketplaces which has evoked research on the behavior of the main actors – investors and borrowers. Several studies have examined the investors' funding behavior and credit default risk of borrowers. Loan characteristics (Emekter et al., 2015), borrowers' characteristics and appearance (e.g. Pope and Sydnor, 2011; Duarte et al., 2012; Ravina, 2018), the social network (Lin et al., 2013; Freedman and Jin, 2017), soft facts in the narrative (Dorfleitner et al., 2016) have been proven to be main predictors of funding success and loan repayment. Additionally, Herzenstein et al. (2011) and Zhang and Liu (2012) observe herding behavior of investors following the 'wisdom of crowd' with the expectation to gain better insights by observing and imitating the crowd (Surowiecki, 2004). Furthermore, the narratives provided by borrowers to share information about themselves and the project idea are shown to be crucial with regards to the reduction of information asymmetries (e.g. Dorfleitner et al., 2016; Larrimore et al., 2011).

Even though the mentioned studies do not at all represent a complete list of the different stands of literature[1], it illustrates the great interest of researchers on commercial peer to peer lending in recent years. Commercial peer-to-peer lending itself and the listed empirical results are of interest for this thesis. One can assume that the investors' and borrowers' behavior on commercial debt-based marketplaces are similar to the ones in the context of microfinance. However, as the market conditions are totally different, the investors' funding decision and the borrowers' repayment performance are worth to be researched separately for crowdlending of microloans without interest.

1.3 Crowdlending as a source of debt capital in microfinance

Microcredits as the starting point of the classical microfinance movement found global attention when in 2005 the United Nations announced the 'year of microcredit' and shortly afterwards in 2006, the Grameen Bank and its founder Muhammad Yunus were awarded the Nobel Peace Price (United Nations, 1998; Nobel Peace Price Committee, 2006). Almost simultaneously with the rising interest of socially-oriented investors, the first online microfinancing platforms such as Kiva, Deki and Rang De were launched with the idea to enable individual investors to participate in the microfinancing development. The platforms connect a worldwide crowd of socially-oriented investors with microentrepreneurs in financial need. Despite differences in terms of lending model, size and concept, all platforms aim to materialize crowdlending as a source of debt capital for the microfinance sector.

[1]For a more extensive summary, the review papers of e.g. Bachmann et al. (2011) and Gonzalez and McAleer (2011) provide an informative overview. Furthermore, the research paper of Dorfleitner et al. (2016) spends an introductory part on existing literature on commercial p2p lending.

Kiva is the pioneer of this business model. The success of facilitating microfinancing through the crowd is illustrated by Kiva's impressive numbers: A funded loan volume of 1.2 billion USD by 1.7 million lenders to 3.0 million borrowers located in 83 countries since Kiva's foundation in 2005 until September 2018 (Kiva.org, 2018a). Kiva emphasizes its own strong social mission and requests a high social commitment from participants.

Kiva enables microfinancing trough two different microfinancing models. The first and most famous one is the *intermediation-based model* based on financial intermediation by MFIs. Kiva partners with several local MFIs in developing countries after conducting a due diligence process[2]. The partnered MFIs are responsible for selecting and monitoring borrowers and enforcing loan repayment. These MFIs post the granted loans on Kiva's webpage with the aim to receive refinancing through potential investors. The loan amount in USD is transferred to the MFI as soon as the request is fully funded which has been the case for nearly all loan requests in the last years.

The second and more recent model follows the *direct peer-to-peer* concept by connecting investors directly with borrowers in the United States without any financial intermediation. Additional to Kiva's due diligence process[3], borrowers have to emphasize their creditworthiness by mobilizing their personal network to support the loan request. The 'social underwriting' is expected to strengthen the borrower's commitment to successful loan management, even though the social underwriter is not financially responsible. Additionally, borrowers can be endorsed by a third-party trustee. This is not the case for all borrowers. Afterward, borrowers are allowed to post the loan application on Kiva's online webpage in order to reach potential investors. In contrast to the indirect model, the past records show that only around two third of the applications have been successfully funded.

The socially-oriented investors do not receive any interest rate on the employed capital, but fully bear the risk of credit default in both the intermediation-based model and the direct p2p model. Despite the fact of donating the interest rate, crowdfunding through Kiva differs from purely charitable giving as investors highly value the repayment of the loan principal in order to further empower several borrowers in the long run (Ly and Mason, 2012a). While investors contribute to refinancing microloans granted by MFIs in the intermediation-based model, investors enable microloans to borrowers in the direct peer-to-peer model.

Regarding the microborrowers, there is a notable difference between the two models. Loans to microborrowers who are located in developing countries around the globe are refinanced through the indirect model. These borrowers are requested to pay interest rates to the MFIs. In contrast, the direct peer-to-peer model is only available to US citizens who are in pursuit of an entrepreneurial

[2]Kiva staff reviews the MFI's financial stability, value, possible risks and especially its social commitment.

[3]Kiva staff reviews the borrower's financial history, his personal constitution and the pursued business idea.

activity but lack financial resources. These borrowers do not pay any interest rate for the debt capital directly provided by socially-oriented investors.

The main actors in the two different microfinancing models established and maintained by the online platform Kiva are summarized in Figure 1.1.

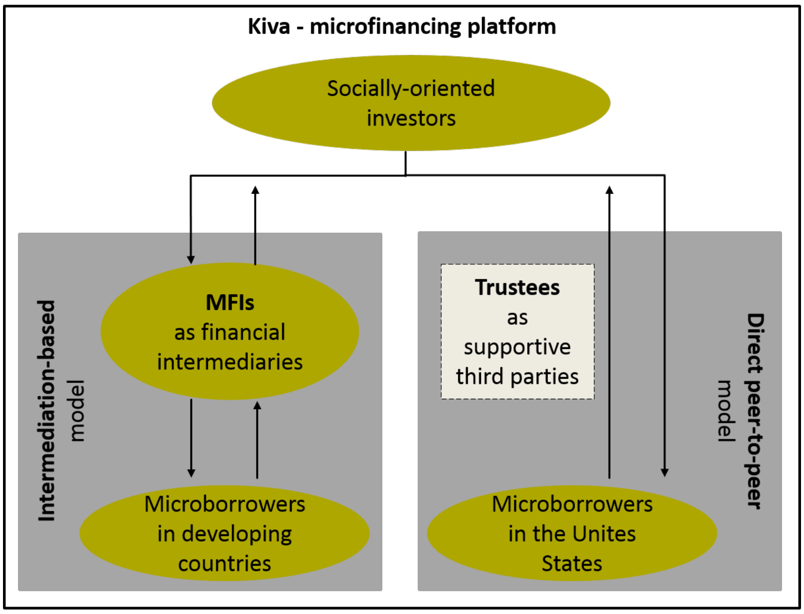

Figure 1.1: Main actors in the intermediation-based model and the direct peer-to-peer model on the microfinancing platform Kiva

In recent years, Kiva's social mission, the socially-oriented lenders, microborrowers and partnered MFIs have been subject to several studies. First, with respect to Kiva's mission, Bajde (2013) studies Kiva's ideology and Schwittay (2014) sheds light on Kiva's social impact in terms of poverty alleviation. Second, the decision making process of investors has found high attention. The cultural and physical difference, social distance, transaction costs, the personal motivation as well as the characteristics of the narratives describing the borrower and the underlying project are discussed and identified as predictors of the funding behavior of investors (e.g. Burtch et al., 2014; Galak et al., 2011; Meer and Rigbi, 2013; Liu et al., 2012; Allison et al., 2013; Jancenelle et al., 2018). Third, Jenq et al. (2015) studies the borrower's physical and social appearance and draws conclusion mainly on funding success and as a side aspect on the credit default risk of borrowers.

Last but not least, the rising competition between MFIs on Kiva, organizational characteristics and the appearance of MFIs have been examined to impact the MFI's success of attracting investors and receiving interest-free refinancing (Ly and Mason, 2012a; Moss et al., 2015; Berns et al., 2018). It is noteworthy, that all these empirical studies focus on the transactions using the intermediation-based model, whereas to our knowledge research on transactions through the direct peer-to-peer model is missing.

Also, this thesis makes use of the debt capital transactions on Kiva between socially-oriented investors, MFIs and borrowers. Both microfinancing models –

the intermediation-based model and the direct p2p model – are of empirical interest.

1.4 Research objective of this dissertation

This dissertation combines aspects from classical microfinance and online commercial crowdlending in order to investigate several aspects which are important, but still under-researched in the field of crowdlending through socially-oriented investors in microfinance.

As stated above, Kiva's intermediation-based microfinancing model has extensively been researched regarding several topics. However, we noticed a lack of knowledge regarding the credit default risk of microborrowers which results in financial losses for investors. Additionally, very little is known about the MFIs which are the core of this microfinancing model. But this is important as MFIs are simultaneously financial intermediaries and recipients of interest-free capital. This thesis addresses these two gaps in empirical research. It aims to shed light on, firstly, the determinants of credit default risk and, secondly, the characteristics of the MFIs in the context of microfinancing through the worldwide crowd. The third part of this dissertation provides very first insights on the funding behavior of investors who enable microloans requested in developed countries via Kiva's direct peer-to-peer model without intermediation.

The research projects contribute to the literature on microfinance and crowdlending through examining MFIs refinancing their loan portfolio with interest-free debt capital, analyzing credit risk factors and discussing the funding behavior of investors who enable microloans in a developed country.

The following three academic research papers are the core of this dissertation:

1. Repayment behavior in peer-to-peer microfinancing: Empirical evidence from Kiva
2. The access of microfinance institutions to financing via the worldwide crowd
3. From credit risk to social impact: On the funding determinants in interest-free P2P lending

Below, the academic papers are briefly summarized regarding their research objective, the data set, the methodology, empirical findings and the contribution.

1. Repayment behavior in peer-to-peer microfinancing: Empirical evidence from Kiva
Subject of this study is the repayment behavior of microentrepreneurs in the intermediation-based model of Kiva. The research is based on a data sample of microloans which were refinanced by the worldwide crowd of investors between 2010 and 2013.

By performing probit regressions on the probability of credit default, we find evidence that the credit default risk is dependent on the screening and monitoring quality of the respective MFI which grants the microloan. Additionally, credit conditions such as the loan size, the loan term and a grace period before the first repayment obligation is due reveal themselves to be main predictors of credit default. Female individual borrowers appear to be more creditworthy than their male counterparts. However, this phenomenon is not observable for group loans. As a second aspect, the attractiveness of a loan measured by the funding time is analyzed. The results lead us to conclude that investors care about credit risk as well as social purpose when supporting microloans. Regarding credit risk, the funding time does not serve as a predictor.

Our empirical findings on credit risk provide valuable implications mainly for MFIs and investors. MFIs have an incentive to use the gained insights to maintain a good repayment performance. A reliable reputation on Kiva is crucial to attract potential investors and therefore, ensure refinancing of microloans. Knowledge about the determinants of credit default enables investors to adequately choose low-risk loans as the repayment is highly valued in order to support several borrowers in the long-run.

2. The access of microfinance institutions to financing via the worldwide crowd
This study examines the characteristics of MFIs which have access to and make use of refinancing through the worldwide crowd of socially-oriented investors from the demand and supply perspective. The research is based on a panel data set consisting of MFI-specific information such as social performance measures and financial indicators derived from MIX Market. The information about the MFI's access to the microfinancing platform Kiva between 2005 to 2015 is added.

First, binary regressions are performed to explore the probability of access to Kiva. The results show that the MFI's social performance measured by targeting female borrowers, ensuring a reliable portfolio quality and charging low interest rates is a main predictor. The financial performance and the MFI's extent of deposits are negatively associated with access to Kiva. We find evidence that mature MFIs and MFIs operating in less-developed countries are more likely to refinance microloans using Kiva. Second, the termination of the partnership between an MFI and Kiva, which is observable in some cases, is examined. The female share within the MFI's portfolio and the MFI's extent of deposits appear to be main predictors as these MFIs appear to be less likely to retain the partnership with Kiva.

This research paper contributes valuable insights about the characteristics of MFIs which make use of the refinancing possibility of microloans through the crowd. Empirical evidence identifies the determinants which are crucial for Kiva's and the MFI's decision to enter into a partnership. Additionally, the study clarifies what encourages MFIs to be reluctant to partially refinancing their loan portfolio using Kiva.

3. From credit risk to social impact: On the funding determinants in interest-free P2P lending

This study investigates the funding behavior of investors who have both financial and prosocial concerns once providing interest-free capital to US citizens via the direct p2p model of Kiva. The unique data set of more than 6,000 US direct loans is highly expanded by the addition of detailed information directly obtained from original loan campaigns.

By performing logistic regressions on funding success and tobit regressions on funding time, we find evidence that a third-party endorsement for loan applications is highly appreciated by investors. The borrower's willingness to share information is positively related to funding success. The possibility to empower women and groups of borrowers appears to positively attract investors. The borrower's responsibility for family members does not appear to be favorable with regards to funding success. The result shows that immigrants are more likely to be funded by investors choosing non-endorsed loans. But this is not observable for loans endorsed by a trustee.

To conclude, we gain the insights that prosocial investors strive for both minimizing credit risk and maximizing social impact of their investment. The study also contributes to the field of microfinance as a measurement to reduce financial exclusion in developed countries such as the United States. Socially-oriented investors reveal themselves to be willing to enable interest-free microloans to US citizens in financial need.

The remainder of this dissertation is organized as follows. Chapter 2 represents the research paper on the repayment behavior of microborrowers in the intermediation-based microfinancing model of Kiva. In chapter 3, the empirical findings on the access of microfinance institutions to debt capital from the worldwide crowd of socially-oriented investors are outlined. Chapter 4 consists of the research paper on the investors' funding behavior concerning credit risk and social impact in the direct peer-to-peer model of Kiva. Chapter 5 concludes with a brief summary of the implications and limitations of the conducted research.

Chapter 2

Repayment behavior in peer-to-peer microfinancing: Empirical evidence from Kiva

This research project has been carried out jointly by Gregor Dorfleitner and Eva-Maria Oswald. The article has been published as: Dorfleitner, G., Oswald, E., 2016. Repayment behavior in peer-to-peer microfinancing: Empirical evidence from Kiva. *Review of Financial Economics*, 30(1), 45-59

Abstract: Based on a sample of microloans (to individuals and to groups) that were refinanced through the peer-to-peer microfinancing platform Kiva, we study the determinants of the repayment behavior of micro-entrepreneurs whose loans are available to international charitable lenders. We perform binary regressions and account for influential factors such as the time required for funding or the type of entrepreneurial activity. The screening and monitoring quality of the microfinance institution which selects the borrowers is a main driver of credit default. We find evidence that the loan size, the loan term and the length of a possible grace period influence the probability of default. Moreover, women demonstrate better repayment behavior which is, however, not the case for groups of women.

Keywords: Crowdfunding, microfinance, financial intermediation

JEL Classification: D64 D82 G21

2.1 Introduction

In recent years, microfinance has been growing rapidly with more than 195 million clients having received microloans from microfinance institutions (MFIs) by the end of 2011 (Reed, 2013). The MFIs refinance the loans they grant partly through deposits and partly through international investors who provide capital through indirect or direct investments. The rising interest of socially oriented investors in contributing to microfinance development is recognized by several online microfinancing platforms, such as Deki, Babyloan, Rang De and Kiva. The most popular of these platforms is Kiva, which enables individual lenders to fund microloans to poor entrepreneurs around the world without receiving interest but, at the same time, fully bearing the credit risk. Lenders donate their interest in the sense of charitable giving. However, microfinancing via Kiva is beyond charitable giving as lenders are able to use the same funds after loan repayment to empower several low-income borrowers.

In contrast to conventional P2P platforms, Kiva builds on the financial intermediation performed by the participating MFIs which select and monitor the borrowers. MFIs seek to appeal to investors in order to receive microloan-related refinancing on Kiva.

The aim of this study is to identify the determinants of the repayment behavior on Kiva which is crucial for investors who cannot compensate losses through a risk-adjusted interest rate. To this end, we investigate the influence of several variables such as loan characteristics on the default probability of a microloan refinanced by individual lenders on Kiva. As Kiva selects the loans with respect to their attractiveness to international investors, the default drivers may be different to those known from other studies. Furthermore, we investigate the impact of the MFIs' screening and monitoring abilities on the default probability. By identifying the credit risk drivers of Kiva loans we can also address the question of financial motives (here minimization of losses) versus social ones in the investment decision of the charitable lenders by utilizing the time to complete funding as a measure of a loan's attractiveness.

Kiva has been of academic interest in recent years. Its ideology has been studied by Bajde (2013), the competition faced by the MFIs on the platform has been considered by Ly and Mason (2012a) and Kiva's impact on poverty alleviation has been discussed by Schwittay (2014). While the decision making process of the lenders with respect to the entrepreneurial narrative representing a microborrower's profile, social distance, motivation and transaction costs are addressed by Burtch et al. (2014), Liu et al. (2012), Galak et al. (2011) and Meer and Rigbi (2013), little is known about the repayment behavior on Kiva. Only Jenq et al. (2015), who focus on the impact of the borrowers' appearance on the funding behavior of lenders, consider the impact of these characteristics (and some controls) on credit default as a peripheral aspect. Due to their rather small sample and their different focus, they only find the loan term and the loan amount to be significant credit risk drivers.

Information asymmetry is known to be a main challenge in microfinance when it comes to repayment behavior. Credit default and innovative means to overcome this problem are explored by several theoretical studies of Ghatak (1999), Stiglitz (1990), Besley and Coate (1995) and Armendáriz de Aghion and Morduch (2000). In classical microcredit literature, the influence of variables such as group lending, loan conditions or gender on the repayment have been studied by Gine et al. (2010); Godquin (2004); Field et al. (2013); D'Espallier et al. (2011).

Review papers on commercial P2P lending demonstrate the academic interest in online P2P lending platforms (Gonzalez and McAleer, 2011; Bachmann et al., 2011). Credit default on commercial P2P lending platforms is studied in terms of, for instance, financial intermediation, herding behavior, social networks and personal characteristics of the borrowers (Berger and Gleisner, 2009; Herzenstein et al., 2011; Lin et al., 2013; Pope and Sydnor, 2011).

In this study we connect aspects of classical microfinance and crowdfunding, as we are interested in the determinants that play a role in the repayment by borrowers on microfinancing platforms. Thereby, we contribute to the literature analyzing credit risk aspects in microfinance. As Kiva is a microfinance platform, which actually aims at refinancing MFIs through philanthropic investors, our findings are very important for exactly these two groups of microfinance actors.

We focus on researching the influence of the funding behavior, the financial intermediary, the borrower's gender and the credit conditions on the repayment behavior. We investigate the impact on the repayment behavior of individual borrowers and of groups of borrowers by conducting several binary regressions. Kiva connects social investors from developed countries with low-income borrowers from developing countries based on the *indirect model* which contrasts with classical P2P lending. Kiva works with local partner MFIs which screen potential microfinance borrowers and submit internet profiles representing entrepreneurial and personal characteristics and the contractual conditions with Kiva. Potential lenders from all over the world can browse the borrowers' internet profile and lend to individual borrowers or groups of borrowers. Usually, all loan requests are fully funded and Kiva transfers the money to the MFI that is in charge of the loan. In less than 1% of all cases Kiva has to refund loans to lenders which is mainly due to a violation of Kiva's policy and occasionally due to incomplete funding. MFIs acting as local financial intermediaries are responsible for selecting the borrowers. According to Allison et al. (2013), Kiva explicitly requires their partner MFIs to focus on social impact and to select rather poor borrowers, who are in urgent need of funding. Besides meeting this condition, MFIs have an incentive to select creditworthy borrowers in order to repeatedly attract potential lenders to fund their loans because lenders may consider the MFI's overall repayment reputation in their lending decision. From this perspective, it is rational to present the most reliable borrowers in terms of repayment on Kiva in order to ensure a good reputation and a quick funding. As Kiva explicitly recommends lenders to use repaid loans to lend again, the repayment of loans becomes valuable to charitable lenders in terms of supporting several low-income borrowers in the long run. The loan does not yield interest for the lenders. Therefore, lenders are not able to compensate for a potential default through a higher interest rate, making research on the determinants of credit default even more valuable.

To date (Dec/05/2015), the total amount lent through Kiva is more than 787 million US dollars to more than 1.8 million microfinance borrowers. Our empirical analysis is based on a randomized sample representing 29,304 transactions on Kiva between February 2011 and October 2013. The data sample exclusively includes closed, i.e. matured, loans that are successfully repaid or defaulted upon. The overall repayment rate is 98.78%.

Our research yields some interesting findings. We find evidence to support the fact that MFIs with fewer loan defaults in the previous period are also able to limit the credit risk of their new loans, emphasizing the importance of adequately selecting and highly monitoring the borrowers. Furthermore, loan conditions such as the loan size and term play a significant role in the repayment. Women also appear to make a more ambitious effort to repay loans than men, while group loans are more risky up to a size of seven members.

An analysis of the funding time which proxies the attractiveness of the loan applications to the social investors, yields deeper insights into the motives of the lenders. The first important finding is that lenders indeed do care about the credit risk of a loan which shows that they have financial motives even though they abstain from receiving interest payments. However, also variables indicating a social purpose such as loans to groups of women, can also make a loan attractive even if the credit risk is increased by this purpose. Altogether the funding time is not a significant determinant of the creditworthiness of borrowers.

The remainder of this article is organized as follows. In Section 2 we develop the hypotheses from the findings of previous research. After describing the data set and methodology in Section 3, Section 4 represents the results of the probit regression models. Section 5 discusses several robustness checks that were carried out. Section 6 concludes with possible implications for P2P microfinancing and future research.

2.2 Theoretical background and hypotheses

2.2.1 Information asymmetry in the microcredit market

Risk of uncertainty due to information asymmetry in credit markets has been widely researched (e.g. Hoff and Stiglitz, 1990; Sufi, 2007). Yum et al. (2012) state that the information asymmetry problem exists to a larger extent in the (online) P2P microcredit markets as private lenders lack information on microfinance borrowers and on the MFIs which act as financial intermediaries. Additionally, the majority of private lenders are non-professional investors and thus not experienced in assessing creditworthiness (Yum et al., 2012). Private lenders are unable to monitor and impose social sanctions against borrowers in the case of bad repayment performance which increases the repayment risk (Herzenstein et al., 2011). Not only the lenders but also the MFIs themselves face the problem of imperfect information and imperfect enforcement. The severity of information asymmetry and the lack of effective loan enforcement cause adverse selection problems and moral hazard risk. Additionally, the missing collateral reinforces moral hazard behavior.

MFIs have the possibility of employing indirect or direct mechanisms to obtain information on the characteristics and actions of borrowers to ensure loan repayment. The contract itself can serve as an indirect mechanism. MFIs are able to obtain information on the borrower's riskiness and actions by requiring an appropriate interest rate, using reputation effects and interlinking loan contracts with other transactions in related markets (Stiglitz and Weiss, 1983; Hoff and Stiglitz, 1990). Therefore, a direct mechanism is established as lenders are able to select and monitor clients based on additional information obtained by market participation and communication (Siamwalla et al., 1990). Moreover, MFIs rely on the direct screening and monitoring of borrowers to prevent adverse selection, to support a borrower's success and to inhibit strategic defaults. The direct screening and monitoring process is quite often costly and difficult. Geography and the kinship group have revealed themselves to be crucial in successful monitoring and loan enforcement as living near each other provides a source of information and enforcement mechanisms such as social sanctions. In the past, local moneylenders, for instance, were more likely to grant unsecured loans more successfully than financial institutions without access to local information on borrowers (Stiglitz, 1990; Hoff and Stiglitz, 1990). Thus, the main challenges for MFIs are obtaining information on the riskiness of borrowers, to creating incentives for borrowers to exert efforts to succeed and enforcing repayment to limit the probability of default.

To conclude, indirect and direct mechanisms are used by MFIs to resolve the three main problems which are endemic to the credit market in developing countries. The MFI's resources to screen and monitor clients and to enforce contracts are crucial in inhibiting credit default. Therefore, we expect the probability of default to depend on the screening and monitoring abilities of MFIs.

> **Hypothesis 1 (H1).** *The loans of MFIs which select and monitor borrowers more carefully have a lower probability of default.*

In addition to the traditional screening, monitoring and enforcing elements, the Grameen bank, as a pioneer of the MFIs in Bangladesh, has established new mechanisms to ensure loan repayment by low-income borrowers without collateral. Group lending, progressive lending, regular repayment schedules and targeting women as borrowers are the key innovations which have largely made microfinance possible and are still widely employed. We discuss these items in the subsequent subsections.

2.2.2 Group lending with joint-liability

Group lending with joint liability is a key innovation in microfinance which is uncommon in standard banking. Loans are provided to a group of borrowers who are burdened with joint liability payments in the case of one group member defaulting. The MFI transfers screening, monitoring and enforcing costs to the borrowers by establishing an interdependence among group members regarding borrowing costs (Morduch, 1999). Borrowers utilize local information embodied in social networks to screen and self-select group members. Ghatak (1999) demonstrates the fact that borrowers tend to form homogeneous groups. This homogeneous grouping enables MFIs to price discriminate even though all borrowers receive the same loan contract because the effective borrowing costs are less for safe types of borrowers than for risky ones burdened with higher expected joint liability payments. Therefore, safe types of borrowers are driven back into the market and the average probability of default decreases (Ghatak, 1999; Morduch, 1999). In addition to peer selection, group lending provides benefits in terms of peer monitoring and peer pressure as mechanisms to inhibit ex-ante and ex-post moral hazard risks. Group members are willing to monitor each other because one's utility is dependent on the success of the projects undertaken by the peers. Monitoring is done by borrowers who have local information of each other's entrepreneurial project and the level of effort employed by their peers to succeed (Stiglitz, 1990; Morduch, 1999). Moreover, peers have local knowledge about the return on the project and can judge whether the group member may refuse payment. In the case of strategic default, group members have the possibility to apply peer pressure to each other to ensure loan repayment by their peers (Besley and Coate, 1995). Group lending has been researched intensively. Gine et al. (2010) and Ahlin (2010) acknowledge the self-selection of borrowers into risk homogenous groups.

According to the theory, the anecdotal studies by Wydick (1999), Karlan (2007), Ahlin and Townsend (2007) and Gine et al. (2010) show that peer monitoring and peer pressure improve the repayment performance of groups. In a laboratory experiment, Abbink et al. (2006) also observe that groups of borrowers outperform individual borrowers. However, the findings of Abbink et al. (2006), Gine et al. (2010) and Fischer (2013) are partly contradictory regarding the risk-taking of borrowers under joint liability. In a field experiment, Giné and Karlan (2014) do not find any evidence of the advantage of group lending over individual lending. Additionally, the findings of Wydick (1999) and Karlan (2007) do not acknowledge the fact that group lending outperforms individual lending.

By considering peer selection, peer monitoring and peer pressure as important mechanisms in ensuring loan repayment in theory and the empirical evidence found in several studies, we expect groups of borrowers to have a better repayment rate ompared with individual borrowers.

> **Hypothesis 2 (H2).** *Groups of borrowers are less likely to default compared to individual borrowers.*

2.2.3 Progressive lending

Regardless of the question of whether group or individual lending is applied, progressive lending serves as a dynamic incentive for loan repayment. The

MFI grants the borrower access to future loans of increasing size over time conditioned on the repayment history of previous and current loans (Churchill, 1999). Reliable customers with a good repayment performance can expect to receive larger loans over time whereas customers in arrears are denied access to future loans. Through this mechanism, the MFI is able to increase the opportunity costs of default faced by borrowers and thus to enforce repayment and to prevent strategic default. Progressive lending is widely implemented in microfinance programs (Morduch, 1999; Armendáriz de Aghion and Morduch, 2000). Robinson (2001, p.111ff) reports that the repayment of nearly all loans disbursed by 18 different microfinance programs in various countries is ensured through progressive lending as an enforcement element. The study of Gine et al. (2010) shows that the possibility of having access to future loans decreases the choice of riskier projects associated with ex-ante moral hazard by 21.5% and increases the repayment rate by 12.3%. The threat of not providing refinancing to bad risk/defaulted borrowers enables the MFI to test borrowers regarding their reliability and trustworthiness. Vogelgesang (2003) reports that loan officers provide smaller loans to clients who are more likely to default. Despite this caution, loan size and credit risk appear to be positively correlated. According to Sharma and Zeller (1997) and Godquin (2004), there is a positive relationship between the loan size and credit default. The higher the loan size, the higher the probability of default as the difficulty in meeting repayment obligations in case of project failure increases as well as the gain of moral hazard behavior in terms of non-repayment increases.

Regarding the loan term, in classical credit risk literature it is a stylized fact that a borrower's probability of default increases over time (Hull, 2015). Various authors also confirm this finding for microloans (e.g. Roslan and Abd Karim, 2009; Van Gool et al., 2012). Generally, Ledgerwood (1999) states that the cash flow partially determines the debt-serving capacity of borrowers. On the one hand, long loan terms may exceed the maturity of businesses undertaken by borrowers and borrowers struggle to save enough revenue to meet the repayment obligations in the future. Additionally, a long loan term may lead to a decrease in a borrower's discipline in repaying a loan over time as current revenues are spent instead of saved for repayment obligations due in the future. On the other hand, short loan terms may make it difficult for borrowers to generate enough revenue to meet repayment obligations on time. In line with the latter argument, there is also evidence (Mokhtar et al., 2012; Awunyo-Vikor, 2012) that longer loan terms can reduce the borrower's difficulty in repaying loans. However, as Kiva focuses on very poor borrowers, who may have more difficulties in buffering cash flows over a longer period, we tend to expect the classical credit risk term structure in the Kiva setting.

In summary, we state two hypotheses.

> **Hypothesis 3a (H3a).** *The loan size is positively related to the probability of default.*
> **Hypothesis 3b (H3b).** *The length of the loan term is positively related to the probability of default.*

2.2.4 Regular repayment schedule

A standard feature of the classic microloan contract is to require small regular installments one or two weeks after loan disbursement. Despite high transaction costs, it is relatively common that MFIs demand weekly, fortnightly or monthly payments, even before investment returns are realized by microfinance borrowers. One reason is that the regular repayment schedule serves as an early warning system. Credit officers become aware of emerging problems due to the steady flow of information regarding repayment capacity and repayment discipline. The credit officer is immediately able to expand the monitoring activities if a borrower is in arrears with payments. Borrowers who have difficulties in saving their income are disciplined through regular installments. Furthermore, the regular repayment schedule helps MFIs select low-risk microfinance borrowers. Due to the repayment obligations beginning immediately after loan disbursement, microfinance borrowers need to have another source of earnings besides the entrepreneurial activity to repay installments. Therefore, MFIs effectively lend partly against a borrower's outside income ensuring loan repayment even if the investment does not generate the expected revenues (Armendáriz de Aghion and Morduch, 2000).

The impact of a regular repayment schedule on the probability of default is only explored by a few studies. Field and Pande (2008) do not identify a relation between highly frequent repayment installments and the probability of default in a field experiment in urban India. McIntosh (2008) finds no difference in repayment performance between borrowers paying weekly installments and borrowers paying fortnightly installments either. In a further field experiment in India, Field et al. (2013) note a positive correlation between the grace period and the probability of default. Loans with a grace period of two months are more likely to default in the short- and long-run compared with classic loan contracts. Furthermore, the regular repayment schedule gives credit officers the ability to establish a personalized relationship by frequently communicating with the microfinance borrowers. Credit officers become acquainted with clients and their needs.

