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Financial returns or social impact? What motivates impact investors' lending to firms in low-income countries☆

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A B S T R A C T

I analyze 70,000 transactions by retail impact investors on a peer-to-peer lending platform that intermediates loans to firms in low-income countries. Loans pay interest to investors and publicize indicators of expected social impact. Financial returns significantly influence investors' decisions: a one percentage point increase in the interest rate increases funding speed seven-fold, investment probability two-fold and transaction size by 122 Euro. Expected social impact influences investors' perception but has no influence (for female empowerment, employees and beneficiaries) or limited influence (for turnover) on investors' funding decisions. When all available loans pay the same interest rates, female borrowers - but not firms with many employees or beneficiaries - are more likely to be chosen, suggesting that variation in financial returns can crowd out salient dimensions of social impact. The study implies that peer-to-peer lending platforms should function as gatekeepers of social impact and cannot outsource the evaluation of social impact to retail impact investors.

1. Introduction

I study the decisions of retail impact investors to understand how they trade off potentially conflicting objectives between generating financial returns and generating social impact. Many people in high-income countries struggle to find investments that provide financial returns *and* align with their values. At the same time many firms in low-income countries struggle to gain access to finance (World Bank Enterprise Survey, 2017). A response to this mismatch is impact investing, where investors with a social vision lend to firms with a social mission, with the understanding that the relationship has to be financially sustainable for both sides. Impact investing has grown rapidly in the last decade and currently an estimated 502 billion US Dollar is managed by impact investors (Global Impact Investing Network, 2019).[1] By definition, impact investors want to allocate their investments to specific borrowers. How, then, do impact investors use their influence and which type of borrowers do they prefer, those that offer high financial returns or those that offer a high expected social impact?

An ideal environment to study individual investment decisions is peer-to-peer lending, because investors choose directly and repeatedly among many different borrowers.[2] In this paper, I analyse transactions on a peer-to-peer lending platform operated by the Dutch Fintech company Lendahand. Loans on Lendahand pay annualised interest rates between three and eight percent and at the same time publicize a variety of social impact indicators.[3] That investors choose loans that generate financial returns and social impact is unusual for peer-to-peer lending, but common in large-scale impact investing. Combined with transaction-level data,

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[1] The Global Impact Investment Network defines impact investments as investments that "intentionally contribute to social and environmental solutions", "measure and report the social and environmental performance" and "seek a financial return on capital that can range from below market rate to risk-adjusted market rate" (Global Impact Investing Network, 2018).

[2] Peer-to-peer lending is a type of crowdfunding, where individual funders – who collectively form *the crowd* – make small contributions to one fundraiser. Belleflamme et al. (2015) categorize crowdfunding platforms into donation-based (for example Indigogo or GoFundMe), reward-based (for example Kickstarter) and investment-based platforms (for example Lendahand and other peer-to-peer lending platforms).

[3] The total loan size mostly falls between 2600 Euro (1st decile) and 23,670 Euro (9th decile). A typical loan on Lendahand is thus *mesocredit* to established firms, rather than microcredit to poor households and micro-entrepreneurs. The loans have a cross-border element: most investors come from high-income countries and all borrowers come from low-or middle-income countries.

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this setting allows me to answer the following research questions: What predominantly determines individual investment decisions: financial returns or social impact? Does the existence of varying interest rates crowd out investors intrinsic motivation to choose high social impact borrowers? And, do the answers to these questions differ by investors' characteristics, such as age, gender or nationality?

I analyze almost 70,000 transactions on the Lendahand peer-to-peer lending platform, each constituting a small loan by one of over 3000 investors to one of over 2100 firms (borrowers). I use information about each loan's expected social impact and financial returns and estimate their relation to three measures of funding success: total funding duration, investor-and time-specific funding probability and amount per transaction.[4] With a fixed total loan size, a short time until funding is an indication for a popular loan application and I estimate log-linear regressions that relate the logarithm of funding duration to measures of expected social impact and financial returns. Additionally, on each day an investor makes an investment, I group together all available loan applications into choice sets and record which loan applications have been selected and what the invested amount was. Conditioning on the choice set means that I only exploit variation between loan applications that were actually available to an investor at the time of making their investment.[5]

Interest rate and loan maturity are significantly related to all three measures of funding success, while indicators of expected social impact are not. A one percentage point increase in the interest rate increases funding speed seven-fold, investment probability two-fold and transaction size by 122 Euro. Investors also prefer shorter loan maturities: a one year shorter loan maturity means the loan is funded 2.5 times faster, has a 40% higher chance of being chosen and attracts 46 Euro more funding. In contrast, female empowerment, income generation and the number of beneficiaries do not significantly influence funding success.[6]

Comparing the investment behavior by age, gender and nationality, I find that young or male investors are driven more by considerations of financial returns, whereas older or female investors are driven by financial returns as well as by considerations of social impact. However, the heterogeneity in investment behavior across demographic characteristics of the investors is small compared to the influence of financial returns.

Investors often simply choose the loan with the highest interest rate and it is possible that the varying degrees of financial returns crowd out investors' intrinsic motivation to choose high social impact loans. I therefore analyze if social impact matters more in situations when all available loans promise the same financial returns, so that the heuristic of choosing the loan with the highest interest rate cannot be used. I find that the number of employees, the firms' turnover and the number of beneficiaries do not significantly influence funding success, even if all available loan applications promise the same financial returns, consistent with the baseline result using the full sample of transactions. However, investors are more likely to choose loan applications by female borrowers, suggesting an increased attention towards supporting female empowerment. A loan by a female borrower is 21% more likely to be chosen when all available interest rates are the same, compared with an increase of just 3% in the sample of all transactions. I interpret this as evidence that varying financial returns take away attention from the most salient dimensions of social impact (such as the gender of the borrower) and that the number of beneficiaries and employees seemingly lack salience.

The findings have important implications for peer-to-peer lending platforms with a social mission: they face the same challenges as impact investment funds, in that they need to carefully select borrowers that align with the platform's social mission. Platforms need to function as gatekeepers of social impact and cannot outsource the decision about which firm should receive funding from a social impact perspective to the crowd. For loans on the Lendahand platform, financial returns and expected social impact are negatively correlated, so that low social impact borrowers that promise high financial returns might out-compete high social impact borrowers.

This paper contributes to the understanding of individual investment decisions when impact investors pursue a double bottom line of generating financial returns and generating social impact. To my knowledge, it is the first empirical analysis of transactions on a peer-to-peer lending platform on which investors are paid interest and loans publicize a standardized set of social impact indicators.[7] Previous studies based on investment decisions on financially oriented peer-to-peer lending platforms viewed the behavior of investors mainly through the lens of optimal financial decision making and studied problems of asymmetric information (Zhang and Liu (2012), Hildebrand et al. (2017)), risk aversion (Paravisini et al. (2017)), trust (Chen et al. (2014)), and behavioral biases such as home bias (Lin and Viswanathan, 2016), identification bias (Riggins and Weber, 2017) and discrimination based on appearance (Jenq et al., 2015). To analyze how indicators of expected social impact influence investment decisions, researches have analyzed data from the US-based platform Kiva. On Kiva, philanthropic investors provide interest-free loans to micro-entrepreneurs in low-income countries. We know from previous studies, that Kiva's investors prefer to fund female borrowers and micro-entrepreneurs who generate impact in the health, education and environmental sector (Heller and Badding (2012), Ly and Mason (2012b)).[8] However, loans on Kiva are interest-free, so investors do not need to balance the two objectives of generating financial returns and generating social impact, a dilemma inherent to large-scale impact investment.[9]

[4] I use the interest rate and the loan maturity as measures of each loan's financial return and control for investment risk by only exploiting variation within risk-pooling intermediaries (so-called local partners). Social impact has many dimensions and I proxy for motives related to female empowerment and income generation by using the gender of the borrower, the firms' number of employees, the firms' turnover and a general measure for the reported number of beneficiaries. In an separate survey among 200 investors I confirm that these variables indeed influence investors' perception of the social impact created through the loan (see Appendix C). Furthermore, I control for the target amount and the number of competing loan applications, which Ly and Mason (2012a) show to influence investment decisions.

[5] I only observe investors' actions if their search leads to an investment, so the results should be interpreted as representing decisions on the intensive margin (choosing between competing loan application), as opposed to decisions on the extensive margin (choosing whether to engage in impact investment in the first place).

[6] In some specifications a low turnover is associated with higher funding success. However, the estimated effect sizes are small compared to the influence of financial returns.

[7] Previously studied peer-to-peer lending platforms focus either exclusively on the financial aspect of the loans (like Upstart, Funding Circle or Prosper) or operate as charities and focus exclusively on the social aspect of the (then interest-free) loans (like Kiva or Zidisha). Charity-focused platforms do not pay out interest to *the crowd*, but may nonetheless collect interest from borrowers to cover the cost of running the platform.

[8] Additionally, Ly and Mason (2012a) use peer-to-peer lending on Kiva to study the impact of competition between similar NGOs on fundraising and various studies in the business literature have studied the role of entrepreneurial narratives (Moss et al. (2015), Herzenstein et al. (2011), Allison et al. (2015)) and social proximity (Galak et al. (2011)). A limitation of these studies is that one cannot separate social impact from investment risk. For example, investors may prefer female borrowers because they want to contribute to female empowerment or because women have a better track record of repaying microcredit loans (Morduch, 1999).

[9] Outside of peer-to-peer lending, Barber et al. (2020) show that investors in dual-objective VC funds accept below-market financial returns. Døskeland and Pedersen (2016) show experimentally that a wealth framing is more effective than a

Lastly, this study applies the theory of motivation crowding out (see Frey and Jegen (2001), Bénabou and Tirole (2006) and Deci et al. (1999)) to financial markets, in a context where investors' intrinsic motivation to select loan applications that align with their values might be crowded out by the existence of varying financial returns. One recent study by Chen, Foster and Putterman (2019) tries to experimentally analyze the extent of motivation crowding out in impact investing by replicating a peer-to-peer lending environment with financial returns and social impact in the lab.[10] They find that a poverty reduction framing as well as financial incentives matter for the total amount investors decide to lend. In the experiment, there is no evidence for crowding out of intrinsic pro-social motives: in the high financial incentive environment, participants are as likely to react to the poverty reduction framing as in the low financial incentive environment.

The remainder of this paper is structured as follows. Section 2 introduces Lendahand, the peer-to-peer lending platform studied in this paper, and provides a framework to think about the decisions of the investors. Section 3 describes the transaction-level data and descriptive insights about the available loans, the investors and their investment behavior. Section 4 presents the empirical strategy to estimate which loan- and firm-specific characteristics determine funding success and how financial returns and social impact interact – possibly heterogeneously for different groups of people – to shape individual investment decisions. The results are presented in Section 5, together with additional robustness tests. Finally, Section 6 discusses limitations and concludes.

2. The lendahand platform and conceptual framework

2.1. The lendahand platform

The peer-to-peer lending platform studied in this paper is operated by the Dutch Fintech company Lendahand. Since 2014, Lendahand has passed on more than 100 million Euro from retail impact investors to over 2800 firms in low-income countries.[11] Lendahand explicitly advertises the expected social impact generated through the loans and aims to address the credit gap for small and medium-sized firms in low-income countries (*the missing middle*). At the same time, loans pay annualized interest rates between three and eight percent, a considerable financial return for the impact investors. Fig. 1 shows the Lendahand business model.

From the perspective of investors, the platform works as follows: Interested investor see a list of available loan applications of different prospective borrowers (for example a Kenyan solar company that needs funding to scale up, a South African manufacturing firm that wants to hire additional workers, or a Cambodian shop owner who wants to increase inventory). Clicking on a loan application opens a more detailed profile page (Fig. A.6 in Appendix A shows an example). These profile pages provide information about the social impact created through the loan, the financial terms of the loan, and key financial performance indicators of the local partner. Additionally, each profile also shows since when the loan application is online, how much total funding was requested and how much of this amount is still missing. After comparing loan applications from different borrowers, investors lend between a minimum of 50 Euro and the total missing amount.

From the perspective of borrowers, the platform works as follows: First, the borrower applies for a loan from one of Lendahand's local partners.[12] The borrower is then screened and selected by the local partner, and – upon acceptance – uploads a profile page to the platform. If the crowdfunding campaign is successful, the funds are transferred to the local partner, who passes them on to the borrower. If the target amount is not reached within 60 days, the loan would be canceled and the previous contributions returned to the investors. Until publication of this article, all loans have been funded within the 60-day limit.[13]

Local partners play a crucial role in the lending process. They screen, select, and monitor borrowers; sign the loan contract with the investors, and manage repayments. An important feature of Lendahand's business model is that local partners pool the investment risk from all borrowers in their portfolio and will repay a loan to investors even if the specific borrower advertised on the platform defaults.[14] This means that investors face the default risk of the local partner and not of the borrower. Therefore, after controlling for the local partner, firm-specific characteristics do not influence investment risk.[15] Investors are aware of the risk-pooling by the local partner according to a survey (see Appendix C), where theycorrectly named the local partner as the most important determinant of the investment risk. The risk-pooling of local partners notwithstanding, investors browse profile pages of individual borrowers on the platform and still choose individual borrowers rather than portfolios of local partners.[16]

2.2. Conceptual framework

How can we conceptualize the activities of impact investors on the platform? A priori, we assume that investor i maximizes a combination of financial returns and social impact[17] by choosing the amount y_i to contribute to loan application, l, intermediated by local partner, p, subject to an exogenous budget w_i. Denote with C_i the choice set of all available loan applications on a given day.[18]

moral framing in advertising socially responsible mutual funds to investors of a Norwegian bank.

[10] The authors present participants with a choice between different borrower profiles from Kiva, frame investment decisions in a neutral or in a poverty reduction setting and experimentally vary the intensity of financial incentives.

[11] The company operates two other crowdfunding platforms that focus exclusively on solar energy in African countries and on high-risk agricultural start-ups.

[12] These local partners are usually non-bank financial institutions with experience in providing micro- and mesocredit. Local partners are regulated by the financial authorities in the respective country and selected after a due diligence process by Lendahand.

[13] Sometimes local partners pre-finance the loan and backfill it after funding on the platform. If a funding campaign would exceed the 60-day limit, the local partner would have to finance the loan from other funds.

[14] Local partners are also the residual claimant to the total interest paid by the borrowers, of which they pass on a part to the investors and a part to the platform. This set-up is crucial as it assures that local partners have enough *skin in the game* to take the selection and monitoring of borrowers seriously.

[15] Theoretically, the default of many firms can lead to the default of the local partner and therefore the default risk of any particular firm has a small influence on the default risk of the local partner. However, local partners typically have more than 1000 firms in their portfolio and the influence of one single firm on the default risk of the whole local partner is therefore negligible.

[16] Most loans are intermediated by local partners as described here. Since 2016 Lendahand also offers direct loans, where investors sign a contract with only one borrower. These loans pay higher returns and are riskier. They are much high volume and constitute 21% of total funding volume, but only 2.5% of total loan applications. I either exclude or control for direct loans in the empirical analysis because the different risk structure makes direct loans difficult to compare to intermediated loans.

[17] Investors may value the creation of social impact because of pure altruism or because of a warm-glow type of impure altruism as in Andreoni (1990).

[18] We only observe investors' actions on the platform if their search for an investment opportunity leads to a completed transaction. I therefore do not model the search behavior explicitly and assume that investors form an opinion over the available loan applications on the day they actually made a transaction and that they necessarily invest a strictly positive amount: $\sum_{C_i} y_i > 0$. C_i is investor-specific, because investors visit the platform on different days and therefore face different sets of available loans. In Section 3 I discuss the construction of the choice sets in more details.

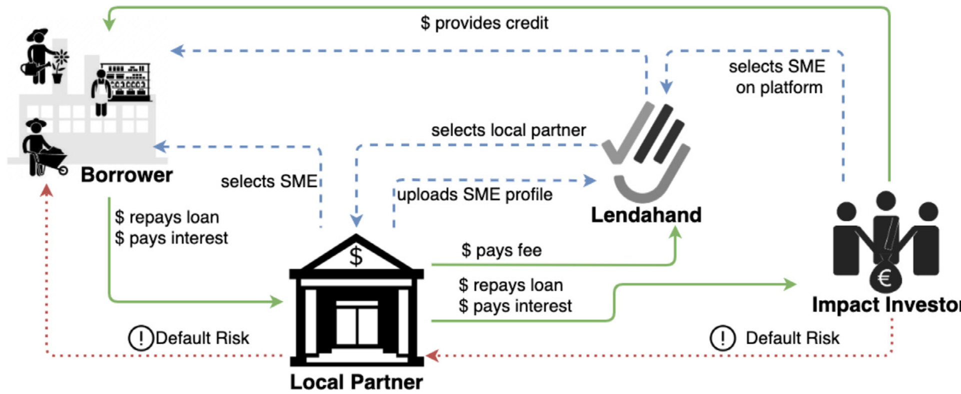

Fig. 1. The Lendahand business model: Investors provide credit to firms they select on the Lendahand platform. Investors receive repayments and interest from local partners, who have previously screened borrowers and uploaded their profile to the Lendahand platform for funding. Local partners handle repayments during the loan period and face the default risk with respect to the individual borrower. Default risk for investors is thus on the local partner level and not on the borrower level.

Then the investor maximizes the following utility function:

$$\max_{y_i \in C_i} U_i = U_i(F_l, D_p, S_l) \quad s.t. \quad 0 < \sum_{C_i} y_i \le w_i \tag{1}$$

Loans differ by their financial returns – a function of the loan-specific interest rate and loan maturity (F_l) and the local partner-specific default risk (D_p). Loans also differ by their (expected) social impact – a function of the loan-specific factors that influence social impact (S_l). In principle we would expect both, financial returns and social impact, to matter for the decisions of the investors but their relative importance is an empirical question. Further, U_i allows for differences across investors which motivates an analysis into the heterogeneity across demographic groups.

Investors face a trade off between financial returns and social impact because the loan which provides the highest social impact will not generally be the loan which yields the highest financial return. On the contrary, because borrowers and local partners know that investors value social impact, they may offer lower interest rates for loans which they predict to be popular based on social impact alone. We would therefore expect a negative correlation between financial returns and social impact characteristics in the data.

U_i is increasing in F_l and S_l. It is unclear, however, whether financial returns and social impact would empirically be substitutes or complements, put differently, whether the financial returns offered on the platform would crowd out or crowd in pro-social preferences (Bowles and Polanía-Reyes, 2012). If investors rely on heuristics to make decisions on the platform we may observe that financial returns influence the weight placed on social impact even with an additive utility function of the form $U_i = U_i(F_l, D_p) + V_i(S_l)$. For example, investors may choose the loan which offers the highest interest rate regardless of the social impact characteristics. Indeed, investors frequently choose the loan with the highest interest rate. If pro-social preferences are crowded out, we would expect them to be more important when all available interest rates are the same and the heuristic of choosing the loan with the highest interest rate cannot be used.

From Eq. 1 it follows that the transaction amount (y_i) and whether a loan was funded ($\mathcal{I}[y_i > 0]$) in a given choice set C_i are suitable measures for the success of a loan application. On the Lendahand platform the total size of each loan is fixed, so that the sum of all contributions to a given borrower ($\sum_i y_i = Y$) is a fixed amount. Therefore, borrowers who attract frequent or large (or both) contributions by individual investors will be funded faster and I can use funding duration as a third (aggregate) measure of success.

The business model of Lendahand is different from traditional and charity-focused peer-to-peer lending platforms for many reasons. First, in contrast to traditional peer-to-peer lending platforms, investors can compare standardized measures of social impact across all borrowers and could therefore actively seek out loans that create more social impact. The borrowers on the platform are firms located in low-income countries, a different applicant pool from traditional peer-to-peer lending platforms where borrowers are households or entrepreneurs in high-income countries. Second, in contrast to charity-focused peer-to-peer lending platforms like Kiva, investors are paid interest and need to balance the objectives of generating financial returns and generating social impact. Loans on the Lendahand platform are also larger (between 2000 Euro and 250,000 Euro) than loans on Kiva (on average 700 Euro).

The behaviour of investors on the Lendahand platform can thus best be understood as impact investment for *mesocredit*, as opposed to traditional crowdfunding or charitable (loan) giving for *microcredit*. This combination makes the Lendahand platform a unique opportunity to study investment decisions of impact investors and analyze the determinants of funding success for borrowers in low-income countries.

3. Data

Lendahand shared anonymized records of all transactions between June 2014 and October 2018. I link them to additional information about the borrowers and the local partners. Each of the almost 70,000 transactions represents a small loan by one of over 3000 investors to one of over 2100 firms.[19] Access to transaction-level data is a major advantage to previous studies of crowdfunding because it allows us to study the influence of financial returns and social impact on individual investment decisions, rather than on proxies of aggregate investment success.

In the following, I present summary statistics about the borrowers and investors that are active on the platform and first descrip-

[19] Originally, there are 72,525 transactions, see Appendix A for a detailed summary of the data cleaning process and the rules for exclusion of loan applications or transactions. In short, I excluded 2663 transactions associated with 61 loan applications because of missing data or incorrectly recorded timestamps. This leaves 69,862 transactions. When analyzing funding probability and transaction amount, I combine transactions by the same investor on the same day, resulting in 45,370 choice sets. When analyzing funding duration, I further exclude 14,230 transactions associated with 64 direct loan applications because their risk structure is not comparable to intermediated loans which are the focus of my analysis. Direct loans have a larger volume, which explains why there are so many transactions connected to only 64 loans.

Table 1
Summary statistics of loan applications.

	Mean (Std. Dev.)	Min.	Max.
Outcome			
Funding Duration (in Hours)	85.36 (130.85)	0.05	916.8
Financial Characteristics			
Total Loan Size (1000 Euro)	11.36 (16.69)	0.8	250
Interest Rate (% p.a.)	3.48 (0.65)	2.5	8.5
Loan Maturity (in Months)	25.13 (12.48)	6	48
Social Characteristics			
Female Borrower	57.71%		
Employees	15.76 (47.15)	1	780
Beneficiaries	19.95 (67.06)	0	1200
Turnover (1000 Euro)	384.36 (4,840.66)	0	217,539
Sectors			
Trade 32.8%	Financial Services 6.3%		
Services 22.9%	Processing 2.8%		
Agriculture 18.5%	Sustainable Energy 0.5%		
Manufacturing 16.2%			
Number Firms	2114		
Number Local Partners	16		

tive insights into the observed investment behavior. A comprehensive overview of all variables included in the data is available in Table A.7 in Appendix A.

Borrowers' Loan Applications I link transactions to financial (interest rate, loan maturity, loan size and the name of the intermediating local partner) and social characteristics (gender of the borrower, sector, country, turnover, number of employees and beneficiaries).[20] Table 1 reports summary statistics for loan- and firm-specific characteristics. The borrowers are connected to 16 local partners which are active in twelve different countries.[21]

Loan applications compete for funding along two dimensions: financial returns and social impact. In 46% of the transactions, investors select a loan application that did not provide the highest available interest rate. This indicates that investors are indeed trading off generating financial returns with generating social impact and that they are willing to forgo higher financial returns to satisfy their preferences about social impact, countries or sectors. The bottom row of Fig. 2 shows that such a trade-off also exists on an aggregate level: loan applications associated with higher social impact (a female borrowers, many employees or many beneficiaries) pay a slightly smaller interest rate to investors.[22] On the other hand, individual social impact characteristics are, with the exception of gender, positively correlated with each other.

All loan applications are funded completely within Lendahand's 60-day limit, but the time between the start and the end of the funding campaign varies considerably. Fig. 3 shows the share of incomplete funding campaigns by elapsed time after the start of the campaign. 44% of loan applications are funded within one day and only 16% need longer than one week. The median funding duration is 29 hours. Such a fast completion of funding campaigns is not uncommon for crowdfunding, showing the importance of measuring funding duration in small intervals, rather than relying on aggregated data by, say, day. Being able to exploit differences in funding

Fig. 2. Correlation between a loan's interest rate and various characteristics of social impact. The number of employees, the number of beneficiaries and the turnover are divided by the total loan size. The social impact can thus be interpreted as *impact per Euro*.

Table 2
Summary statistics for investors (Panel A) and choice sets (Panel B).

	Mean (Std. Dev.)	Min.	Max.
Panel A:			
Investor Characteristics			
Age at Registration	45.17 (14.16)	18	91
Female Investor	33.70%		
Nationality: Dutch	95.24%		
Portfolio Choices			
Total Nr. Investments	18.23 (34.41)	1	394
Amount First Investment (Euro)	479.25 (808.32)	40	10,000
Avg. Investment Amount (Euro)	464.10 (682.49)	42	10,000
Total Amount Invested (Euro)	7,784.45(18,597.93)	42	327,700
Number Investors	3086		
Panel B:			
Investment Behaviour by Choice Sets			
Investments per Choice Set	1.47 (1.00)	1	15
One Investment per Choice Set	72.40%		
Two Investments per Choice Set	17.26%		
Three or more Investments	10.34%		
Number of Available Loans	5.97 (2.62)	2	23
Amount Invested (Euro)	664.20 (1,254.56)	40	50,000
Number Choice Sets	45,370		

The minimum observed investment is below 50 Euro even though Lendahand requires a minimum investment of 50 Euro. The discrepancy comes from loans that are denominated in USD, where the minimum required investment is 50 USD, which translated to 40.20 Euro at the time of these investments.

duration of only a few hours is important for identification, but in this context matters little for whether a loan application will be successfully funded within Lendahand's 60-day limit. Nonetheless we can easily imagine a situation where peer-to-peer lending platforms such as Lendahand scale up, accept more loan applications and reach a point where credit supply by investors is (more) scarce. In such a context, differences in investors' preference would influence overall funding success.

Investors Fig. 4 shows that the number of registered investors (Fig. 4a) and the number of daily website visitors (Fig. 4b) increased over the past four years. I link transactions to demographic characteristics of the investors (gender, date of birth and nationality) and report summary statistics in Table 2, Panel A. 67% of Lendahand investors are men, 95% are Dutch (mostly from the urban areas of the Netherlands: Amsterdam, Rotterdam, The Hague and Utrecht) and the average investor is 45 years old at the time of registration. Table 2, Panel A shows the portfolio choices of impact

[20] This is precisely the information provided to investors at the time of their investment decision. Fig. A.6 in Appendix A shows how Lendahand presents loan applications on the website. Investors additionally see a profile picture and a text description by the borrower (sometimes written by the borrower, sometimes written by the local partner), but these were not retrievable for all loan applications.

[21] Cambodia, Philippines, Mongolia, Columbia, India, Uganda, Ghana, Kenya, Zambia, Georgia, South Africa and Indonesia in decreasing order of frequency. See Fig. A.7 in Appendix A.

[22] To approximate an investors individual contribution to the total advertised social impact, I standardize the number of employees, beneficiaries and turnover by the total loan size. After controlling for investment-risk by analyzing correlation within local partner, the pattern is less pronounced but qualitatively similar (Fig. A.5).