> **Hypothesis 4a (H4a).** *Loans with highly regular repayment obligations are less likely to default.*
> **Hypothesis 4b (H4b).** *Loans with a grace period default more often.*

2.2.5 Targeting Women

In microfinance it is relatively common to give priority to female borrowers because they demonstrate better repayment behavior when compared with men (see Gibbons and Kasim (1990), Roslan and Abd Karim (2009), Hulme (1991), Sharma and Zeller (1997) and Kevane and Wydick (2001) for evidence supporting this fact in various countries). A global study surveyed by D'Espallier et al. (2011) shows a significantly negative relationship between the proportion of female clients and both the portfolio risk and the portfolio write-offs of MFIs.

The global study identifies women as being better credit risks and also the fact that giving loans to women prevents credit default. Apart from the pure financial aspects, there is evidence that businesses run by female entrepreneurs out-survive businesses owned by male entrepreneurs (Kalnins and Willians, 2014). The phenomenon that women appear to be more reliable than their male counterparts can be explained in terms of more risk-averse investments and lower moral hazard risk (Kevane and Wydick, 2001). Women's lower level of mobility, their sensitivity to social sanctions, lacking credit alternatives and the missing female labor market appear to be reasons for the lower moral hazard risk (Demirgüç-Kunt et al., 2008, p. 124; Emran et al., 2011). Due to the lower mobility level, credit officers and peers are better able to monitor women's investment activities, to intervene in terms of arrears and to enforce loan repayment (Armendáriz de Aghion and Morduch, 2010; Goetz and Gupta, 1996). Additionally, women appear to be more sensitive to social sanctions in terms of peer pressure or financial exclusion by credit officers as microfinance credit programs provide an important socializing opportunity for women. (Goetz and Gupta, 1996). Demirgüç-Kunt et al. (2008, p. 124) and Armendáriz de Aghion and Morduch (2010) report that women are better customers due to fewer alternative sources of credit caused by cultural, social or legal constraints. Women tend to honor their loan contracts and the access to financial services more than men. Additionally, access barriers to the formal labor market in many developing countries could be a reason (Emran et al., 2011). By being excluded, to an extent, from the formal labor market, women are dependent on microfinance credit programs if they seek to attain self-employment through entrepreneurial activity. The economic opportunity to generate returns serves as an incentive to successfully repay loans in order to ensure the business opportunity.

In summary, we state our last hypothesis.

> **Hypothesis 5 (H5).** *Women and groups of women as microborrowers are less likely to default.*

2.2.6 Lender's behavior and the funding time

Kiva lenders are charitable lenders and do not seek a financial return. However, one can assume that lenders value the repayment of loans in order to subsequently use the amount of money to support several projects in a row, which differentiates microlending from charitable giving (Ly and Mason, 2012a). Besides these credit risk aspects though, which comprise the focus of this paper, lenders also appear to consider social aspects when funding a loan request, such as the empowerment of women or the preference of poor borrowers (Liu et al., 2012). As for each funded loan, we can observe the time that was required to fully fund the loan, we can draw conclusions from this variable concerning the attractiveness of a loan request for the lenders. A higher level of attractiveness can be due to more advantageous credit risk characteristics as well as to a perceived greater social impact.

By including the funding time in the analysis of credit risk, we can draw conclusions about whether the loans preferred by investors have a lower or higher credit risk which would indicate that the investors either put more emphasis on the credit risk component (if they are able to assess it correctly ex ante) or more on the social impact component, which they could pursue while consciously sacrificing financial interests. A third possibility is that the funding time does not explain much of the credit risk. Thus, we do not formulate an ex ante hypothesis on this issue.

An additional analysis of the funding time can be used for a direct estimation of the determinants of a loan's attractiveness. Analyses of this kind have already been performed in previous literature. Galak et al. (2011), Ly and Mason (2012a), Allison et al. (2013) and Jenq et al. (2015) all use the funding time to assess the attractiveness of a loan request and to analyze how it is influenced by the social distance, the competition between MFIs, the entrepreneurial rhetoric of the description texts and the appearance of the borrowers, respectively. We mainly add the connection of the funding time to the drivers of credit risk to this literature, but only as a side aspect of our research.

2.3 Data and methodology

2.3.1 Data description

All individual loan data and MFI-specific information used in our analysis have been retrieved via Kiva's public Application Programming Interface provided online. We study loans posted on Kiva between February 1, 2010, when Kiva changed the default protection rules (Kiva.org, 2010), and October 13, 2013.

This change of the protection rules ensures that the loans of defaulted borrowers are not repaid by the MFI itself, which used to be common practice before the change.[1] MFIs considered the option to compensate a borrower's default in approximately 90% of all posted loans in 2006 to 2008, in 75% and 69% of all loan requests in 2009 and 2010 before the policy change in February 2010 was implemented. As we are not able to observe the defaults of those loans paid back by the MFI itself, we conclude that the default variable was biased before the change and consequently exclude loans posted on Kiva before February 2010 from our research.

All of these loans either have the status *repaid*, i.e. repaid fully, or *defaulted*, i.e. not repaid fully. We make use of simple random sampling to obtain 30,110 representative observations. Moreover, macroeconomic indicators such as GDP per capita and Crop production index and geographical regions are obtained from the World Bank. After removing observations with missing macroeconomic

[1] Such behavior is only rational if the (average) screening costs per loan for selecting better credit risks are higher than the (average) losses and consequently a thorough screening does not take place. Thus, for those MFIs that frequently used to pay back defaulted loans to Kiva we can assume that the selection process has become more stringent since the change.

data and unrealistic values regarding loan term and activity term of partner MFIs the final data sample contains 29,304 observations and includes individual and group loans.

Credit default is the dependent binary variable with a value of one if the loan is defaulted and zero otherwise. Kiva defines a loan as defaulted if repayment by a borrower or partner MFI is doubtful or if the amount expected as of 180 days previously is not cumulatively repaid as of a quarterly reconciliation (Kiva.org, 2014). Of the 29,304 considered loans, 650 loans are defaulted. These loans are attributable to 71 different MFIs. The default rate over the entire sample data is 2.22%.

All explanatory variables are defined in detail in Table 2.1.

As pointed out above, we use the variable *funding time* as a proxy for the lenders' behavior in the sense that the faster a loan is funded the more attractive it must have been for the lenders.

The *default rate* of the previous year is employed as a proxy for the screening and monitoring quality of an individual MFI. Loans are considered to belong to a respective calender year if the majority of the loan term (more than 50%) is in that year. Therefore, considering a loan of year x, the default rate of the year $x - 1$ is used as proxy. The default rate of the previous year displays the share of requested and defaulted loans in year $x - 1$. Several partner MFIs did not have a default rate in the previous year. The metric variable is imputed with its mean conditioned on the year in order to prevent the loss of these observations.

The *activity term* of an MFI describes its experience in credit financing on Kiva and is included as a control variable. Kiva reviews partner MFIs in a full or basic due diligence to obtain information on the financial stability of each MFI. Based on the due diligence process, Kiva provides a one-to-five star *risk rating*, indicating the financial risk related to the failure of a MFI. A five star-rating represents the lowest risk. A dummy variable for the type of *due diligence* and the MFI-specific risk rating are included as MFI-specific control variables. Relatively frequently, MFIs use the possibility of refunding loans which have already been disbursed to the respective borrowers. Therefore, we include a dummy variable indicating *disbursement* before or after publication on Kiva.

Loan characteristics are considered to be possible determinants of credit default. To this end, a dummy variable for *group loans* is included in the analysis. Furthermore, the *number of borrowers* in a group compared with individual borrowers is of interest and included as a control variable. The *loan size* requested on Kiva and the *loan term* until the loan matures are included in order to test H3a and H3b. The classic microloan contract requires regular repayments, starting immediately after loan disbursement. The metric variable *grace period* describes the time period before the initial repayment is due. The categorical variable *repayment obligations* is classified by the categories weekly, fortnightly, monthly, every three to four months, twice a year and annual. Dummy variables represent the corresponding categorical values.

We also include dummy variables representing the *gender* of an individual borrower. Moreover, if a group loan is granted to a mixed group, we include the *percentage of women* in these groups to explore the gender effect.

To account for the stated (mostly entrepreneurial) purpose of the requested loan, *sectors of activity* are included as loan-specific control variables.

To display macroeconomic influences, we include control variables such as the *GDP per capita*, the *CROPI* as a proxy for the agricultural production in a country and geographical *regions*.

Variable	Expected effect	Description	
Funding time		Time to funding	Time period in hours from posting the loan on Kiva to being fully funded by Kiva lenders.
Default rate	+	Imputed default rate	MFI-specific default rate in the previous year. Obtained by dividing the value of requested and defaulted loans in the previous year by the total value of requested and ended loans in the previous year.
Activity term			Activity term of MFI in days on Kiva. Obtained by calculating time period starting with first activity on Kiva to present.
Due diligence			Type of due diligence processed by Kiva in order to define the financial stability and risk rating of each MFI. Dummy variable with the value of one if full due diligence is processed, zero if basic due diligence is processed.
Rating		MFI-specific risk rating	1–5 star risk rating of each MFI provided by Kiva. Risk categories are defined as low risk (4–5 stars), moderate risk (2.5–3.5 stars), high risk (1–2 stars), not-rated and no rating available. Dummy variables.
Disbursement			Dummy variable with the value of one if a loan has been disbursed before being posted and funded on Kiva, zero otherwise.
Group loan	−		Indicating if loan is granted to an individual or a group of a minimum of 2 individuals with joint liability. Dummy variable.
NB	−	Number of borrowers	Number of borrowers that request a loan. In the case of individual borrowers the value is one, in the case of group loans the group size is represented.
Loan size	+		Loan size in USD requested by an individual borrower or a group of individuals.
Loan term	+		Time period in days from the disbursal date to the due date of the last repayment obligation.
Grace period	+		Time period in days between the disbursal date and the initiative repayment, taking into account the required repayment obligation. Calculated as days between disbursal date and initiative repayment date minus regular payment period.
Repayment	+	Repayment obligation	Dummy variables for weekly repayment, fortnightly repayment, monthly repayment, repayment each 3–4 month, repayment twice a year and annual repayment.
Gender	−	Gender of borrower	Dummy variable for female individual, male individual, group of women, group of men and mixed group.
PCfemale	−	Percentage of women	Percentage of group members who are female within a mixed group of women and men.
Sector		Sectors of activity	Sectors of activity are agriculture, arts, clothing, construction, education, entertainment, food, health, housing, manufacturing, personal use, retail, service, transportation and wholesale.
GDP_{pC}		Gross domestic product per capita	USD value of the gross domestic income of the country, where the microfinance borrower is located, divided by its midyear population.
CROPI		Crop production index	The crop production index accounts for the agricultural production with the exception of fodder crops, for each year and country. Base period: 2004–2006.
Region			The geographical regions are Latin America and Caribbean (LAC), Middle East and North Africa (MENA), Sub-Saharan Africa (AFRICA), South Asia (SA), Eastern Europe and Central Asia (EECA), North America (NA) and East Asia and the Pacific (EAP).

Table 2.1: Definition of explanatory variables

2.3.2 Methodology

As the dependent variable is a binary variable, we use a probit regression model with the following specification:

$$probit\{P(Y_i = 1|(U_i, V_i, X_i, Z_i))\} = \beta_0 + \beta_1 U_i + \beta_2 V_i + \beta_3 X_i + \beta_4 Z_i + \epsilon_i \, ,$$

where U_i represents the variable describing the funding behavior of individual Kiva lenders (the funding time) and V_i describes characteristics of the loan contract, such as loan size, loan term, grace period, repayment obligations, type of lending, purpose and gender. X_i is a vector of variables at the level of the partner MFI and Z_i is a vector of macroeconomic and geographical variables. The symbol $\epsilon_i \sim N(0, \sigma^2)$ is the error term. We apply Eicker–Huber–White heteroskedastic-consistent standard errors in all regressions.

2.3.3 Descriptive statistics

The descriptive statistics for the metric and the categorical variables based on the data set are reported in Table 2.2 and 2.3, respectively.

The average time to funding on Kiva.org is 133.37 hours which does not differ greatly between individual loans and group loans. The average default rate in the previous year is 1.06%, whereby some MFIs display a default rate of zero and one MFI even has a default rate of 66.2%. The median value of 0.06% indicates the skewness of the distribution. More than 98% of loans are already disbursed before being posted on Kiva. Approximately 85% of loans are given to individual borrowers and the remaining loans to groups of at least two individuals up to a maximum of 45 individuals. The average loan size is \$794.42. The average loan size given to groups of borrowers (\$1,758) is more than twice as high as the loan size given to individual borrowers (\$624.09). In contrast, the average loan term of individual loans exceeds the loan term of group loans. The grace period ranges from –366 days to 441 days. Both extreme cases correspond to loans with an annual repayment. The median grace period is zero days. After an average grace period of 3.65 days, 21.77% of loans require weekly repayment and 63.30% monthly repayment. Slightly less than 12% comprise part of the remaining categories of repayment obligations. The largest part of the loans is obtained by female individuals or groups of women. Male and mixed groups are rare.

The average GDPpc is \$2,933, including countries with a GDPpc of \$219 as well as countries with a GDPpc of \$51,748. It is obvious that there are no group loans in North America.

All data (N=29,304) Variable	Mean	S.D.	Min	Median	Max
Funding time	1.33e+2	2.06e+2	1.67e−2	3.53e+1	1.59e+3
Default rate	1.06e−2	3.16e−2	0.00e+0	6.00e−4	6.62e−1
Activity term	9.21e+2	4.42e+2	0.00e+0	9.09e+2	2.23e+3
Loan size	7.94e+2	7.87e+2	5.00e+1	5.75e+2	1.00e+4
Loan term	2.85e+2	1.42e+2	7.00e+0	2.80e+2	1.11e+3
Grace period	3.65e+0	2.04e+1	−3.66e+2	0.00e+0	4.41e+2
NB	2.11e+0	3.43e+0	1.00e+0	1.00e+0	4.50e+1
GDPpc	2.93e+3	2.96e+3	2.19e+2	2.29e+3	5.18e+4
CROPI	1.31e+2	2.94e+1	7.32e+1	1.23e+2	2.91e+2
Individual loans (N=24,902)					
Variable	Mean	S.D.	Min	Median	Max
Funding time	1.34e+2	2.13e+2	1.67e−2	3.16e+1	1.59e+3
Default rate	1.05e−2	2.83e−2	0.00e+0	6.00e−4	6.62e−1
Activity term	9.05e+2	4.36e+2	0.00e+0	8.85e+2	2.22e+3
Loan size	6.24e+2	4.95e+2	5.00e+1	5.00e+2	1.00e+4
Loan term	2.97e+2	1.45e+2	7.00e+0	3.00e+2	1.11e+3
Grace period	4.27e+0	2.08e+1	−3.66e+2	0.00e+0	4.41e+2
GDPpc	3.03e+3	2.99e+3	3.26e+2	2.36e+3	5.18e+4
CROPI	1.30e+2	3.02e+1	7.32e+1	1.21e+2	2.90e+2
Group loans (N=4,402)					
Variable	Mean	S.D.	Min	Median	Max
Funding time	1.28e+2	1.66e+2	2.81e−2	5.27e+1	8.57e+2
Default rate	1.12e−2	4.60e−2	0.00e+0	6.31e−4	5.89e−1
Activity term	1.01e+3	4.63e+2	0.00e+0	1.06e+3	2.09e+3
Loan size	1.76e+3	1.28e+3	1.00e+2	1.33e+3	7.60e+3
Loan term	2.15e+2	9.35e+1	2.80e+1	1.83e+2	1.08e+3
Grace period	1.54e+1	1.74e+1	−1.84e+2	0.00e+0	4.39e+2
NB	8.36e+0	5.67e+0	2.00e+0	7.00e+0	4.50e+1
GDPpc	2.37e+3	2.62e+3	2.19e+2	1.21e+3	1.55e+4
CROPI	1.29e+2	2.39e+1	9.59e+1	1.26e+2	1.95e+2

Table 2.2: Descriptive statistics for metric variables based on the imputed data set
Notes: The data set is derived from the Kivas official webpage for researchers and the World Banks data base. The entire data sample contains 29,304 loans. It is divided into the subsample of individual loans with N=24,902 and the subsample of group loans with N=4,402. Mean, S.D., maximum, median and minimum of metric variables are displayed. The variables are defined in Table 2.1. *Data source:* Kiva, World Bank.

	All data N=29,304		Individual loans N=24,902		Group loans N=4,402	
Variable	Obs.	Relative	Obs.	Relative	Obs.	Relative
Defaulted loans	650	0.022	452	0.018	198	0.045
Repaid loans	2,8654	0.978	2,4450	0.982	4,204	0.955
Due diligence full	29,244	0.998	24,864	0.998	4,380	0.995
Due diligence basic	60	0.002	38	0.002	22	0.005
Rating_high	2,198	0.075	1,623	0.065	575	0.131
Rating_moderate	17,502	0.597	15,093	0.606	2,409	0.547
Rating_low	7,692	0.263	7,143	0.287	549	0.125
Rating_not-rated	184	0.006	43	0.002	141	0.032
Rating_not available	1,728	0.059	1,000	0.040	728	0.165
Disbursed before posted	28,817	0.983	24,520	0.985	4,297	0.976
Disbursed after posted	487	0.017	382	0.015	105	0.024
Repayment_weekly	6,380	0.218	5,409	0.217	971	0.221
Repayment_fortnightly	2,177	0.074	1,569	0.063	608	0.138
Repayment_monthly	18,550	0.633	16,155	0.649	2,395	0.544
Repayment_3–4month	430	0.015	390	0.016	40	0.009
Repayment_twice a year	1,124	0.038	965	0.039	159	0.036
Repayment_annual	643	0.022	414	0.017	229	0.052
Group loan	4,402	0.150				
Individual loan	24,902	0.849				
Female individual	17,561	0.599	17,561	0.705		
Male individual	7,341	0.251	7,341	0.295		
Group of women	2,706	0.092			2,706	0.615
Group of men	69	0.002			69	0.016
Mixed group	1,627	0.056			1,627	0.369
Sector_Agriculture	6,601	0.225	5,661	0.227	940	0.214
Sector_Arts	547	0.019	417	0.017	130	0.029
Sector_Clothing	1,976	0.067	1,581	0.064	395	0.089
Sector_Construction	564	0.019	503	0.020	61	0.014
Sector_Education	296	0.010	263	0.011	33	0.008
Sector_Entertainment	47	0.002	43	0.002	4	0.001
Sector_Food	7,264	0.248	6,062	0.243	1,202	0.273
Sector_Health	211	0.007	176	0.007	35	0.008
Sector_Housing	863	0.029	828	0.033	35	0.008
Sector_Manufacturing	401	0.014	353	0.014	48	0.011
Sector_Personal Use	346	0.012	325	0.013	21	0.005
Sector_Retail	6,775	0.231	5,659	0.227	1,116	0.254
Sector_Service	2,277	0.078	1,959	0.079	318	0.072
Sector_Transportation	1,080	0.037	1,025	0.041	55	0.013
Sector_Wholesale	56	0.002	47	0.002	9	0.002
Region_EAP	8,442	0.288	7,776	0.312	666	0.151
Region_EECA	1,604	0.055	1,420	0.057	184	0.042
Region_LAC	9,787	0.334	8,388	0.337	1,399	0.318
Region_MENA	806	0.028	791	0.032	15	0.003
Region_NA	31	0.001	31	0.001	0	0.000
Region_SA	585	0.019	142	0.006	443	0.101
Region_AFRICA	8,049	0.275	6,354	0.255	1,695	0.385

Table 2.3: Descriptive statistics for categorical variables based on the imputed data set
Notes: The data set is derived from the Kivas official webpage for researchers and the World Banks data base. The entire data sample contains 29,304 loans. It is divided into the subsample of individual loans with N=24,902 and the subsample of group loans with N=4,402. Absolute values and relative values of the dummy variables are displayed. The variables are defined in Table 2.1. *Data source:* Kiva, World Bank.

To gain deeper insights into the MFIs' process of selecting loans which they finally post on Kiva, we compare key figures of our data sample with key figures for the entire loan portfolio of the respective MFIs as reported on MIX Market. The results are displayed in Table 2.4.

First, we consider the average share of female borrowers in our data sample and the one within the entire loan portfolio of the MFIs. We can observe the fact that those loans posted on KIVA have a higher percentage of female borrowers on average than the entire loan portfolios of the respective MFIs. This indicates that MFIs tend to post loans granted to female borrowers on Kiva in order to attract potential investors. Furthermore, we consider the average default rate of the MFIs on Kiva with the write-off ratio and the loan loss rate of the respective MFIs as reported on MIX Market. The comparison indicates that the loans posted on Kiva are of lower risk than the overall loans of the respective MFIs. Note that this is a conservative estimate as we implicitly assume a loss rate of 100% for the defaulted loans on Kiva which is higher than the real loss. The means of the default rate on Kiva and the means of the write-off ratio and the loan loss rate on MIX Market are even significantly different in 2009 and 2010, but not in 2011. We conclude that MFIs prefer posting less risky loans on Kiva compared with their entire loan portfolio. Altogether, low-risk and female-borrower loans appear to be overrepresented to a certain extent on Kiva.

		Posted at KIVA		Reported at MIX			
year	N	Mean	S.D.	Mean	S.D.	t-statistic	p-value
		Average share of female borrowers		Average share of female borrowers			
2010	71	$7.56e{-1}$	$2.76e{-2}$	$6.95e{-1}$	$2.79e{-2}$	$1.56e{+0}$	0.122
2011	84	$7.29e{-1}$	$2.61e{-2}$	$7.01e{-1}$	$2.44e{-2}$	$7.88e{-1}$	0.432
2012	80	$6.92e{-1}$	$2.67e{-2}$	$6.61e{-1}$	$2.57e{-2}$	$8.59e{-1}$	0.392
		Average default rate at KIVA		Average write-off ratio			
2009	70	$7.19e{-4}$	$2.45e{-4}$	$1.70e{-2}$	$2.38e{-3}$	$-6.84e{+0}$	0.000***
2010	86	$1.02e{-2}$	$2.60e{-3}$	$2.03e{-2}$	$3.48e{-3}$	$-2.33e{+0}$	0.021**
2011	93	$1.31e{-2}$	$2.30e{-3}$	$2.40e{-2}$	$7.37e{-3}$	$-1.41e{+0}$	0.159
		Average default rate at KIVA		Average loan loss rate			
2009	77	$7.03e{-4}$	$2.23e{-4}$	$1.37e{-2}$	$2.23e{-3}$	$-5.82e{+0}$	0.000***
2010	87	$1.01e{-2}$	$2.58e{-3}$	$1.75e{-2}$	$3.18e{-3}$	$-1.80e{+0}$	0.074*
2011	96	$1.49e{-2}$	$3.00e{-3}$	$1.92e{-2}$	$6.97e{-3}$	$-5.73e{-1}$	0.568

Table 2.4: Key figures of our data sample vs. the respective key figures of the same MFIs' entire loan portfolios as reported on MIX Market
Notes: The *average default rate at Kiva* is calculated as described in Table 2.1, while the *write-off ratio* is calculated by the total amount of loans written off during a period divided by the average of all outstanding principals due for all outstanding client loans. Loans are written off if these loans are recognized as being uncollectable. The *loan loss rate* is obtained by dividing the total amount of loans written off minus the value of loans recovered by the average of all outstanding principals due for all outstanding client loans. *N* is the number of MFIs for which we have an observation on KIVA and on MIX at the same time.
Values labeled with the symbols *, ** and *** are significant at the 10% level, the 5% level and the 1% level. *Data source:* Kiva, MIX Market.

We do not expect an issue regarding multi-collinearity as the majority of correlations between metric variables are below 30% and only a few are as high as 50%. The Bravais-Pearson correlation coefficients are displayed in Table 2.5.

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1.	Funding time	1.00e+0									
2.	Default rate	2.97e−2*	1.00e+0								
3.	Activity term	6.50e−2*	−5.44e−2*	1.00e+0							
4.	log(loan size)	3.00e−1*	5.71e−2*	1.29e−1*	1.00e+0						
5.	Loan term	2.38e−1*	1.12e−1*	1.64e−2*	2.41e−1*	1.00e+0					
6.	Grace period	6.93e−2*	−2.99e−2*	−1.70e−2*	2.86e−2*	1.63e−1*	1.00e+0				
7.	NB	1.06e−2	−2.17e−2*	9.10e−2*	5.07e−1*	−2.13e−1*	−6.35e−2*	1.00e+0			
8.	PCfemale	2.50e−2*	−1.20e−3	−2.10e−3	3.27e−1*	−1.46e−1*	−2.78e−2*	5.79e−1*	1.00e+0		
9.	log(GDPpc)	1.00e−1*	−4.04e−2*	3.20e−2*	1.13e−1*	−1.36e−2*	−2.30e−2*	−8.39e−2*	−9.81e−2*	1.00e+0	
10.	CROPI	−4.70e−3	2.60e−3	1.62e−1*	9.46e−2*	2.68e−1*	3.99e−2*	−3.00e−3	−1.08e−2	−2.44e−1*	1.00e+0

Table 2.5: Bravais-Pearson correlation coefficients for metric exogenous variables based on the imputed data set
Notes: Values labeled with the symbol * are significant at the 5% level. The variables are defined in Table 2.1.

2.4 Results

Table 2.6 shows the mean values of the metric variables when differentiating between the group of defaulted and the group of repaid loans. While the means of funding time appear not to differ between the groups, the average default rate and average activity term are significantly different. Also, the expected values of the loan-specific variables are significantly different, with the exception of the loan size. Additionally, the result shows a significant difference between the means of GDPpc and the means of CROPI.

	Defaulted loans (N=650)		Repaid loans (N=28,654)			
Variable	Mean	S.D.	Mean	S.D.	t-statistic	p-value
Funding time	1.22e+2	1.94e+2	1.34e+2	2.07e+2	1.39e+0	0.166
Default rate	5.70e−2	1.25e−1	9.50e−3	2.47e−2	−3.89e+1	0.000***
Activity term	7.80e+2	4.45e+2	9.23e+2	4.42e+2	8.24e+0	0.000***
Loan size	8.44e+2	8.13e+2	7.93e+2	7.86e+2	−1.64e+0	0.101
Loan term	3.21e+2	1.76e+2	2.84e+2	1.41e+2	−6.68e+0	0.000***
Grace period	8.00e+0	2.70e+1	4.00e+0	2.00e+1	−4.88e+0	0.000***
NB	2.00e+0	3.00e+0	2.00e+0	3.00e+0	−2.49e+0	0.013**
GDPpc	2.59e+3	5.82e+3	2.94e+3	2.86e+3	2.95e+0	0.003**
CROPI	1.26e+2	2.40e+1	1.31e+2	2.90e+1	3.82e+0	0.000**

Table 2.6: Independent t-test for metric variables among defaulted loans and repaid loans based on the imputed data set

Notes: The data set is derived from the Kiva official webpage for researchers and the World Banks data base. The entire data sample contains 29,304 loans. It is divided into the subsample of defaulted loans with N=650 and the subsample of repaid loans with N=28,654. Mean and S.D. of metric variables and t-statistic and p-values are displayed. 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 2.1. *Data source:* Kiva, World Bank.

Table 2.7 exhibits the frequencies of the categorical variables based on the imputed data set for the defaulted and the repaid loans. Considering the disbursement, we notice that, on average, defaulted loans are less often disbursed before posted on Kiva compared with repaid loans. More than 75% of defaulted loans have been considered to be repaid monthly. The repaid loans are mainly redeemed on a monthly basis but the share of weekly repayment obligations is higher compared with defaulted loans. A share of 30% of the defaulted loans is provided to groups of borrowers whereas only 15% of the repaid loans are group loans.

	Defaulted loans N=650		Repaid loans N=28,654	
Variable	Obs.	Relative	Obs.	Relative
Due diligence full	649	0.998	28,595	0.998
Due diligence basic	1	0.002	59	0.002
Rating_high	83	0.128	2,115	0.074
Rating_moderate	314	0.483	17,188	0.599
Rating_low	30	0.046	7,662	0.267
Rating_not-rated	20	0.031	164	0.006
Rating_not available	203	0.312	1,525	0.053
Disbursed before posted	585	0.900	28,232	0.985
Disbursed after posted	65	0.100	422	0.015
Repayment_weekly	110	0.169	6,270	0.219
Repayment_biweekly	22	0.034	2,155	0.075
Repayment_monthly	489	0.752	18,061	0.630
Repayment_3-4month	5	0.008	425	0.015
Repayment_twice a year	5	0.008	1,119	0.039
Repayment_annual	19	0.029	624	0.022
Group loan	198	0.305	4,204	0.147
Individual loan	452	0.695	24,450	0.853
Female individual	279	0.429	17,282	0.603
Male individual	173	0.266	7,168	0.250
Group of women	73	0.112	2,633	0.092
Group of men	8	0.012	61	0.000
Mixed group	117	0.180	1510	0.053
Sector_Agriculture	120	0.185	6,481	0.226
Sector_Arts	16	0.025	531	0.019
Sector_Clothing	66	0.102	1,910	0.067
Sector_Construction	14	0.022	550	0.019
Sector_Education	1	0.002	295	0.010
Sector_Entertainment	2	0.003	45	0.002
Sector_Food	170	0.262	7,094	0.248
Sector_Health	13	0.020	198	0.007
Sector_Housing	11	0.017	852	0.029
Sector_Manufacturing	5	0.008	396	0.014
Sector_Personal Use	3	0.005	343	0.012
Sector_Retail	145	0.223	6,630	0.231
Sector_Service	62	0.095	2,215	0.077
Sector_Transportation	21	0.032	1,059	0.037
Sector_Wholesale	1	0.002	55	0.002
Region_EAP	20	0.031	8,422	0.294
Region_EECA	1	0.002	1,603	0.056
Region_LAC	171	0.263	9,616	0.336
Region_MENA	6	0.009	800	0.028
Region_NA	7	0.011	24	0.001
Region_SA	51	0.078	534	0.019
Region_AFRICA	394	0.606	7,655	0.267

Table 2.7: Descriptive statistics for categorical variables based on the imputed data set for defaulted loans and repaid loans
Notes: The data set is derived from the Kiva official webpage for researchers and the World Banks data base. The entire data sample contains 29,304 loans. It is divided into the subsample of defaulted loans with N=650 and the subsample of repaid loans with N=28,654. Absolute values and relative values of the dummy variables are displayed. The variables are defined in Table 2.1. *Data source:* Kiva, World Bank.

The results of the estimated probit models are reported in Table 2.8. Model specification (I) is the basic model with a dummy variable for a group loan versus an individual loan to test the advantage of group loans over individual loans in terms of credit default. In model specification (II) three dummy variables indicating the type of group regarding gender are added. Model specification (III) corresponds to model specification (II) and includes the percentage of female members in a mixed group.