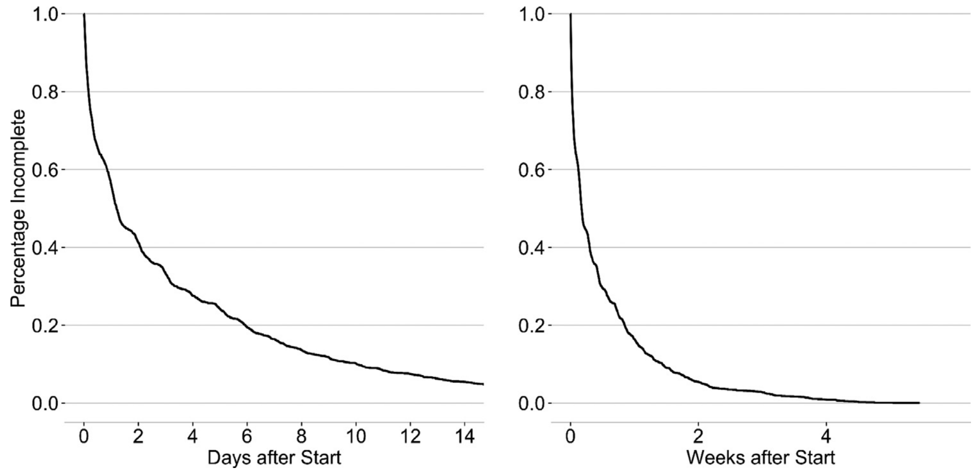

Fig. 3. Percentage of incomplete campaigns after X days (left) or weeks (right). The median funding duration is 29 hours. 44% of loan applications are funded in one day and only 16% need longer than one week.

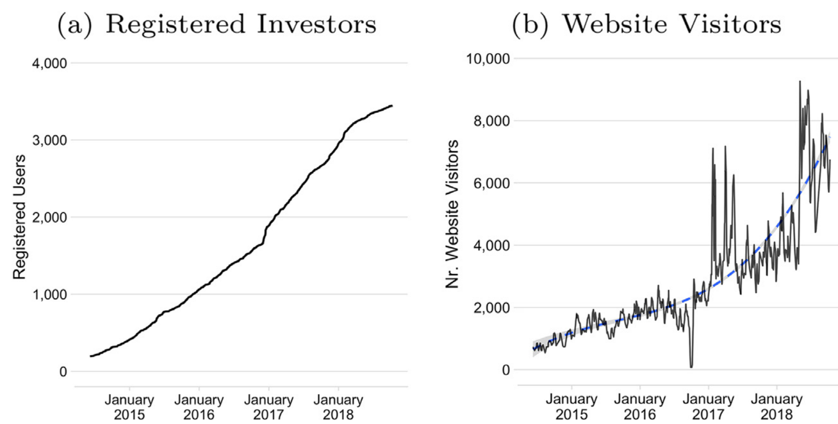

Fig. 4. Growth of userbase over time. The number of registered users (left) and daily website visitors (right) increase between 2014 and 2018. The three positive outliers in website visitors of 2017 and the one negative outlier in website visitors of 2016 were advertising campaigns and a period of technical website problems respectively. The dashed (blue) line shows a smoothed third degree polynomial of daily website visitors.

investors, who invest on average 7784 Euro in 18 distinct loans. There is no evidence that investors start with smaller trial loans, as the amount invested in the first loan (479 Euro) is slightly higher than the average transaction amount of all loans (464 Euro).

Choice Sets I construct the choice sets of all loan applications that were available for an investor on every day they made an investment, by combining the information on the exact timing of all funding campaigns with the timestamps of the transactions.[23] These investor- and time-specific choice sets allow us to define funding success as the probability that a loan was chosen, given the available alternatives. Within each choice set at least one loan was chosen by the investor. In the empirical analysis I compare loans that were chosen with loans that were available but were not chosen. We only observe investors' actions on the platform if their search for an investment opportunity leads to a completed transaction, but do not observe investors who visit the website but make no investment on a given day.[24] The results should therefore be interpreted as representing decisions on the intensive margin (choosing between competing loan applications), as opposed to decisions on the extensive margin (choosing whether to engage in impact investment at all).

Table 2, Panel B shows summary statistics of the 45,370 choice sets, representing 69,862 transactions by over 3000 investors to over 2100 firms. At the time of the investment decision, investors could choose from, on average, six different loan applications. 50% of the investors have made investments on the platform on at least different five days.

4. Empirical methodology

Three questions guide the empirical analysis in this paper: What firm- and loan-specific characteristics determine the investment decisions of retail impact investors? Do financial returns crowd out peoples' intrinsic pro-social motivation to choose borrowers with more social impact? And do the answers to these questions differ by investors' demographic characteristics, such as age, gender or nationality?

[23] My data would allow me to define choice sets as the available loan applications at each instance when an investment is made, rather than aggregating all loan applications of the same day. However, I argue that transactions on the same day by the same investor should be viewed as the same decision-making environment and therefore treat multiple transactions by the same investor on the same day as one choice set with more than one transaction, rather than as multiple independent choice sets.

[24] Similarly, we do not observe if an investor has formed an opinion about a loan application on an earlier date (prior to making an investment) and therefore only compare the chosen loans to the available alternatives on the day of the transaction. My results persist when I include available loans from a three-day window into a choice set to allow for the possibility that an investor saw earlier loans before making a transaction.

4.1. Determinants of investment decisions

I study the investment decisions from two perspectives: First, I use transaction-level data and estimate which firm- and loan-specific characteristics of financial returns and expected social impact influence the probability of funding and the amount invested for a particular loan, given the set of available alternatives. Mechanically, loan applications that are chosen often and receive a lot of funding should raise the requested amount faster. I confirm this by, secondly, focussing on the determinants of funding duration, as in Ly and Mason (2012b) and Heller and Badding (2012). Funding durations is a suitable aggregate measure for success, because it can be used without imposing an arbitrary threshold after which we would classify a funding campaign as unsuccessful.[25]

I regress each of the three outcome variables (whether an investment occurred, the invested amount and total funding duration) on variables that record financial returns (interest rate and loan maturity) and social impact (gender of the borrower, turnover, number of employees, and number of beneficiaries). The association of funding success with financial returns and social impact can inform us about the causal effect only after appropriately controlling for confounders. Most importantly, I control for the investment risk of loan applications by including local partner fixed effects (η_p) in all regressions. For intermediated loans, investors face the default risk of the local partner and not the default risk of the individual borrower. Therefore, any within-partner variation in firm-specific characteristics is unrelated to the default risk.[26]

In the transaction-level data, I further include investor-day fixed effects (μ_C). I therefore exploit variation within a given choice set, controlling for the unobserved heterogeneity between different investors and across time. When the unit of observation is a loan application and not a individual transaction, I include time fixed effects (the year, month, day-of-week and hour-of-day at which the funding campaign started), as well as control variables for the total loan amount that was requested and for the average number of competing loan applications at the start and end of the funding campaign.[27]

$$\log(T_{l,p}) = \beta_0 + \beta_1 F_l + \beta_2 S_l + \beta_3 Z_l + \eta_p + \varepsilon_{l,p} \tag{2}$$

$$y_{l,p,C} = \beta_0 + \beta_1 F_l + \beta_2 S_l + \beta_3 Z'_{l,C} + \eta_p + \mu_C + \varepsilon_{l,p,C} \tag{3}$$

Eq. 2 shows the log-linear regression to estimate the effect of financial returns (F_l contains the interest rate and loan maturity) and social impact (S_l contains the gender of the borrower, the number of employees, the number of beneficiaries, the turnover and the sector) on the logarithm of total funding duration in hours ($\log(T_{l,p})$). Control variables (Z_l) are the logarithm of total loan amount requested, the number of competing loan applications and time fixed effects. The unit of observation is a loan application, l, intermediated by a local partner, p. Eq. 3 shows the regression equation based on transaction-level data, where the outcome $y_{l,p,C}$ is the amount invested by investor i in the transaction or $(\mathcal{I}[y_{l,p,C} > 0])$, a binary indicator for whether loan l was chosen in a given choice set C. The control variables ($Z'_{l,C}$) are the logarithm of the total loan amount requested and an indicator variable for direct loans. Here, the unit of observation is a loan application, l, intermediated by a local partner, p, but within a given choice set, C. I include local partner fixed effects, η_p, in all regressions to control for investment risk, and investor-day fixed effects, μ_C, in Eq. 3 to control for investor- and time-specific differences. Heteroskedasticity robust standard errors are clustered at the level of the fixed effects – local partner in Eq. 2, local partner and choice set in Eq. 3.

Robustness As an alternative model specification I create two indicators: a *high financial return* indicator and a *high social impact* indicator and estimate if loans with exceptionally high returns or exceptionally high impact receive more funding, compared to otherwise similar loan applications. The high financial return indicator, $HighFin_{l,p}$ equals one for loan applications that pay an interest rate in the top quartile, corresponding to an interest rate of four or higher. The high social impact indicator, $HighSoc_{l,p}$ equals one for loan applications where at least two of the following apply: the number of employees is in the top quartile, the number of beneficiaries is in the top quartile, or the borrower's gender is female.[28] In a first step I estimate propensity scores by a logit regression of the indicators on the covariates not used in the construction of the indicators (see Eq. 4 and Eq. 5). X_l is an extended set of control variables.[29] I then match loan applications with similar propensity scores but different high financial return or high social impact indicators by nearest neighbour matching and generate two matched samples corresponding to the two indicators, high financial returns and high social impact.

$$\log\left(\frac{\mathcal{P}[HighFin_{l,p} = 1|S_l, X_l]}{P[HighFin_{l,p} = 0|S_l, X_l]}\right) = \beta_0 + \beta_1 S_l + \beta_2 X_l + \eta_p + \varepsilon_{l,p} \tag{4}$$

$$\log\left(\frac{\mathcal{P}[HighSoc_{l,p} = 1|F_l, X_l]}{P[HighSoc_{l,p} = 0|F_l, X_l]}\right) = \beta_0 + \beta_1 F_l + \beta_2 X_l + \eta_p + \varepsilon_{l,p} \tag{5}$$

I repeat the log-linear regression of Eq. 2 using the matched samples, but replace the respective set of covariates – F_l or S_l – by the corresponding indicator for high financial return or high social impact (see Eq. 6 and Eq. 7). Heteroskedasticity robust standard errors are calculated by bootstrapping (to incorporate uncertainty from the calculation of the propensity scores) and clustered at the local partner level.

$$\log(T_{l,p}) = \beta_0 + \beta_1 \text{HighFin}_{l,p} + \beta_2 S_l + \beta_3 Z_l + \eta_p + \varepsilon_{l,p} \tag{6}$$

$$\log(T_{l,p}) = \beta_0 + \beta_1 F_l + \beta_2 \text{HighSoc}_{l,p} + \beta_3 Z_l + \eta_p + \varepsilon_{l,p} \tag{7}$$

[25] Other studies on crowdfunding use alternative aggregate measures, such as the total amount raised, the number of individual transactions, or the average transaction size. However, these measures are only informative if funding campaigns can raise money in excess of the initial target amount, which is not the case on Lendahand. For example, a low number of transactions could imply that a loan is unpopular (because few investors are willing to contribute) or popular (because early investors have already financed the whole loan with few large investments).

[26] This specific risk-structure only holds for loans intermediated by local partners, which are 80% of all loans. When the outcome variable is funding duration, I excluded direct loans (made directly to a firm without intermediation by a local partner). However, when constructing the choice sets, excluding direct loans would misrepresent the set of available alternatives that investors have at the time of making their decision. In this situation I instead add a control variable for the loan type (direct or intermediated). Alternatively, I could exclude all choice sets where *any* direct loan was available, which would leave roughly 25,000 choice sets. The results from estimating all regressions on this restricted sample (see Appendix B, Tables B.15, B.16, B.17 and B.18) are similar to my baseline results.

[27] The results are robust to measuring competition only at the beginning of a funding campaign, the measure used in Ly and Mason (2012a), or to using a continuous average of the competition measure at each time a transaction to the loan application of interest was made. Ly and Mason (2012a) also show that the number of registered users influences funding duration in peer-to-peer lending. Given the gradual growth of registered users on Lendahand (recall Fig. 4), this is well approximated by including time fixed effects. Including the number of registered users or the number of website views before the start of the funding campaign does not influence the results.

[28] I do not include turnover in the construction of the indicator because it is a priori not clear if, from a social impact perspective, investors would prefer higher or lower turnover.

[29] Besides the logarithm of the total loan amount, the number of competing loan applications and time fixed effects that are also included in Z_l of Eq. 2, I also include the number of registered users, the number of website views before the start of the funding campaign and two indicators for changes to the website design.

4.2. Crowding out of pro-social motivation

Contrary to charity-based peer-to-peer lending platforms like Kiva, impact investments offers financial returns to investors. How do interest rates influence the willingness of investors to choose loans with more social impact? To find evidence whether such crowding out exists I compare choice sets where the interest rates of all available loans are the same with choice sets where the interest rates are different.

I estimate the same model as in Eq. 3, but interact loan- and firm-specific characteristics with an indicator variable ($\mathcal{D}_{l,C}$) which equals one when the interest rates of all available loans in the choice set are the same and zero otherwise (see Eq. 8).[30]

$$y_{l,p,C} = \beta_0 + \beta_1 F_l + \gamma_1 F_l * \mathcal{D}_{l,C} + \beta_2 S_l + \gamma_2 S_l * \mathcal{D}_{l,C} + \beta_3 \boldsymbol{Z'}_{l,C} + \eta_p + \mu_C + \varepsilon_{l,p,C} \tag{8}$$

4.3. Investment behavior of different groups

Lastly, I use demographic information about the investors to understand how the answers to the previous two questions vary by age, gender or nationality. I construct three variables that indicate if an investor is female ($Female_i$), born in or after 1980 ($Young_i$), or has the Dutch nationality ($Dutch_i$) and repeat the baseline choice set regression (Eq. 3) and the regression including the same interest rate interaction (Eq. 8) but include interaction effects of the demographic characteristics with the financial and social variables. Eq. B.1 and Eq. B.2 in Appendix B show the regression equations.

5. Results

5.1. Determinants of investment decisions

Table 3 reports the results to our first question: What loan- and firm-specific measures of financial return and social impact determine the investment decisions of retail impact investors? The first two columns show that higher financial returns – a high interest rate or a short loan maturity – have a large and statistically significant influence on individual investment behaviour. Increasing the interest rate of a loan by one percentage point almost doubles funding probability and leads to 122 Euro more funding per investment. Investors also prefer shorter loan maturities: a one year shorter loan maturity means the loan is 39% more likely to be chosen and leads to 46 Euro more funding.

In contrast, the firm-specific variation that indicates social impact through female empowerment, the number of employees and the number of beneficiaries does not influence investment behaviour. The gender of the borrower, the number of employees and the number of beneficiaries have no statistically significant influence on the probability that a loan application is chosen or on the amount invested. Investors seem to prefer firms with low turnover, but the effect size (a 3.7% higher funding probability per 1000 Euro lower turnover) is small compared to the estimated effect sizes of the interest rate and of the loan maturity.[31]

When many investors prefer the same loan, these individual decisions add up to a shorter overall funding duration, my aggregate measure of funding success. Columns 3–5 of Table 3 show that – in line with the determinants of individual investment decisions – funding duration is shorter for firms that promise high interest rates and short loan maturities but unaffected by social impact. Column 3 shows large effects of financial returns: all else being equal, a one percentage point higher interest rate means a loan is funded almost seven times faster and a one year shorter loan maturity means a loan is funded 2.23 times faster.[32] We observe the same pattern in Column 4, which reports the result of the propensity score matching regression. Loan applications that were classified as *high financial return* fund 4.3 times faster, even after restricting the sample to loans that are similar on all observable characteristics, but differ in their interest rates.

Firm-specific characteristics of social impact have no effect on the aggregate measure of funding success. Neither the individual components of social impact (in Column 3) in the unrestricted sample, nor the *high social impact* indicator (in Column 5) in the matched sample have a significant effect on the funding duration. This is in line with the results on individual investment behaviour, where firm-specific characteristics of social impact did not significantly influence investment behaviour.

The influence of control variables on funding duration is in line with the results reported in Ly and Mason (2012a) for peer-to-peer lending on Kiva. Mechanically, loans with a larger target amount need longer to complete funding, as do loans that face a lot of competition. Interestingly, while a large target amount does not make it more likely that a loan application is chosen, it does increase the amount invested per transaction.

The results are robust to alternative model specifications. In the analysis of funding duration, I try an alternative measure of funding duration (the time between *first lending* and end of the funding campaign), include squared terms of the social impact variables and exclude loan applications with exceptionally high values (above the 98th percentile) for the turnover, the number of employees or the number of beneficiaries (see Table B.10). I perform the propensity score matching with and without caliper matching to match only close neighbours (see Table B.11) or alternatively estimate the model with inverse probability weighting, with and without truncation of extreme weights (see Table B.12). The results in each of these alternative specifications remain virtually the same.

Rajan et al. (2015) propose an alternative way to measure whether (unobserved) soft borrower characteristics matter, by comparing the explanatory power of a restricted model in two situations that differ by the availability of soft characteristics. Using their methodology, I confirm that financial returns matter for the funding decisions of the investors and find no conclusive evidence to revert my previous result that social impact characteristics matter (much) less. The methodology and results are presented in more detail in Tables B.13 and B.14 in Appendix B.

5.2. Crowding out of pro-social motivation

On Kiva – where loans generate no financial returns to investors – funding success is influenced by characteristics of social impact (Ly and Mason (2012b), Heller and Badding (2012)), but in our context – where loans do generate financial returns to investors – funding success is not influenced by characteristics of social impact.

Table 4 shows that this observation cannot conclusively be attributed to crowding out of investors' intrinsic pro-social motivation. If crowding out would be the reason for the limited influence

[30] Note that the interest rates of all available investment opportunities is the same in only 3697 choice sets (8.15% of all choice sets). In a robustness test, I further restrict the sample by focussing on choice sets where the interest rate *and* the loan maturity are the same. This is the case for only 1022 choice sets (2.25% of all choice sets). Loan applications that are available in choice sets where the interest rates are the same are on average similar to loan applications that are available in choice sets where interest rates differ.

[31] A one standard deviation lower turnover increases funding probability by 0.04 standard deviations. In contrast a one standard deviation higher interest rate or a one standard deviation shorter loan maturity increase funding probability by 0.58 and 0.26 standard deviations respectively.

[32] For the interest rate: $\log(\hat{T}^1_{l,p}) - \log(\hat{T}^0_{l,p}) = \hat{\beta}(x^1 - x^0) = -1.933 \iff \hat{T}^1_{l,p} = \frac{1}{6.9}\hat{T}^0_{l,p}$

Table 3
The influence of financial returns and social impact on funding success.

	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent Variable:	Invested (y/n)	Amount Invested	log(funding duration)	log(funding duration)	log(funding duration)
Financial Return					
Interest Rate	0.242 (0.032)***	121.985 (14.471)***	-1.933 (0.200)***		-1.823 (0.143)***
Loan Maturity (in Months)	-0.008 (0.001)***	-3.832 (0.497)***	0.067 (0.007)***		0.064 (0.006)***
High Financial Return				-1.434 (0.101)***	
Social Impact					
Female Borrower	0.007 (0.008)	2.156 (4.145)	-0.057 (0.056)	0.070 (0.082)	
Employees	0.006 (0.006)	2.366 (5.222)	-0.066 (0.074)	-0.060 (0.061)	
Beneficiaries	0.000 (0.010)	-2.464 (5.205)	-0.024 (0.091)	-0.104 (0.100)	
Turnover (1000 EURO)	-0.009 (0.003)**	-8.000 (2.727)***	0.006 (0.038)	-0.031 (0.048)	
High Social Impact					-0.052 (0.079)
Sector (Base: Manufacturing)					
Wholesale, Retail	-0.010 (0.014)	-3.449 (7.013)	0.138 (0.100)	0.137 (0.117)	
Agriculture	0.024 (0.014)	12.297 (8.193)	-0.138 (0.116)	-0.194 (0.142)	
Services	-0.008 (0.012)	-2.403 (7.608)	0.154 (0.114)	0.189 (0.119)	
Processing	0.015 (0.020)	2.953 (12.590)	-0.182 (0.078)**	-0.153 (0.201)	
Financial Services	-0.090 (0.115)	15.761 (39.407)	1.114 (0.585)*	1.801 (0.691)**	
Sustainable Energy	-0.224 (0.036)***	-145.047 (20.836)***	1.173 (0.465)**		
Controls					
Loan Target (1000 EURO)	-0.010 (0.010)	26.500 (8.440)***	1.231 (0.108)***	1.368 (0.092)***	1.161 (0.076)***
Direct Loan	-0.032 (0.050)	48.131 (56.866)			
Competition			0.119 (0.033)***	0.099 (0.017)**	0.104 (0.016)**
Time FE	yes	yes	yes	yes	yes
Local Partner FE	yes	yes	yes	yes	yes
Investor-Day FE	yes	yes	n.a.	n.a.	n.a.
Dep. Variable, Unconditional Mean	0.246				
Adj. R^2	0.248	0.183	0.569	0.537	0.574
Joint F-Test, Social Variables	2.83	3.12	1.63	1.68	
Num. obs.	45,370	45,370	2114	1396	1468

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. Financial return (high interest rate and short loan maturity) significantly increase funding success, whereas social impact does not. Column 1–3 are estimated with (log) linear least square regressions. Column 4–5 follow a doubly robust estimation procedure where least squares regression is performed on a nearest-neighbor matched sample based on propensity scores. The high financial return indicator (Column 4) indicates loan applications that pay an interest rate above the 75th percentile (N = 857). The high social impact indicator (Column 5) indicates loan applications where two out of three social impact measures score above the 75th percentile (N = 734). In Column 4–5, loan applications are matched to exactly one other loan application with similar observable characteristics but a different financial or social indicator, reducing the number of observations to two times the number of high financial- or high social indicator observations. Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. Column 1–2 include investor-day fixed effects, exploiting only variation within choice sets, where the 45,370 choice sets are constructed as the set of available loan applications to a given investor on every day they made an investment. Among the available loan applications, loans that were chosen by the given investor are coded as invested = yes (dependent variable Column 1) and the investment amount is recorded (dependent variable Column 2). Local partner fixed effects control for investment risk in all regressions. The F-Test on joint significance tests the unrestricted model against the restricted model, where all four social impact variables are restricted to equal zero. Heteroskedasticity robust standard errors clustered at local partner and choice set level (Column 1–2) or the local partner level (Column 3–5). Standard errors are calculated by bootstrapping in Column 4, 5 to incorporate uncertainty from estimating the propensity scores.

of social impact characteristics, we would expect social impact to matter when all available loans pay the same financial returns. However, the interaction effects in Table 4, Column 2–3 show that most social impact characteristics still do not influence the funding probability in choice sets where the interest rate (Column 2) or the interest rate and the loan maturity (Column 3) are the same. One exception is the gender of the borrower, which matters more when all available financial returns are the same. In these situations, loans by female borrowers are 21% more likely to be chosen, compared with just 3% across all situations.[33] One possible interpretation is that the gender of the borrower is a more salient dimension of social impact than the number of beneficiaries or the number of employees.

5.3. Heterogeneity in investment decisions

Lastly, I discuss heterogeneity in investment decisions by gender, age and nationality. These results tell us whether considerations of social impact drive some people's investment decisions more than they drive other people's investment decisions. The results also improve our understanding of how investment decisions would look like in a different setting, with a different pool of investors. The descriptive statistics in Table 5 show that female and younger investors (born after 1980) invest less frequently and a smaller amount in total.

Table 6 shows how the influence of financial returns and social impact on investment behaviour differs by demographic characteristics of the investors.[34] First, we observe that the results presented in Section 5.1 persist: characteristics of financial return have a large influence on whether a loan is chosen and on the amount invested, whereas characteristics of social impact have less influence. The exception, again, is that investors prefer female borrowers and those with a lower turnover, but as in Table 3 the effect size is small compared to the influence of financial returns. To understand whether the determinants of people's investment decisions differ by their demographic characteristics, we turn to the interaction effects presented in Table 6. Column 1 presents evidence that the decisions of female investors are driven more by characteristics of social impact than those of male investors: female investors are 4 percentage points more likely to choose a loan application if the borrower is also female. This is almost double the effect size of male investors, who are just 2.1 percentage points more likely to chose loans by female borrowers.[35] Female investors are

[33] Table B.9 in Appendix B shows that when the interest rate of all alternatives is the same, loans by female borrowers also attract a larger amount per transaction.

[34] Table 6 shows the results for investor age and gender, were the differences are most pronounced. The heterogeneity by investor nationality is shown in Table B.19 in Appendix B.

[35] We should note that this result could also be due to identification bias (when investors choose borrowers which are similar to them Riggins and Weber (2017).

Table 4
Does social impact matter more when interest rates are the same?

	Baseline	Model 2	Model 3
Dependent Variable:	Invested (y/n)	Invested (y/n)	Invested (y/n)
Financial Return			
Interest Rate	0.242 (0.032)***	0.235 (0.032)***	0.242 (0.032)***
Loan Maturity (in Months)	-0.008 (0.001)***	-0.008 (0.001)***	-0.008 (0.001)***
Social Impact			
Female Borrower	0.007 (0.008)	0.005 (0.007)	0.006 (0.008)
Employees	0.006 (0.006)	0.006 (0.006)	0.005 (0.006)
Beneficiaries	0.000 (0.010)	-0.001 (0.010)	0.000 (0.010)
Turnover (1000 EURO)	-0.009 (0.003)**	-0.008 (0.003)**	-0.009 (0.003)**
Interact w. Same Interest			
Loan Maturity x Same Interest		-0.013 (0.002)***	
Female Borrower x Same Interest		0.046 (0.020)**	
Employees x Same Interest		0.003 (0.012)	
Beneficiaries x Same Interest		-0.007 (0.015)	
Turnover (1000 EURO) x Same Interest		-0.016 (0.012)	
Interact w. Same Interest, Maturity			
Female Borrower x Same Interest, Maturity			0.102 (0.035)***
Employees x Same Interest, Maturity			0.022 (0.019)
Beneficiaries x Same Interest, Maturity			-0.079 (0.043)*
Turnover (1000 EURO) x Same Interest, Maturity			-0.008 (0.018)
Sector (Base: Manufacturing)			
Wholesale, Retail	-0.010 (0.014)	-0.010 (0.014)	-0.010 (0.014)
Agriculture	0.024 (0.014)	0.023 (0.014)	0.023 (0.014)
Services	-0.008 (0.012)	-0.008 (0.012)	-0.008 (0.012)
Processing	0.015 (0.020)	0.014 (0.020)	0.014 (0.020)
Financial Services	-0.090 (0.115)	-0.086 (0.113)	-0.091 (0.115)
Sustainable Energy	-0.224 (0.036)***	-0.217 (0.036)***	-0.225 (0.036)***
Controls			
Loan Target (1000 EURO)	-0.010 (0.010)	-0.010 (0.010)	-0.009 (0.010)
Direct Loan	-0.032 (0.050)	-0.016 (0.047)	-0.032 (0.050)
Local Partner FE	yes	yes	yes
Investor-Day FE	yes	yes	yes
Dep. Variable, Unconditional Mean	0.246	0.246	0.246
Joint F-Test, Social Variables	2.83	3.7	4.78
Joint F-Test, Interaction Terms		3.41	2.85
Adj. R^2	0.248	0.250	0.249
Num. obs.	45,370	45,370	45,370

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. Even when all interest rates in a choice set are the same, investment decisions are still hardly influenced by variation in social impact characteristics. One exception is the gender of the borrower which increases funding probability more when interest rates are the same. The 45,370 choice sets are defined as the set of available loan applications to a given investor on a given day where they made an investment. The dependent variable is coded as invested = yes if the specific loan was chosen in the given choice set. There are 3697 choice sets where all interest rates are the same (8.15%) and 1022 choice sets where all interest rates and all loan maturities are the same (2.25%). All columns show results of linear probability models, the dependent variable is if an investor chooses a specific loan application among the set of available loan applications. Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. All columns use investor-day fixed effects, exploiting only variation within choice sets. Local partner fixed effects control for investment risk in all regressions. The F-Test on joint significance tests the unrestricted model against two restricted models, where (first) all four social impact variables are equal to zero or (second) all interaction terms with the same interest (or the same interest and same maturity) indicator are zero. Heteroskedasticity robust standard errors clustered at local partner and choice set level.