The default rate in the previous year representing the selection and monitoring quality of MFIs has a significant positive sign in all model specifications. Loans issued by MFIs with a high default rate in the previous year are positively associated with probability of default. The result illustrates the important role of MFIs in terms of selecting and monitoring microfinance borrowers in order to ensure loan repayment. The result supports H1. This finding can also be an indication that some MFIs permanently manage to select low-risk loans while others fail to do so or may have a different policy. The negative and significant coefficient of the activity term implies that the more experienced an MFI is on Kiva, the less likely one of its loans is to be defaulted. The dummy variable for full due diligence versus basic due diligence processed by Kiva shows a positive sign. The result is significant and surprising as loans distributed by MFIs which have been reviewed in more detail by Kiva are more likely to default. Regarding the risk rating of each MFI, loans of low risk-rated MFIs appear to perform better compared with loans of high risk-rated MFIs. The result is slightly significant in specification II and III. It is obvious that the probability of default increases if the MFI is not rated or if the risk rating is no longer available due to the termination of activity on Kiva. The coefficient of the dummy variable indicating whether a loan is disbursed beforehand or not is negative and significant. Loans which have already been disbursed exhibit a lower probability of default which could be an indication that MFIs seek to refund relatively reliable loans on Kiva in order to ensure a good repayment performance on Kiva.

The dummy variable for group loans has an unexpected positive and significant coefficient. Groups of borrowers perform worse than individual borrowers regarding repayment in our data set. However, this finding needs to be interpreted together with the significant negative coefficient of the number of borrowers in the group. The joint effect of both implies that groups of eight and more members ceteris paribus have a lower default probability than a single borrower. In fact, only small groups are more likely to default. This effect could be linked to the insurance effect of bigger groups as the bigger the group, the smaller the joint liability burden per group member. Group members appear to be able to jointly repay the entire loan amount even in the case of a peer defaulting. Therefore, hypothesis H2 cannot be directly confirmed, but in a modified interpretation for large groups instead. In the context of the MFIs' loan selection problem, this also can be due to a bias toward high-risk group loans as the MFIs may be aware of the investors' preference in favor of group loans (see discussion around Table 2.9 below).

The loan size has a significantly positive impact on the probability of default in all model specifications. It appears to be more difficult for microfinance borrowers and groups of borrowers to repay larger loans. The result corresponds well with H3a. The positive and significant sign of the loan term supports our expectation of H3b in terms of the borrower's difficulty in saving returns in the long run. As the self-discipline in repaying a loan may decrease over time and more adverse events can occur, the probability of default increases.

The relationship between regular repayment obligations and the probability of default is not definitely clarified. Loans requiring monthly repayment are more likely to default compared to loans requiring weekly repayment. When comparing the most popular types of repayment obligations, the results are slightly significant in specifications II and III and support H4a. To gain a deeper insight into this issue, it is important to distinguish between individual loans and group loans. It is obvious that individual loans requiring weekly repayment are advantageous over loans requiring monthly repayment (see column IV in Table 2.8). However, this is not the case for group loans (see Table 2.10). In total, the impact of the required repayment obligation on the probability of default is only weakly supported in the entire data set. Additionally, loans requiring annual repayment are proven to have a significantly lower probability of default compared with loans requiring weekly repayment. This result is contradictory to our expectation and may be linked to the fact that none of the individual loans requiring annual repayment have defaulted. If we examine the individual loans with annual repayment in closer detail, it is mentionable that these are mainly distributed to Latin America and the Caribbean and mainly granted for agricultural purposes and not as spread out as all other loans requiring more frequent payments. These loans may be special in the sense that they could be regarded as being very low risk by the partner MFIs and thus rewarded with annual payments. As pointed out above, such low-risk loans can be very attractive to investors and therefore be over-represented in the selection process of the MFI. None of the coefficients of the remaining types of repayment obligations are significant. As expected, the grace period has a significant positive influence on credit default. The result favors H4b and corresponds to the findings obtained by Field et al. (2013).

Next, we examine the gender effect. Female individual borrowers are associated with a lower probability of default when compared with to their male counterparts as the sign of the gender dummy is negative and significant in all model specifications. Hence, we observe evidence in favor of H5. Groups of women and mixed groups appear to have greater difficulties in repayment than male individual borrowers, whereas the coefficient of groups of male is also positive but not significant. Furthermore, we test whether the dummy variables indicating the type of group regarding gender have equal effects by comparing groups of women and mixed groups as well as groups of men and mixed groups. The equality of effects can be rejected in both cases. The equality of effects between groups of women and groups of men cannot be rejected. The coefficient of the percentage of female members in a mixed group is positive but not significant and does not contribute to clarifying whether female borrowers have a better repayment performance. When revisiting the MFIs' loan selection problem, this observation can also be due to a bias toward groups, particularly groups with a high percentage of women as these kind of loans appear to be attractive to investors (see Table 2.9). In general, such a selection does not necessarily increase the credit risk, but some MFIs may tend to select even those women or group loans that are riskier than the average loan.

All included macroeconomic factors appear to influence credit default. The GDPpc and the crop production index are negatively related to the probability of default, indicating that the higher the GDPpc and the agricultural production in a country, the lower the probability of default is.

Last, the funding time as a proxy for the attractiveness of a loan for Kiva lenders is notably insignificant in all specifications. Therefore, we do not observe an additional explanatory power of quickly-funded loans for credit risk.[2] This is an indication that various different social factors beside the repayment of loans may influence the lending decision of charitable lenders.

To gain deeper insights into this issue, we regress the funding time on the other available variables. We refrain, however, from using the CROPI as the agricultural production output of a country, which ex post influences repayment, cannot be forecast easily and thus is very unlikely to influence the attractiveness of a loan. Table 2.9 presents the corresponding results.[3]

Obviously, the funding time is related to many of the explanatory variables. However, with R^2 values of approximately 28 per cent, it is not perfectly explained by the rest of the variables, which is consistent with the above-mentioned papers which provide evidence that the funding time is influenced by further soft factors. Therefore, the first conclusion is that we do not have a multi-collinearity problem in our default regressions. Secondly, as the logarithm of the loan size has a positively significant coefficient, we can state that the loan size, which obviously has a positive influence in the funding time, is already accounted for. Thus, the other effects can be interpreted in a ceteris paribus manner. A closer analysis of the significant effects supports the view that lenders are obviously attracted by variables indicating low credit risk and likewise by social impact measures. The negative impact of the group loan and the gender dummies, indicating a quicker funding for groups and for female individuals, can clearly be interpreted as being social-impact driven behavior. Also, the positive coefficient of the disbursed dummy indicates that lenders prefer to fund loans that have not been disbursed before, indicating that the lenders prefer to *enable* projects instead of just refinancing already enabled ones. The social claim holds even more if we look at the credit risk implications of these

[2]Note that this effect is robust and not a result of the specific definition of the attractiveness measure. When plugging in the logarithm of the funding time or the funding time per loan amount or the logarithm of the funding time per loan amount, the coefficient remains insignificant in all of the cases.

[3]Note that a more conservative approach would be to estimate the probit regression and the regression of the funding time simultaneously. However, as the standard way of implementing this is a 2SLS approach which regresses the funding time first and plugs the estimated values of the funding into the probit model second, the already now insignificant coefficient of the funding time remains insignificant. Thus, we refrain from pursuing the 2SLS variant for the ease of representation.

variables (Table 2.8). Group loans and previously undisbursed loans do have a higher default risk. Merely loans to female individuals are not only regarded as a social investment, but also reveal a lower credit risk. However, lenders appear to be reluctant to support poorer borrowers as the coefficient of the logarithm of GDPpc is negative, indicating that lenders do not give money to poorer countries willingly as the credit risk of poorer country loans is higher (Table 2.8).

There are further indications that point to the fact that lenders do consider variables indicating higher credit risk. A high default rate of the MFI or an unrated MFI as well as long grace periods or long loan terms not only increase the repayment risk but also lead to a reluctance among the lenders to fund such a loan. Summarizing, the lenders are relatively strongly attracted by the credit risk issues, again proving the importance of our research question. However, they also consider some social issues when lending, even if this is harmful to the repayment expectations.

The results of the probit regression on the individual loan sample are similar to the findings of the main model. The majority of coefficients remain stable with similar signs and confidence levels. Compared with the complete data sample, the results regarding MFI-specific variables also confirm the impact of the MFIs' characteristics on repayment performance. The coefficient of the default rate in the previous year is positive and significant at the 1% level. Thus, H1 is approved. The coefficient of the activity term of MFIs remains negative and significant. In contrast to the complete sample, the dummy variable indicating the type of due diligence is negative and significant. Regarding risk rating, unrated MFIs appear to be more likely to ensure loan repayment when compared with high risk-rated MFIs. The remaining relationships are similar to the complete data sample. The possibility of the MFIs to refund loans disbursed beforehand to individual borrowers is still in favor of loan repayment. We detect loan characteristics to influence credit default. The sign of loan size is significantly positive as predicted in H3a. The sign of the loan term remains significantly positive and our suggestion in H3b is supported. Therefore, individual borrowers face greater difficulties in repaying a loan if the loan size or the loan term increases. The significance level of the dummy variable indicating monthly repayment increases to the 1% level. However, the influence of regular repayment obligations on credit default is not obvious as Hypothesis H4a is not clearly supported by the different frequencies of repayment. We find evidence in favor of H4b as a positive relation between the grace period and the probability of default is obvious. In accordance with the result considering the complete sample, the gender effect is approved. This finding favors our prediction in H5 and supports the widely discussed priority given to women as borrowers in microfinance. Regarding macroeconomic variables, the GDPpc and the crop production index are again negatively related to probability of default.

	Entire data set			Individual loans
	(I)	(II)	(III)	(IV)
Investor's decision				
Funding time	$-1.53e{-4}$	$-1.77e{-4}$	$-1.74e{-4}$	$-1.23e{-4}$
	$(1.08e{-4})$	$(1.09e{-4})$	$(1.09e{-4})$	$(1.15e{-4})$
MFI-specific variables				
Default rate	$5.63e{+0}^{***}$	$5.52e{+0}^{***}$	$5.52e{+0}^{***}$	$4.84e{+0}^{***}$
	$(4.18e{-1})$	$(4.20e{-1})$	$(4.20e{-1})$	$(4.71e{-1})$
Activity term	$-2.48e{-4}^{***}$	$-2.45e{-4}^{***}$	$-2.45e{-4}^{***}$	$-2.18e{-4}^{***}$
	$(5.23e{-5})$	$(5.25e{-5})$	$(5.25e{-5})$	$(5.61e{-5})$
Due diligence	$2.60e{+0}^{***}$	$2.47e{+0}^{***}$	$2.48e{+0}^{***}$	$-2.19e{+0}^{***}$
	$(5.11e{-1})$	$(5.14e{-1})$	$(5.14e{-1})$	$(6.20e{-1})$
Rating_moderate	$-7.03e{-2}$	$-9.28e{-2}$	$-9.34e{-2}$	$-9.43e{-2}$
	$(7.04e{-2})$	$(7.09e{-2})$	$(7.09e{-2})$	$(8.19e{-2})$
Rating_low	$-1.41e{-1}$	$-1.63e{-1}^{*}$	$-1.63e{-1}^{*}$	$-1.96e{-1}^{*}$
	$(9.70e{-2})$	$(9.79e{-2})$	$(9.79e{-2})$	$(1.06e{-1})$
Rating_not rated	$2.16e{+0}^{***}$	$1.98e{+0}^{***}$	$1.99e{+0}^{***}$	$-2.79e{+0}^{***}$
	$(3.18e{-1})$	$(3.22e{-1})$	$(3.23e{-1})$	$(4.49e{-1})$
Rating_not available	$9.87e{-1}^{***}$	$9.37e{-1}^{***}$	$9.36e{-1}^{***}$	$7.34e{-1}^{***}$
	$(7.85e{-2})$	$(7.98e{-2})$	$(7.97e{-2})$	$(9.64e{-2})$
Loan-specific variables				
Disbursement	$-2.95e{-1}^{***}$	$-2.91e{-1}^{***}$	$-2.91e{-1}^{***}$	$-4.14e{-1}^{***}$
	$(8.58e{-2})$	$(8.61e{-2})$	$(8.61e{-2})$	$(9.35e{-2})$
Group loan	$3.17e{-1}^{***}$			
	$(8.88e{-2})$			
NB	$-4.36e{-2}^{***}$	$-6.10e{-2}^{***}$	$-6.20e{-2}^{***}$	
	$(1.10e{-2})$	$(1.23e{-2})$	$(1.22e{-2})$	
log(loan size)	$1.06e{-1}^{***}$	$1.09e{-1}^{***}$	$1.08e{-1}^{***}$	$1.14e{-1}^{***}$
	$(3.91e{-2})$	$(3.94e{-2})$	$(3.94e{-2})$	$(4.28e{-2})$
Loan term	$1.14e{-3}^{***}$	$1.16e{-3}^{***}$	$1.16e{-3}^{***}$	$1.10e{-3}^{***}$
	$(1.59e{-4})$	$(1.59e{-4})$	$(1.59e{-4})$	$(1.65e{-4})$
Grace period	$1.79e{-3}^{***}$	$1.79e{-3}^{***}$	$1.79e{-3}^{***}$	$1.97e{-3}^{***}$
	$(6.49e{-4})$	$(6.51e{-4})$	$(6.51e{-4})$	$(6.48e{-4})$
Repayment_fortnightly	$-1.39e{-1}$	$-1.42e{-1}$	$-1.45e{-1}$	$-6.40e{-2}$
	$(1.03e{-1})$	$(1.04e{-1})$	$(1.04e{-1})$	$(1.42e{-1})$
Repayment_monthly	$1.02e{-1}$	$1.13e{-1}^{*}$	$1.14e{-1}^{*}$	$3.35e{-1}^{***}$
	$(6.24e{-2})$	$(6.39e{-2})$	$(6.40e{-2})$	$(8.81e{-2})$
Repayment_3-4month	$-1.60e{-2}$	$-3.91e{-2}$	$-2.93e{-2}$	$1.44e{-1}$
	$(2.21e{-1})$	$(2.25e{-1})$	$(2.25e{-1})$	$(2.71e{-1})$
Repayment_twice a year	$-3.10e{-1}$	$-3.44e{-1}$	$-3.23e{-1}$	$-2.91e{-1}$
	$(1.98e{-1})$	$(2.10e{-1})$	$(2.06e{-1})$	$(3.56e{-1})$
Repayment_annual	$-1.45e{+0}^{***}$	$-1.48e{+0}^{***}$	$-1.48e{+0}^{***}$	
	$(2.78e{-1})$	$(2.81e{-1})$	$(2.81e{-1})$	
Female individual	$-9.56e{-2}^{*}$	$-1.05e{-1}^{**}$	$-1.03e{-1}^{*}$	$-8.79e{-2}^{*}$
	$(5.33e{-2})$	$(5.32e{-2})$	$(5.32e{-2})$	$(5.31e{-2})$
Group of women		$1.98e{-1}^{**}$	$2.05e{-1}^{**}$	
		$(9.80e{-2})$	$(9.75e{-2})$	
Group of men		$2.51e{-1}$	$2.54e{-1}$	
		$(2.44e{-1})$	$(2.44e{-1})$	
Mixed group		$6.87e{-1}^{***}$	$5.82e{-1}^{***}$	
		$(1.13e{-1})$	$(2.01e{-1})$	
PCfemale x Mixed group			$1.78e{-1}$	
			$(2.56e{-1})$	
Sectors	yes	yes	yes	yes
Macroeconomic and geographical variables				
log(GDPpc)	$-1.81e{-1}^{***}$	$-1.46e{-1}^{***}$	$-1.47e{-1}^{***}$	$-8.93e{-2}^{*}$
	$(3.95e{-2})$	$(4.05e{-2})$	$(4.04e{-2})$	$(4.64e{-2})$
CROPI	$-4.58e{-3}^{***}$	$-4.50e{-3}^{***}$	$-4.50e{-3}^{***}$	$-2.22e{-3}^{**}$
	$(1.17e{-3})$	$(1.16e{-3})$	$(1.16e{-3})$	$(1.13e{-3})$
Regions	yes	yes	yes	yes
_cons	$-4.10e{+0}^{***}$	$-4.23e{+0}^{***}$	$-4.23e{+0}^{***}$	$-3.47e{-1}$
	$(6.70e{-1})$	$(6.76e{-1})$	$(6.75e{-1})$	$(8.18e{-1})$
Number of observations	29,304	29,304	29,304	24,488
Pseudo R^2	0.263	0.267	0.267	0.209
Akaike information criterion	$4.68e{+3}$	$4.66e{+3}$	$4.66e{+3}$	$3.64e{+3}$
Bayesian information criterion	$5.04e{+3}$	$5.03e{+3}$	$5.04e{+3}$	$3.97e{+3}$

Table 2.8: Coefficients of the probit models – entire data set and individual loans
Notes: Model specification I, II and III are probit regressions for the probability of default based on the entire data set which includes individual loans and group loans. Model specification IV is a probit regression for the probability of default of exclusively individual loans. The dependent variable is a dummy variable. Values labeled with the symbols *, ** and *** are significant at the 10% level, the 5% level and the 1% level. Robust standard errors are in parentheses. Reference categories: For *Rating* category *high risk*, for *Repayment* category *weekly repayment*, for *Gender* category *male individual*, for *Sector* category *agriculture* and for *Region* category *EAP*. The variables are defined in Table 2.1.

	Entire data set		
	(I)	(II)	(III)
MFI-specific variables			
Default rate	1.91e+2***	1.73e+2***	1.63e+2***
	(3.98e+1)	(4.01e+1)	(4.02e+1)
Activity term	3.13e−2***	3.24e−2***	3.23e−2***
	(2.58e−3)	(2.58e−3)	(2.58e−3)
Due diligence	3.54e+2***	3.31e+2***	3.19e+2***
	(2.99e+1)	(2.97e+1)	(2.94e+1)
Rating_moderate	2.44e+1***	2.26e+1***	2.25e+1***
	(3.41e+0)	(3.42e+0)	(3.41e+0)
Rating_low	1.64e+1***	1.61e+1***	1.57e+1***
	(4.12e+0)	(4.11e+0)	(4.11e+0)
Rating_not rated	2.85e+2***	2.61e+2***	2.49e+2***
	(2.68e+1)	(2.66e+1)	(2.63e+1)
Rating_not available	−2.39e+0	−7.13e+0*	−6.47e+0
	(4.02e+0)	(4.05e+0)	(4.05e+0)
Loan-specific variables			
Disbursement	5.21e+1***	5.28e+1***	5.29e+1***
	(7.37e+0)	(7.40e+0)	(7.40e+0)
Group loan	−1.32e+2***		
	(5.19e+0)		
NB	−3.00e+0***	−3.78e+0***	−3.44e+0***
	(4.90e−1)	(5.01e−1)	(5.02e−1)
log(loan size)	6.35e+1***	6.26e+1***	6.26e+1***
	(1.76e+0)	(1.76e+0)	(1.76e+0)
Loan term	1.63e−1***	1.68e−1***	1.68e−1***
	(1.03e−2)	(1.03e−2)	(1.03e−2)
Grace period	3.13e−1***	3.08e−1***	3.08e−1***
	(1.01e−1)	(1.00e−1)	(1.00e−1)
Repayment_fortnightly	−1.18e+1***	−1.33e+1***	−1.19e+1***
	(4.06e+0)	(4.06e+0)	(4.06e+0)
Repayment_monthly	−1.43e+1***	−1.50e+1***	−1.50e+1***
	(2.74e+0)	(2.73e+0)	(2.73e+0)
Repayment_3-4month	−2.03e+1**	−2.25e+1***	−2.38e+1***
	(7.90e+0)	(7.80e+0)	(7.74e+0)
Repayment_twice a year	1.30e+1***	1.37e+1***	1.26e+1***
	(4.45e+0)	(4.42e+0)	(4.42e+0)
Repayment_annual	3.61e+1***	3.67e+1***	3.69e+1***
	(8.51e+0)	(8.52e+0)	(8.53e+0)
Female individual	−1.32e+2***	−1.32e+2***	−1.33e+2***
	(3.24e+0)	(3.24e+0)	(3.24e+0)
Group of women		−1.42e+2***	−1.45e+2***
		(5.23e+0)	(5.24e+0)
Group of men		−6.60e+1***	−6.61e+1***
		(2.24e+1)	(2.25e+1)
Mixed group		−9.88e+1***	−3.05e+1*
		(7.02e+0)	(1.59e+1)
PCfemale x Mixed group			−1.04e+2***
			(2.18e+1)
Sectors	yes	yes	yes
Macroeconomic and geographical variables			
log(GDPpc)	−9.06e+0***	−7.42e+0***	−7.05e+0***
	(2.37e+0)	(2.39e+0)	(2.39e+0)
Regions	yes	yes	yes
_cons	−6.50e+2***	−6.35e+2***	−6.25e+2***
	(3.73e+1)	(3.70e+1)	(3.67e+1)
Number of observations	29,751	29,751	29,751
R^2	0.276	0.278	0.278
Akaike information criterion	3.92e+5	3.92e+5	3.92e+5
Bayesian information criterion	3.92e+5	3.92e+5	3.92e+5

Table 2.9: Coefficients of the linear regression – entire data set
Notes: Model specification I, II and III are linear regressions of the funding time based on the entire data set which includes individual loans and group loans. The dependent variable is a metric variable. Values labeled with the symbols *, ** and *** are significant at the 10% level, the 5% level and the 1% level. Robust standard errors are in parentheses. Reference categories: For *Rating* category *high risk*, for *Repayment* category *weekly repayment*, for *Gender* category *male individual*, for *Sector* category *agriculture* and for *Region* category *EAP*. The variables are defined in Table 2.1.

Table 2.10 now provides the results of the group loan subsample. Some adjustments regarding the MFI rating, sectors of activity and geographical regions are necessary. The rating categories of low risk and moderate risk are united in order to prevent a loss of observations. Loans used for housing are added to the category of loans used for construction. Entrepreneurial activity such as retail, wholesale and entertainment are united and reported as entrepreneurial activity by retail. However, 44 loans requested for education or personal use are not included because the dummy variables predict failure perfectly and we do not consider the combination with remaining categories advisable as we aim to maintain the difference between commercial and non-commercial purposes. The regions of the Middle East and North Africa and Eastern Europe and Central Asia are added to the reference category of East Asia and the Pacific in order to keep the observations for the analysis. After these adjustments, 4,348 observations are used. Model specification I is equal to the main model. Model specification II includes the loan size per group member instead of the overall loan size.

Funding time now becomes negative and slightly significant in model specification I. Considering the fact that group loans are usually granted to very low-income and vulnerable borrowers, the result could be linked to the philanthropic decision making of Kiva lenders in terms of funding loans according to neediness.

Again, the positive relationship between the MFI's default rate in the previous year and the probability of default supports our suggestions in H1. The coefficients of the activity term continue to be negative and significant. The dummy variable for the type of due diligence is not included because basic due diligence predicts failure perfectly and observations would become lost. Regarding the risk rating, there are no considerable changes. The sign of the dummy variable for disbursement remains negative. However, the result becomes insignificant.

As in the main model, it appears to be easier for bigger groups to ensure repayment in the case of default of a single group member as the need for repayment compensation is spread over several group members.

When considering loan characteristics as possible determinants of credit default, the coefficient of the loan size continues to be positive whereas the coefficient of the loan size per group member is negative. However, the results are not significant and we find no evidence to support H3a for group loans. The loan term remains positively related to the probability of default and is consistent with hypothesis H3b stating the decrease of borrower's self-discipline over time.

In contrast to the complete sample, neither the grace period nor the dummy variables for the frequency of repayment obligations provide information for the analysis of repayment. Hence, there is no evidence to support H4a and H4b for group loans.

The gender effect is not detected within group loans. Groups of women do not prove themselves to have a better repayment performance than groups of men. The result does not favor H5. Mixed groups and the percentage of female members in a mixed group display a positive sign, while the coefficients are not significant. The equality of effects of female groups and mixed groups can be rejected in either of the model specifications.

As in the previous findings, the macroeconomic variables influence the probability of default in the same way as the signs remain stable.

Compared with the findings referring to the entire data set and to individual loans, in the subsample of group loans some coefficients become insignificant. The change in confidence level may be explained by the reduced data set containing 4,348 observations. However, variables at the level of partner MFIs remain stable. The coefficients of important loan characteristics such as loan size and grace period remain positive as they do in the main model whereas the signs of the dummy variables for repayment obligations change to some extent.

	Group loans	
	(I)	(II)
Investor's decision		
Funding time	$-5.10e{-4}$*	$-4.63e{-4}$
	($3.06e{-4}$)	($3.03e{-4}$)
MFI-specific variables		
Default rate	$9.37e{+0}$***	$9.51e{+0}$***
	($1.77e{+0}$)	($1.77e{+0}$)
Activity term	$-3.70e{-4}$**	$-3.74e{-4}$**
	($1.53e{-4}$)	($1.54e{-4}$)
Rating_moderate/low	$-3.70e{-2}$	$-1.96e{-2}$
	($1.64e{-1}$)	($1.64e{-1}$)
Rating_not rated	$6.70e{-1}$***	$6.71e{-1}$***
	($2.34e{-1}$)	($2.34e{-1}$)
Rating_not available	$1.07e{+0}$***	$1.06e{+0}$***
	($1.92e{-1}$)	($1.93e{-1}$)
Loan-specific variables		
Disbursement	$-1.21e{-1}$	$-1.31e{-1}$
	($1.85e{-1}$)	($1.85e{-1}$)
NB	$-4.63e{-2}$***	$-3.99e{-2}$***
	($1.43e{-2}$)	($9.84e{-3}$)
log(loan size)	$6.54e{-2}$	
	($9.90e{-2}$)	
log(loan size/NB)		$-1.33e{-2}$
		($1.11e{-1}$)
Loan term	$2.47e{-3}$***	$2.50e{-3}$***
	($6.64e{-4}$)	($6.74e{-4}$)
Grace period	$2.30e{-3}$	$2.21e{-3}$
	($2.16e{-3}$)	($2.15e{-3}$)
Repayment_fortnightly	$-9.56e{-2}$	$-8.08e{-2}$
	($1.94e{-1}$)	($1.94e{-1}$)
Repayment_monthly	$-2.32e{-1}$	$-2.13e{-1}$
	($1.47e{-01}$)	($1.48e{-01}$)
Repayment_3-4month	$-8.41e{-2}$	$-7.06e{-2}$
	($4.54e{-1}$)	($4.53e{-1}$)
Repayment_twice a year	$-4.68e{-1}$	$-4.47e{-1}$
	($3.63e{-1}$)	($3.62e{-1}$)
Repayment_annual	$-2.28e{-1}$	$-2.70e{-1}$
	($2.70e{-1}$)	($2.76e{-1}$)
Group of women	$5.10e{-2}$	$4.17e{-2}$
	($2.74e{-1}$)	($2.76e{-1}$)
Mixed group	$3.24e{-1}$	$3.14e{-1}$
	($3.12e{-1}$)	($3.13e{-1}$)
PCfemale x Mixed group	$2.14e{-1}$	$2.21e{-1}$
	($3.07e{-1}$)	($3.08e{-1}$)
Sectors	yes	yes
Macroeconomic and geographical variables		
log(GDPpc)	$-2.15e{-1}$**	$-1.97e{-1}$**
	($9.49e{-2}$)	($9.10e{-2}$)
CROPI	$-6.77e{-3}$**	$-7.04e{-3}$**
	($3.00e{-3}$)	($3.03e{-3}$)
Regions	yes	yes
_cons	$-1.66e{+0}$*	$-1.27e{+0}$
	($8.47e{-1}$)	($8.77e{-1}$)
Number of observations	4,348	4,348
Pseudo R^2	0.410	0.410
Akaike information criterion	$1.02e{+3}$	$1.02e{+3}$
Bayesian information criterion	$1.23e{+3}$	$1.23e{+3}$

Table 2.10: Coefficients of the probit models – group loans
Notes: Model specification I and II are probit regressions for the probability of default of exclusively group loans. The dependent variable is a dummy variable. Values labeled with the symbols *, ** and *** are significant at the 10% level, the 5% level and the 1% level. Robust standard errors are in parentheses. Reference categories: For *Rating* category *high risk*, for *Repayment* category *weekly repayment*, for *Gender* category *group of men*, for *Sector* category *agriculture* and for *Region* category *EAP, MENA, EECA*. There are no group loans to NA. The variables are defined in Table 2.1.

2.5 Robustness checks

To assess the robustness of the results, we estimate further probit models employing clustered standard errors. In the entire data set, we distinguish between 151 MFIs which select and monitor borrowers and ensure loan repayment. Columns 1–3 in Table 2.11 report the results. Even if in our setting this can be considered to be a very conservative approach, most of the effects remain unchanged. However, the disbursement variable loses its significance and there are differences regarding loan-specific variables. Also, the coefficients of loan size and grace period do not remain significant in all model specifications. Similarly, the dummy variables representing female individual borrowers and groups of women now have insignificant coefficients.

Moreover, outlier robustness checks are carried out as outliers may influence the results. Extreme observations below the 2.5th and above the 97.5th percentile are dropped. Some adjustments are necessary to prevent the loss of observations. Loans used for wholesale are added to the category of loans used for retail. Loans distributed to Eastern Europe and Central Asia are added to the reference category consisting of loans to East Asia and the Pacific. The results are shown in columns 4–6 in Table 2.11. While the majority of variables reveals itself to be consistent with our main results, the coefficient of loan size becomes insignificant and negative in all model specifications. By contrast, the dummy variables representing fortnightly repayment and repayment twice a year turn out to be negative and significant, supporting a rejection of H4a. The overall picture, however, is robust.

Additionally, we conduct probit regressions with clustered standard errors and probit regressions without outliers on the two subsamples of individual loans and group loans. All results are reported in Table 2.12 and Table 2.13.

When considering the individual loan subsample, we can distinguish between 137 MFIs. A considerable difference arises regarding the type of due diligence processed by Kiva. The sign of the dummy variable turns out to be negative and significant. Regarding loan-specific variables, some coefficients change and become insignificant such as the dummy variable for disbursement, the loan size, the grace period and the dummy variable for female borrowers. The macroeconomic variables do not remain significant.

We carry out the robustness checks for outliers after some adjustments in both subsamples regarding sectors of activity and regions have been made. Loans used for retail and for wholesale are united and reported as retail. Loans to Eastern Europe and Central Asia and to North America are added to the reference category of loans to East Asia and the Pacific. The dummy variable representing the type of due diligence is dropped due to collinearity. A considerable difference is that the relation between the grace period and the probability of default appears to be negative and significant. This result is not consistent with our finding of the main model. The coefficient of the loan size is not significant anymore. The remaining results appear to be similar to the previous findings in Section 2.4.

Considering the group loan subsample, we conduct the probit regression with standard errors clustered in 70 MFIs. The results shown in columns 3–4 remain stable and support our hypotheses. Similarly, the results of the outliers robustness check are mainly stable. The dummy variable for monthly repayment obligations becomes significant. In total, the results remain stable with similar confidence levels and values indicating the robustness of our results.

As an additional robustness check, we have employed logistic regressions on the entire data set and the subsamples. The findings are very similar and thus not reported here due to space restrictions.