Table 5
Investment Behaviour by Gender, Age and Nationality.

	Investments	Avg. Amount	Total Amount	Observations
Gender				
Male	20.76	461.71	8,572.87	2046
Female	13.25	468.80	6,233.39	1040
Age				
Old	22.20	555.55	10,344.24	2014
Young	11.94	289.44	3,256.72	932
Nationality				
Foreign	13.31	342.08	3,740.47	145
Dutch	18.72	471.02	8,091.41	2899

Young means born in or after 1980, the date of birth is missing for 140 investors. Other common nationalities are Belgian (70) and German (19). Nationality is missing for 42 investors.

However, if we expect identification bias to occur symmetrically for men and women, then we would expect male investors to prefer male borrowers, contrary to what is reported in Table 6.

also more likely to invest when the borrower reaches many beneficiaries. Each additional beneficiary increases the funding probability by one percentage point, whereas it does not influence funding probability for male investors.

From Table 5, we already know that, on average, young investors have a smaller portfolio and make smaller transactions than older investors. Column 2 of Table 6 shows one possible reason. When the interest rate is high or the loan maturity is short, young investors do not increase their transaction amount by as much as old investors do, perhaps lacking the funds to take advantage of these opportunities. Column 1 shows that the impact of financial return characteristics and social impact characteristics on the likelihood to chose a specific loan is not systematically different between young and old investors. Table B.20 in Appendix B shows that there is no indication that different demographic groups behave differently when the interest rate of all available loans is the same compared to when it is different.

Table 6
Heterogeneity in investment decisions by age and gender.

	Model 1	Model 2
Dependent Variable:	Invested (y/n)	Amount Invested
Financial Return		
Interest Rate	0.242 (0.033)***	122.907 (16.713)***
Loan Maturity (in Months)	-0.007 (0.001)***	-2.112 (0.508)***
Social Impact		
Female Borrower	0.021 (0.020)	17.500 (8.315)**
Employees	0.014 (0.009)	4.567 (6.632)
Beneficiaries	-0.000 (0.011)	1.643 (6.948)
Turnover (1000 EURO)	-0.015 (0.005)***	-9.366 (3.942)**
Female Investors		
Interest Rate x Female Investor	-0.003 (0.005)	-3.441 (3.689)
Loan Maturity x Female Investor	0.001 (0.000)*	-0.378 (0.243)
Female Borrower x Female Investor	0.019 (0.006)***	-0.927 (4.274)
Employees x Female Investor	-0.001 (0.002)	-1.087 (2.454)
Beneficiaries x Female Investor	0.010 (0.004)**	-1.646 (2.929)
Turnover (1000 EURO) x Female Investor	0.005 (0.002)**	3.464 (1.862)*
Young Investors		
Interest Rate x Young Investor	0.009 (0.006)	-44.813 (6.712)***
Loan Maturity x Young Investor	-0.001 (0.000)*	1.156 (0.366)***
Female Borrower x Young Investor	-0.016 (0.006)**	-8.974 (4.168)**
Employees x Young Investor	-0.003 (0.004)	-13.660 (2.821)***
Beneficiaries x Young Investor	0.005 (0.003)	9.525 (3.339)***
Turnover (1000 EURO) x Young Investor	-0.001 (0.002)	5.088 (2.440)**
Sector (Base: Manufacturing)		
Wholesale, Retail	-0.009 (0.014)	-3.200 (7.035)
Agriculture	0.024 (0.014)	12.387 (8.266)
Services	-0.008 (0.012)	-2.324 (7.525)
Processing	0.015 (0.020)	2.725 (12.901)
Financial Services	-0.091 (0.115)	16.426 (40.349)
Sustainable Energy	-0.224 (0.036)***	-145.098 (20.666)***
Controls		
Loan Target (1000 EURO)	-0.010 (0.010)	26.963 (8.479)***
Direct Loan	-0.033 (0.050)	49.394 (56.966)
Interaction with Investor Nationality	omitted	omitted
Local Partner FE	yes	yes
Investor-Day FE	yes	yes
Dep. Variable, Unconditional Mean	0.246	
Adj. R^2	0.251	0.186
Num. obs.	45,370	45,370

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. The 45,370 choice sets are defined as the set of available loan applications to a given investor on a given day where they made an investment. Within each choice set, loans that were chosen by the given investor are coded as invested = yes (dependent variable Column 1) and the investment amount is recorded (dependent variable Column 2). Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. All columns use investor-day fixed effects, exploiting only variation within choice sets. Local partner fixed effects control for investment risk in all regressions. Young investors are defined as those born in or after 1980. Heteroskedasticity robust standard errors clustered at local partner and choice set level.

6. Conclusion

The importance of impact investments in financial markets has grown rapidly in the last decade, from a niche product for rich philanthropists to a mainstream product available to regular people. I analyse almost 70,000 transactions from a peer-to-peer lending platform and show that investment decisions are predominantly driven by considerations of financial returns, even if loans vary considerably in their expected social impact. One way to think about the economic significance of the results is by asking what borrowers would have to change to raise a larger amount of funding. The median loan application receives 17 transactions during the duration of the funding campaign, until the target loan size is reached. Table 3, Column 2 shows that the median project could collect 2074 Euro in additional funding by increasing the interest rate by one percentage point (17 times 121.985) or collect 391 Euro in additional funding by decreasing the loan maturity by 6 months. While these amounts might not seem large in absolute terms, they reflect an 33 percent and 6.3 percent increase over the median loan size of 6200 Euro respectively and make a sizable difference for a small- or medium-sized firm in a low-income country. In contrast, the analysis of this paper suggests that borrowers would not be able to significantly change their funding success on the crowdfunding platform by improving their characteristics of social impact.

Funding success on the Lendahand platform is not significantly influenced by the borrowers' characteristics of social impact, a finding which contrasts previous studies in a context without financial incentives (the American peer-to-peer lending platform Kiva). For crowdfunding platforms that focus on impact investing, this observations has important implications. If individual impact investors are unable to identify high social impact borrowers on peer-to-peer lending platforms, these platforms – just like impact investment funds – need to function as gatekeepers of social impact. Platforms should perform continued monitoring of borrowers' social impact, just as impact investment funds do. The platform studied in this paper currently operates in an environment where so much funding is available, that even unpopular borrowers eventually reach their target amount. Nonetheless, we can easily imagine a situation where peer-to-peer lending platforms face lower credit supply or increase the number of competing loan applications. Unpopular loan applications would then receive no funding (rather than just slow funding). This study can be also be seen as a cautionary tale in the attempt of scaling up impact investment by outsourcing funding decisions to individual investors. Such a strategy could backfire, especially if financial returns and social impact are negatively correlated, and low social impact borrowers promising high financial returns can out-compete high social impact borrowers.

We observe how investors decide between competing borrowers within the platform but do not observe what determines their decision to take part in impact investment in the first place. This is unfortunate, because ideally we also want to understand whether social impact matters on the extrinsic margin for the decision to participate in impact investing. Such a hypothesis is supported by Lendahand's experience and by qualitative evidence collected by the author. In a survey of 200 Lendahand investors, many respondents said that they value social impact but that they trust Lendahand to have selected borrowers carefully in this respect. While my data does not allow me to estimate the determinants of funding behavior on the extrinsic margin, such a research project could be an important complement to better understand the motivation of individual impact investors.

It is possible that investors on peer-to-peer lending platforms are younger, richer, more urban and have higher financial literacy than customers of traditional retail banks. However, it is unclear whether customers of traditional banks would be more or less driven by financial returns – vis a vis social impact – than the investors active on platforms like Lendahand or Kiva. Investors on Lendahand or Kiva might be more pro-social since they actively sought out a platform where they can combine generating financial returns with generating social impact. On the other hand, investors active on peer-to-peer lending platforms participate in a relatively young, innovative and risky financial market that suggests that they are less risk-averse and generally better informed about – and potentially place more importance on – financial returns. The results from estimating the extent of heterogeneity in investment decisions by age, gender and nationality provide us with some insights into the external validity of the conclusions. For example, if investors in regular financial markets are on average older than investors on Lendahand, the results in Table 6 suggest that they would focus slightly less on financial returns and put more importance on the gender of the loan applicant.

Declaration of Competing Interest

None

CRediT authorship contribution statement

Philipp Kollenda: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing, Visualization.

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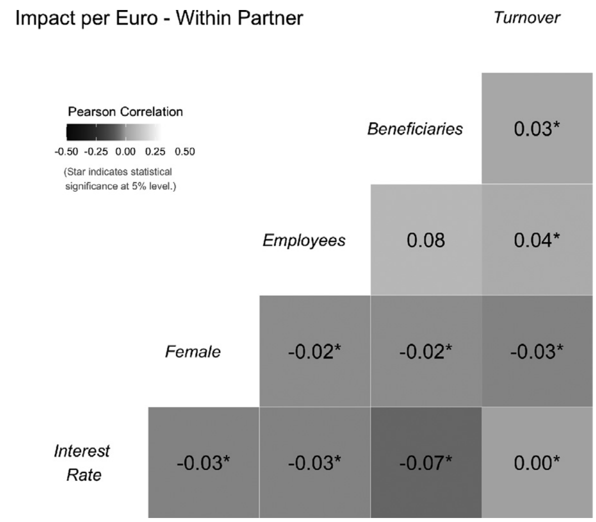

Fig. A.5. Correlation between a loan's interest rate and various characteristics of social impact within local partner. The number of employees, the number of beneficiaries and the turnover are divided by the total loan size. The social impact can thus be interpreted as *impact per Euro*. Correlations come from regressions of scaled bivariate pairs with local partner fixed effects to adjust for the role of local partners in confounding firm-specific social impact characteristics and investment risk.

Appendix A. Data Appendix

Lendahand shared anonymized records of all transactions on their peer-to-peer lending platform between June 2014 and October 2018, which I link to information about the investors, the borrowers and the local partners.[36] The following appendix describes the details of the data collection and cleaning process.

Data Collection The main data source is the internal database of Lendahand, where all transactions are recorded and information about borrowers, local partners and investors is stored. The information about borrowers and local partners is also visible on Lendahand's website. The database has been accessed on October 13th 2018 to obtain the latest version of the data. The unit of observation is one transaction, which represents a loan by one investor to one firm. The system automatically attaches an investor ID, a firm ID and a local partner ID to each transaction and I merge transactions to information about investors, firms and local partners using these IDs. In principle, I have access to older transactions as well, since the Lendahand platform started operating on a small scale in 2013. However, I use only loans after June 2014 because earlier the system did not consistently record the exact start time of the funding campaign for previous loan applications. Additionally, there were very few loans in the starting months of the platform and the environment was not comparable to a full-scale peer-to-peer lending platform. I access the number of website visits from Google Analytics.

Exclusion criteria for loan applications The original dataset consists of 72,525 transactions, by 3445 investors to 2302 firms. To make the data suitable for further analysis I exclude a number of transactions for various reasons, detailed below.

Twenty loan applications were funded by a single investor through a private invitation. Because these loans were never publicly available on the website and thus should not be considered crowdfunding, they are excluded. Additionally, some funding campaigns were temporarily suspended (for example to add missing information to the borrower's profile). While loans are suspended,

[36] For convenience, I use the information about investors, borrowers, and local partners provided by Lendahand. But, except for confidential information about investors all information is publicly available on Lendahand's website.

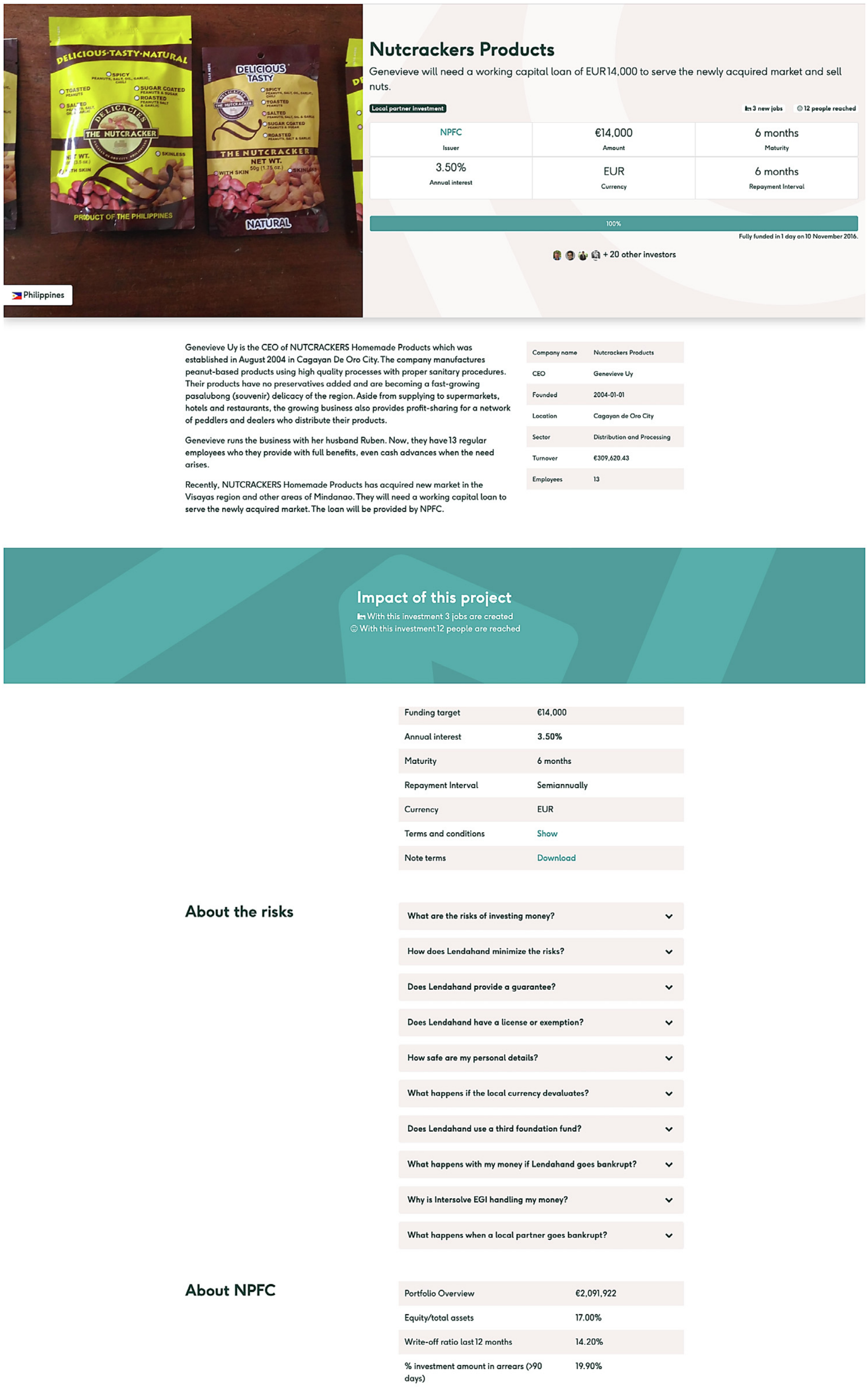

Fig. A.6. A borrower profile page on the Lendahand platform.

they are not visible on the website and cannot attract funding. Unfortunately, the database only records the time at which the funding campaign started and not the timestamps when funding campaigns were suspended and resumed. This makes it impossible to calculate exact *net* funding duration for suspended loans. Therefore, I exclude 41 loan applications with funding duration above the 99th percentile (more than 29 days and 2 hours) and/or above the 99th percentile of time between the recorded start and the time of the first lending.

I further exclude investors that only invested in loans that are excluded after applying my exclusion criteria, which excludes some early investors that have not returned to the platform.

As explained in Section 2, 80% of all loans via the Lendahand platform are intermediated by a local partner in the respective

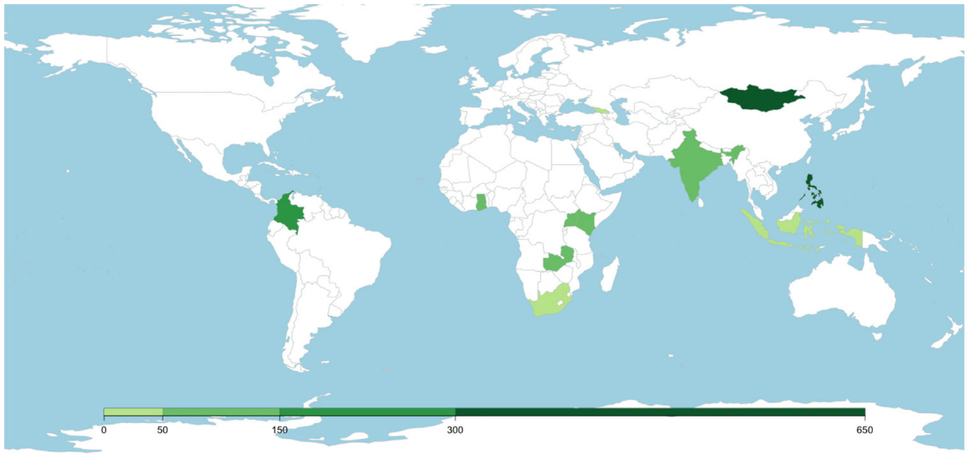

Fig. A.7. Map of countries where borrowers are active.

low-income country. With these loans, we can control for investment risk by including local partner fixed effects in the regression analysis. Some loans, however, are not intermediated by a local partner but made directly to a firm. Since we cannot accurately control for investment risk for these loans, direct loans are excluded from the analysis of funding duration that uses loan-level data. However, I do not exclude them from the construction of the choice sets because doing so would misrepresent the set of available investment opportunities that the investors faced. Instead, I include a control variable for the loan type (intermediated or direct) in the analysis of individual investment decisions using transaction-level data. As Tables B.15, B.16, B.17 and B.18 show, the results are robust to instead excluding all choice sets where at least one direct loan was available.

Data Cleaning Some observations had clearly identifiable data errors that were corrected before further analysis. Loan applications intermediated by a local partner in India, Milaap, are usually further distributed as microloans to a large number of beneficiaries. While the head of the microfinance institution that applies for the loan is often male (and the loans are therefore coded as male borrower in the dataset), the loans are usually distributed further to explicitly benefit female microlenders. Whenever the fact that the end-beneficiaries are exclusively female was clearly visible from the text description of the loan, the loan was re-coded as a female borrower to indicate that the recipients of the loan are female.

After an update to the website the variable *numbers of beneficiaries* was included in borrower profiles after January 1st 2018. Lendahand calculates this variable as the number of new jobs multiplied with 4 and I follow this convention to retrospectively calculate the number of beneficiaries for loans before January 2018.

Loans from the local partner in Georgia are disbursed in USD. While the influence of the loan currency on funding success is interesting in itself, there is only one local partner that offered USD loans to impact investors. Instead of controlling for the currency, I therefore translate the loan target- and transaction amount to Euro with the exchange rate valid at the time when the loan was disbursed. The difference between loans denoted in USD and loans denoted in Euro (all for firms in non-Euro countries) is that in the latter case the local partner is subject to the risk of currency fluctuations.

To construct the competition variable, I look at overlaps in the start and end times of funding campaigns to count the number of competing loan applications at the start of the funding campaign as my preferred competition variable. The results are robust to using the number of competing loan applications at the end of the funding campaign (as in Ly and Mason (2012a)) or an average over all the times a transaction occurred.

Correction of starting time Before November 2017, the database by default only recorded the day on which a funding campaign started and not the exact time. Because 45% of the loans are funded within one day, this would have introduced a considerable degree of measurement error, making reliable analysis of the determinants of funding success impossible. To correct this, I manually inferred each loan application's exact starting time using additional information from the Lendahand database. In short, whenever a loan application is *set live*, the database records a mutation of the loan application's status (from non-active to active). While the database records the date of the mutation as the starting time, the mutation itself has a timestamp which is exact to the second. I use these timestamps to correct the vast majority of starting times. In cases where this was not possible and where the corrected start times lead to obvious mistakes (for example if the start time was recorded as being after the first transaction occurred), I manually set the start time as thirty minutes before the first transaction, the median duration from start to first lending. This only affects a handful of loan applications. Before using the timestamps of the mutations I corrected inconsistencies in the recorded time zone. Some timestamps were mistakenly coded one or two hours too early. They were corrected by constructing an algorithm based on the assumption that the assigned IDs of the mutations reflect the true order of the timestamps.

The correction of the start times to accurately measure within-day variation is important for the analysis. However, because it introduces additional researcher degrees of freedom in the exact data cleaning process, I report the results in Table B.10, Column 1 with using the time of the first transaction as the start time of the funding campaign. While this is less exact, it is recorded consistently for all loan applications and requires no further corrections of the data. The baseline results are not affected by using this alternative measure.

Additional data description The main description of the data is provided in Section 3. The rest of this appendix provides an additional overview of the dataset. Table A.7 gives an overview of the variables generated or recorded in the dataset and their classification into loan- and firm-specific characteristics. For the most part, the variables captured in the dataset contain exactly the information that investors have available when making their investment decision. The only information that is not coded in the dataset is the profile picture and the text description. The firms

Table A.7
Overview of variables used in analysis.

Name of variable	Description
Outcome ($y_{l,p,C}$ and $T_{l,p}$):	
Transaction (yes / no)	Binary variable indicating if a transaction to loan application (l) intermediated by local partner (p) occurred in choice set C.
Transaction amount (in Euro)	The amount of the transaction in Euro. Amounts in USD are translated to Euro using the exchange rate at the time of the investment.
log Funding Duration (in hours)	Total number of hours between start and end of funding campaign.
Financial characteristics (F_l):	
Interest rate (annualized)	
Loan maturity (in months)	
Social characteristics (S_l):	
Gender of Borrower	1 = female, 0 = male
Turnover of Firm in 1000 Euro	
Number of Employees	As reported by the firm.
Number of Beneficiaries	As estimated by firm and local partner. Often newly created jobs or – in sustainable energy sector – installed solar house systems
Amount of jobs created	Reported expectation of job creation as a result of the loan. Not included in analysis because used to construct number of beneficiaries.
Firm's sector (rel. to manufacturing)	Coded as agriculture, distribution/processing, financial services, manufacturing/production, services or wholesale/retail.
Control variables (Z_l or $Z'_{l,C}$)	
Target funding in 1000 Euro	Total loan amount requestion by firm.
Competition	Average number of competing loan applications at the start and end of the funding campaing.
Local Partner fixed effect	
Time fixed effect	Includes year and month fixed effects for the start of the funding campaign, the day of the week and the hour of the day.
Investor-Day Fixed Effect	Set of fixed effects to exploit only within-choice set variation, where one choice set reflects the set of available loan applications for an investor on every day they made an investment. This keeps constant unobserved heterogeneity in investment behaviour between investors and across time.

Table A.8
Financial and social characteristics by length of funding duration.

	Mean (faster)	Mean (slower)	Difference in Means
Financial Characteristics			
Interest Rate	3.56	3.28	0.28***
Loan Maturity	24.06	27.70	-3.64***
Social Characteristics			
Female Borrower	0.56	0.61	-0.05*
Employees	14.39	19.05	-4.66**
Beneficiaries	18.98	22.30	-3.32
Turnover (1000 Euro)	404.04	337.03	67.01

***$p<0.01$; **$p<0.05$; *$p<0.1$. Column 1 displays averages for loans that have been funded faster than average (below 85 hours), Column 2 displays averages for loans that have been funded slower than average (above 85 hours).

that seek funding on the Lendahand website are situated in 15 different countries: Cambodia (683), Philippines (366), Mongolia (308), Columbia (281), India (132), Uganda (99), Ghana (76), Kenya (70), Zambia (61), Georgia (22), South Africa (11), Mozambique (6), Indonesia (5), Cameroon (4) and Mexico (2)). Since most local partners are only active in one country, there is almost no country variation after including local partner fixed effects. The information on the country is therefore not included and the analysis can give no insights into preferences of investors for certain countries.

Comparing fast and slow loans Complimentary to the empirical analysis presented in Section 5, we can split the loans by funding duration and explore differences-in-means of financial and social characteristics between faster- and slower-funding loans. Table A.8 shows that loans that were funded faster than average have a higher interest rate and lower loan maturity, in line with the results presented in Table 3. For the social characteristics, the differences are statistically significant for the number of employees, but not for the gender of the borrower, the number of beneficiaries or the firm's turnover. It is important to keep in mind that a comparison of means does not take into account the influence of the loan size on funding duration and - to the extent that loan size is correlated with the number of employees, beneficiaries and turnover - will give a less accurate picture than the multivariate regressions in Section 5 that control for loan size.

Appendix B. Results Appendix

In Section 5 I report the answers to the three questions that guide this study: What firm- and loan-specific characteristics determine the investment decisions of impact investors? Do financial returns crowd out peoples' intrinsic pro-social motivation to choose borrowers with more social impact? And do the answers to these questions differ by the gender, age and nationality of the impact investors? I show that it is predominantly financial returns that influence investment decisions, even when there is considerable variation in the amount of social impact that loans create. I further show that these results are most likely not driven by crowding out of intrinsic pro-social motivation and are relatively stable across different investor demographics. In this appendix, I present some additional results and further robustness tests.

B1. Model specification of heterogeneity by investor characteristics

I use demographic information about the investors to understand how the answers to the previous two questions vary by age, gender or nationality. The estimation complements the baseline transaction-level regressions presented in Section 4 by including interaction effects of investors' demographic characteristics with financial and social loan characteristics. The two model equations

Table B.9
Does social impact matter more when interest rates are the same? - Amount invested.