	Clustered SE			Without outliers		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Investor's decision						
Funding time	−1.53e−4	−1.78e−4	−1.74e−4	8.80e−5	5.44e−5	5.46e−5
	(1.68e−4)	(1.68e−4)	(1.67e−4)	(1.40e−4)	(1.41e−4)	(1.41e−4)
MFI-specific variables						
Default rate	5.63e+0***	5.52e+0***	5.52e+0***	5.93e+0***	5.82e+0***	5.82e+0***
	(1.03e+0)	(1.01e+0)	(1.01e+0)	(4.55e−1)	(4.57e−1)	(4.57e−1)
Activity term	−2.48e−4**	−2.45e−4**	−2.45e−4**	−3.30e−4***	−3.17e−4***	−3.17e−4***
	(1.17e−4)	(1.15e−4)	(1.15e−4)	(5.65e−5)	(5.68e−5)	(5.69e−5)
Due diligence	2.60e+0***	2.47e+0***	2.48e+0***			
	(4.63e−1)	(4.69e−1)	(4.69e−1)			
Rating_moderate	−7.03e−2	−9.28e−2	−9.34e−2	−3.89e−3	−2.58e−2	−2.58e−2
	(1.50e−1)	(1.42e−1)	(1.42e−1)	(7.54e−2)	(7.60e−2)	(7.60e−2)
Rating_low	−1.41e−1	−1.63e−1	−1.63e−1	−7.41e−2	−9.20e−2	−9.20e−2
	(1.97e−1)	(1.91e−1)	(1.91e−1)	(1.03e−1)	(1.04e−1)	(1.04e−1)
Rating_not rated	2.16e+0***	1.98e+0***	1.99e+0***	1.09e+0***	9.61e−1***	9.61e−1***
	(3.93e−1)	(3.96e−1)	(3.96e−1)	(1.48e−1)	(1.51e−1)	(1.51e−1)
Rating_not available	9.87e−1***	9.37e−1***	9.36e−1***	8.86e−1***	8.21e−1***	8.21e−1***
	(2.85e−1)	(2.81e−1)	(2.81e−1)	(8.33e−2)	(8.58e−2)	(8.58e−2)
Loan-specific variables						
Disbursement	−2.95e−1	−2.91e−1	−2.91e−1	−4.60e−1***	−4.61e−1***	−4.61e−1***
	(2.53e−1)	(2.55e−1)	(2.55e−1)	(9.26e−2)	(9.28e−2)	(9.27e−2)
Group loan	3.17e−1*			3.33e−1***		
	(1.79e−1)			(9.31e−2)		
NB	−4.36e−2***	−6.10e−2***	−6.20e−2***	−3.62e−2***	−5.19e−2***	−5.19e−2***
	(1.43e−2)	(1.52e−2)	(1.50e−2)	(1.21e−2)	(1.34e−2)	(1.34e−2)
log(loan size)	1.06e−1	1.09e−1*	1.08e−1	−2.41e−2	−2.27e−2	−2.27e−2
	(6.67e−2)	(6.61e−2)	(6.61e−2)	(4.32e−2)	(4.34e−2)	(4.34e−2)
Loan term	1.14e−3***	1.16e−3***	1.16e−3***	8.25e−4***	8.61e−4***	8.61e−4***
	(3.43e−4)	(3.42e−4)	(3.41e−4)	(1.76e−4)	(1.75e−4)	(1.75e−4)
Grace period	1.79e−3	1.79e−3	1.79e−3	−1.38e−2***	−1.42e−2***	−1.42e−2***
	(1.35e−3)	(1.38e−3)	(1.39e−3)	(4.61e−3)	(4.66e−3)	(4.66e−3)
Repayment_fortnightly	−1.39e−1	−1.42e−1	−1.45e−1	−3.86e−1***	−3.80e−1***	−3.80e−1***
	(1.87e−1)	(1.81e−1)	(1.80e−1)	(1.30e−1)	(1.30e−1)	(1.30e−1)
Repayment_monthly	1.02e−1	1.13e−1	1.14e−1	−5.23e−2	−4.92e−2	−4.91e−2
	(1.36e−1)	(1.31e−1)	(1.31e−1)	(6.79e−2)	(6.98e−2)	(6.98e−2)
Repayment_3-4month	−1.60e−2	−3.91e−2	−2.93e−2	−7.32e−2	−9.83e−2	−9.77e−2
	(2.90e−1)	(2.95e−1)	(2.95e−1)	(2.34e−1)	(2.40e−1)	(2.41e−1)
Repayment_twice a year	−3.10e−1	−3.44e−1	−3.23e−1	−4.33e−1**	−4.69e−1**	−4.68e−1**
	(2.43e−1)	(2.27e−1)	(2.28e−1)	(2.10e−1)	(2.20e−1)	(2.19e−1)
Repayment_annual	−1.45e+0***	−1.48e+0***	−1.48e+0***	−6.85e−1***	−7.21e−1***	−7.21e−1***
	(3.29e−1)	(3.32e−1)	(3.32e−1)	(1.24e−1)	(1.28e−1)	(1.29e−1)
Female individual	−9.56e−2	−1.05e−1	−1.03e−1	−1.08e−1*	−1.19e−1**	−1.19e−1**
	(6.93e−2)	(6.82e−2)	(6.77e−2)	(5.78e−2)	(5.77e−2)	(5.77e−2)
Group of women		1.98e−1	2.05e−1		2.16e−1**	2.16e−1**
		(1.77e−1)	(1.77e−1)		(1.03e−1)	(1.03e−1)
Group of men		2.51e−1	2.54e−1		3.67e−1	3.67e−1
		(2.49e−1)	(2.50e−1)		(2.48e−1)	(2.48e−1)
Mixed group		6.87e−1***	5.82e−1**		6.68e−1***	6.62e−1***
		(1.87e−1)	(2.49e−1)		(1.15e−1)	(2.22e−1)
PCfemale x Mixed group			1.78e−1			1.02e−2
			(2.32e−1)			(3.00e−1)
Sectors	yes	yes	yes	yes	yes	yes
Macroeconomic and geographical variables						
log(GDPpc)	−1.81e−1*	−1.46e−1	−1.47e−1	−1.59e−1***	−1.25e−1***	−1.25e−1***
	(1.04e−1)	(1.01e−1)	(1.01e−1)	(4.08e−2)	(4.19e−2)	(4.19e−2)
CROPI	−4.58e−3*	−4.50e−3*	−4.50e−3*	−3.43e−3***	−3.38e−3**	3.38e−3**
	(2.63e−3)	(2.60e−3)	(2.60e−3)	(1.31e−3)	(1.32e−3)	(1.32e−3)
Regions	yes	yes	yes	yes	yes	yes
_cons	−4.10e+0***	−4.23e+0***	−4.23e+0***	−7.55e−1*	−1.02e+0**	−1.02e+0**
	(1.21e+0)	(1.19e+0)	(1.19e+0)	(4.29e−1)	(4.38e−1)	(4.38e−1)
Number of observations	29,304	29,304	29,304	24,226	24,226	24,226
Pseudo R^2	0.263	0.267	0.267	0.254	0.258	0.258
Akaike information cri.	0.68e+3	4.66e+3	4.66e+3	4.01e+3	3.99e+3	3.99e+3
Bayesian information cri.	5.04e+3	5.03e+3	5.04e+3	4.33e+3	4.33e+3	4.34e+3

Table 2.11: Coefficients of the probit models with clustered SE and without outliers – entire data set.
Notes: Model specification I, II and III are probit regressions with clustered standard errors for the probability of default based on the entire data set. The clusters are determined by 151 different MFIs. Model specification IV, V and VI are probit regressions without outliers for the probability of default. Robust standard errors are employed. Extreme observations below the 2.5th and above the 97.5th percentile are excluded as outliers. Values labeled with the symbols *, ** and *** are significant at the 10% level, the 5% level and the 1% level. Reference categories are analogous to Table 2.8. The variables are defined in Table 2.1.

	Individual loans	
	Clustered SE	Without outliers
	(I)	(II)
Investor's decision		
Funding time	$-1.23e{-4}$	$6.44e{-5}$
	$(1.57e{-4})$	$(1.51e{-4})$
MFI-specific variables		
Default rate	$4.84e{+0}^{***}$	$5.11e{+0}^{***}$
	$(1.02e{+0})$	$(5.08e{-1})$
Activity term	$-2.18e{-4}^{*}$	$-2.68e{-4}^{***}$
	$(1.14e{-4})$	$(6.24e{-5})$
Due diligence	$-2.19e{+0}^{***}$	
	$(4.56e{-1})$	
Rating_moderate	$-9.43e{-2}$	$-5.01e{-2}$
	$(1.48e{-1})$	$(8.76e{-2})$
Rating_low	$-1.96e{-1}$	$-1.71e{-1}$
	$(1.97e{-1})$	$(1.17e{-1})$
Rating_not rated	$-2.79e{+0}^{***}$	$6.70e{-1}$
	$(4.86e{-1})$	$(5.13e{-1})$
Rating_not available	$7.34e{-1}^{**}$	$4.46e{-1}^{***}$
	$(3.59e{-1})$	$(1.06e{-1})$
Loan-specific variables		
Disbursement	$-4.14e{-1}$	$-6.71e{-1}^{***}$
	$(2.97e{-1})$	$(1.01e{-1})$
log(loan size)	$1.14e{-1}$	$2.57e{-2}$
	$(6.95e{-2})$	$(4.89e{-2})$
Loan term	$1.10e{-3}^{***}$	$5.78e{-4}^{***}$
	$(3.63e{-4})$	$(1.87e{-4})$
Grace period	$1.97e{-3}$	$-1.99e{-2}^{***}$
	$(1.50e{-3})$	$(5.82e{-3})$
Repayment_fortnightly	$-6.40e{-2}$	$1.60e{-1}$
	$(1.85e{-1})$	$(1.94e{-1})$
Repayment_monthly	$3.35e{-1}^{***}$	$4.78e{-1}^{***}$
	$(1.24e{-1})$	$(1.34e{-1})$
Repayment_3-4month	$1.44e{-1}$	$3.20e{-1}$
	$(3.70e{-1})$	$(2.97e{-1})$
Repayment_twice a year	$-2.91e{-1}$	$-1.90e{-1}$
	$(3.38e{-1})$	$(3.70e{-1})$
Female individual	$-8.79e{-2}$	$-1.17e{-1}^{**}$
	$(6.14e{-2})$	$(5.78e{-2})$
Sectors	yes	yes
Macroeconomic and geographical variables		
log(GDPpc)	$-8.93e{-2}$	$-6.91e{-2}$
	$(1.09e{-1})$	$(4.72e{-2})$
CROPI	$-2.22e{-3}$	$-2.83e{-3}^{**}$
	$(2.32e{-3})$	$(1.15e{-3})$
Regions	yes	yes
_cons	$-3.47e{-1}$	$-1.69e{+0}^{***}$
	$(1.38e{+0})$	$(5.04e{-1})$
Number of observations	24,488	19,916
Pseudo R^2	0.209	0.186
Akaike information criterion	$3.64e{+3}$	$3.03e{+3}$
Bayesian information criterion	$3.97e{+3}$	$3.31e{+3}$

Table 2.12: Coefficients of the probit models with clustered SE and without outliers – subsamples

Notes: Considering individual loans, model specification I is a probit regression with clustered standard errors. The clusters are determined by 137 different MFIs. Model specification II is a probit regression without outliers. Values labeled with the symbols *, ** and *** are significant at the 10% level, the 5% level and the 1% level. Reference categories are analogous to Table 2.8 and Table 2.10.

	Group loans			
	Clustered SE		Without Outliers	
	(III)	(IV)	(V)	(VI)
Investor's decision				
Funding time	−5.10*e*−4	−4.63*e*−4	−2.24*e*−4	−1.86*e*−4
	(5.07*e*−4)	(5.06*e*−4)	(3.80*e*−4)	(3.81*e*−4)
MFI-specific variables				
Default rate	9.37*e*+0**	9.51*e*+0**	8.60*e*+0***	8.70*e*+0***
	(4.16*e*+0)	(4.17*e*+0)	(1.84*e*+0)	(1.84*e*+0)
Activity term	−3.70*e*−4	−3.74*e*−4	−3.70*e*−4**	−3.71*e*−4**
	(3.07*e*−4)	(3.12*e*−4)	(1.64*e*−4)	(1.65*e*−4)
Rating_moderate/low	−3.70*e*−2	−1.96*e*−2	−6.92*e*−2	−5.51*e*−2
	(2.42*e*−1)	(2.39*e*−1)	(1.75*e*−1)	(1.74*e*−1)
Rating_not rated	6.70*e*−1	6.71*e*−1	6.83*e*−1***	6.87*e*−1***
	(5.11*e*−1)	(2.46*e*−1)	(2.45*e*−1)	(2.45*e*−1)
Rating_not available	1.07*e*+0***	1.06*e*+0***	1.02*e*+0***	1.01*e*+0***
	(3.94*e*−1)	(3.94*e*−1)	(2.10*e*−1)	(2.11*e*−1)
Loan-specific variables				
Disbursement	−1.21*e*−1	−1.31*e*−1	−2.53*e*−2	−3.53*e*−2
	(3.03*e*−1)	(3.02*e*−1)	(2.24*e*−1)	(2.24*e*−1)
NB	−4.63*e*−2***	−3.99*e*−2***	−5.68*e*−2***	−4.95*e*−2***
	(1.73*e*−2)	(1.12*e*−2)	(1.69*e*−2)	(1.11*e*−2)
log(loan size)	6.54*e*−2		7.28*e*−2	
	(1.41*e*−1)		(1.18*e*−1)	
log (loan size/NB)		−1.33*e*−2		8.58*e*−3
		(1.69*e*−1)		(1.32*e*−1)
Loan term	2.47*e*−3***	2.50*e*−3***	3.40*e*−3***	3.40*e*−3***
	(7.42*e*−4)	(7.76*e*−4)	(8.08*e*−4)	(8.16*e*−4)
Grace period	2.30*e*−3	2.21*e*−3	−4.30*e*−3	−5.07*e*−3
	(2.44*e*−3)	(2.43*e*−3)	(1.25*e*−2)	(1.26*e*−2)
Repayment_fortnightly	−9.56*e*−2	−8.08*e*−2	−6.93*e*−2	−6.05*e*−2
	(2.54*e*−1)	(2.52*e*−1)	(2.11*e*−1)	(2.11*e*−1)
Repayment_monthly	−2.32*e*−1	−2.13*e*−1	−3.16*e*−1**	−3.08*e*−1*
	(2.32*e*−1)	(2.26*e*−1)	(1.61*e*−1)	(1.61*e*−1)
Repayment_3-4month	−8.41*e*−2	−7.06*e*−2	5.25*e*−2	5.21*e*−2
	(4.02*e*−1)	(4.01*e*−1)	(5.00*e*−1)	(5.03*e*−1)
Repayment_twice a year	−4.68*e*−1	−4.47*e*−1	−4.46*e*−1	−4.38*e*−1
	(4.38*e*−1)	(4.43*e*−1)	(3.56*e*−1)	(3.57*e*−1)
Repayment_annual	−2.28*e*−1	−2.70*e*−1	−3.13*e*−1	−3.51*e*−1
	(5.06*e*−1)	(5.14*e*−1)	(2.74*e*−1)	(2.79*e*−1)
Group of women	5.10*e*−2	4.17*e*−2		−4.39*e*−2
	(2.56*e*−1)	(2.51*e*−1)		(2.83*e*−1)
Mixed group	3.24*e*−1	3.14*e*−1	3.87*e*−1	3.50*e*−1
	(3.44*e*−1)	(3.38*e*−1)	(2.35*e*−1)	(3.21*e*−1)
PCfemale x Mixed group	2.14*e*−1	2.21*e*−1	9.38*e*−2	9.17*e*−2
	(1.96*e*−1)	(1.98*e*−1)	(3.23*e*−1)	(3.25*e*−1)
Sectors	yes	yes	yes	yes
Macroeconomic variables				
log(GDPpc)	−2.15*e*−1	−1.97*e*−1	−1.25*e*−1	−1.09*e*−1
	(1.69*e*−1)	(1.67*e*−1)	(9.41*e*−2)	(9.16*e*−2)
CROPI	−6.77*e*−3*	−7.04*e*−3*	−8.19*e*−3**	−8.44*e*−3**
	(3.90*e*−3)	(3.83*e*−3)	(3.28*e*−3)	(3.35*e*−3)
Regions	yes	yes	yes	yes
_cons	−1.66*e*+0	−1.27*e*+0	−2.45*e*+0***	−2.07*e*+0**
	(1.27*e*+0)	(1.27*e*+0)	(8.98*e*−1)	(9.59*e*−1)
Number of observations	4,348	4,348	3,704	3,704
Pseudo R^2	0.410	0.410	0.403	0.403
Akaike infor. criterion	1.02*e*+3	1.02*e*+3	9.04*e*+2	9.07*e*+2
Bayesian infor. criterion	1.23*e*+3	1.23*e*+3	1.11*e*+3	1.12*e*+3

Table 2.13: Coefficients of the probit models with clustered SE and without outliers – subsamples continued

Notes: Model specification III and IV are probit regressions with clustered standard errors. The clusters are determined by 70 different MFIs. Model specifications V and VI are probit regressions without outliers. Extreme observations below the 2.5th and above the 97.5th percentile are excluded as outliers. Values labeled with the symbols *, ** and *** are significant at the 10% level, the 5% level and the 1% level. Reference categories are analogous to Table 2.8 and Table 2.10.

2.6 Conclusion

Credit risk on P2P microfinancing platforms has so far been under-researched. In this analysis, we study the determinants of credit default by using data from Kiva.

By conducting several probit regressions, we can conclude that some results from classical microfinance research also apply to online P2P microfinancing. Financial intermediation by MFIs appears to have a high impact on the probability of default as the screening and monitoring quality of MFIs is crucial for a prevention of repayment problems by individual micro-entrepreneurs and groups of borrowers. In contrast to the results from classical microfinance research, we do not detect a negative relationship between group lending and the probability of default. Furthermore, we find evidence to support the fact that loan conditions, e.g. the loan size, the loan term and the grace period are important variables that positively influence the probability of default. There is weak evidence suggesting that women perform better regarding successful repayment which supports the highly discussed gender effect. Contrary to the results based on commercial P2P lending platforms, we do not find any evidence that a quickly-funded loan request could be an indicator of good creditworthiness. We note that the belief in the wisdom of the crowd appears to be overrated regarding the prediction of credit default in the case of microlending. However, the analysis of the funding time yields deeper insights into the objective function of the lenders. It turns out that they indeed consider credit risk aspects, but additionally social aspects of their investments. Thus, one can say that they try to minimize the financial loss and try to maximize the social impact of their investments even though the trade-off between the two dimensions may be handled differently by each investor.

Even though our results are derived from loans posted before 2014, they are still representative for more recent loans, but not for loans posted before the change in repayment rules on Kiva in 2010 which may have changed the selection process of the MFIs. However, the latter issue is only a small limitation within our research as today's investors still face the policy that was in place in our observation period.

Considering the real-world implications of our research, we state the following. As information on the performance of MFIs and on loan-specific conditions are relevant and publicly available on Kiva, we advise social investors to screen loan applications very carefully. From an investor's perspective, providing a loan to an MFI with a good repayment rate in the previous year is the most important and secure measure in preventing a loss of the investment. Therefore, MFIs have incentives to screen and monitor microfinance borrowers effectively in order to ensure their good reputation on Kiva and their access to interest-free refinancing.

As microfinancing platforms have been growing quickly in recent years, further research is necessary. Data from other online microfinance platforms such as Babyloan, Deki or Rang De could be utilized to gain further insights into the robustness of our findings.

Chapter 3

The access of microfinance institutions to financing via the worldwide crowd

This research project has been carried out jointly by Gregor Dorfleitner, Eva-Maria Oswald and Michaele Röhe. The paper has been submitted to the journal Quarterly Review of Economics and Finance and is currently under review.

Abstract: The rising funding demand in the microfinance industry prompts microfinance institutions (MFIs) to seek additional, emergent debt capital sources such as crowdfunding. As the crowd-based approach has experienced widespread growth, we study the characteristics of MFIs having and using access to refinancing microloans via crowdfunding based on a panel data set obtained from the peer-to-peer microfinance platform Kiva. By performing binary regressions, we find evidence that the MFI's social performance regarding granting loans to women and the interest rate charged from borrowers are main predictors of refinancing through Kiva. We observe that mature MFIs exhibit better access to funding from Kiva than those which are new to the market. The results show that the likelihood of refinancing microloans through Kiva is negatively related to the financial performance and to the extent of deposits of an MFI. MFIs operating in less-developed countries appear to be more likely to have access to Kiva's refinancing model. Additionally, we examine those cases in which the partnership between the MFI and Kiva has been terminated and find strong evidence that MFIs with a high share of deposits are more likely to discontinue the partnership with Kiva.

Keywords: Crowdfunding, microentrepreneurs, microcredit, financial intermediation

JEL Classification: G15 G21 O16

3.1 Introduction

Due to their rising funding demand, microfinance institutions (MFIs) tend to seek additional, emergent sources of debt capital such as crowdfunding. In the recent years, the crowd-based approach has experienced a widespread growth. This paper is the first to study the characteristics of those MFIs that have and also use access to refinancing their microloans via crowdfunding. Thereby the paper sheds light on the question under which conditions this refinancing source can play a role in the capital structure of an MFI.

Crowdlending as a new, crowd-based approach to fund loans to individuals and to small businesses, has emerged in the financial capital market since 2005 and is steadily growing regarding market size and importance. The concept of crowdlending implies that several individual investors enable the funding of a loan requested by another private person without the intermediation by a financial institution (Lin et al., 2013). The interest of individual investors to contribute with private capital to the debt market has been recognized by several commercial online peer-to-peer lending platforms (e.g. Prosper.com, Zopa, Auxmoney). Commercial online peer-to-peer lending platforms have been of academic interest in recent years (e.g. Emekter et al., 2015; Freedman and Jin, 2017; Hornuf and Cumming, 2017). However, this strand of literature is not directly related to our analysis, as we focus on crowdlending concepts with intermediaries and specifically analyze the relationship between the intermediary and the microfinancing platform.

In the microfinance industry, which aims at financing microentrepreneurs in developing countries, an increasing funding gap has become apparent in recent years as the funding demand of microfinance institutions exceeds the amount of donor capital, which remains the main source of debt capital (Mersland and Urgeghe, 2013). A promising innovation that has the potential to diminish these credit constraints is crowdlending (Bruton et al., 2015). Crowdlending has started to matter as source of debt capital provided by individuals as it is beyond charitable giving but much more a source of implicit subsidies in terms of low or no interest obligation against the investors (see Cull et al., 2018). Crowdlending offers the potential to be used as a source of debt capital by MFIs during their transition from the dependency on donor capital towards the ability to gain access to the mainstream capital market. The increasing relevance of crowdlending in the field of microfinance is reflected in a number of online microfinancing platforms (MYC4, Veecus, myELEN, Zidisha, unitedprosperty etc.). The most popular microfinancing platform is Kiva. Several studies on the decision making process and funding behavior as well as on the repayment behavior and credit risk provide valuable insights into the behavior of Kiva investors and microborrowers (Jenq et al., 2012; Meer and Rigbi, 2013). Besides Kiva investors and the microentrepreneurs at both ends, the core of this microfinancing model are the microfinance institutions (MFIs) which act as financial intermediaries. Thus, one cannot talk of (direct) peer-to-peer lending in this case but rather of an indirect form of lending from the crowd to the MFI. Kiva's microfinancing model is based on the financial intermediation by local MFIs which select and grant loans to microborrowers and monitor the repayment of the loans to Kiva investors. Kiva provides MFIs the possibility to refinance their loans without paying interest to the charitable investors. This paper is the first to analyze the characteristics of those MFIs that receive refinancing through international crowdfunding platforms. We thereby contribute to clarifying the question of how the leading microfinancing platform Kiva actually chooses MFIs to be funded as well as the question concerning what encourages MFIs to leave the partnership and abandon such a funding possibility.

Previous studies have found that microfinancing via Kiva is beyond charitable giving as the investors highly value the repayment of their capital. Therefore, Kiva itself and the MFIs have an incentive to ensure repayment and the MFI's positive financial and social reputation in order to appeal to potential investors and preserve the possibility of interest-free refinancing (Ly and Mason, 2012a).

On the one hand, it is the responsibility of Kiva to establish requirements, to select and partner with MFIs and to connect the MFI's needs with the expectations of the social investors. On the other hand, the MFI itself has to be willing to adopt Kiva's requirements and to approach the investors' expectations.

We derive a set of hypotheses from theoretical considerations, taking into account both the supply and the demand side perspective. In our empirical strategy, we connect information derived from MIX Market with information available on Kiva's Application Programming Interface (API) in order to identify the determinants of having access to Kiva and making use of it. Note that the access notion we employ in the remainder of this paper captures the fact that Kiva is willing to provide access to refinancing and at the same time that the MFI makes use of it. Our panel data set includes several social and financial performance indicators. By performing binary regressions, we ascertain that the MFI's social performance in terms of granting loans to women and charging low interest rates is a main predictor of having and using access to Kiva. Several maturity variables appear to show a significant correlation with the probability of access, which leads us to the conclusion that mature, more experienced MFIs have access to funding from Kiva more frequently than new, less-experienced MFIs. Furthermore, we find evidence that MFIs with a solid operational self-sufficiency[1] and a large extent of deposits are less likely to have access to Kiva. MFIs operating in poorer countries appear to exceed their peers in high-GDP countries in terms of having access to funding through Kiva. Additionally, we examine those cases in which the partnership between Kiva and an MFI has been terminated. Based on the same influential variables, we perform binary regressions and Cox proportional hazard models. As the termination of the partnership is initiated[2] by the MFI, either directly or indirectly by intentionally violating certain requirements, this approach enables us to shed some light on demand side aspects. The share of female borrowers reveals itself to be not only

[1]Operationally self-sufficient MFIs are able to cover their operating costs by their revenues resulting in an OSS ratio > 100% (e.g. Schäfer and Fukasawa, 2011; Bogan, 2012).

[2]Kiva's explanations on terminated partnerships published on its webpage reveal that either the MFI has lost its interest in refinancing through Kiva due to internal changes (e.g. a new management, a change in the overall strategy, a shift towards other funding sources) or has violated Kiva's requirements by loan program failures or even fraud. In the latter case, Kiva is forced to react in order to secure its mission and reputation towards investors.

a positive driver of access to Kiva, but also a predictor of the termination of the partnership. In contrast to the access results, neither the maturity, the portfolio quality, nor the operational self-sufficiency have predictive power. However, we find strong evidence that MFIs which are able to mobilize deposits as a sustainable, independent source of debt capital have a lower tendency to retain the partnership with Kiva, which requests an MFI to fulfill certain (ethical and financial) requirements.

The remainder of this article is organized as follows: In Section 2, the Kiva microfinancing model is outlined. In Section 3, we develop a theory and derive some hypotheses regarding the influence of institutional determinants. Section 4 describes the data and the regression models employed. Empirical findings regarding refinancing through Kiva and termination of the partnership as well as several robustness checks are reported in Section 5. Section 6 concludes.

3.2 The Kiva microfinancing model

Kiva, a donation-based NGO, is an online crowdlending platform that facilitates microborrowing by connecting socially oriented investors with the poor aiming to support their small businesses. Until mid of 2018, microloans of 1.2 billion USD have been transferred into 85 countries through partnering with local MFIs (Kiva.org, 2014). The core of Kiva's microfinancing model is the partnership with local MFIs. The main actors in Kiva's microfinancing model are displayed in Figure 3.1.

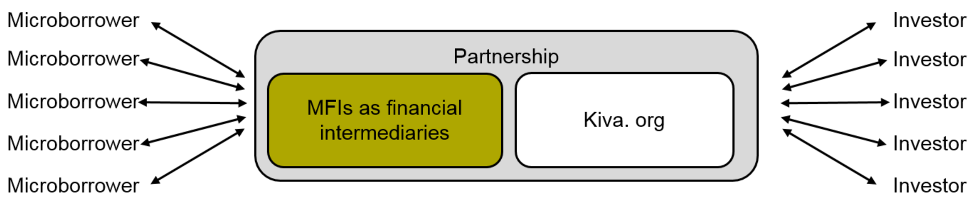

Figure 3.1: Kiva's microfinancing model

MFIs act as financial intermediaries in terms of selecting microborrowers and granting loans. The majority of loans requires microborrowers to pay an interest rate[3] defined by the individual MFI. Almost all loans are already disbursed to borrowers (see Jenq et al., 2015; Dorfleitner and Oswald, 2016). Subsequently, MFIs post loan requests on Kiva's online webpage in order to reach potential investors. As soon as a loan request is fully funded, which happens with nearly all of the loan applications[4], the loan amount is transferred to the MFI. The MFIs do not pay any interest to Kiva investors, even though investors fully bear

[3]The particular interest rate per loan is not publicly shown, only the information whether or not an interest obligation exists. The overall real portfolio yield, a proxy for the average interest rate, of MFIs with access to Kiva is on average 26% (details are shown in Table 3.2).

[4]This kind of investors' behavior, which is reported by references examining the funding time on Kiva (e.g. Dorfleitner et al., 2017), is a clear difference to usual crowdlending.

the credit default risk of the corresponding loan and, as the loans are granted in USD, also the risk of depreciation[5]. Even though the MFIs play a central role in Kiva's microfinancing model, very little is known about these MFIs.

It is obvious that Kiva itself has a very strong social mission. Thus, it is not surprising that Kiva requires a high level of social commitment from its partner MFIs. Kiva's social performance scorecard (existing of 7 different categories) records in which areas the MFI is involved in order to serve the needs of the low-income, vulnerable and excluded population. The institution's strong social commitment is shown to Kiva investors (Kiva.org, 2016a). In addition to the requested social commitment, Kiva has established some minimum financial requirements regarding e.g. assets[6], its lending program[7], and the volume of loan portfolio[8]. MFIs have to fulfill these requirements in order to partner Kiva. Furthermore, Kiva conducts an institutional due diligence process in order to assess the MFI's value and risks before partnering the MFI. Several documents, such as financial statements, portfolio reports, and financial projections are evaluated by Kiva staff. However, the financial requirements for receiving access to the interest-free capital are not disclosed.

To summarize, besides Kiva's claim for social commitment and some minimum requirements, no detailed characteristics regarding the MFIs in terms of portfolio quality, operating experience, financial performance or capital structure are published. Thus, the question of how MFIs with access to refinancing through Kiva can be characterized remains so far unanswered. In order to obtain an impression of the MFIs' view on this topic, we interviewed three MFIs cooperating or having cooperated with Kiva in November 2018. These MFIs reported that in their experience Kiva monitors the financial as well as the social performance and that the fulfillment of the corresponding requirements comes with certain costs for them. One MFI reported that it has stopped the cooperation exactly because of these costs. The feedback also does not reveal any contradictory information regarding other claims stated by Kiva.

3.3 Theory and hypotheses development

In this section, we first give a short summary of MFI funding, then develop a theory regarding the access to refinancing via the crowd and finally employ this theory to derive a set of hypotheses in a second step.

3.3.1 MFI funding in general

The typical MFI with regard to its funding sources is often pictured as small unregulated NGO with donations as main funding source when it starts its

[5]Currency devaluations over 10% are covered by Kiva investors (Kiva.org, 2016a).
[6]The assets are required to be more than 100,000 USD.
[7]An existing lending program with an appropriate portfolio quality is required.
[8]The loan volume is required to be more than 50,000 USD in the first year after incorporation with Kiva.

operations. As the institution matures, it goes through a commercialization process, in which subsidized funding is subsequently replaced by commercial sources, e.g. retained earnings or commercial debt[9]. During the commercialization, the MFI often is transformed into a regulated entity, which enables the institution to consider deposits as additional source of funding (see e.g. Ledgerwood and White, 2006). At the end of this process even the emission of securities (e.g. bonds or a securitization of part of the loan portfolio) is possible (see e.g. Bystrøm, 2008). Contrary to the expectation that larger, more mature MFIs which have undergone a commercialization process should be less dependent on subsidies, Cull et al. (2018) identify these MFIs to show the highest level of subsidization per borrower. D'Espallier et al. (2013) show that a majority of MFIs operate with subsidies. In addition to the persisting use of traditional subsidized funding sources, the ongoing digitization of the microfinance industry affects the refinancing of MFIs. Especially crowdfunding, which serves as implicit subsidies, is a promising innovation employed by an increasing number of institutions (Bruton et al., 2015).

3.3.2 Theoretical considerations on the MFI's access to and use of refinancing through Kiva

Generally speaking, the supply side, namely Kiva and its investors, requires – or at least desires – some properties of an MFI to be eligible for funding through Kiva. Consequently, meeting these requirements is a necessary, but not a sufficient condition. Additionally, the MFI which fulfills Kiva's criteria, also needs to be willing to accept the refinancing offered by Kiva. Only if both sides – namely Kiva and the MFI – esteem the partnership as being profitable, it becomes reality. In this case, Kiva grants and the MFI uses the access to refinancing microloans through the crowd of Kiva investors. We next detail on the motivations and reasoning of both the supply and the demand side.

Supply side Kiva states relatively clearly that it aims to support MFIs with a strong social mission. Consequently, to partner Kiva, MFIs are required to submit an application revealing the MFI's mission and the intention to use the interest-free funding for loans with a high social or environmental impact (Kiva.org, 2016a). However, this information remains rather unspecific, even if the scorecard mentions concrete categories. As Kiva is a platform that needs to generate revenues for the possibility to maintain its services and thus can be assumed to strive for having many transactions, it has a clear incentive to consider the preferences of its users, the investors. While we do not know much about Kiva's precise criteria, a lot is known about the needs and preferences of the investors. It is undoubtedly clear that we do have socially oriented investors on this platform (Ly and Mason, 2012a), which perceive a warm-glow effect by

[9] According to Cull et al. (2009), donors recommend that MFIs should include subsidized funding sources in their capital structure only in the start-up phase, and generally support the concept of commercialization.

providing funding to microborrowers (Allison et al., 2013). Besides capturing a financial return, these investors have a preference for taking responsibility (Jessen, 2012). An easy and straight-forward way to model the result for an investor is to set up an aggregate return

$$r + \alpha \cdot s \tag{3.1}$$

where r represents the financial return and s the social return as a measurement of portfolio responsibility, and $\alpha > 0$ is a weighting factor. On Kiva, investors receive no interest but have to bear the credit risk of a loan which they refinance. Therefore, their expected financial return $E(r)$ is less than zero. Thus, if the investors are not completely irrational, they can be assumed to only refinance loans with $E(s)$. The higher the weighting factor α, the more positive the social return is perceived by the investor under consideration. Thus α measures the relevance of the social return component of the investor against the expected financial return. From several studies investigating the investor behavior on Kiva, one can draw conclusions concerning which features provide investors with such a positive social return. These are e.g. lending to women or to groups. However, from (3.1), one can also derive that loans with a lower default risk are preferred, as for these, the negative expected return $E(r)$ is at least close to zero. This is also supported by the evidence of Dorfleitner and Oswald (2016), who study the drivers of credit risk on Kiva. Naturally, Kiva has an incentive to prefer refinancing those MFIs which fulfill all these aspects that are relevant for the investors.

Demand side An MFI that seeks to attain refinancing is confronted with a specific level of refinancing costs, the so-called financial expenses FE. It is clear that (partial) refinancing through interest-free loans[10] comes at minimal costs and therefore decreases FE. However, the MFI considers not only financial expenses, but the entire profit from microlending, i.e.

$$P = I - FE - LL - OE\,, \tag{3.2}$$

with I being the interest (including fees), LL being the loans losses due to defaults and OE being the operating expenses. An additional advantage for an MFI being refinanced on Kiva is that it can transfer the default risk of the respective loans to the investors, implying that some of the potential loan losses are not to be borne by the MFI anymore. However, while FE and LL are lowered through the Kiva refinancing, OE tends to increase as Kiva monitors the MFIs and these have to make efforts to prove that they fulfill the reporting obligations by e.g. providing financial statements and updates on the loan portfolio, and supporting on-site visits of Kiva staff. Additionally, MFIs are responsible to maintain their loan profiles and the channel for capital transfers (Kiva.org, 2016a).

[10] Comparing the MFI's credit amount raised through Kiva, averaged over the years from establishing the partnership until July 2017, and the MFI's average gross loan portfolio reported to MIX Market in the respective years, illustrates that half of the MFIs refinance 10% and more of their gross loan portfolio through Kiva. The data are obtained from Kiva's API and MIX Market.

Additionally, the anti-poverty focus can have a rather lowering influence on I. Although Kiva allows MFIs to charge interest rates from their clients, Kiva points out that these interest rates have to be justifiable in terms of sustainably maintaining the operation (Kiva.org, 2016a). Kiva acknowledges the economic necessity of interest rates, but is not willing to provide its interest-free funds to highly profit-oriented MFIs. Altogether, an MFI will only use refinancing through Kiva if the cost reduction on FE and LL is larger than the cost increase on OE plus the reduction on I. MFIs with powerful access to other cost-efficient debt capital sources with the same risk characteristics such as deposits or subsidized debt from microfinance investment vehicles (MIVs) can be expected to make less use of Kiva loans.

3.3.3 Hypotheses

Social performance of the MFI The theoretical considerations regarding the supply side in Section 3.3.2 directly lead to the hypothesis that the social return s is relevant in the decision making process of Kiva investors. Indeed, as already mentioned above, Kiva demands a strong social performance from its partner institutions. Although Kiva does not state any measurable key figures for the MFI's social engagement, it assigns certain social performance badges to its partner MFIs. For example, institutions that – among other things – focus on granting small loans qualifying for the 'Anti-Poverty Focus' badge. A second category comprises 'Vulnerable Group Focus', which is awarded to MFIs engaged in providing services to the excluded and vulnerable population, e.g. ethnic and religious minorities, unbanked farmers, and women (Kiva.org, 2016b). Measures that capture the focus on female clients as well as poorer clients are often used to proxy the social performance in empirical investigations (Schreiner, 2002; Cull et al., 2007).

Several studies (e.g. Allison et al., 2013; Burtch et al., 2014; Galak et al., 2011; Jenq et al., 2015; Liu et al., 2012; Ly and Mason, 2012a; Meer and Rigbi, 2013) consider the decision making process of Kiva lenders. Ly and Mason (2012a) find evidence that loans granted to female borrowers receive much faster funding than loans granted to men. Jenq et al. (2015) specifically study the borrower's characteristics and appearance as determinants of a loan's funding success and also find evidence in favor of gender preferences. Female borrowers and groups of female borrowers appear to be favored and faster funded by Kiva investors.

Based on these empirical findings and our theoretical framework regarding the supply side, we expect MFIs with a better social performance to be more likely to obtain access to subsidized debt funding from Kiva, because social returns are relevant for Kiva's investors.

> H1: Access to funding from Kiva is positively related to the social performance of the MFI.

Maturity of the MFI To apply for the partnership with Kiva, MFIs have to meet several minimum requirements in terms of assets and operating volume. Also, MFIs may have to exhibit a certain track record in order to be evaluated by Kiva. Therefore, from a supply side point of view, one can expect mature MFIs to be more likely to receive funding from Kiva investors.

Considering the demand side, we take into account the life-cycle theory in order to assess an MFI's request for funding from Kiva. Applying this theory to microfinance, MFIs pass through three different phases of development – the youth phase, growth phase and maturity – and develop different needs for funding. While in the youth phase, the MFI's need for risk-tolerant capital is extensive (de Sousa-Shields and Frankiewicz, 2004; Bogan, 2012), the growth phase is often associated with the transformation into a regulated institution. The transformation accompanied with regulation not only broadens the access to commercial funding but is also a main step in order to be allowed to maintain deposit programs (D'Espallier et al., 2017). However, the transformation process is also costly for the MFI (de Sousa-Shields and Frankiewicz, 2004; Helms, 2006; Bogan, 2012). Therefore, even mature, well-experienced MFIs receive subsidized loans from socially oriented investors (de Sousa-Shields and Frankiewicz, 2004; Mersland and Urgeghe, 2013). However, the fact that the loans on Kiva are denominated in hard currency is a slight indication that MFIs have to be well-established and, to a certain extent, experienced in order to manage currency risks. The ability to adopt mechanisms to handle and overcome the difficulty in hedging currency risks is a challenge for the majority of MFIs (Reille and Forster, 2008; de Sousa-Shields and Frankiewicz, 2004). This task may be easier for more mature institutions. To summarize, we expect large and established MFIs to strive for interest-free debt funds via Kiva as long as the MFIs are not able to overcome their dependency on subsidized capital.

> H2: Mature MFIs have a higher probability to have access to debt funding from Kiva than MFIs that are new to the market.

Financial performance of the MFI Lately, the growth, the commercialization of the microfinance industry, and the challenge of attracting commercial investors have widely been discussed. Accordingly, the importance of financial performance and sustainability of MFIs has increased (Mersland and Urgeghe, 2013; Schäfer and Fukasawa, 2011; Hoque et al., 2011; Fehr and Hishigsuren, 2006). Kiva could prefer to give access to MFIs with both a good social and financial performance, as investors not only value social returns but also high repayment rates, which are more likely for MFIs with better financial returns. However, as Kiva emphasizes not to support higher-than-average interest rates – as already mentioned in Section 3.3.2–, it could withhold its interest-free funds from MFIs which are operational self-sufficient in the long run as these MFIs are less dependent on the subsidized capital to continue their operation. We expect this effect to prevail regarding the supply side perspective.

As the pressure on MFIs to become less subsidy-dependent has increased

(Hoque et al., 2011), the MFIs have an incentive to strive for a good financial performance. In particular, a good management of the profit as described in (3.2) enables MFIs to run their business without external subsidies. To conclude, an increasing operational self-sufficiency appears to reduce the MFI's demand for access to Kiva capital as well as Kiva's willingness to provide access.

> H3: Financial performance is negatively associated with access to funding from Kiva.

Deposits as cost-efficient funding approach Kiva appreciates the provision of saving opportunities, which is indicated by the social performance badge 'Facilitation of Savings'. Thus, deposits are relevant from the supply side perspective.

However, from the demand side perspective, deposit programs have revealed themselves as an approach with the potential to substitute subsidized debt capital. Cozarenco et al. (2016) investigate that MFIs taking voluntary savings have received less subsidized or even donated equity and debt capital than their peers focusing on credit programs. Furthermore, empirical studies considering the relationship between funding sources and the MFI's development in terms of costs, profitability and sustainability reveal interesting aspects regarding deposits as a source of funding (e.g. Caudill et al., 2009; Muriu, 2011; Bogan, 2012). Mostly, MFIs have to transform themselves into legal banks and comply with prudential regulations in order to be allowed to mobilize deposits. Complying with regulations can be costly for the MFI (Helms, 2006; Cull et al., 2011). However, taking deposits has been proven to be a cost efficient, stable, and sustainable source of funds in the long run (Caudill et al., 2009; Helms, 2006). Caudill et al. (2009) show that MFIs which rely more on deposits instead of subsidies become more cost effective over time. One reason could be that deposits are an indication of a maturing client base with good financial records. Furthermore, deposit mobilization as an alternative source of domestic funding helps MFIs to establish a reliable and relatively stable flow of funds and to avoid foreign exchange risks (Helms, 2006; Mersland and Urgeghe, 2013). In the long run, the mobilization of deposits enables MFIs to become more and more independent from donors, subsidies, and external investors (Muriu, 2011; Bogan, 2012). As already suggested in Section 3.3.2, deposits represent a cheap source of funding for an MFI, and are therefore expected to lower the overall FE of the institution. MFIs that are able to collect deposits may prefer to make use of this type of funding instead of subsidized funding via Kiva, as collecting deposits does not impose restrictions on OE and I (cf. formula (3.2)). Therefore, we expect MFIs which are able to mobilize deposits as a sustainable source of funds to have less incentive to fund their lending program via Kiva.

> H4: The deposit volume of the MFI is negatively related to the probability of access to refinancing through Kiva.

Poverty level of the country in which the MFI operates According to the theoretical considerations regarding the supply side in Section 3.3.2, the investor may c.p. assume the social return s of an investment of a certain amount of money (e.g. 100 USD) into a loan, to be higher if the country is less developed. This consideration corresponds to the simple fact that in a poor country one can achieve more progress with 100 USD than in a richer country. Although this has nothing to do with the social performance of the MFI itself, it is a well-documented phenomenon regarding the funding preferences of Kiva investors (Jenq et al., 2015). Therefore, we also expect this effect to hold regarding the willingness of Kiva to support MFIs in a poorer country. As a result, we receive another supply side-related hypothesis. Additionally, Hudon and Traca (2011) consider the aspect that donors tend to target low-GDP countries in the context of providing subsidies to MFIs.

> H5: The poverty level of the country in which the MFIs is located
> is positively related to access to funding from Kiva.

3.4 Data and methodology

3.4.1 Data description

In our study, we combine MFI-specific financial and social performance indicators reported to the online platform of the Microfinance Information Exchange (MIX Market) with the information on the MFI's activity on Kiva as a source of subsidized debt funding. MFI-specific data, such as scale variables, social performance indicators, and financial ratios, are derived from MIX Market. In order to maintain good data quality, only data classified with a minimum of a disclosure rating of 3 diamonds[11] on MIX Market are used. We clean the data with respect to unrealistic values regarding operational self-sufficiency (values < 0) and deposits-to-assets ratio (values > 1), which slightly reduces our original data set by 44 observations. Furthermore, following Dorfleitner et al. (2016) 102 observations with an average loan size of more than 15,000 USD are excluded because in these cases the engagement in microfinance is not obvious. The information about the MFI's access to funds from Kiva lenders in the period of 2005 to 2015 is retrieved from Kiva's public API. To comprise the macroeconomic environment in which the MFI mainly operates, we add geographical regions and the GDP per capita derived from the World Bank data base.

We merge the data sets for partnered MFIs with available MIX data which builds a representative basis for our analysis[12]. The final unbalanced panel data

[11] MFIs classified with a 1 or 2 diamond disclosure rating do not report financial data which is essential to our analysis.

[12] These MFIs are representative for the total of partnered MFIs with regard to Kiva's risk rating and the social performance badges assigned to partnered institutions as well as the

set contains financial and social performance indicators of 909 MFIs with 5,621 observations in the period of 2005 to 2015[13]. Therein, 125 MFIs[14] had access to Kiva and collaborate with Kiva on average for 6.9 years with a minimum of 0.4 years and a maximum of more than 9.6 years until end of the observation period.

The MFI's activity on Kiva per year is linked to the lagged variables indicating the maturity, the social mission, and financial aspects of the respective MFI reporting to MIX Market. The data set may have a certain sample selection bias as only organizations which report to MIX Market are included. However, these are the ones that are willing to expose themselves to a worldwide public, which is also the case for those seeking a cooperation with Kiva. Therefore, the bias may not be too alarming.

The dependent variable, access to Kiva, is a binary variable with a value of one if the MFI has access to subsidized funding via Kiva in the respective year and zero otherwise. All explanatory variables used in our analysis to test the hypothesis are explained in detail in Table 3.1.

To measure the MFI's *social performance*, we include several variables indicating 1) depth of outreach, and 2) interest rate charged.

1) Depth of outreach. The most commonly applied measures for the depth of outreach, which is indicated by the poverty of the borrowers, are the average loan size, the percentage of female borrowers, the lending methodology, and the share of rural borrowers (Schreiner, 2002; Cull et al., 2007; Mersland and Strøm, 2010; Hermes et al., 2011).[15] A deeper outreach is measured by lower values for the average loan size, as borrowers who obtain smaller loans tend to be poorer. A higher fraction of borrowers who are female, received their loans via group lending and/or live in rural areas is associated with a higher depth of outreach, as these clients are expected to be poorer. We use the average loan size as a percentage of gross national income (GNI) per capita to ensure the comparability between countries. In order to prevent the loss of many observations due to missing values, we impute the variable illustrating the percentage of female borrowers with its mean. We consider the MFI's lending methodology in terms of group lending versus individual lending, also indicating a higher community empowerment, as group lending implies that the loan is beneficial to several borrowers and most likely for even more people than the

regional distribution. Additionally, the importance of these MFIs is given as more than 90% of the raised loan volume through Kiva is requested by and transferred to these MFIs. All other partnered institutions appear to be very minor players.

[13] Prolonging the observation period does not appear to be promising as the MIX data quality has lessened in recent years. Nevertheless, the data set is still representative for more recent observations.

[14] A set of 125 MFIs is included in our analysis, as 52 MFIs of the 203 MFIs with access to Kiva and a MIX profile do not have a disclosure rating of at least 3 diamonds on MIX Market. An additional 26 MFIs are lost due to missing values and unrealistic values.

[15] Note that other studies may use alternative measures to proxy the poverty of an MFI's clients. For example, Beisland et al. (2017) include the fraction of young clients as well as the proportion of clients with disabilities in addition to the share of loans less than 3000 USD.

borrowers themselves.

2) Interest rate. Following previous studies (e.g., Cull et al., 2007; Hudon and Ashta, 2013), the real portfolio yield as a proxy for the interest rate charged by the MFI is included. Even though high (nominal) portfolio yields are not uncommon in the field of microfinance (Mersland and Strøm, 2009), (extremely) high interest rates are considered critically (Yunus, 2007). The interest rate serves as an indication of to which extent the MFI strives to transfer its costs to clients.

The *maturity of the MFI* is measured by 1) assets, 2) operating age and 3) debt-to-asset ratio.

1) Assets. As a proxy for the MFI's size, we include the MFI's sum of assets in USD.

2) Operating age. As stated by de Sousa-Shields and Frankiewicz (2004) in the context of life-cycle theory, MFIs pass through different stages of development. First, following Bogan (2012), we classify MFIs into new (0–4 years), young (5–8 years) and mature MFIs (>8 years) dependent on their age which is defined by the number of years in operation as a financial service provider.

3) Debt-to-asset ratio. We include the debt-to-asset ratio as a further maturity measure, indicating the stage of development according to the degree to which the MFI is leveraged.

To measure the MFI's *financial performance*, the operational self-sufficiency (OSS) is commonly considered in microfinance (e.g. Hartarska and Nadolnyak, 2007; Schäfer and Fukasawa, 2011; Mersland and Urgeghe, 2013). The operational self-sufficiency illustrates whether or not the MFI is able to cover all its costs (financial expenses, impairment loss, operating expense) by its financial revenue (Schäfer and Fukasawa, 2011; Hartarska and Nadolnyak, 2007).

In order to test the *deposits as a cost efficient funding approach* hypothesis, the ratio of deposits-to-assets is considered as the relevant variable.

As a proxy for the *development status of a country*, the GDP per capita is employed. The GDP per capita denotes the general economic performance and wealth of the country in which the MFI mainly grants loans to microborrowers.

We control for MFI-specific characteristics, such as the refinancing costs. As a proxy, we include the ratio of financial expense to assets. Considering the legal status, our data set contains banks and rural banks, nonbank financial institutions, nongovernmental organizations, credit unions, and others. A dummy variable with the value of one indicates that the MFI is a bank or rural bank, otherwise the value is zero. Furthermore, the portfolio at risk (30 days) accounts for the portfolio quality of the MFI. Besides external influences and borrower behavior as roots of over-indebtedness, the MFI itself as lender bears responsibility. The MFI needs to evaluate the repayment capacity of its clients correctly to establish appropriate lending policies and to install lending practices suitable to customer needs in order to avoid the negative impact of the individual borrower's over-indebtedness on its own portfolio quality and stability (Schicks, 2013).

To control for the year in which the MFI has access to subsidized funding on Kiva, we include a year index variable, which ranges from 1 to 11 in an ascending order and represents the access to Kiva in the years between 2005 and 2015. Additionally, we also include the square of the year index to control for a potential non-linearity.

Furthermore, to display the macroeconomic environment, we include dummy variables for the geographical regions such as Latin America and Caribbean, the Middle East and North Africa, Sub-Saharan Africa, Eastern Europe and Central Asia, South Asia, and East Asia and the Pacific.

Variable	Expected effect	Description
Social performance		
AVLB_GNI	−	Average loan balance per borrower as a % of the gross national income per capita.
Female	+	Share of female borrowers within the MFI's total number of clients.
Portfolio yield (real)	−	The real portfolio yield illustrates the revenue from loans relative to average gross loan portfolio adjusted for the inflation.
Group lending share	+	Share of clients engaged in group lending compared with the MFI's total number of clients.
Rural lending share	+	Share of rural borrowers compared to the MFI's total number of clients located in rural or urban areas.
Maturity		
Assets	+	Total value of assets, calculated as the sum of each individual asset accounts.
Age of MFI	+	Dummy variables for the MFI's years of operation. New MFIs (0-4 years), young MFIs (5-8 years) and mature MFIs (>8 years). Reference category: New MFIs.
Debt-to-asset	+	The debt-to-asset ratio is calculated as (total debt)/(total assets) in the respective year.
Financial performance		
OSS	−	Operational self-sufficiency ratio is calculated as (financial revenue)/(financial expense + impairment loss + operating expense). An OSS value > 1 indicates the operational self-sufficiency of the MFI.
Funding approach		
Deposits-to-assets	− / +	Total deposits include voluntary, compulsory, retail and institutional deposits. The ratio is calculated as (deposits)/(total assets).
Poverty level		
GDP per capita	−	USD value of the gross domestic product of the country, in which the MFI is located and mainly operates, divided by its midyear population.
MFI specific controls		
Financial expenses		The ratio of financial expense to assets measures the refinancing costs of the MFI. The ratio is calculated as the (average total financial expense)/(total assets).
PAR30		The portfolio at risk 30 days represents the sum of principals of all outstanding loans that have at least one installment past due more than 30 days. The total is divided by the gross loan portfolio.
Legal type		Dummy variables with the value of 1 for banks/rural banks and zero for others. Others include nonbank financial institutions (NBFI), nongovernmental organizations (NGO), Credit unions (CU), and others. Reference category: Others
Year Index		Index variable for each year of Kiva activity in an ascending order (e.g. value of 1 for 2005 and 11 for 2015).
Macroeconomic controls		
Region		The geographical regions are Latin America and Caribbean (LAC), Middle East and North Africa (MENA) , Sub-Saharan Africa (AFRICA), South Asia (SA), Eastern Europe and Central Asia (EECA), North America (NA), and East Asia and the Pacific (EAP). Reference category: EECA.

Table 3.1: Definition of explanatory variables
Notes: All MFI-specific variables such as the MFI's social performance, maturity, financial performance, funding approach and controls are derived from MIX Market. Macroeconomic indicators are derived from the World Bank data base.

3.4.2 Methodology

To account for the panel structure of the data, we use pooled logit regression models with cluster-robust standard errors. The specification is as follows:

$$logit\{P(Y_{i,t} = 1|(S_{i,t-1}, F_{i,t-1}, C_{i,t-1})\} = \beta_0 + \beta_1 S_{i,t-1} + \beta_2 F_{i,t-1} + \beta_3 C_{i,t-1} + u_{i,t}$$

In our main research setting $Y_{i,t}$ is the binary dependent variable with the value of 1 if the MFI has access to debt funding from Kiva in the respective year, zero otherwise. $S_{i,t-1}$ is a vector of social performance measures. $F_{i,t-1}$ is a vector of variables measuring the financial key figures in terms of maturity, portfolio quality, sustainability and the ability of deposit mobilization. $C_{i,t-1}$ represents MFI-specific and geographical controls. The standard errors are clustered by MFIs.

In our second research setting regarding the termination of a partnership between Kiva and the MFI, we apply the pooled logit model accordingly. The binary dependent variable we use is *closing event* with the value of 1 in case the partnership was terminated in the respective period, zero otherwise. Additionally to the mere fact that the partnership was terminated, the time period between entering the partnership and terminating the partnership is observable which is the second dependent variable. We apply a Cox proportional hazard model to analyze the 'survival time' of the partnership between Kiva and the MFI. The specification is as follows:

$$h(t; (S_{i,t-1}, F_{i,t-1}, C_{i,t-1})) = h_0(t) \cdot exp(\beta_0 + \beta_1 S_{i,t-1} + \beta_2 F_{i,t-1} + \beta_3 C_{i,t-1})$$

It should be noted that the empirical setup is not suited to completely rule out endogeneity and that the identified relationship can therefore not be interpreted to be a causal one. In order to account for a potential omitted variable bias, we perform fixed effect and lagged-dependent variable models in the robustness subsection.

3.4.3 Descriptive statistics

Table 3.2 and Table 3.3 report the descriptive statistics for metric and categorical variables. The observations in our sample show that the percentage of female borrowers in the MFIs' portfolio is on average as high as 66%, whereby the variable ranges from 0% to 100%. However, for MFIs with access to Kiva, the minimum value stands at 10% of female borrowers. The mean of the real portfolio yield amounts to 26%. The maximum yield value of MFIs with Kiva access differs significantly from the maximum value of MFIs without Kiva access. Most of the MFIs have an operating age of more than 8 years. In the subsample of MFIs with access to Kiva, almost 75% of the observations stem from mature MFIs, whereas less than 10% stem from new MFIs. Regarding the MFI's size in terms of assets, MFIs with access to Kiva are, on average, smaller than MFIs without access. Overall, the MFIs are highly leveraged with a debt-to-asset ratio of 0.68 on average and a median value of 0.75. The mean value differs slightly between the subsamples of MFIs with Kiva access and MFIs without Kiva access. The OSS mean and median are higher than 100% in both subsamples, which illustrates that for the majority of MFIs the operation-related costs are covered by their revenues (Schäfer and Fukasawa, 2011). While the overall portfolio quality with a PAR30 value of 6.0% is low, the mean and median of PAR30 is even lower in the sample of MFIs with Kiva access compared with the sample of MFIs without Kiva access. The deposits-to-assets ratio with a median value of 0.0% reveals that deposit mobilization has, until now, not been a main funding source of the MFIs in our sample. The average GDP per capita is $3,500. The respective mean and median values are lower in the subsample of MFIs with access to Kiva compared with the subsample of MFIs without access to Kiva. More than 40% of the observations are from the region of Latin America and the Caribbean, followed by 18% from Eastern Europe and Central Asia, and 17% from South Asia.

In addition to the descriptive statistics, we run an independent *t*-test to compare all metric variables between the subsamples of MFIs with access and those without access to Kiva. It is obvious that the means of some metric variables are significantly different. The results are shown in Table 3.4.

Total						
Variable	Obs.	Mean	S.D.	Min	Median	Max
AVLB_GNI	5,592	0.55	1.04	0.00	0.27	31.89
Female	5,592	0.66	0.25	0.00	0.66	1.00
PAR30	5,592	0.06	0.08	0.00	0.03	1.00
Portfolio yield (real)	5,592	0.26	0.18	-0.22	0.22	1.79
Group lending share	4,723	0.44	0.44	0.00	0.32	1.00
Rural lending share	3,289	0.53	0.33	0.00	0.58	1.00
Assets	5,592	72.00	263.00	0.01	9.76	6130.00
Debt-to-asset	5,592	0.68	0.25	0.00	0.75	2.87
OSS	5,592	1.16	0.39	0.00	1.13	7.83
Deposits-to-assets	5,592	0.19	0.27	0.00	0.00	0.99
GDP per capita	5,592	3.50	3.10	0.14	2.45	15.74
Financial expenses	5,592	0.05	0.04	0.00	0.05	0.39

With Kiva access						
Variable	Obs.	Mean	S.D.	Min	Median	Max
AVLB_GNI	617	0.48	0.54	0.02	0.29	4.00
Female	617	0.70	0.23	0.10	0.70	1.00
PAR30	617	0.04	0.05	0.00	0.03	0.30
Portfolio yield (real)	617	0.26	0.14	-0.22	0.25	0.86
Group lending share	543	0.50	0.43	0.00	0.55	1.00
Rural lending share	401	0.56	0.29	0.00	0.64	1.00
Assets	617	29.40	83.70	0.37	9.35	1,100.00
Debt-to-asset	617	0.71	0.23	0.01	0.74	2.20
OSS	617	1.09	0.26	0.22	1.10	2.41
Deposits-to-assets	617	0.11	0.18	0.00	0.00	0.80
GDP per capita	617	3.00	2.50	0.24	2.05	14.58
Financial expenses	617	0.05	0.03	0.00	0.06	0.16

Without Kiva access						
Variable	Obs.	Mean	S.D.	Min	Median	Max
AVLB_GNI	4,975	0.55	1.09	0.00	0.27	31.89
Female	4,975	0.65	0.25	0.00	0.66	1.00
PAR30	4,975	0.06	0.09	0.00	0.04	1.00
Portfolio yield (real)	4,975	0.25	0.18	-0.22	0.21	1.79
Group lending share	4,180	0.44	0.44	0.00	0.27	1.00
Rural lending share	2,888	0.53	0.34	0.00	0.58	1.00
Assets	4,975	77.20	277.00	0.01	9.84	6,130.00
Debt-to-asset	4,975	0.68	0.25	0.00	0.75	2.87
OSS	4,975	1.17	0.41	0.00	1.14	7.83
Deposits-to-assets	4,975	0.20	0.28	0.00	0.00	0.99
GDP per capita	4,975	3.56	3.17	0.14	2.49	15.74
Financial expenses	4,975	0.05	0.04	0.00	0.05	0.39

Table 3.2: Descriptive statistics for metric variables
Notes: The entire data sample contains 5,592 observations. It is divided into the subsample of 617 year-observations of MFIs with access to Kiva and 4,975 year-observations of MFIs without access to Kiva in 2005 to 2015. Assets and GDP per capita are reported in million and in thousand USD, respectively. The variables are defined in Table 3.1.