	Baseline	Model 2	Model 3
Dependent Variable:	Amount Invested	Amount Invested	Amount Invested
Financial Return			
Interest Rate	121.985 (14.471)***	118.314 (14.406)***	121.842 (14.500)***
Loan Maturity (in Months)	-3.832 (0.497)***	-3.635 (0.513)***	-3.834 (0.499)***
Social Impact			
Female Borrower	2.156 (4.145)	1.159 (3.990)	1.574 (4.175)
Employees	2.366 (5.222)	2.311 (4.984)	1.790 (5.165)
Beneficiaries	-2.464 (5.205)	-2.705 (5.341)	-2.176 (5.248)
Turnover (1000 EURO)	-8.000 (2.727)***	-7.900 (2.838)***	-8.126 (2.757)***
Interact w. Same Interest			
Loan Maturity x Same Interest		-6.143 (1.615)***	
Female Borrower x Same Interest		24.024 (9.038)**	
Employees x Same Interest		5.315 (8.563)	
Beneficiaries x Same Interest		-18.212 (12.266)	
Turnover (1000 EURO) x Same Interest		-0.477 (8.442)	
Interact w. Same Interest, Maturity			
Female Borrower x Same Interest, Maturity			56.376 (24.643)**
Employees x Same Interest, Maturity			40.243 (20.782)*
Beneficiaries x Same Interest, Maturity			-46.656 (24.854)*
Turnover (1000 EURO) x Same Interest, Maturity			15.433 (11.640)
Sector (Base: Manufacturing)			
Wholesale, Retail	-3.449 (7.013)	-3.904 (7.101)	-3.779 (7.136)
Agriculture	12.297 (8.193)	11.962 (8.317)	11.702 (8.191)
Services	-2.403 (7.608)	-2.579 (7.540)	-2.555 (7.704)
Processing	2.953 (12.590)	2.060 (13.175)	2.571 (12.647)
Financial Services	15.761 (39.407)	17.740 (39.000)	15.433 (39.575)
Sustainable Energy	-145.047 (20.836)***	-142.006 (20.697)***	-145.440 (21.003)***
Controls			
Loan Target (1000 EURO)	26.500 (8.440)***	26.601 (8.559)***	26.578 (8.428)***
Direct Loan	48.131 (56.866)	53.897 (57.389)	47.539 (56.879)
Local Partner FE	yes	yes	yes
Investor-Day FE	yes	yes	yes
Joint F-Test, Social Variables	3.12	2.74	7.03
Joint F-Test, Interaction Terms		2.29	3.3
Adj. R^2	0.183	0.184	0.183
Num. obs.	45,370	45,370	45,370

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. The 45,370 choice sets are defined as the set of available loan applications to a given investor on a given day where they made an investment. There are 3697 choice sets where all interest rates are the same (8.15%) and 1022 choice sets where all interest rates and all loan maturities are the same (2.25%). All columns show results of linear regression models, the dependent variable is the amount invested in a given choice set. Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. All columns use investor-day fixed effects, exploiting only variation within choice sets. Local partner fixed effects control for investment risk in all regressions. The F-Test on joint significance tests the unrestricted model against two restricted models, where (first) all four social impact variables are equal to zero or (second) all interaction terms with the same interest (or the same interest and same maturity) indicator are zero. Heteroskedasticity robust standard errors clustered at local partner and choice set level.

are specified below.

$$\begin{aligned} y_{l,p,C} = {} & \beta_0 + \beta_1 F_l + \delta_1 F_l * Female_i + \delta_2 F_l * Young_i + \delta_3 F_l * Dutch_i + \\ & \beta_2 S_l + \delta_4 S_l * Female_i + \delta_5 S_l * Young_i + \delta_6 S_l * Dutch_i + \\ & \beta_3 Z'_{l,C} + \eta_p + \mu_C + \varepsilon_{l,p,C} \end{aligned} \tag{B.1}$$

$$\begin{aligned} y_{l,p,C} = {} & \beta_0 + \beta_1 F_l + \gamma_1 F_l * \mathcal{D}_{l,C} + \beta_2 S_l + \gamma_2 S_l * \mathcal{D}_{l,C} + \\ & \delta_1 F_l * Female_i + \delta_2 F_l * Young_i + \delta_3 F_l * Dutch_i + \\ & \delta_4 S_l * Female_i + \delta_5 S_l * Young_i + \delta_6 S_l * Dutch_i + \\ & \gamma_3 F_l * \mathcal{D}_{l,C} * Female_i + \gamma_4 F_l * \mathcal{D}_{l,C} * Young_i + \\ & \gamma_5 F_l * \mathcal{D}_{l,C} * Dutch_i + \\ & \gamma_6 S_l * \mathcal{D}_{l,C} * Female_i + \gamma_7 S_l * \mathcal{D}_{l,C} * Young_i + \\ & \gamma_8 S_l * \mathcal{D}_{l,C} * Dutch_i + \\ & \beta_3 Z'_{l,C} + \eta_p + \mu_C + \varepsilon_{l,p,C} \end{aligned} \tag{B.2}$$

B2. Same interest rate choice sets: Loan amount

Table 4 in the main text reports how the probability that an investor chooses a given loan differs in choice sets when available interest rates are the same, versus when they are different. Table B.9 answers the same question but uses the amount invested as the dependent variable of the regression. When the interest rate is the same, loan applications by female borrowers and those with shorter maturities receive larger transactions. This is in line with the results from Table 4, which shows that these type of loans also have a higher funding probability when interest rates are the same.

B3. Robustness of least squares and propensity score regressions.

I present alternatives to the baseline specification (Table 3, Columns 3–5) below. Table B.10 reports alternative ways of specifying the log-linear model used to estimate the determinants of funding duration on a loan-level. The first column uses an alternative measure of funding duration to reduce researcher degrees of freedom in the correction of accurate timestamps as described in Appendix A. Column 2 uses the loan target, the firms' turnover, the number of employees and the number of beneficiaries in their original form without log-transformation, Column 4 instead excludes loan applications with exceptionally high values (above the 98th percentile) for the firms' turnover, the number of employees and the number of beneficiaries. Column 3 includes squared terms of social impact variables to incorporate potential non-linearity in the effect on funding duration.

Table B.10
Robustness I - alternative specifications: The influence of financial returns and social impact on funding success.

	Model 1 Alt. Funding Duration	Model 2 No Log Transformation	Model 3 Squared Terms	Model 4 No Outliers
Dependent Variable:	log(alt. funding duration)	log(funding duration)	log(funding duration)	log(funding duration)
Financial Return				
Interest Rate	-1.950 (0.206)***	-1.648 (0.239)***	-1.651 (0.240)***	-1.776 (0.233)***
Loan Maturity (in Months)	0.068 (0.006)***	0.080 (0.008)***	0.080 (0.008)***	0.084 (0.007)***
Social Impact				
Female Borrower	-0.099 (0.081)	-0.133 (0.068)*	-0.124 (0.066)*	-0.137 (0.071)*
Employees	-0.056 (0.079)	-0.000 (0.001)	0.001 (0.005)	0.003 (0.005)
Employees squared			-0.000 (0.000)	
Beneficiaries	-0.038 (0.095)	-0.000 (0.000)	-0.001 (0.002)	-0.001 (0.004)
Beneficiaries squared			0.000 (0.000)	
Turnover (1000 EURO)	0.004 (0.044)	0.000 (0.000)***	0.000 (0.000)	-0.000 (0.000)
Turnover squared			-0.000 (0.000)	
Sector (Base: Manufacturing)				
Wholesale, Retail	0.254 (0.109)**	0.290 (0.121)**	0.295 (0.110)**	0.266 (0.118)**
Agriculture	-0.050 (0.117)	-0.010 (0.167)	-0.005 (0.164)	-0.033 (0.170)
Services	0.276 (0.120)**	0.270 (0.111)**	0.271 (0.110)**	0.256 (0.117)**
Processing	-0.054 (0.062)	-0.033 (0.117)	-0.030 (0.118)	-0.025 (0.111)
Financial Services	1.172 (0.574)*	1.359 (0.630)**	1.317 (0.640)*	0.959 (0.653)
Sustainable Energy	1.357 (0.473)**	1.120 (0.467)**	1.125 (0.455)**	0.836 (0.435)*
Controls				
Loan Target (1000 EURO)	1.358 (0.122)***	0.041 (0.010)***	0.041 (0.010)***	0.054 (0.009)***
Competition	0.118 (0.030)***	0.114 (0.031)***	0.114 (0.031)***	0.110 (0.030)***
Time FE	yes	yes	yes	yes
Local Partner FE	yes	yes	yes	yes
Joint F-Test, Social Variables	2.73	7.03	1.26	1.04
Adj. R^2	0.521	0.508	0.508	0.521
Num. obs.	2114	2114	2114	2016

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. The unit of observation is one loan application, the outcome variable is funding duration, and all models are estimated with log-linear least square regressions. Column 1 uses an alternative measure of funding duration as the time between the first lending and the end of the funding campaign, which is less precice but also less prone to problems with erroneously recorded timestamps. Column 2 leaves number of employees, number of beneficiaries, turnover and loan target as is, without log transformations. Column 3 includes squared terms for employees, beneficiaries and turnover. Column 4 excludes loan applications with exceptionally high values (abover 98th percentile) for employees, beneficiaries and turnover. Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed in columns 1, 3 and 4. All models include time fixed effects and local partner fixed effects, to control for investment risk. The F-Test on joint significance tests the unrestricted model against the restricted model, where all social impact variables are equal to zero. Heteroskedasticity robust standard errors clustered at the local partner level.

In Table B.11 I specify alternative ways of conducting the doubly robust propensity score matching regressions and Table B.12 uses inverse probability weighting, rather than matching based on propensity scores.

B4. Explanatory power of restricted models in different situations (following Rajan, Seru and Vig (2015))

Rajan et al. (2015) show that the performance of statistical default models for subprime mortgages breaks down when those models have been estimated in a low securitization period, when (unobserved) soft borrower characteristics played a more important role. As part of their analysis they regress hard borrower characteristics (the FICO score and the loan-to-value ratio) on the interest rate and note that this model has higher explanatory power in a high securitization environment (when soft borrower characteristics are arguably not reported to investors) than in a low securitization environment. They take this as evidence that soft borrower characteristics mattered when securitization of loans was less common. Their methodology can be generalized into the following framework: there are two distinct environments (F and G) and two sets of explanatory variables (X and Z), of which only X is observable in both environments and Z matters (more) in environment F. Then, if Z matters at all, the mapping y = g(X) should provide explanatory power for data from the environment G (where Z was not available or did not matter as much) than in the environment F (where Z may help explain the variation in y). The explanatory power is compared with the R^2 from the two regressions.

To use the framework to study the importance of financial return I proceed as follows: For financial returns, I define same-interest-rate and different-interest-rate environments (choice sets). X is the set of social characteristics of a loan (always available) and Z is the set of financial characteristics (only available – or rather, relevant – in the different-interest-rate environment). This assumes that the interest rate is the only relevant financial characteristics, as an alternative I define "same interest rate and same loan maturity" choice sets. I estimate a regression of only the social characteristics (gender of borrower, number of employees, beneficiaries, turnover and sector) on i) whether a loan was chosen in a given choice set and on ii) the transaction amount and report the R^2 and the within-R^2 (accounting for the investor-day fixed effects). Table B.13 shows that the R^2 is higher when the interest rates (Panel A) or the interest rates and the loan maturities (Panel B) are the same. This suggests that the model which includes only social variables has more explanatory power when information on financial returns cannot be used to differentiate between different loan applications. Following the argumentation of RSV, this can be understood as additional evidence for the fact that financial characteristics of the loan are important determinants of investors' decisions and that - when they are available to differentiate between different loans - crowd out the informational role of social characteristics. The within R squared is very small, in line with the result that social characteristics explain very little of the observed variation in investment choices and transaction amount. Similarly, the model coefficients for the social characteristics are almost always statistically insignificant.

To find evidence that social impact characteristics matter (contrary to my main results) I need to define environments that differ

Table B.11
Robustness II - alternative propensity score matching specifications: The influence of financial returns and social impact on funding success.

	No X	No X, Caliper	Caliper	No X	No X, Caliper	Caliper
Dependent Variable:	log(Funding Duration) - Financial Return			log(Funding Duration) - Social Impact		
Financial Return						
High Financial Return	-1.177 (0.098)***	-1.555 (0.159)***	-1.523 (0.138)***			
Interest Rate						-1.769 (0.198)***
Loan Maturity (in Months)						0.060 (0.008)***
Social Impact						
High Social Impact				-0.033 (0.093)	-0.010 (0.110)	-0.036 (0.093)
Female Borrower			0.171 (0.156)*			
Employees			-0.007 (0.126)			
Beneficiaries			-0.335 (0.238)*			
Turnover (1000 EURO)			-0.170 (0.099)***			
Sector (Base: Manufacturing)						
Wholesale, Retail			0.227 (0.262)			
Agriculture			-0.436 (0.309)			
Services			0.112 (0.263)			
Processing			0.383 (0.476)			
Financial Services			1.156 (0.746)*			
Controls						
Loan Target (1000 EURO)			1.613 (0.203)***			1.102 (0.110)***
Competition			0.091 (0.033)			0.074 (0.023)**
(Intercept)	3.790 (0.073)***	4.080 (0.125)***		3.494 (0.074)***	3.471 (0.098)***	
Time FE	yes	yes	yes	yes	yes	yes
Local Partner FE	yes	yes	yes	yes	yes	yes
Adj. R^2	0.096	0.155	0.540	-0.001	-0.001	0.606
Num. obs.	1396	480	480	1468	846	846

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. The unit of observation is one loan application and the outcome variable is log(funding duration) in all regressions. All columns follow a doubly robust estimation procedure, where least squares regression is performed on a nearest-neighbor matched sample based on propensity scores. In Column 1 and 4, loan applications are matched to exactly one other loan application with similar observable characteristics but a different financial or social indicator, reducing the number of observations to two times the number of high financial- or high social indicator observations. In Columns 2,3,5,6, matching is done with a caliper-setting (0.25) to match only close neighbours. Regressions in the matched sample include covariates that were not used in the construction of the respective indicator in Column 3 and 6. The high financial return indicator (Column 4) indicates loan applications that pay an interest rate above the 75th percentile. The high social impact indicator (Column 5) indicates loan applications where two out of three social impact measures score above the 75th percentile. Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. All regressions include time and local partner fixed effects, to control for investment risk. Heteroskedasticity robust standard errors are clustered at the local partner level and calculated via bootstrapping, to incorporate the uncertainty from estimating the propensity scores.