	Total N=5,592		With Kiva access N=617		Without Kiva access N=4,975	
Variable	Obs.	Relative	Obs.	Relative	Obs.	Relative
Age of MFI						
New	701	12.54	52	8.43	649	13.05
Young	1,083	19.37	105	17.02	978	19.66
Mature	3,808	68.10	460	74.55	3,348	67.30
Legal Type						
Bank/Rural Bank	758	13.56	35	5.67	723	0.15
Others	4,834	86.44	582	94.33	4,252	0.85
Geographic regions						
EECA	1,009	18.04	100	16.21	909	18.27
EAP	565	10.10	98	15.88	467	9.39
Africa	559	10.00	108	17.50	451	9.07
LAC	2,321	41.51	266	43.11	2,055	41.31
MENA	169	3.02	18	2.92	151	3.04
SA	969	17.33	27	4.38	942	18.93
Year Index						
2005	217	3.88	0	0.00	217	4.36
2006	305	5.45	7	1.13	298	5.99
2007	433	7.74	36	5.83	397	7.98
2008	510	9.12	52	8.43	458	9.21
2009	595	10.64	64	10.37	531	10.67
2010	638	11.41	71	11.51	567	11.40
2011	662	11.84	84	13.61	578	11.62
2012	666	11.91	87	14.10	579	11.64
2013	596	10.66	73	11.83	523	10.51
2014	479	8.57	67	10.86	412	8.28
2015	491	8.78	76	12.32	415	8.34

Table 3.3: Descriptive statistics for categorical variables
Notes: The entire data sample contains 5,592 observations. It is divided into the subsample of 617 year-observations of MFIs with access to Kiva and 4,974 year-observations of MFIs without access to Kiva in 2005 to 2015. Running Pearson's chi-squared tests for the MFI's age, the MFI's legal status and geographical regions shows p-values < 0.01 indicating a statistically significant relationship. Absolute values and relative values of the categorical variables are displayed. The variables are defined in Table 3.1.

	Total N=5,592		With Kiva access N=617		Without Kiva access N=4,975		
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.	Difference
AVLB_GNI	0.55	1.04	0.48	0.54	0.55	1.09	1.6236
Female	0.66	0.25	0.70	0.23	0.65	0.25	−4.0918***
PAR30	0.06	0.08	0.04	0.05	0.06	0.09	4.3551***
Portfolio yield (real)	0.26	0.18	0.26	0.14	0.25	0.18	−1.2641
Group lending share	0.44	0.44	0.50	0.43	0.44	0.44	−2.8683***
Rural lending share	0.53	0.33	0.56	0.29	0.53	0.34	−1.3316
Assets	72.00	263.00	29.40	83.70	77.20	277.00	2.5534
Debt-to-asset	0.68	0.25	0.71	0.23	0.68	0.25	−3.1197***
OSS	1.16	0.39	1.09	0.26	1.17	0.41	4.6746***
Deposits-to-assets	0.19	0.27	0.11	0.18	0.20	0.28	8.2151***
GDP per capita	3.50	3.10	3.00	2.50	3.56	3.17	4.2686***
Financial expenses	0.05	0.04	0.05	0.03	0.05	0.04	−0.4111

Table 3.4: Independent t-test for metric variables among year-observations of MFIs with access to Kiva and MFIs without access to Kiva
Notes: Mean and standard deviation of metric variables and p-values are displayed. The number of observations for group lending share and rural lending share are different from the overall number of observations as stated in Table 3.2. Assets and GDP per capita are reported in million and in thousand USD, respectively. 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 3.1.

Table 3.5 presents the Bravais-Pearson correlation coefficients for metric exogenous variables which are included in our estimation models. According to Kennedy (2008), correlation coefficients with a value of 0.8 are critical for the detection of potential multicollinearity problems between metric variables. Even though some correlations are significant, the correlation coefficients are far below 0.8 and we do not expect a multicollinearity issue.

	Variable	1.	2.	3.	4.	5.	6.
1.	AVLB_GNI	1.0000					
2.	Female	−0.2682*	1.0000				
3.	PAR30	0.005	−0.1178*	1.0000			
4.	Portfolio yield (real)	−0.1622*	0.1374*	−0.0117	1.0000		
5.	Group lending share	−0.2918*	0.5310*	−0.0807*	0.1284*	1.0000	
6.	Rural lending share	−0.0059	0.0583*	−0.0305	−0.1324*	0.1667*	1.0000
7.	Assets	0.0843*	−0.0509*	−0.0039	−0.0994*	−0.1551*	−0.0254
8.	Debt-to-asset	0.0839*	0.012	0.0406*	−0.1946*	−0.0742*	0.0526*
9.	OSS	0.0361*	−0.0479*	−0.1814*	−0.0301*	−0.0790*	0.0748*
10.	Deposits-to-assets	0.2095*	−0.1340*	0.0972*	−0.1609*	−0.2515*	−0.0473*
11.	GDP per capita	−0.1755*	−0.1859*	0.0142	0.2965*	−0.2142*	−0.2540*
12.	Financial expenses	−0.0335*	0.0219	−0.0044	0.0254	−0.0445*	0.0588*

	Variable	7.	8.	9.	10.	11.	12.
7.	Assets	1.0000					
8.	Debt-to-asset	0.1430*	1.0000				
9.	OSS	0.0404*	−0.2177*	1.0000			
10.	Deposits-to-assets	0.2587*	0.3738*	−0.0415*	1.0000		
11.	GDP per capita	0.0714*	−0.0974*	0.0285*	−0.0503*	1.0000	
12.	Financial expenses	0.0184	0.4457*	−0.0909*	0.0055	0.1304*	1.0000

Table 3.5: Bravais-Pearson correlation coefficients for metric exogenous variables
Notes: Values labeled with the symbol * are significant at the 5% level. The variables are defined in Table 3.1.

3.5 Regression analysis

3.5.1 Results on the access to debt capital from Kiva

In this section, we investigate the access to funding from Kiva as dependent variable. As already noted, access can only be observed if both Kiva and the MFI mutually agree upon the funding relationship. Table 3.6 exhibits the results of the estimated pooled logistic models. Model I includes the entire 5,621 observations in the panel data set. Model I is extended by the squared debt-to-asset ratio, resulting in model II. Model III is the base model including the real portfolio yield as a further social performance indicator. Additionally, model IV includes the share of group lending within the MFI's portfolio.

The relationship between the MFI's social performance and the probability of access to Kiva is tested by several variables. The average loan balance per borrower has a negative but insignificant coefficient. The share of female borrowers in the portfolio is positively associated with the access to Kiva. The result is significant at the 5% level which illustrates that targeting women is a crucial predictor. Adding the real portfolio yield in model II and III as a proxy for the interest rate charged from borrowers enriches the insights into the MFI's social performance. The higher the portfolio yield, the lower the probability of being granted access to Kiva. Kiva allows MFIs to charge interest from microborrowers for the interest-free refinanced loans. However, Kiva does not support (extremely) high interest rates as Kiva requires the interest-free capital to result in lower costs not only for the MFI but also for its borrowers. Considering the MFI's lending methodology, we do not find evidence that MFIs focusing on group lending—which implies that borrowers of these might be poorer—are more likely to have access. In summary, H1 is confirmed from the supply side's perspective. Kiva highly values the MFI's social performance in terms of targeting women as a vulnerable group and taking social responsibility for its clients.

The logarithm of the assets as a size measure is positive but insignificant. This might be a first indication that the probability of having access to Kiva is positively related to the development of purely new and small sized MFIs towards well-growing MFIs throughout years of operation. The MFI's years of operation are represented by dummy variables, which are positive and significant in model specifications I to III. This supports the expectation that better established MFIs are more likely to partner Kiva compared with MFIs which are new to the market. From the perspective of the supply side, Kiva's requirements regarding assets, loan programs and operating volume might be more likely to be fulfilled by more mature and larger MFIs. From the demand side's perspective, it is obvious that also mature MFIs are still in need for subsidized debt capital (e.g. Mersland and Urgeghe, 2013). Additionally, these MFIs might be more experienced in hedging currency risks.

Considering the level of leverage as an indication of the MFI's life cycle stage, we observe evidence in favor of H2. The coefficient of the debt-to-asset ratio is positive and significant at the 1% level in all model specifications. This result strengthens the reflection that more mature MFIs experience a higher probability of having access to and using refinancing through Kiva. However, increasing levels of leverage may also be an indication that the MFI has already gained access to commercial debt capital and is less dependent on subsidized debt capital. Therefore, from the supply side's point of view, Kiva may tend to withhold its interest-free capital from MFIs at a certain point of leverage. When including the quadratic term of the debt-to-asset ratio in model II, we consider this U-shaped relation. The quadratic term of the debt-to-asset ratio has the expected negative sign which indicates that, up to a certain level, the rising leverage is negatively associated with the probability of Kiva access. However, the result is not significant.

The OSS variable has a significant negative sign in all model specifications, which supports H3. This result illustrates that MFIs with a better financial performance and a lower dependency on external subsidies in the long run are less likely to receive and use debt funding through Kiva. The reason behind this finding may be ambiguous. First, sustainable MFIs may focus on commercial funding instead of striving for subsidized funds from Kiva and second, Kiva may prefer MFIs which are dependent on the subsidized capital in order to run their businesses.

Considering the MFI's funding approach, the negative and highly significant coefficient of the deposits-to-assets ratio in all model specifications confirms the negative relationship between the extent of deposits and the probability of access to Kiva. This finding supports the view that MFIs which implement deposits as a stable and cost efficient source of funding, do not strive for the partnership with Kiva. A higher extent of deposits reduces the MFI's demand for interest-free refinancing through Kiva. Although Kiva honors the opportunity of savings for borrowers with its social performance badge, the majority of the partner MFIs does not collect deposits at all (median = 0.00%, see Table 3.2), resulting in a negative relationship between the MFI's ability to mobilize deposits and the use of refinancing through Kiva. Altogether, H4 is supported by the empirical evidence.

Considering the poverty level of the country in which the MFI mainly operates, we find evidence in favor of H5. MFIs operating in poorer countries have a higher probability of access to Kiva compared with MFIs operating in richer countries. One reason for this result could be that – although microfinance itself implies that all borrowers receiving loans from MFIs are perceived as needy – independently of the MFI's social mission, the social impact of providing capital to low-GDP countries is recognized as being more beneficial.

The MFI-specific controls, such as financial expenses and legal type do not appear to have any influence. However, there is a significant negative relation between the PAR30 and the probability of access to Kiva. This result is likely to be driven by the supply side perspective as Kiva highly values an MFI's experience in ensuring a reliable portfolio of sustainable clients in order to keep repayment rates to investors at a high level and therefore is expectable from the borrower's perspective. To take the respective years of activity on Kiva into account, we include a year index variable representing each year between 2005 and 2015. The coefficient of the index variable is positive while the coefficient of the quadratic term of the index variable is negative. Both results are significant and illustrate that the probability of having access to Kiva has increased accordingly with Kiva's fast growth and stagnates since 2013 onwards.

To control for the macroeconomic environment, dummy variables for the regions are included. While MFIs located in South Asia are less likely to participate on Kiva, MFIs located in Africa are more likely to have access to Kiva compared with the reference group of MFIs located in Eastern Europe and Central Asia.

In total, our regression results provide valuable information based on social and financial aspects to answer the question of which MFIs are likely to strive for and be granted access to subsidized debt capital through the partnership with Kiva.

	(I)	(II)	(III)	(IV)
Social performance				
AVLB_GNI	−0.1191	−0.1219	−0.1479	−0.2960
	(0.1369)	(0.1373)	(0.1461)	(0.2390)
Female	1.1532**	1.1831**	1.3099**	1.2635**
	(0.5279)	(0.5307)	(0.5306)	(0.5993)
Portfolio yield (real)			−1.0135*	−1.3875**
			(0.5968)	(0.6876)
Grouplending share				−0.2898
				(0.3246)
Maturity				
ln(Assets)	0.0276	0.0126	0.0134	−0.0307
	(0.0601)	(0.0609)	(0.0608)	(0.0669)
Age_young	0.5333**	0.5051**	0.5246**	0.3085
	(0.2552)	(0.2498)	(0.2571)	(0.2791)
Age_mature	0.7661**	0.7271**	0.7202**	0.4730
	(0.2992)	(0.2957)	(0.3033)	(0.3287)
Debt-to-asset	1.6032***	2.8222***	1.6881***	1.8626***
	(0.4048)	(0.9300)	(0.4017)	(0.4612)
Debt-to-asset^2		−0.7166		
		(0.4821)		
Financial performance				
OSS	−0.8018***	−0.8097***	−0.7950***	−0.5645*
	(0.2999)	(0.3074)	(0.3000)	(0.3060)
Funding approach				
Deposits-to-assets	−2.8837***	−2.9589***	−2.9391***	−3.2111***
	(0.5724)	(0.5867)	(0.5625)	(0.6128)
Poverty level				
GDP per capita	−0.1862***	−0.1841***	−0.1761***	−0.1641***
	(0.0481)	(0.0481)	(0.0492)	(0.0551)
MFI-specific controls				
Financial expenses	−0.2905	−1.1051	0.2045	−0.4270
	(2.4239)	(2.5279)	(2.4218)	(2.7963)
PAR30	−4.7740***	−4.6574***	−4.7758***	−4.8119***
	(1.4118)	(1.4511)	(1.3780)	(1.5732)
Legal Type	−0.3569	−0.3375	−0.3242	−0.4752
	(0.4549)	(0.4546)	(0.4559)	(0.5640)
Year Index	0.6486***	0.6337***	0.6357***	0.6234***
	(0.0774)	(0.0767)	(0.0783)	(0.0848)
Year Index^2	−0.0349***	−0.0337***	−0.0337***	−0.0306***
	(0.0051)	(0.0051)	(0.0052)	(0.0057)
Macroeconomic controls				
Region_EAP	0.2236	0.2260	0.2080	0.4252
	(0.4385)	(0.4400)	(0.4451)	(0.4733)
Region_AFRICA	0.7830*	0.7941*	0.8816**	1.3321***
	(0.4351)	(0.4382)	(0.4431)	(0.4820)
Region_LAC	0.1792	0.1734	0.2110	0.1858
	(0.3222)	(0.3231)	(0.3228)	(0.3426)
Region_MENA	−0.3250	−0.3070	−0.2892	−0.1368
	(0.7336)	(0.7371)	(0.7342)	(0.8875)
Region_SA	−2.7379***	−2.7215***	−2.9036***	−2.8360***
	(0.5385)	(0.5377)	(0.5486)	(0.5948)
_cons	−5.2375***	−5.3561***	−4.9059***	−4.1188***
	(1.0703)	(1.0964)	(1.0917)	(1.1825)
N	5,621	5,621	5,592	4,723
pseudo R^2	0.1744	0.1761	0.1775	0.1932

Table 3.6: Coefficients of pooled logistic regressions with access as dependent variable
Notes: Model I is extended by the squared debt-to-asset ratio, resulting in model II. Model III includes a further social performance indicator in terms of the real portfolio yield. Additionally, model IV includes the share of group lending within the MFI's portfolio. Standard errors clustered at MFI level are in parentheses. 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 3.1.

3.5.2 Results on the termination of the partnership

Within our observation period, it was possible to observe some cases of a termination of the partnership between the MFI and Kiva. These cases provide valuable data, from which we can obtain further insights, especially into the demand side perspective. A necessary condition for a termination of the partnership is the requirement for it to have been established before. Thus, all corresponding MFIs have once complied with Kiva requirements. Therefore, one can assume that a termination of the partnership is either caused by a direct cancellation through the MFI or by an intentional violation of Kiva's requirements through the MFI. The latter will take place in cases in which the gains (lower refinancing costs) outweigh the disadvantages (less revenues, higher operational costs) in the sense of the above demand side theory. In any case, one can exclude the fact that the MFI has no opportunity to receive the partnership for a general mismatch with Kiva requirements.

To make use of these observations, we run logistic regressions analoguously to our main models for the probability of the closing event. The regression results are reported in Table 3.7. Models I–III include the entire 620 year-observations of all MFIs with access to Kiva in the years 2005 to 2015. Therein, as the termination of the partnership is a rare event, 26 MFIs faced a closing event. As in this approach non-closing events are over-represented, we reduce the data set by allowing MFIs (with Kiva access) to be considered only once in a second step. The respective year-observation of the MFIs are selected by random selection without replacement. These results are shown in columns IV–VI.

Looking at the social performance measures, the results are surprising. A higher percentage of female borrowers is positively related to the probability of terminating the partnership. In model specifications IV–V, additionally, the variable for the average loan size per borrower turns out to be negative and significant. In contrast, the real portfolio yield does not appear to be significantly associated with the closing event. The results indicate that the partnership between Kiva and an MFI with a high level of social commitment in terms of depth of outreach is more likely to be terminated. An explanation for this phenomenon may lie in the fact that such MFIs are often offered debt capital from other external sources, such as, for instance, MIVs (Dorfleitner et al., 2016).

While nearly all other variables are insignificant, only the deposits-to-assets variable shows a positive and significant coefficient in all models. Therefore, MFIs which are able to mobilize deposits to a greater extent are positively related to the probability of the closing event. Again, together with the negative relationship between the ability of deposit mobilization and Kiva access, this finding provides an overall clear picture. MFIs which are able to mobilize deposits appear to have a lower incentive to strive for and, even after using refinancing through Kiva, remain in the partnership.

	(I)	(II)	(III)	(IV)	(V)	(VI)
Social performance						
AVLB_GNI	−1.0727	−1.0700	−0.8304	−1.9762**	−1.9855*	−2.2453
	(0.9711)	(1.0378)	(1.0906)	(0.9425)	(1.0798)	(1.6062)
Female	3.2012**	3.1755**	2.3490	3.4789**	3.4951*	3.2568*
	(1.3155)	(1.3762)	(1.7111)	(1.6283)	(1.8408)	(1.9494)
Portfolio yield (real)		0.1699	0.2584		−0.0883	−0.0714
		(2.1662)	(2.2577)		(3.3231)	(3.5376)
Grouplending share			0.8952			0.9630
			(0.6929)			(0.8662)
Maturity						
ln_Assets	0.2162	0.2199	0.3082	0.4103	0.4111	0.4533
	(0.2099)	(0.2103)	(0.2652)	(0.2624)	(0.2668)	(0.3270)
Age_young	−0.4466	−0.4262	−0.3160	−0.9584	−0.9623	−0.8171
	(0.8472)	(0.8489)	(0.8209)	(1.1460)	(1.1423)	(1.2886)
Age_mature	−1.0619	−1.0284	−1.1459	−1.7382	−1.7448	−1.8917
	(0.9971)	(1.0063)	(1.0677)	(1.2464)	(1.2989)	(1.5053)
Debt-to-asset	−2.5981	−2.6088	−3.2507*	−2.9438	−2.9635	−3.4079
	(1.5810)	(1.6317)	(1.7373)	(1.9489)	(2.1346)	(2.2759)
Financial performance						
OSS	0.4235	0.4060	−0.0882	0.1482	0.1456	−0.0931
	(1.0886)	(1.0887)	(1.2778)	(1.0342)	(1.0395)	(1.2251)
Funding approach						
Deposit-to-assets	3.9961***	4.0320***	4.6379***	4.0061**	4.0030**	4.0785**
	(1.1628)	(1.2095)	(1.5034)	(1.5796)	(1.6099)	(1.8967)
Poverty level						
GDP per capita	0.0931	0.0919	0.1175	0.0792	0.0803	0.1406
	(0.1097)	(0.1098)	(0.1211)	(0.1680)	(0.1751)	(0.1990)
MFI-specific controls						
Financial expenses	12.1978	12.0657	14.4732	6.4673	6.5492	12.7860
	(9.8021)	(10.9328)	(11.3945)	(13.4903)	(14.6191)	(15.5824)
PAR30	3.8820	3.8731	3.5673	6.8305	6.8605	9.3680
	(3.3883)	(3.4107)	(4.3734)	(5.4901)	(5.5479)	(8.9239)
Legal type	0.6265	0.5846	1.1278	1.7885	1.7942	4.7928**
	(0.9409)	(1.0391)	(0.9311)	(1.2232)	(1.2807)	(2.1090)
Year Index	−0.2966	−0.2749	−0.2165	−0.2426	−0.2429	−0.2204
	(0.4443)	(0.4468)	(0.4340)	(0.7028)	(0.7043)	(0.8540)
Year Index^2	0.0314	0.0299	0.0261	0.0122	0.0122	0.0102
	(0.0301)	(0.0303)	(0.0305)	(0.0493)	(0.0493)	(0.0593)
Macroeconomic controls						
Region_EAP	−1.2206	−1.2013	−0.7246	−2.6746*	−2.6806*	−2.0984
	(1.0628)	(1.0546)	(1.1370)	(1.5844)	(1.5823)	(1.6728)
Region_AFRICA/Mena	−1.3242	−1.3169	−1.2448	−2.8233**	−2.8247**	−2.2039
	(1.0747)	(1.0676)	(1.1203)	(1.3958)	(1.3949)	(1.5511)
Region_LAC	−1.2734	−1.2919	−0.9561	−1.9594*	−1.9607*	−1.7293
	(0.9079)	(0.9128)	(1.0124)	(1.1297)	(1.1277)	(1.3913)
Region_SA	−0.9967	−0.9712	−0.5236	−2.3338*	−2.3496	−2.1667
	(1.2507)	(1.3517)	(1.2687)	(1.3952)	(1.6079)	(1.8866)
_cons	−6.9391*	−7.0799*	−8.1944**	−5.1414	−5.1207	−6.5431
	(3.6271)	(3.6256)	(4.0989)	(4.3732)	(4.3444)	(5.2974)
N	620	617	543	114	114	103
Pseudo R^2	0.1396	0.1408	0.1711	0.2356	0.2356	0.2982

Table 3.7: Coefficients of pooled logistic regressions with the termination of the partnership as dependent variable

Notes: Out of the 125 MFIs with access to Kiva, 26 MFIs faced a closing event within the observation period. Models I–III include all year-observations of MFIs having access to Kiva between 2005 and 2015. Models IV–VI include only selected year-observations of MFIs. MFIs are selected by a random selection without replacement. Standard errors clustered at MFI-level are in parentheses. 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 3.1.

As a further analysis regarding temporal aspects of the closing event, we run Cox proportional hazard models, which analyze the ‘survival time’ of the partnership between the MFI and Kiva. When applying the Cox model, we look at all MFIs which have had access to Kiva since 2005 and observe at which point of time the event of terminating the partnership occurred. As our study ended in February 2016, most of the partnerships have not been determined, which is something the Cox model can deal with. From Kiva’s API, we retrieve the information concerning at which point of time the MFI partnered Kiva and in the case of terminating the partnership, at which point of time the closing event occurred. Due to lacking data in the respective year when the cooperation between the MFI and Kiva was decided, our data set reduces to 107 MFI-year observations including 25 closing events (compared to the logit model, one MFI facing a closing event is lost due to lacking data). We run Cox proportional hazard models with the same model specifications as the logistic regressions. The results are reported in Table 3.8.

The overall picture is consistent with our findings based on the logistic regressions. Considering the social performance of the MFI, the percentage of female borrowers reveals itself to be positive and significant at the 5% level in models I and II. We find clear evidence that the MFI’s ability to mobilize deposits tends to shorten the partnership. Accordingly, we summarize that deposit-taking MFIs have a lower incentive to stick to subsidized debt capital as they gain independency by using deposits as source of debt capital. In contrast to the logit regressions, the coefficient of the GDP per capita is positive and significant in all model specifications. This could be an indication that MFIs operating in better developed countries spend less time focusing on interest-free refinancing through Kiva as other funding sources may become available and more attractive. However, as this variable was not significant in the logit regressions, the finding should not be over-interpreted either.

	(I)	(II)	(III)
Social performance			
AVLB_GNI	0.6843	0.8854	0.3930
	(0.7093)	(0.8946)	(1.4521)
Female	3.4456**	3.1867**	2.5800
	(1.6535)	(1.5519)	(1.8099)
Portfolio yield (real)		2.0663	2.7546
		(3.4438)	(4.4542)
Grouplending share			0.6455
			(1.2466)
Maturity			
ln_Assets	0.3044	0.3465	0.4202
	(0.3194)	(0.2857)	(0.3515)
Age_young	−1.6987	−1.9051**	−1.2272
	(1.0547)	(0.9466)	(1.1999)
Age_mature	−0.8418	−1.0017	−0.5169
	(1.0511)	(1.0078)	(1.0438)
Debt-to-asset	−2.6130	−2.6563	−2.8414
	(1.6879)	(1.7145)	(1.8370)
Poverty level			
GDP per capita	0.3685**	0.3681**	0.3056*
	(0.1696)	(0.1695)	(0.1691)
Financial performance			
OSS	−0.1810	−0.0035	−0.0751
	(1.1977)	(1.2908)	(1.9533)
Funding approach			
Deposits-to-assets	2.8946**	3.1578**	3.3268*
	(1.1811)	(1.4304)	(1.6979)
MFI-specific controls			
Financial expenses	13.3350	10.5496	9.0955
	(10.9061)	(12.0907)	(18.0512)
PAR30	−3.0505	−2.3108	0.4395
	(3.5055)	(4.0565)	(5.8767)
Legal type	0.7544	0.6256	1.1984
	(1.0283)	(1.1618)	(1.0171)
Year Index	−1.0337	−0.9783	−0.1090
	(0.9712)	(1.0125)	(1.3166)
Year Index^2	0.0964	0.0952	0.0308
	(0.0796)	(0.0803)	(0.1032)
Macroeconomic controls			
Region_EAP	−0.3079	−0.0869	−0.0670
	(1.0712)	(1.0463)	(1.1358)
Region_AFRICA/Mena	0.0275	−0.0820	−0.3794
	(0.9675)	(0.9828)	(1.1843)
Region_LAC	−0.5981	−0.5718	−0.9026
	(1.0169)	(1.0357)	(1.0746)
Region_SA	0.2065	0.4986	0.3753
	(1.5251)	(1.6945)	(1.7930)
N	107	107	94
Pseudo R^2	0.1420	0.1460	0.1710

Table 3.8: Coefficients of Cox proportional hazards models on the event that the partnership between Kiva and the MFI is terminated before February 2016
Notes: Within the observation period, 25 closing events occurred. Model specifications are analogous to pooled logistic regressions in Table 3.7. Robust standard errors are in parentheses. 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 3.1.

3.5.3 Robustness checks

To assess the robustness of the first part of our findings, further logistic regressions are run.

First, we add the share of rural lending as an additional social performance measure. The coefficient of the rural lending share is insignificant and does not provide further insights regarding our hypotheses on the MFI's social performance. The majority of the variables do not change, but the real portfolio yield and the OSS variable become insignificant. However, the validity is limited as the data set is significantly reduced due to missing data of the added variable.

Second, we exclude all MFIs from countries which do not have at least one MFI with access to Kiva. The regression results are shown in column II. Third, we conduct a logistic regression with standard errors clustered by countries instead of by MFIs, as applied in our main models. The results are shown in column III. In both models, the overall picture is robust as all variables, except the dummy variables for the MFI's years of operation, reveal themselves to be consistent with our main findings. However, the debt-to-asset ratio remains stable and significant at the 1% level.

Furthermore, a fixed-effects model clustered by countries is estimated. MFI-fixed effects help to overcome endogeneity issues related to unobserved time-invariant variables on the MFI level. While the debt-to-asset ratio and PAR30 are in accordance with our previous findings, several variables such as the share of female borrowers, the real portfolio yield, OSS, and deposits-to-assets ratio do not remain significant. The insignificance of some variables could be linked to the fact that these variables do not change greatly with time. Unfortunately, it is not possible to carry out a country-fixed-effects model due to data restrictions as we only have the data of a few MFIs available for some countries.

As another way to alleviate endogeneity of the MFI level, we lastly establish regression models including the lagged dependent variable (access to Kiva). The results are reported in column V. The majority of the variables do not change and are similar to our main results. A slight difference arises as the variable indicating the percentage of female borrowers becomes insignificant. However, the real portfolio yield remains unchanged in support of H1. The lagged access variable turns out to be positive and significant. This result supports the understanding that MFIs are likely to continue the partnership with Kiva once refinancing through Kiva has been used.

Furthermore, we perform several robustness checks without showing the detailed results in a separate table.

First, we run the regressions without the 130 observations of rural banks as these represent a unique organizational type, which we cannot use as a separate category for statistical reasons. However, the main findings are not significantly altered by this sample reduction.

Second, we exclude all 30 observations of MFIs with an average loan volume of more than 10,000 USD in order to account for a different view on the question beyond which loan amount level microfinance ends. However, the results confirm the robustness of our findings in the main model.

Third, we substitute the OSS variable with a self-constructed financial self-sustainability (FSS) variable in order to account for grants and subsidies received by MFIs[16]. The significant negative coefficient of the FSS variable is in accordance with our findings on the OSS variable and therefore confirms the validity of using the OSS variable.

[16]This robustness check is only possible for a set of 3,691 MFI-year observations, for which we know the amount of donations. This information is only available on a smaller data set ending in 2013. On this subset, we obtain the FSS variable analogously to the OSS but with the financial revenues *net* of donations.

	(I)	(II)	(III)	(IV)	(V)
Social performance					
AVLB_GNI	0.0462	−0.2363	−0.2960	−0.0042	−0.2527
	(0.1960)	(0.2368)	(0.2003)	(0.0113)	(0.2038)
Female	1.3934*	1.7265**	1.2635**	0.0484	0.6115
	(0.7718)	(0.7007)	(0.5788)	(0.0355)	(0.5853)
Portfolio yield (real)	−1.2743	−1.5315**	−1.3875**	−0.0446	−1.4915**
	(1.0516)	(0.7222)	(0.6637)	(0.0458)	(0.6296)
Group lending share	−0.4718	−0.3496	−0.2898		−0.2214
	(0.4116)	(0.3321)	(0.3320)		(0.3099)
Rural lending share	0.1091				
	(0.4590)				
Maturity					
ln_Assets	−0.0884	−0.0274	−0.0307	0.0095	−0.0814
	(0.0903)	(0.0707)	(0.0738)	(0.0140)	(0.0646)
Age_young	0.5349	0.2937	0.3085	−0.0362*	0.0102
	(0.3563)	(0.2750)	(0.2936)	(0.0197)	(0.3842)
Age_mature	0.5014	0.5205	0.4730	−0.0378	0.0486
	(0.4331)	(0.3233)	(0.3478)	(0.0311)	(0.3435)
Debt-to-asset	2.4963***	1.9892***	1.8626***	0.1515***	0.8857**
	(0.5820)	(0.4816)	(0.4888)	(0.0447)	(0.4316)
Financial performance					
OSS	−0.5995	−0.6939**	−0.5645*	−0.0052	−0.7935**
	(0.4143)	(0.3428)	(0.3102)	(0.0125)	(0.3274)
Funding approach					
Deposits-to-assets	−3.4770***	−3.2543***	−3.2111***	−0.0475	−2.1088***
	(0.9022)	(0.6354)	(0.5462)	(0.0693)	(0.6041)
Poverty level					
GDP per capita	−0.1659**	−0.1072*	−0.1641***	−0.0080	−0.1509***
	(0.0682)	(0.0649)	(0.0488)	(0.0060)	(0.0454)
MFI-specific controls					
Financial expenses	2.8144	−0.8061	−0.4270	0.2612	1.3897
	(3.6054)	(3.2415)	(2.3617)	(0.1924)	(2.6343)
PAR30	−4.1902**	−4.5444***	−4.8119***	−0.1169***	−6.1161***
	(1.8609)	(1.5145)	(1.5970)	(0.0333)	(1.9380)
Legal Type	−0.4884	−0.6215	−0.4752		−0.4879
	(0.6845)	(0.5671)	(0.4697)		(0.4850)
Year_Index	0.6858***	0.6124***	0.6234***	0.0477***	0.5664***
	(0.1149)	(0.0892)	(0.0793)	(0.0086)	(0.1371)
Year_Index^2	−0.0321***	−0.0305***	−0.0306***	−0.0024***	−0.0475***
	(0.0074)	(0.0059)	(0.0057)	(0.0006)	(0.0115)
Kiva_access_lagged					5.5265***
					(0.3432)
Macroeconomic controls					
Region_EAP	0.5451	0.0236	0.4252		0.5299
	(0.5666)	(0.5092)	(0.4628)		(0.4257)
Region_AFRICA	1.3773**	1.3193**	1.3321***		0.8350*
	(0.6415)	(0.5230)	(0.4341)		(0.4541)
Region_LAC	0.2644	−0.2848	0.1858		0.4024
	(0.4141)	(0.3941)	(0.3115)		(0.3126)
Region_MENA	0.2735	1.6209	−0.1368		0.2300
	(1.3404)	(1.2117)	(1.2372)		(0.6131)
Region_SA	−2.6066***	−3.2086***	−2.8360***		−1.8207***
	(0.6759)	(0.6382)	(0.6530)		(0.5070)
_cons	−4.4695***	−4.0320***	−4.1188***	−0.2788	−1.7628
	(1.6517)	(1.2272)	(1.1918)	(0.2110)	(1.1440)
N	3,107	3,952	4,723	4,723	4,497
Pseudo R^2	0.2113	0.2086	0.1932		0.5341

Table 3.9: Regression results of robustness analysis
Notes: Model I is the base model extended by the share of rural lending. Model II is the base model including only countries with at least one MFI that has access to Kiva. Model III follows the base model, but standard errors are clustered across countries. Model IV is a fixed-effects model. Model V is the base model extended by the lagged access variable as independent variable. 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 3.1.

3.6 Conclusion

We empirically study the access of MFIs to subsidized funding provided via the online peer-to-peer platform Kiva between 2005 and 2015 based on a worldwide dataset of 909 MFIs. By employing logit regressions, we identify a positive relationship between the MFI's social performance and access to funding from Kiva. Regarding the MFI's maturity, we find strong evidence that more mature MFIs in terms of debt-to-asset ratio have and use access to Kiva more frequently than MFIs which are new to the market. Furthermore, the MFI's financial performance and the ability of mobilizing deposits are main predictors for the likelihood of access to Kiva. Moreover, MFIs operating in less developed countries with lower values for GDP per capita demonstrate a more frequent use of subsidized funding via Kiva. Regarding the possible termination of the funding relationship between an MFI and Kiva we find a positive correlation between the share of female borrowers and the probability of terminating the partnership. A similar finding emerges for the deposits-to-asset ratio. Altogether, the termination of the partnership appears to be driven primarily by factors on the MFI side, rather than to be initiated by Kiva.

Our results lead to the conclusion that crowdlending effectively expands the MFI's possibilities to obtain access to subsidized debt capital without interest obligation and provides the opportunity to transfer the credit default risk from the MFI to investors. With regards to the intensively discussed topic of credit risk in classical microfinance, crowdlending enables the MFI to spread the credit default risk of one single loan to multiple investors. Furthermore, crowdlending through Kiva also requests the MFIs to fulfill certain requirements mainly based on the social investors' expectations. These requirements in turn are likely to increase the MFI's operating expenses. Therefore, we can draw the implication that Kiva as well as the MFIs carefully consider the impact of the refinancing through the crowd on the MFI's overall profit, as an MFI only seeks the partnership with Kiva as long as this is beneficial. In the long run, the requirements may not be in accordance with the MFI's ambition to become independent and to gain access to the mainstream capital market. Therefore, crowdlending appears to have the potential to be supportive for and used by MFIs to a certain extent, but depending on the MFI's growth strategy, not in the long run. In our view, this is the most interesting theoretical takeaway on the topic of refinancing microcredit.

Our study also contributes to the literature on crowdfunding in general by providing results on the motivation of the involved investors. Our findings suggest that Kiva appears to attract investors which strongly value the social performance of an MFI and also prefer to invest into poor countries. This supports the view that at least a part of crowdfunding investors are affine to prosocial motivations.

With the increasing relevance of crowdfunding in general and in the field of microfinance in particular, research on the influence of institutional factors will also gain more importance. This study, is the first to provide evidence relating to this issue. As a possible limitation of our study, we have to mention that the self-reported data on MIX Market could be biased. To overcome possible sample selection issues due to the fact that we can only use data on MFIs with access to Kiva and available MIX data, an expansion of this research to other platforms appears to be a promising prospect. Another limitation lies in the fact that the empirical setup cannot completely rule out endogeneity. In order to figure out what makes MFIs to prefer the source Kiva instead of other cheap sources of funding (e.g. subsidized debt), one would need a different data set comprising all available funding sources and could then implement a propensity score matching to compare the decisions of similar MFIs.

Chapter 4

From credit risk to social impact: On the funding determinants in interest-free P2P lending

This research project has been carried out jointly by Gregor Dorfleitner, Eva-Maria Oswald and Rongxin Zhang. The paper has been submitted to the Journal of Banking and Finance and is currently under review.

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 as well as information in the description text fostering the investors' trust are shown to be main predictors of successful funding. Regarding social impact, the possibility to empower women and groups of borrowers appears to attract investors, whereas an 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. Investors enabling non-endorsed loans clearly prefer to support borrowers with immigration backgrounds. In contrast, investors who fund endorsed loans are reluctant to invest in loans to immigrants.

Keywords: Text analysis, crowdlending, microfinance, funding probability, funding time

JEL Classification: D64 D91 O16

4.1 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. Obviously, 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 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.

Kiva is well-known as an online crowdlending platform that enables microlending to the poor by mobilizing debt capital from the worldwide crowd of altruistic investors. The standard model on Kiva is devoted to the crowdlending of loans that are intermediated through local microfinance institutions (MFIs). Under this intermediated microfinancing model, investors refinance microloans which have already been granted to applicants by MFIs. Previous Kiva studies have focused on this intermediated loan model for borrowers in developing countries (e.g. Ly and Mason, 2012a; Burtch et al., 2014; Allison et al., 2015; Moss et al., 2015; Dorfleitner et al., 2017).

Apart from the intermediation-based microfinancing model, Kiva also facilitates a direct P2P lending model in which micro borrowers and socially-oriented lenders interacting directly without any financial intermediation. 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 (unlike in the Kiva intermediated model). From the standpoint of classical P2P lending, the fact that borrowers do not need to pay any interest and that investors therefore do not receive any financial compensation for the credit risk they take is very unusual.

The investors' decision-making behavior in the intermediated model of Kiva has been intensively studied. Several studies show that these investors are socially oriented and prefer to support loan applications signalling higher social value (e.g. Allison et al., 2015; Moss et al., 2017). Furthermore, despite a prosocial setting, they are risk-averse and are concerned with the credit profile of the intermediating MFIs (e.g. Heller and Badding, 2012; Berns et al., 2018). Additionally, the investors prefer to fund loans in poorer countries (Jenq et al., 2015).

While these findings are interesting, they cannot directly be transferred as the lending decision is heavily influenced by the presentation of a loan through the MFI and the MFI's track record and operating country. In contrast, Kiva's direct model features real P2P lending with borrowers from a homogeneous economic region, namely the United States. Additionally, Kiva direct loan investors make lending decisions based on limited information of borrowers, while intermediated loan investors can easily utilize the information of MFIs, such as credit ratings and repayment history. Another difference lies in the fact that while investors do not receive interest in either Kiva model, most borrowers in the intermediated model still refrain from paying interest to Kiva's local partners. Moreoever, Kiva direct loan borrowers in the US are responsible for their loan descriptions, while the MFIs do this in a far more standardized manner in the intermediated model as many borrowers may not even be able to complete a P2P loan application process. Without the intermediation of MFIs, the investors' behavior in terms of deciding which borrower to support with interest-free capital, increases in importance. Given the limited information provided by the borrowers themselves, the question arises concerning how Kiva direct loan investors make lending decisions, especially when they have both financial and social concerns. Additionally, recent research on standard P2P lending has proven that the self-written description texts of the applicants are important in terms of the lending decision (see e.g. Larrimore et al., 2011). Information of this type can be expected to be even more relevant if there is no interest rate serving as a quality signal.

In this study, we investigate the determinants of successful funding under a real P2P lending model with an interest rate of zero through a financial and social lens based on a data set of more than 6,000 US direct loans. The data set is unique due to several facts. First, the loan applicants are exclusively US citizens facing financial exclusion from the formal capital market. Second, these loans adopt Kiva's direct P2P lending model, which is completely different from Kiva's intermediation-based model. Third, the data set provided by Kiva's API is comprehensively expanded through valuable information obtained from original campaign webpages.

Logistic regression on the funding success and tobit regression on the reversed funding time provide interesting insights. First, evidence of the importance of third-party endorsement of loan applications can be found. Borrowers endorsed by a trustee attract investors more successfully and faster. Second, it has been proven that the description text as a measure used to build trust between investors and borrowers can influence the fundraising result. In addition, investors appear to consider several social aspects such as the preference of group loans and the empowerment of women. The empowerment of others beyond the borrowers themselves does not appear to be a crucial predictor of funding success and funding speed. In the subsample of non-endorsed loans, keywords indicating the borrower's responsibility for family members are even negatively related to funding success. Regarding the borrower's vulnerability, the empirical result is two sided and provides interesting insights into the varying behavior of investors. Borrowers with immigration background are clearly preferred by investors who support loans without trustee endorsement. In contrast, investors of loans that are socially underwritten by a trustee are more reluctant to invest into immigrants. There is evidence that investors place more emphasis on the social impact in case the borrowers are not supported by a trustee. In summary, our findings lead to the conclusion that socially-oriented investors care about the credit risk as well as the social impact of their investments.

To our knowledge, this is the first study that sheds some light on the financial and prosocial considerations of investors funding interest-free P2P loans.

Moreover, we contribute to the research of microfinance in developed countries as the borrowers are from the United States. Despite the growing interest in microfinance in developed countries, there is still limited academic research on this topic available (Pedrini et al., 2016).

The reminder of the paper is organized as follows: Kiva's funding model for direct loans is introduced in Section 2. In Section 3, four hypotheses are derived from theoretical considerations and existing studies. Section 4 describes the data and the employed methodology. The results of regressions and robustness checks are displayed in Section 5. Sections 6 concludes.

4.2 Kiva's funding model for direct loans

Kiva direct loans focus on US citizens who wish to develop a promising business idea but struggle with access to capital and enables them to receive interest-free loans of up to 10,000 USD. borrowers neither pay nor do investors receive any interest on the loan. Investors fully bear the credit default risk. In order to minimize the risk of fraud, Kiva staff carry 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 personal network (family, friends) is asked to fund the loan application to further affirm the applicant's creditworthiness and to already collect a portion of the loan. Additionally, the loan applicant can be endorsed by a trustee (an organization or an individual) that is in a relationship with the loan applicant. Even though the trustees do not have any financial reliability, it helps 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. 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), whereas the optional trustee is a property that is not given for every application.

Kiva's direct P2P model is summarized in Figure 4.1.

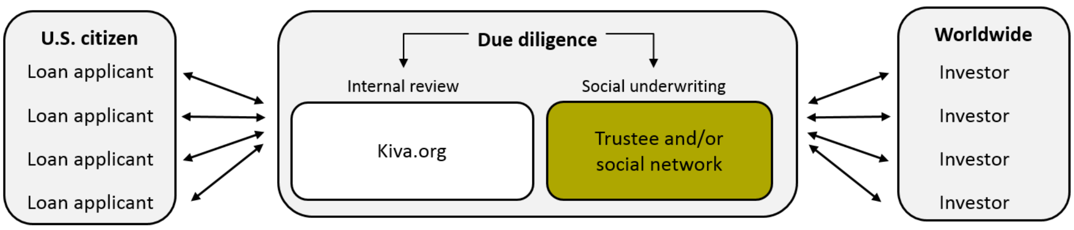

Figure 4.1: Kiva's direct P2P model for direct loans in the United States

[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.

4.3 Theory and hypotheses development

4.3.1 Theoretical basics

P2P lending is doubtlessly one of the most innovative recent forms of financing as it relies on the wisdom of the crowd to make lending decisions. P2P lending is sometimes also referred to as 'crowdlending', which points towards the fact that it is the most important type of crowdfunding (Ziegler et al., 2017). Numerous studies investigate the investment and repayment behavior in P2P lending. In addition to the investigation of the role of classical hard facts such as the credit rating or repayment history of borrowers (Lin et al., 2013), recent studies have been paying attention to soft facts in descriptive texts of loan applications (e.g. Moss et al., 2015; Allison et al., 2015; Dorfleitner et al., 2016). For instance, Dorfleitner et al. (2016) find that social or emotional keywords, which appear in descriptive texts of loan applications are positively related to funding probability.

Another non-classical source of debt capital is microlending, which has existed in developing countries since the 1970s (Ledgerwood, 1999). Microlending, being the main form of microfinance, provides small amounts of credit to people who are normally excluded from formal credit markets. Many studies on microfinance find that MFIs can achieve very high repayment rates by adopting group lending methodology or other contractual innovations (e.g. Ghatak and Guinnane, 1999; Morduch, 1999). In the recent years, the microfinance movement has also spread to the western economies. However, the literature on microfinance in developed countries is comparatively scarce as the industry is still in its infancy (Pedrini et al., 2016; Bourlès and Cozarenco, 2017). To cite an example, Bourlès and Cozarenco (2017) investigate the link between borrowers' motivation and the repayment of microloans in France and find that 'necessity entrepreneurs' have more difficulty repaying loans than 'opportunity entrepreneurs'.

As a prosocial microfinancing platform, Kiva has achieved huge success and drawn the special attention of researchers to its innovative forms of connecting microfinance and crowdfunding. 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. (2017) 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 investors supporting Kiva's intermediated loans and find that investors favor 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 investors prefer to support loan applicants who position their ventures as an opportunity to help others.

By connecting real P2P lending and microfinance, Kiva direct loan provides a new way to finance the unbanked population in the United States. In this direct loan model, borrowers provide loan applications by themselves and investors (instead of MFIs) decide whom to support based on their own judgement. To answer the question concerning how Kiva P2P investors make their investment decisions toward providing their capital to borrowers through an uncollateralized and interest-free loan without intermediation, we must consider the selection of the borrowers and theorize on the utility function of the lenders.

Unprivileged borrower Kiva set the minimum requirements for direct loans that only US-citizens who are restricted in their entrepreneurial activities due to being financially excluded, can become borrowers of direct loans (Kiva.org, 2018b). These borrowers strive for the opportunity to become entrepreneurially involved through self-employment or to expand an existing business and therefore, these borrowers exhibit the need for capital.

Socially-oriented investor Kiva investors reveal themselves as being socially oriented, highly valuing the social impact of their investment and perceiving a warm-glow effect through supporting others (Ly and Mason, 2012b; Allison et al., 2013). Following Dorfleitner et al. (2017), the investor's personal utility comprises the financial return r and the social return s weighted with the factor $\alpha > 0$:

$$r + \alpha \cdot s \tag{4.1}$$

At first glance, the investor – similar to kinship groups – refrains from paying interest and, furthermore, agrees to fully bear the credit risk. Therefore, the expected financial return is negative ($E(r) < 0$). At second glance, empirical evidence clarifies the assumption that investors stress credit risk to be closest to zero (Dorfleitner and Oswald, 2016; Jenq et al., 2015). In contrast to kinship groups, Kiva investors are not acquainted with the borrowers 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 investors are willing to provide capital only under the condition of a positive personal utility. Consequently, the expected social return $\alpha \cdot E(s)$ must overcompensate for the expected negative financial return. Besides the fact that other people are supported, it evidently becomes relevant whom to support (Cull et al., 2007; Mersland and Strøm, 2010; Jenq et al., 2015).

4.3.2 Hypotheses development

The information asymmetry problem prevails in every lending situation and is even more serious for P2P lending investors since they are not professionals like banks or institutional investors (Yum et al., 2012; Lee and Lee, 2012). Indeed, the information that Kiva direct loan investors can obtain is often very limited. 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 credit rating is never available and even the repayment history of the borrower is difficult to obtain due to protection of the borrowers' privacy. In this case, investors have to overcome adverse selection and the risk of moral hazard (Bruton et al., 2011).

To help investors evaluate the credit risk of borrowers, P2P platforms usually adopt several identifiable or quantifiable mechanisms such as the assignment of credit rating or cooperation with partners. Several studies show that Kiva investors in the intermediated loan model make lending decisions based partly on field partners' information (Allison et al., 2015; Berns et al., 2018; Ly and Mason, 2012a). However, a borrower applying for a direct loan on Kiva neither has a credit score nor a field partner. Instead, the direct loan applications on Kiva can have trustees who endorse borrowers.

Trustee existence As mentioned earlier, Kiva adopts the process of 'social underwriting' as part of its due diligence for direct loans. During this process, direct loan applicants are required to demonstrate their ability to attract a network of familiar people, trustees or referees to support them. Some studies show that social ties are very important in the reduction of information asymmetry for online P2P lending (Liu et al., 2015; Lin et al., 2013). Kiva trustees are individuals or organizations that help Kiva to identify credible direct loan applicants. Even though trustees have no financial obligation concerning the loans they endorse, they bear a reputation risk by endorsing borrowers and should thus have an interest in the repayment of loans. Therefore, Kiva direct loans with an endorsement from trustees could be perceived as being safer because trustees have to evaluate the creditworthiness of borrowers beforehand in order to minimize reputation risk and also to monitor borrowers' repayment behavior. By taking the above into consideration, we expect that Kiva direct loans with trustee endorsement to be more likely to be funded.

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

Although some Kiva direct loans do have a trustee endorsement, the investors require more information to help them to reduce the information asymmetry problem.

Foundation of Trust Apart from hard facts such as credit scores or third-party endorsement, as significant amount of studies investigate the soft factors in the descriptive texts of loan applications that may influence investors' lending decisions on P2P lending platforms (e.g. Allison et al., 2015; Moss et al., 2017). For instance, the empirical fact that descriptive texts can reduce information asymmetries and thus contribute to fundraising has been documented several times (e.g. Larrimore et al., 2011; Michels, 2012). A longer and more detailed descriptive text can serve as a signal concerning the borrowers, which prove his or her level of involvement in the project, which can help build the foundation of trust between Kiva direct loan borrowers and investors. However, descriptive texts which are too long could be troublesome for non-professional Kiva direct loan investors to evaluate, we also expect the positive effect of a longer descriptive text on funding probability to be dampened when the number of words exceeds a certain amount.

Compared with consumption-oriented loans, business-oriented loans can be perceived as being more trustworthy regarding debt repayment. Dorfleitner et al. (2016) suggest that keywords addressing a business purpose in the loan application are related to a higher funding probability because business activities are likely to create positive cash flows, which can help repay loans. From this perspective, business-orientation in loan descriptions could be considered to be a positive signal of successful debt repayment in the future and attract more attention from investors. Even though all direct loans are intended for entrepreneurial purposes, according to Kiva's official requirements, the descriptions of loan applications can differ greatly regarding this topic as the texts are written by different individuals. We anticipate that a clear signal of the willingness to do business with the loan proceeds can help to convince the investors to support these loans.

Additionally, borrowers of Kiva direct loans who document their education in descriptive texts can be perceived as being more trustworthy for the following reason. With the help of loan proceeds, they are more likely to complete their education. Several studies show that education can make a considerable contribution to reduction of poverty (e.g. Appleton, 2001; Tilak, 2007). In other words, these borrowers can improve their repayment ability through higher educational achievements. Indeed, Dorfleitner et al. (2016) find empirical evidence that borrowers on a German P2P platform who mention their education background in descriptive texts have a lower probability of default. Based on these considerations, we expect signals in descriptive texts that build trust between Kiva direct loan investors and borrowers to play an important, positive role for the funding success.

> **H2 (Trust):** Signals in descriptive texts that build trust are positively associated with the funding success.

The theoretical considerations regarding investors' personal utility lead directly to the general hypothesis, being that the investors are more likely to support loans with greater social impact to maximize their personal utility. Investors on prosocial P2P platforms such as Kiva are expected to help other people to alleviate impoverishment as they do not receive any interest from loans. In fact, 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 the socially-oriented investors on Kiva (Allison et al., 2013; Moss et al., 2017; Jancenelle et al., 2018). To develop our hypotheses, we discuss two major fields in which a social contribution can be made, namely empowerment and vulnerability.

Empowerment Empowerment is a process of change by which individuals or groups with little or no power, e.g. women or poor communities, gain in their power and ability to make choices that can change their lives (Cheston and Kuhn, 2002). According to this definition, we discuss several sub-fields that are relevant in the context of our study.

Women's empowerment, particularly women's economic empowerment, is the core mission of United Nations Industrial Development Organization (UNIDO.org, 2018). Kiva offers a special loan category, exclusively to female borrowers, and prioritizes it on the loan requests list. As of October 2017, 81% borrowers supported through Kiva have been female (Kiva.org, 2018a). Most researchers agree that prosocial lenders prefer female borrowers. Heller and Badding (2012) find that Kiva female borrowers in the intermediation-based model are funded 40% faster than their male counterparts. Ly and Mason (2012a) also confirm that it takes female borrowers of Kiva intermediated loans less time gain funding. Therefore, we expect female borrowers of Kiva direct loans to receive more support from investors.

Compared with individual direct loans, group direct loans are expected to attract more investment as they involve more people and a higher level of social contribution is probable. In the intermediated model, group loans have been found to be more likely to raise funds (Berns et al., 2018). In contrast, Ly and Mason (2012a) find that individual loans can be funded faster than group loans in the Kiva intermediation-based model, but they attest to the fact that if the group size is relatively large, group loans are definitely preferred because more beneficiaries profit from these loans.

Kiva direct loan investors can be expected to appreciate loan applicants who express their expectations for the future in the descriptive text. Moss et al. (2015) argue that entrepreneurs who signal their confidence to succeed in their future businesses are more likely to make a considerable effort to overcome unfavorable conditions and to accomplish their goals. By showing their strong expectations in the loan proceeds, borrowers present a picture to investors concerning how their lives could be changed by receiving the loan. Loan applications with clear individual visions regarding the future can thus convince investors that a social impact is very likely to be made through the support of these people. By taking this perspective, we assume that borrowers with purpose statements will probably gain more support from Kiva direct loan investors.

Furthermore, the investors could pay attention to an emphasis on family, with a view to supporting social empowerment. As suggested by Freedman and Jin (2008), loans requests on Prosper which mention family members are more likely to be funded. Allison et al. (2015) also find that words for family members and generic terms that refer to humans in the description texts, written by the MFI, can reduce time to funding for Kiva intermediated loans.

Moreover, we expect that borrowers who place emphasis on helping the community receive more support from investors. As Calic and Mosakowski (2016) suggest, orientation of crowdfunding campaigns on Kickstarter towards sustainability can positively affect the fundraising result. Moss et al. (2017) also demonstrate that Kiva intermediated loan investors are more quick to lend to borrowers that highlight their social positioning. By supporting prosocial borrowers, Kiva direct loan investors do not only help borrowers to fulfill their personal goals but also help more people indirectly. Therefore, we expect these prosocial loan applications to be preferred by the direct loan investors.

> **H3 (Empowerment):** A description text indicating empowerment possibilities is positively related with the funding success.

Vulnerability Besides empowering women, family and the community, Kiva direct loan investors can focus on borrowers who are in a very vulnerable position and need help urgently to make a social contribution. Borrowers can evoke strong emotions by expressing their misery in descriptive texts. Jenq et al. (2015) find that perceived neediness is positively related to the funding speed of Kiva intermediated loans. According to Dorfleitner et al. (2016), who study German P2P platforms, loans with negative keywords in descriptive texts have a higher funding probability. Allison et al. (2013) also demonstrate that mentioning concerns leads to a more rapid funding process in the Kiva intermediated loans.

Among the needy and vulnerable borrowers, Kiva direct loan applicants with an immigration background are of special interest to us in this study. Immigrants often suffer from a lack of resources and financing support in a foreign country. According to the survey of Aldén and Hammarstedt (2016), non-European immigrants in Sweden report upon more discrimination by traditional finance institutions. Since one of the biggest concerns for investors on Kiva is to help the needy (Allison et al., 2015), borrowers with an immigration background are very likely to be the target group to whom Kiva direct loan investors prefer to lend their helping hand. 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.

4.4 Data and methodology

4.4.1 Data description

Our analysis is based on interest-free direct loans which are requested by US citizens 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 'non-successfully funded'. The data set is extended through the addition of information extracted from the original campaign webpages. Loan applications include information on loan conditions and the trustee endorsement if a trustee is provided. The applicant's personality and the purpose for the loan request are described in a descriptive text, written individually by the borrower. The data set is cleared by removing observations with unrealistic values regarding the loan amount > 10.000 USD (strict limit defined by Kiva) and 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 6,121 observations. Therein, 4,077 loans are successfully funded and 2,044 loans have expired.

All variables relevant to our analysis are explained in detail in Table 4.1. 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 defined by calculating 1,000 divided by the funding time in days, thereby, setting the reversed funding time of non-funded loans below the smallest calculated value (numerically equal to zero), representing an infinite funding time. Values are logarithmized.

All four hypotheses stated above are tested through several explanatory variables. First, one of the most obvious differences amongst loan applications is whether it is *endorsed by a trustee* or not, which is the subject of the first hypothesis. Whether or not a *trustee* is given is incorporated with a dummy variable. The *trustee type* can be distinguished between individuals, non-profit organizations and others. For loan applications with trustee endorsement, we are able to calculate the *trustee's experience* in days at Kiva at the point of time the respective, new loan application is posted publicly. Furthermore, we include a dummy variable for the *trustee's proximity* to the loan applicant by comparing the US-state in which the trustee and the loan applicant are located. The proximity of trustees and loan applicants located in the same US-state are perceived as being higher.

Insights into the applicant's personality and the purpose of the loan are mainly provided in the description text which we have used and in which we have searched for keywords in order to gather further details. All keywords are defined and reported in Table 4.2.

Second, in order to test whether the applicant's effort to *build trust* helps to attract potential investors, signals within the description text are considered. A first indication of the applicant's willingness to share information with potential investors is the extent of the description text. The extent of the description text is summarized by the *number (#) of words*. With the text analysis using *Business Keywords* the applicant's intention of planned entrepreneurship can be discovered. The variable *Keyword Education* clarifies whether the applicant appears to have 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 investors, being the subject of H3. A dummy variable for *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 in microfinance and crowdlending is considered, in order to illustrate if explicitly female borrowers are empowered (e.g. D'Espallier et al., 2011; Heller and Badding, 2012). Female/male individuals or groups of only female/only male borrowers are defined as being female/male, respectively. Groups consisting of male and female individuals are categorized as being mixed. The applicant's expectation associated with the access to and usage of the loan is represented by the dummy variable *Keyword Purpose*. Furthermore, empowerment beyond the applicant's own benefit is measured by the *Keyword Family* and the *Keyword Community*, which measure the mentioning of family members and the community in which the loan applicant belongs respectively.

Last but not least, the *applicant's vulnerability* is measured by the immigration background and negative keywords following the findings of e.g. Allison et al. (2013) and Dorfleitner et al. (2016). 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-citizen 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 already have faced severe difficulties and social abuse.

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. In contrast to negative keywords, *Positive Keywords* support the applicant in being perceived as having a balanced social constitution, which is included as a control variable. While all loan applicants are visualized in a photograph, only a few loan applicants use a video to further emphasize their personality. A dummy variable for the availability of a *video* is included. Additionally, the *US-state* in which the loan applicant is located and the year in which the loan was posted are also considered. As a last control variable we include the time until *expiration* of an open loan application on Kiva. All loan applications have a defined time period during which the loan must to be fully funded; otherwise the loan application - as a non-funded loan - is removed from Kiva's webpage.

Variable	Expected effect	Description
Dependent variables		
Funding success		Binary variable with the 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 for the funding time (in days) for funded loans. For non-funded loans, the time until expiration is employed as survival time. Values are logarithmized.
H1 Trustee endorsement		
Trustee	+	Dummy variable with the value of one if the loan application has a trustee, zero otherwise.
Type		Trustees are categorized into individuals, non-profit organization, 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 the 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 the value of one if the applicant's planned entrepreneurship is explained, zero otherwise.
Keyword_Education	+	Dummy variable with the 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 the value of one if the loan is a individual loan, zero otherwise.
Keyword_Purpose	+	Dummy variable with the value of one if the applicant's expectation with the help of loan proceeds is stated, zero otherwise.
Keyword_Family	+	Empowerment in terms of family members being positively affected by the loan. Dummy variable with the 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 the value of one if community empowerment is stated, zero otherwise.
H4 Vulnerability		
Immigration	+	Dummy variable with the value of one if immigration background of the applicant is given, zero otherwise.
Keyword_Negative	+	Dummy variable with the 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 the value of one if the applicant's positivity experienced is stated, zero otherwise.
Video		Dummy variable with the value of one if a video is available, zero otherwise.
Expiration		Metric variable (in months) calculated based on the duration between posting date on Kiva and 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		Dummy variable for activities 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 4.1: Definition of variables

Hypothesis	Variable	Keywords
H2 Trust	Keyword_Business	business, career, client, company, customer, employment[1], entrepreneur[1], expand, financial stability, invest, job, network, profession[1], profitability[1], skills[1].
	Keyword_Education	academic, Bachelor, college, degree, education, exam, graduation[1], 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[1], mom, (grand-) mother, (grand-) parents, partner, pregnant, siblings, sister, (grand-) son, uncle, wife.
	Keyword_Purpose	believe, better future, better life, chance, dream, fascination[1], motivation, passion[1], purpose, vision.
	Keyword_Community	community, friend, help[1], serving others, support[1].
H4 Vulnerability	Keyword_Negative	abuse, addiction[1], cancer, civil war, death, defeat me, destiny, difficulty[1], disruption[1] drug, enemy, hard work, incarceration, insane, pain[1], passed away, poverty, prison, sick, ups and downs, victim.
Controls	Keyword_Positive	enjoy, fun, happiness[1], greatness[1], love[1], pleasure, smile[1], thankful, thank you.

Table 4.2: Categorical variables depicting possible keywords in the description text
Notes: 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. [1] indicates that all respective verbs, adjectives, and adverbs are also taken into account as keywords.

4.4.2 Methodology

The main determinants of successful debt funding through Kiva by socially-oriented investors are expected as being credit risk and social impact. Credit risk is measured by the facts of trustee endorsement and a borrower's willingness to share information, summarized in the vector R_i in our models. The borrower's vulnerability and the empowerment of the borrower and others identify the social impact, considered in our model as vector S_i. Vector C_i represents the loan-specific controls and the 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. The dependent variable is – either funding success or reversed funding time. First, 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. Second, 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 and to account for our total data sample consisting of censored (reversed funding time = 0) and uncensored (reversed funding time > 0) observations, we apply tobit models with robust standard errors.

4.4.3 Descriptive statistics

Table 4.4 and Table 4.3 report upon the descriptive statistics for metric and categorical variables which contribute to test our hypothesis. The descriptive statistics for our control variables are displayed in Table A1 in the appendix.

The requested loan amount ranges from 100 USD to 10,000 USD, which is set as the upper credit limit by Kiva. On average, the loan length 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 1,333.3USD/month. Both extreme scenarios correspond to the subsample of non-funded loans. Only a small portion of the loans is requested by groups of at least two individuals as 98% are requested by 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, the 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 public posting of a loan and the commencement of fundraising. Most of the trustees are categorized as being 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. The keyword search reveals that more than 80% of the loan applicants describe their expectations related to the loan. Loan applications which do not state the entrepreneurial activity are seldom. The educational background is frequently stated. 84% of loan applicants provide insights into their family situation and an astonishing 96% about the community the applicant belongs to. In 19% of the cases, an immigration background is explicitly mentioned in the description text. 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 text includes negative aspects, but in more than 72% it contains positive aspects.

Regarding our controls, the availability of a video is unusual in single cases. The loans are widely distributed among the activity sectors with a peak for services, followed by food and retail.

	Total sample N=6,121		Funded loans N=4,077		Non-funded loans N=2,044	
Variable	Obs.	Relative	Obs.	Relative	Obs.	Relative
Funding success						
Yes	4,077	66.61	4,077	100.00	0	0.00
No	2,044	33.39	0	0.00	2,044	100.00
Trustee						
Yes	2,588	42.28	2,255	55.31	333	16.29
No	3,533	57.72	1,822	44.69	1,711	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	1,211	19.78	1,046	25.66	165	8.07
No endorsement	3,533	57.72	1,822	44.69	1,711	83.71
Trustee's proximity						
Yes	2,358	91.15	2,070	91.84	288	86.49
No	229	8.85	184	8.16	45	13.51
Keyword_Business						
Yes	6,053	98.89	4,031	98.87	2,022	98.92
No	68	1.11	46	1.13	22	1.08
Keyword_Education						
Yes	3,873	63.27	2,638	64.70	1,235	60.42
No	2,248	36.73	1,439	35.30	809	39.58
Individual						
Yes	6,020	98.35	3,993	97.94	2,027	99.17
No	101	1.65	84	2.06	17	0.83
Gender						
Male	2,521	41.19	1,532	37.58	989	48.39
Female	3,530	57.67	2,488	61.03	1,402	50.98
Mixed	70	1.14	57	1.40	13	0.64
Keyword_Purpose						
Yes	5,018	81.98	3,416	83.79	1,602	78.38
No	1,103	18.02	661	16.21	442	21.62
Keyword_Family						
Yes	5,180	84.63	3,500	85.85	1,680	82.19
No	941	15.37	577	14.15	364	17.81
Keyword_Community						
Yes	5,897	96.34	3,937	96.57	1,960	95.89
No	224	3.66	140	3.43	84	4.11
Immigration						
Yes	1,183	19.33	889	21.81	294	14.38
No	4,938	80.67	3,188	78.19	1,750	85.62
Keyword_Negative						
Yes	1,954	31.92	1,334	32.72	620	30.33
No	4,167	68.08	2,743	67.28	1,424	69.67

Table 4.3: Descriptive statistics for main categorical variables
Notes: The entire data sample contains 6,121 observations. Absolute values and relative values of the categorical variables are displayed. The variables are defined in Table 3.1.

Total sample						
Variable	Obs.	Mean	S.D.	Min	Median	Max
Loan amount	6,121	4,914.41	3,036.05	100.00	5,000.00	10,000.00
Loan length (in months)	6,121	25.24	8.14	1.00	24.00	51.00
Principal per month	6,121	183.80	86.74	10.42	208.33	1333.33
# of words (in 100 words)	6,121	5.45	2.27	0.66	5.25	26.25
Trustee's experience (in days)	2,588	442.34	472.86	-119.00	280.00	2073.00
Expiration (in days)	6,121	67.74	125.63	15.00	52.50	1,682.01
Funded loans						
Variable	Obs.	Mean	S.D.	Min	Median	Max
Funding time (in days)	4,077	44.15	30.09	0.10	39.04	300.55
Loan amount	4,077	5,206.48	2,994.86	100.00	5,000.00	10,000.00
Loan length (in months)	4,077	25.87	8.10	1.00	24.00	51.00
Principal per month	4,077	191.92	82.07	12.50	208.33	1111.11
# of words (in 100 words)	4,077	5.70	2.22	0.84	5.56	26.25
Trustee's experience (in days)	2,255	440.50	472.36	-119.00	273.00	1986.00
Expiration (in days)	4,077	79.89	150.76	15.01	58.05	1682.01
Non-funded loans						
Variable	Obs.	Mean	S.D.	Min	Median	Max
Loan amount	2,044	4,331.85	3,034.47	125.00	5,000.00	10,000.00
Loan length (in months)	2,044	23.98	8.09	6.00	24.00	42.00
Principal per month	2,044	167.62	93.30	10.42	166.67	1333.33
# of words (in 100 words)	2,044	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)	2,044	43.52	32.48	15.00	34.59	462.76

Table 4.4: Descriptive statistics for metric variables
Notes: The entire data sample contains 6,121 observations. The variables are defined in Table 3.1.

Bravais-Pearson correlation coefficients for exogenous metric variables are shown in Table 4.5. We do not expect any multicollinearity issues as all pairwise correlations are far below 0.8, which is the critical value according to Kennedy (2008).

		1.	2.	3.	4.
1.	Principal per month	1.000			
2.	Trustee's experience	0.1640∗	1.000		
3.	# of words	0.1706∗	0.0799∗	1.000	
4.	Expiration	0.1638∗	−0.0221	0.0613∗	1.000

Table 4.5: Bravais-Pearson correlation coefficients for metric exogenous variables
Notes: Values labeled with the symbol * are significant at the 5% level. The variables are defined in Table 3.1.

4.5 Results

4.5.1 Results regarding the funding success

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 4.6. Model I is the basic model consisting of details which are obvious in the loan applications. It is extended by adding the different types of trustees, resulting 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.

First, the credit risk associated with a loan application and its impact on the probability of funding success is investigated by considering two aspects, namely trustee endorsement and the foundation of trust. 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. Loans which are endorsed by a trustee are more likely to be funded than loans without trustee endorsement. The result is further strengthened by the dummy variables stating the type of trustee in model II. While loans without endorsements are less likely to be funded compared with loans underwritten by an individual, loans promoted by a non-profit organization are even more likely to be funded.

Furthermore, the foundation of trust between the investor 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 the number of words is positive and significant. Therefore, the longer the text description, the higher the probability of successful funding. However, the investor could be overwhelmed if a text description is too long. The squared number of words is included in order to test for such a u-shaped relation. The coefficient of this variable is significant and negative. Regarding the coefficients of *Keyword_Business* and the *Keyword_Education*, we are unable to find any evidence as the coefficients are not significant.

Second, the investor's social return of providing capital is also examined by considering two aspects, namely the empowerment and support of vulnerable borrowers. The dummy variable demonstrating female borrowers is positive and significant in all model specifications. Female borrowers are more likely to receive funding than their male counterparts. Regarding whether the loan is requested by an individual or a group of borrowers, we are able to ascertain that individual applicants have more difficulties to receiving funding than groups of borrowers. The borrower's expectation of entrepreneurship by accessing capital through the loan is examined, but the corresponding coefficient is not significant. Besides the benefits for the loan applicants themselves, it is desirable for family members or the community to benefit from the given capital. However, keywords associated with family prove themselves to be negatively related to funding success. The result is significant and contradictory to our expectation. One possible reason could be that the borrower's dependency on and responsibility for his or her family members appears to be obstructive in terms of entrepreneurship as opposed to positive in terms of empowerment. The second variable demonstrating community empowerment is positive but not significant.

Regarding the borrower's social circumstances, the main difference between loan applications is whether or not the loan applicant has an immigration background. The coefficient of the respective dummy variable is positive and significant at the 1% level, 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 investors perceive immigrants as being more needy based on their individual narratives as well as that they generally associate immigrants as being vulnerable and suffering 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 expiration of the loan application shows a positive and significant coefficient. Loans without a strict time limit for fundraising are more likely to be funded. It is interesting that the year index variable is positive and significant, which could be considered as an indication for the investor's learning curve in terms of supporting US direct loans. Taking into account that the volume of US direct loans on Kiva has increased significantly over the last years (see Table A1) as well as the positive development of funding success, it appears promising that investors are becoming more confident when providing capital directly to US citizens in need. None of the other controls such as *Keyword_Positive*, *Principal per month* and *video dummy* provide any further insights.

Additionally, the data sample is divided into the subsamples of loan applications with trustee endorsement and the subsample of loan applications without trustee endorsement. The subsample regressions support our understanding of whether investors of loans strengthened by social underwriting through trustees behave more risk-aversely or less socially than investors who invest in unsecured loans.

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 trustee endorsement in model IV and V allows us to include further variables that provide details about the trustees and the investors' responses to them. The trustee's experience of supporting loans on Kiva is positive and significant in model IV, but not in model V, which also includes the year index. Consequently, as the trustee's experience in days increases with the years, the result appears to be time-dependent and should not be overvalued. A noteworthy observation is the positive and significant coefficient of a trustee's proximity to the borrower. The fact that trustees and borrowers are located in the same US-state is positively related to the funding success. One reason behind this finding could be that investors assess the ability and power of trustees to guide and monitor borrowers to improve if the proximity to the borrower is given.

Regarding the borrower's willingness to share information in the description text, the results are similar to those in the total data set. The coefficient of the number of words is positive and significant. The u-shaped relation is only significant for the subsample of loans without trustee endorsement in column VI. The keywords illustrating the planned entrepreneurship and the borrower's educational background remain insignificant.

Regarding empowerment, in contrast to the main models, the individual dummy is not significant for either of the subsamples. Female borrowers still appear to be targeted by investors. Keywords associated with family remain negative and significant in the subsample of loans without trustee endorsement. This may signal the investors' doubt about the possibility of the explicitly mentioned care of family members being brought into line with successful entrepreneurship, especially without the support of a trustee. Keywords regarding the community and the borrower's expectations concerning the business remain insignificant.

The vulnerability of borrowers emphasized by the immigration background and negative words does not appear to have any impact on the probability of the funding success in the subsample of loans endorsed by a trustee. In contrast, the immigration dummy is positive and significant in the subsample of loans without trustee endorsement. These investors appear to highly value the social impact of investing in immigrants while other investors are more reluctant to provide capital to immigrants. The coefficient of negative keywords is positive but not significant.

The coefficient of the video dummy is negative and slightly significant in model V. Investors do not appear to view video messages given in the loan application particularly positively. The results of all other included control variables remain unchanged compared with the models on the total data set.

	All observations			with trustee		w/t 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 experience				0.0004***	0.0002	
				(0.0002)	(0.0002)	
Trustee 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_Purpose			0.1307	0.1193	0.1520	0.1046
			(0.0838)	(0.1709)	(0.1692)	(0.1007)
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)
Principal_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***
	(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

Table 4.6: Coefficients of logistic models on funding success
Notes: Models I - III include all observations. Model IV - VI consider the subsamples of loans with and without 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 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 3.1.

4.5.2 Results regarding the funding time

In addition to the funding success, the funding time of loan applications on Kiva can be observed. Subject to our tobit regressions is the calculated reversed funding time. This means that the faster a loan is funded, the higher the reversed funding time and vice versa. Tobit regression is able to deal with censored data, which safeguards against the loss of observations of non-funded loans. The model set up is unchanged and follows the applied logistic models. The results are displayed in Table 4.7. Models I - III include the entire 6,121 observations for funded and non-funded loans independently of trustee endorsement.

First, focusing on the variables measuring credit risk provides us with a clear picture of the fact that credit risk is negatively perceived by investors and results in a longer time until funding is granted. Trustee endorsement has a positive impact and leads to a reduced funding time which is confirmed by both variables, the trustee dummy and the types of trustees.

Signals in the description text as an instrument to build trust and attract potential investors appear to have an influence on the funding time as well. In accordance with the regressions on funding success, a longer description text reduces the funding time, the u-shaped relation is observable and *Keyword_Business* and *Keyword_Education* are insignificant.

Second, the social impact of the investment decision is taken into account while making the decision regarding which loan application to support. Loans requested by groups of borrowers and female borrowers are funded more quickly as the respective variables are significant in all model specifications, whereas keywords for family and community do not appear to be crucial predictors. Additionally, the coefficient of keywords stating the purpose for the loan application appears to be positive and significant. This is a first indication that investors are attracted by the borrower's expectation related to the access to capital.

Regarding the vulnerability of the borrower, the results on funding time follow those on funding success. Borrowers stating an immigration background receive faster funding while the borrower's previous social dislocation does not appear to influence the funding time.

The coefficient of the principal per month is negatively related to the funding time. This could be due to the investor's distrust in the borrower's ability to repay a proportionally high loan amount succeeding a short loan period. Loan applications including positive keywords appear to experience a slower funding process. The included control variable of time until expiration is positive and significant. The year index appears to be significant in all model specifications. This illustrates that the funding time decreases with the years. Taking into account the growing amount of direct loan applications on Kiva, the result is only explicable if either the pool of potential investors increases or the existing investors invest more capital. Both possibilities are interesting in terms of Kiva's future development.

Furthermore, both tobit models for the subsamples of loans with and without trustee endorsement are conducted separately. The results are shown in models IV, V, and VI in Table 4.7. In the subsample of loans with trustee endorsement, loans endorsed by an individual tend to be funded more quickly than loans supported by third parties categorized as non-profit organization or others. Additionally, investors appear to positively react to the trustee's experience and the proximity between trustee and borrower, resulting in a lower funding time for endorsed loans. Regarding the signals in the description text that build trust, the results on funding success for both subsamples are confirmed through the existence of a similar relationship between the variables and the funding time. In terms of empowerment, the coefficients of the variables remain unchanged compared with the findings on funding success. Female borrowers are preferreda and the dummies for individuals, the borrower's expectation and community empowerment are insignificant. Keywords representing the borrower's family are negatively related to funding time in the subsample of loans without trustee endorsement.

Again, the difference between the subsamples is apparent when looking at the borrower's vulnerability. The immigration background appears to be a main predictor for the funding time of loans lacking trustee endorsement. This is not the case for loans endorsed by a trustee. The coefficient of negative keywords is also contrary for both subsamples, but not significant.

The principal per month remains negative, albeit slightly significant only in the subsample of loans without trustee endorsement. All control variables demonstrate the same significant relations as those in the funding success analysis.

	all observations			with Trustee		w/t 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 experince				0.0003***	0.0001***	
				(0.0000)	(0.0001)	
Trustee 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_Purpose			0.1030*	0.0250	0.0446	0.1095
			(0.0545)	(0.0578)	(0.0575)	(0.0957)
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)
Principal_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)
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

Table 4.7: Coefficients of tobit models on reversed funding time
Notes: Models I - III include all observations. Models IV - VI consider the subsamples of loans with and without trustee endorsement separately. Model I is extended by the 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 3.1.

4.5.3 Implication regarding the hypotheses

We hypothesize that investors consider both the credit risk and the social impact of their investment decisions. Credit risk is examined by two hypotheses, namley the existence of a trustee and the borrower's ability to build trust.

All in all, H1, which states that potential investors perceive the existence of a trustee to be supportive in terms of evaluating creditworthiness, limiting credit risk, and ensuring repayment of the employed capital, is supported.

The borrower's willingness to share information is positively related to the funding success and reversed funding time as it builds trust and attracts investors, which supports our expectation in H2. However, text descriptions which are too long are not favorable and tend to deter investors. Signals of entrepreneurship and education in the text description do not appear to influence the investor's behavior.

The social impact of the investment decision is examined by two further hypothesis, namely those of empowerment and support for vulnerable borrowers.

Clear evidence in favor of Hypothesis 3 is observed in terms of empowering women as female borrowers are favored by 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 regression. Signals of the borrower's expectations associated with access to capital are positively recognized by investors throughout the entire sample but not in the subsamples. Empowerment beyond the borrowers themselves does not appear to attract investors. In the subsample of loans without trustee endorsement, investors are even reluctant to provide capital to applicants who explicitly mention their responsibility towards family members.

Hypothesis 4 on the vulnerability of borrowers is confirmed for the complete sample and the subsample of loans without trustee endorsement. The financial needs of immigrants are recognized and investors strive to support these applicants. But this is not the case for investors funding loans with the endorsement of trustees. The clear difference between investors leads us to the conclusion that some investors are already satisfied through investing in these types of interest-free direct loans, whereas others perceive additional value in the act of supporting immigrants. The borrower's previous social dislocation does not appear to evoke investors' emotions at all.

4.5.4 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 dependent variables, namely funding success and funding time, are jointly considered as being the time interval until the event of being successfully funded is estimated. Seven observations are lost due to negative values subsequent to taking the logarithm of the funding time. The regression results are shown in Table 4.8.

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 u-shaped relation of the length of the text description is not confirmed anymore. However, the tendency remains unchanged. Keywords associated with education turn out to be negative and slightly significant. Furthermore, the coefficient of keywords regarding the borrower's family becomes significant. This finding could be influenced by the significant regression result in the event of being successfully funded. 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 trustee endorsement are presented in columns IV - VI. Most of the results remain stable with same values and slightly changed confidence levels. Compared with the main model, Hypothesis 3 is further confirmed by the significant coefficient of the dummy variable, indicating an individual versus group loan. A considerable gain in insight can be seen in the fact that the borrower's vulnerability is able to attract investors who invest in loans without trustee endorsement but outfaces investors who invest in endorsed loans. Both variables - Immigration and Keyword_Negative - demonstrate significant and contrary coefficients in the subsamples. This result clarifies our presumption based on our main results obtained by running tobit regressions. The control variable Keywords_Positive is negative and becomes significant in the subsample of loans endorsed by a trustee, indicating that these investors do not appreciate emotions. Overall, the regression results positively both contribute to and conform to our main models.

	Cox proportional hazard models					
	all observations			with trustee		w/o trustee
	(I)	(II)	(III)	(IV)	(V)	(VI)
Trustee endorsement						
Trustee	0.3743***		0.3537***			
	(0.0386)		(0.0385)			
Type_Non_Profit		0.0270		-0.2021***	-0.0680	
		(0.0655)		(0.0693)	(0.0697)	
Type_Others		-0.0694		-0.2387***	-0.1499**	
		(0.0611)		(0.0654)	(0.0644)	
Type_No_End.		-0.3981***				
		(0.0609)				
Trustee experince				0.0006***	0.0002***	
				(0.0001)	(0.0001)	
Trustee proximity				0.2757***	0.2432***	
				(0.0936)	(0.0908)	
Trust						
# of words			0.0757***	0.0706**	0.0800**	0.1634***
			(0.0248)	(0.0346)	(0.0370)	(0.0429)
# of words^2			-0.0025	-0.0030	-0.0032	-0.0072**
			(0.0017)	(0.0024)	(0.0027)	(0.0030)
Keyword_Business			0.0158	-0.0990	-0.0675	0.1487
			(0.1459)	(0.1589)	(0.1850)	(0.2443)
Keyword_Education			-0.0639*	-0.0266	-0.0260	-0.0475
			(0.0353)	(0.0484)	(0.0494)	(0.0518)
Empowerment						
Individual	-0.5543***	-0.5561***	-0.5338***	-0.3673	-0.4348*	-0.6638*
	(0.1686)	(0.1704)	(0.1736)	(0.2673)	(0.2423)	(0.3890)
Gender_female	0.2706***	0.2717***	0.2632***	0.1411***	0.1444***	0.4043***
	(0.0340)	(0.0340)	(0.0346)	(0.0463)	(0.0471)	(0.0533)
Gender_mixed	-0.3461*	-0.3374	-0.3378	-0.2237	-0.2741	-0.4726
	(0.2068)	(0.2082)	(0.2134)	(0.3050)	(0.2881)	(0.4499)
Keyword_Purpose			0.0570	-0.0106	0.0180	0.0521
			(0.0445)	(0.0620)	(0.0621)	(0.0637)
Keyword_Family			-0.1042**	-0.0105	-0.0359	-0.2223***
			(0.0471)	(0.0638)	(0.0655)	(0.0725)
Keyword_Community			0.0150	0.1690	0.0707	0.0511
			(0.0849)	(0.1056)	(0.1055)	(0.1401)
Vulnerability						
Immigration			0.1833***	-0.1366**	-0.1513**	0.4493***
			(0.0437)	(0.0603)	(0.0613)	(0.0589)
Keyword_Negative			-0.0021	-0.1017**	-0.0950**	0.0960*
			(0.0353)	(0.0465)	(0.0465)	(0.0524)
Controls						
Keyword_Positive			-0.0938**	-0.0881*	-0.0991*	-0.0306
			(0.0376)	(0.0505)	(0.0508)	(0.0555)
Principal_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	-0.0496	-0.0540	-0.0426	-0.0692	-0.2775	0.1116
	(0.1259)	(0.1256)	(0.1242)	(0.1910)	(0.1948)	(0.1888)
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	0.2641***	0.2645***	0.2684***		0.2365***	0.1744***
	(0.0200)	(0.0201)	(0.0205)		(0.0220)	(0.0306)
Activity sector	yes	yes	yes	yes	yes	yes
US-state	yes	yes	yes	yes	yes	yes
N	6,114	6,114	6,114	2,588	2,588	3,526
Pseudo R^2	0.016	0.017	0.017	0.013	0.017	0.054

Table 4.8: Coefficients of Cox proportional hazard models

Notes: Robustness analysis through Cox proportional hazard models for the total data sample and exclusively for the subsamples of loans with trustee endorsement as well as loans without 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 3.1.

Furthermore, we run additional logistic regressions and probit regressions on funding success, which are shown in Table 4.9. First, we include an interaction term of trustee endorsement and an immigration dummy in the main logistic model to further investigate how investors of endorsed loans behave in regards to loan applicants with an immigration background. The interaction term is negative and significant at the 1% level, supporting our findings on subsample regressions, being that investors of endorsed loans tend to pursue minimal credit risk than increased social impact.

Second, all loan applications with an amount of less than 1,000 USD are excluded as these ones are less likely to properly support or enable entrepreneurship. The majority of variables does not change. Keyword_Purpose turns out to be significant, indicating that the borrower's expectation increases in importance concerning higher volume loans. The negative coefficient of Keyword_Family is not anymore significant.

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 - VI. All variables employed to test the hypothesis on credit risk and social impact remain stable and are consistent with our main results.

	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 experince				0.0002**	0.0001	
				(0.0001)	(0.0001)	
Trustee 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_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)
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)
Principal_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)
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	6,121	5,927	6,121	2,550	2,550	3,533
Pseudo R^2	0.276	0.269	0.256	0.128	0.130	0.192

Table 4.9: Robustness analysis through further logistic and probit models on funding success
Notes: 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 > 1,000 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 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 3.1.

4.6 Conclusion

In this paper, we study the funding determinants for interest-free P2P lending by utilizing a unique data set of direct loans requested by US citizens on the microfinancing platform Kiva during the observation interval from 2011 to 2017. The data set is unique due to the newly established direct P2P model, the concept of social financing without interest compensation for credit risk, the homogeneous group of borrowers and the extended volume of information. The underlying Kiva model enables direct P2P lending between micro-entrepreneurs and socially-oriented investors without financial intermediation. Although the investors bear the full credit risk, they are willing to grant interest-free loans to borrowers. Borrowers comprise US citizens who face financial exclusion from the formal capital market. Finally, the data set utilizes information obtained from original loan-application texts.

The running of logistic regression on the funding success and tobit regression on the reversed funding time provide interesting insights into the investors' behavior regarding investment decision making. The existence of social underwriting by a trustee appears to have a high positive impact on the funding success and the reversed funding time. Furthermore, the description length as a measurement with which to share information and generate the investor's trust increases the probability of funding success as well as reducing 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. Evidence of empowerment of others beyond the borrowers themselves is not found. At first glance, the borrower's vulnerability measured by the immigration background is positively related to funding success and funding time in the total sample. The result is refined by the performance of further regressions on the subsamples of both loans with and without trustee endorsement. Investors of loans socially underwritten appear not to support immigrants. These investors do not strive for maximizing social impact, whereas the investors of non-endorsed loans prefer to invest in loan applications requested by an entrepreneur with an immigration background. For these investors, the borrower's vulnerability is an appeal to invest, but not for those focusing on minimal credit risk and investing in loans endorsed by a trustee.

In summary, our findings lead to the conclusion that the investment decisions of socially-oriented P2P investors takes into account the credit risk as well as the social impact of the respective investment. Investors appear to have different preferences regarding the minimization of credit risk versus the maximization of social impact, which influences their decision on whom to support. This research provides insights into the investor's behavior in the context of online P2P microfinacing in developed countries such as the United States.

We are convinced that further research on the innovative direct interest-free P2P model has a promising potential. Up to now, important aspects such as credit risk, competition of loan applications, and the balance between demand and supply have been clearly under-researched.

4.7 Appendix

	Total sample N=6,121		Funded loans N=4,077		Non-funded loans N=2,044	
Variable	Obs.	Relative	Obs.	Relative	Obs.	Relative
Keyword_Positive						
Yes	4,450	72.70	2,992	73.39	1,458	71.33
No	1,671	27.30	1,085	26.61	586	28.67
Video						
Yes	69	1.13	44	1.08	25	1.22
No	6,052	98.87	4,033	98.92	2,019	98.78
Year Index						
2011	4	0.07	4	0.10	0	0.00
2012	107	1.75	101	2.48	6	0.29
2013	361	5.90	337	8.27	24	1.17
2014	708	11.57	545	13.37	163	7.97
2015	1,163	19.00	733	17.98	430	21.04
2016	1,766	28.85	1,049	25.73	717	35.08
2017	2,012	32.87	1,308	32.08	704	34.44
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	1,361	22.23	1,071	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	1,862	30.42	1,103	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

Table A1: Descriptive statistics for categorical variables - controls
Notes: The entire data sample contains 6,121 observations. Absolute values and relative values of the categorical variables are displayed. The variables are defined in Table 3.1.

Chapter 5

Conclusion

5.1 Contribution of this dissertation

This dissertation consists of three research papers on online microfinancing through the worldwide crowd of socially-oriented investors. Theoretical considerations and empirical results from classical microfinance and online peer-to-peer crowdlending are utilized as fundamental knowledge to gain further insights on crowdlending as a source of debt capital for microfinance.

The first research work identifies the MFI's screening and monitoring quality, the lending methodology, the credit contract and the borrower's gender as predictors of credit default in the intermediation-based microfinancing model. The empirical results on credit default provide valuable implications for both the MFIs as financial intermediaries and receivers of interest-free capital and the socially-oriented investors. MFIs have an incentive to be aware of credit default predictors in order to adequately decide concerning which loan requests to post on Kiva for refinancing. The MFI's reputation is essential to attract investors and ensure the refinancing possibility in the long run (e.g. Berns et al., 2018). Investors highly value the repayment of the loan principal in order to continuously empower several borrowers (Ly and Mason, 2012a). Therefore, investors also have a high interest to know credit default predictors in order to be able to adequately decide on which loan requests to support. To conclude, the results on credit default risk are useful for both MFIs and investors for their future participation on Kiva.

The second paper investigates the characteristics of MFIs having and using access to refinancing through the worldwide crowd from the demand and supply side perspective. Main positive predictors of access are the MFI's social performance, the maturity and the economic situation of the country in which the MFI is mainly located. In contrast, the financial performance and the extent of deposit mobilization is negatively associated with the probability of refinancing microloans using Kiva. Regarding the termination of the partnership, the share of female borrowers and the extent of deposits appear to strengthen the MFI's decision to discontinue the partnership. On the one hand, this study illustrates the characteristics of MFIs which are open to innovative sources of refinancing and strive to explore and use crowdlending as a source of debt capital. On the other hand, it shows which MFIs are reluctant to make use of crowdlending using Kiva. Additional, from Kiva's perspective, the determinants of granting access to which MFIs are shown.

The third research work examines the funding determinants of interest-free loans requested by US citizens to socially-oriented investors in the innovative direct peer-to-peer model of Kiva. Main predictors of successful funding are social underwriting by a third-party trustee, an informative narrative about the borrower himself and the underlying project and the possibility to empower women and groups of borrowers. Regarding the vulnerability of borrowers, the funding behavior of lenders differs as lenders enabling loans without trustee endorsement prefer to lend to immigrants. That is not the case for lenders investing in endorsed loans. This study clarifies that socially-oriented investors consider the credit risk and the social impact of their investment under the condition of lending without receiving interest rate but bearing the full credit default risk. Furthermore, it becomes apparent that crowdlending through socially-oriented investors could be a promising approach to foster microfinancing in developed countries such as the United States. Therefore, it highly contributes to the research on microfinance in developed countries which is clearly under-researched so far (Pedrini et al., 2016).

In summary, this dissertation adds further insights to the literature and empirical research on interest-free crowdlending in the context of microfinance in developing and developed countries.

5.2 Limitations and suggestions for future research

The innovative phenomenon of microfinancing through the crowd of socially-oriented investors is worth to be further researched in future studies. The three research papers in this dissertation face some limitations which are discussed in the following.

The first research paper investigates the credit default risk of borrowers with regards to the MFI's ability to manage its credit portfolio, lending methodology, loan characteristics and gender of borrowers. As the narrative of each loan request provides some information about the borrower's personality, future research might want to examine if borrower characteristics such as age, civil status, family situation, education are possible predictors of credit default risk. Additionally, also here the question rises if the repayment behavior of borrowers on other microfinancing platforms than Kiva is impacted by similar determinants or in contrast, does follow other mechanisms.

The empirical results of the second paper are focused on and limited to MFIs having access and using the refinancing possibility using Kiva's intermediation-based model. Apart from MFIs, it is interesting to gain a better understanding about the characteristics of other institutions like schools, social businesses or non-profit organizations acting as financial intermediaries on Kiva. These institutions are not considered in this study due to data restrictions. Additionally to Kiva, some further microfinancing platforms such as Rang De, Microgramm and Deki rely on the intermediation-based model. Therefore, it can be worthwhile to further investigate – from the demand and the supply side perspective – the characteristics of MFIs acting on these platforms and particularly to evaluate, if MFIs intend to access refinancing through the worldwide crowd using more than only one platform.

The last empirical work is the first one to shed some light on direct loans from socially-oriented investors to microentrepreneurs in developed countries by investigating the investors' behavior. To best of our knowledge, nothing is known about the credit default risk. Furthermore, as only two third of the loan applications are successfully funded, it could be interesting to evaluate the balance between the supply and the demand side. Until today, direct loans are only available to US citizens. It is worth to observe if Kiva expands the innovative direct model to other developed or even developing countries, which rises further fields of research. Therefore, there is substantial room to further explore the actors and dynamics of microfinancing via this innovative direct p2p model of Kiva.

It is highly appreciated if these limitations are considered as motivation for further research. Overall, it remains interesting if crowdlending through the worldwide crowd of socially-oriented investors indeed contributes to microfinance as a new source of debt capital in the long run. Further research on the success of crowdlending as a source of debt capital in the context of microfinance is welcome.

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