Table B.12
Robustness III - inverse probability weighting: The influence of financial returns and social impact on funding success.

	Baseline	No X	Truncate Weights	Baseline	No X	Truncate Weights
Dependent Variable:	log(Funding Duration) - Financial Return			log(Funding Duration) - Social Impact		
Financial Return						
High Financial Return	-1.574 (0.193)***	-1.636 (0.512)***	-1.485 (0.203)***			
Interest Rate				-1.530 (0.231)***		-1.959 (0.230)***
Loan Maturity (in Months)				0.065 (0.004)***		0.067 (0.008)***
Social Impact						
High Social Impact				0.001 (0.108)	0.032 (0.138)	-0.100 (0.091)
Female Borrower	0.173 (0.121)		0.016 (0.071)			
Employees	-0.060 (0.076)		-0.084 (0.066)			
Beneficiaries	-0.265 (0.186)		-0.034 (0.083)			
Turnover (1000 EURO)	-0.006 (0.039)		-0.024 (0.038)			
Sector (Base: Manufacturing)						
Wholesale, Retail	-0.397 (0.206)*		0.091 (0.125)			
Agriculture	-0.728 (0.160)***		-0.434 (0.156)**			
Services	0.137 (0.194)		0.152 (0.167)			
Processing	-0.274 (0.109)**		-0.170 (0.147)			
Financial Services	1.174 (0.417)**		1.178 (0.580)*			
Sustainable Energy	0.209 (0.389)		0.536 (0.411)			
Controls						
Loan Target (1000 EURO)	1.192 (0.174)***		1.449 (0.180)***	1.122 (0.107)***		1.288 (0.107)***
Competition	0.164 (0.049)***		0.114 (0.035)***	0.120 (0.032)***		0.110 (0.034)***
Time FE	yes	yes	yes	yes	yes	yes
Local Partner FE	yes	yes	yes	yes	yes	yes
Adj. R^2	0.635	0.155	0.559	0.544	-0.000	0.590
Num. obs.	2114	2114	2080	2114	2114	2074

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. The unit of observation is one loan application and the outcome variable is log(funding duration) in all regressions. All columns follow a doubly robust estimation procedure, where weighted least squares regression is performed with the inverse propensity scores as weights. Extreme weights are truncated in Column 3 and 6, to decrease the leverage of outliers. Regressions include covariates that are not included in the construction of the indicator in Column 1, 3, 4 and 6. The high financial return indicator (Column 4) indicates loan applications that pay an interest rate above the 75th percentile. The high social impact indicator (Column 5) indicates loan applications where two out of three social impact measures score above the 75th percentile. Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. All regressions include time and local partner fixed effects, to control for investment risk. Heteroskedasticity robust standard errors are clustered at the local partner level and (currently not yet, but in the future) calculated via bootstrapping, to incorporate the uncertainty from estimating the propensity scores.

Table B.13
Explanatory power of social impact characteristics when financial returns are the same (interest rate in Panel A, interest rate and loan maturity in Panel B) or different.

Outcome		Coefficients of Social Impact Characteristics				Explanatory Power	
Panel A:		Female Borrower	Employees	Beneficiaries	Turnover (1000 EURO)	R^2	Within R^2
Invested (y/n)	Different Fin. Returns	-0.004 (0.0065)	-0.0007 (0.0072)	-0.0108 (0.0084)	-0.0047 (0.0034)	0.36	0.00
Invested (y/n)	Same Fin. Returns	0.0161 (0.0319)	0.0303 (0.0112)	-0.0426 (0.0386)	-0.0025 (0.0168)	0.37	0.02
Transaction Amount	Different Fin. Returns	-3.5967 (3.8907)	-1.4098 (5.3967)	-7.6695 (4.3521)	-6.3234 (2.1339)*	0.30	0.00
Transaction Amount	Same Fin. Returns	20.1898 (12.0724)	20.7901 (6.7129)*	-31.3494 (26.3101)	11.255 (13.9734)	0.50	0.00
Panel B:		Female Borrower	Employees	Beneficiaries	Turnover (1000 EURO)	R^2	Within R^2
Invested (y/n)	Different Fin. Returns	-0.0028 (0.0074)	-0.0003 (0.0072)	-0.0105 (0.008)	-0.0047 (0.0038)	0.35	0.00
Invested (y/n)	Same Fin. Returns	0.1154 (0.0505)	-0.0109 (0.0287)	-0.0243 (0.044)	-0.0109 (0.0362)	0.37	0.03
Transaction Amount	Different Fin. Returns	-2.6322 (4.1404)	-0.9674 (5.5298)	-7.442 (4.1687)	-5.9646 (2.2484)	0.31	0.00
Transaction Amount	Same Fin. Returns	63.4534 (11.6198)***	53.539 (25.3484)	-63.7246 (25.5736)	35.1981 (18.2336)	0.61	0.01

*** $p < .01$; ** $p < .05$; * $p < .1$. Within fixed effects R squared shows explanatory power of model without fixed effects (at investor and day, i.e. choice set - level). Panel A defines same financial returns as all interest rates being equal, Panel B defines same financial returns as all interest rates and all loan maturities being equal.

Table B.14
Explanatory power of financial return characteristics before and after the website redesign which made social impact more salient.

Outcome		Coefficients of Financial Return Characteristics		Explanatory Power	
		Interest Rate	Loan Maturity (in Months)	R^2	Within R^2
Invested (y/n)	After Redesign (social indicators more salient)	0.0689 (0.1234)	-0.0063 (0.0015)***	0.46	0.01
Invested (y/n)	Before Redesign (social indicators less salient)	0.273 (0.0337)***	-0.0095 (0.0008)***	0.34	0.04
Transaction Amount	After Redesign (social indicators more salient)	45.494 (77.4979)	-2.9079 (0.9247)*	0.40	0.00
Transaction Amount	Before Redesign (social indicators less salient)	130.3027 (15.3214)***	-4.2813 (0.583)***	0.28	0.01
Funding Speed (in Hours)	After Redesign (social indicators more salient)	-1.8785 (1.1747)	0.0834 (0.0153)***	0.80	0.71
Funding Speed (in Hours)	Before Redesign (social indicators less salient)	-1.9914 (0.2016)***	0.0693 (0.0073)***	0.59	0.51

*** $p < .01$; ** $p < .05$; * $p < .1$. Within fixed effects R squared shows explanatory power of model without fixed effects (at investor and day, i.e. choice set - level for outcome invested and amount and at local partner level for outcome funding speed). Website redesign in January 2018 made social characteristics slightly more salient.

in the availability (or salience) of the social impact characteristics. One possibility is to exploit the fact that the website of the Lendahand platform was re-design on January 3rd, 2018 to display social impact characteristics more prominently. I therefore perform a regression of only the financial characteristics on the three outcome variables used in the remainder of the paper (whether a loan was chosen in a given choice set, the transaction amount and the (log) funding duration) for the data before and after the website re-design.[37]

We would expect that the model performs worse after January 3rd, 2018 if social characteristics matter a lot and the re-design provided a big enough change in the salience of social impact characteristics. Table B.14 shows that the evidence for this is not conclusive. The R^2 for the choice set based outcome variables is higher after the re-design, contrary to expectations if social characteristics would matter. The within-R^2 is lower after the redesign, however, in line with the hypothesis that the "financial returns only" model explains less variation after social factors became more salient. For funding speed, the R^2 and the within-R^2 are lower after the re-design - again, contrary to what we would expect if social characteristics would matter.

In summary, using the methodology adapted from Rajan et al. (2015) I find additional evidence that financial returns drive the investment decisions of the impact investors on the crowdfunding platform. I find no conclusive evidence that social impact characteristics matter (much), in line with my previous results.

B5. Excluding direct loans

For 80% of the loans local partners face the default risk of the individual borrower, which allows us to interpret variation in firm-specific characteristics as only indicative of social impact. When the outcome variable is funding duration all loans made directly to a firm (*direct loans*) are excluded. However, when reconstructing the choice sets, excluding these loans would misrepresent the available options that the investor had when making their investment decision. Direct loans are therefore included in the choice sets and controlled for by including a direct loan indicator variable. An alternative is to exclude all choice sets where a direct loan was available, which leaves roughly 25,000 choice sets. Table B.15, B.16, B.17 and B.18 report the results of running the main regressions on this restricted sample.

B6. Heterogeneity by investor nationality

Table B.19 presents the interaction effects with investors nationality which were omitted in Table 6. Only 4.7 percent (145 out of 3,044) investors in the dataset are non-Dutch so the results should be interpreted with caution.

B7. Heterogeneity in crowding out

Table B.20 extends the analysis on crowding out by including interaction effects for investor demographics. There is no indication that different demographic groups behave differently when the interest rate of all available loans is the same versus compared to when it is different. None of the double interactions with the *"Same Interest"* indicator and the demographic characteristic is significantly different from zero. Table B.18 shows the same analysis with the restricted sample where I exclude choice sets with any direct loans.

B8. Active steering of competition

The number of borrowers who seek funding at the same time is relatively small. A concern is that Lendahand's staff actively delays the upload of new loans in order to assure the success of relatively slow funding, unattractive loan application. Funding dura-

[37] For first two outcome variables based on choice sets, I exclude 175 transactions surrounding the days of the redesign, as investors might have looked at some loans with the new version and some with the old version.

Table B.15
Restricted sample I: The influence of financial returns and social impact on funding success.

	Baseline	Baseline	Restricted Sample	Restricted Sample
Dependent Variable:	Invested (y/n)	Amount Invested	Invested (y/n)	Amount Invested
Financial Return				
Interest Rate	0.242 (0.032)***	121.985 (14.471)***	0.283 (0.033)***	140.722 (14.798)***
Loan Maturity (in Months)	-0.008 (0.001)***	-3.832 (0.497)***	-0.010 (0.001)***	-4.722 (0.531)***
Social Impact				
Female Borrower	0.007 (0.008)	2.156 (4.145)	0.016 (0.009)*	8.293 (4.670)*
Employees	0.006 (0.006)	2.366 (5.222)	0.009 (0.010)	3.306 (7.678)
Beneficiaries	0.000 (0.010)	-2.464 (5.205)	-0.009 (0.017)	-5.335 (8.354)
Turnover (1000 EURO)	-0.009 (0.003)**	-8.000 (2.727)***	-0.003 (0.006)	-4.168 (3.285)
Sector (Base: Manufacturing)				
Wholesale, Retail	-0.010 (0.014)	-3.449 (7.013)	-0.020 (0.017)	-13.061 (9.823)
Agriculture	0.024 (0.014)	12.297 (8.193)	0.026 (0.019)	12.472 (12.403)
Services	-0.008 (0.012)	-2.403 (7.608)	-0.004 (0.014)	-1.592 (9.771)
Processing	0.015 (0.020)	2.953 (12.590)	-0.001 (0.022)	-4.488 (13.900)
Financial Services	-0.090 (0.115)	15.761 (39.407)	-0.056 (0.119)	22.982 (34.264)
Sustainable Energy	-0.224 (0.036)***	-145.047 (20.836)***	-0.351 (0.100)***	-181.610 (50.535)***
Controls				
Loan Target (1000 EURO)	-0.010 (0.010)	26.500 (8.440)***	-0.009 (0.012)	29.444 (10.121)**
Direct Loan	-0.032 (0.050)	48.131 (56.866)		
Time FE	yes	yes	yes	yes
Local Partner FE	yes	yes	yes	yes
Investor-Day FE	yes	yes	yes	yes
Dep. Variable, Unconditional Mean	0.2438		0.2438	
Joint F-Test, Social Variables	2.83	3.12	1.01	1.94
Adj. R^2	0.248	0.183	0.245	0.208
Num. obs.	45,370	45,370	25,304	25,304

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. The choice sets are constructed as the set of available loan applications to a given investor on every day they made an investment. Choice sets where a direct loan application was available are excluded in Columns 3 and 4. Among the available loan applications, loans that were chosen by the given investor are coded as invested = yes (dependent variable Column 1 and 3) and the investment amount is recorded (dependent variable Column 2 and 4). All Columns report the results of least squares regressions with time and investor-day fixed effects. Local partner fixed effects control for investment risk in all regressions. Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. The F-Test on joint significance tests the unrestricted model against the restricted model, where all four social impact variables are equal to zero. Heteroskedasticity robust standard errors clustered at local partner and choice set level.

tion for unattractive loan applications would then be biased downwards and there would be reverse causality between the competition variables and the funding duration. Interviews with Lendahand staff suggest that this active steering takes place in order to assure a relatively constant number of projects on the website at the same time, but not to benefit any specific (potentially unpopular) loan application. Because all but ten projects are funded within 30 days, well before the threshold for cancelling of 60 days, there is also little reason for such active steering. In order to empirically test the severity of this issue, the difference in competition across the funding horizon is regressed on funding duration. Specifically, let $C_{l,0}$ be the competition which loan application l faces at the initial posting and $C_{l,1}$ be the competition faced at the time of full funding. Let T_l be the logarithm of funding duration in hours as usual. Eq. B.3 shows the estimated regression.

$$(C_{l,0} - C_{l,1}) = \beta_0 + \beta_1 T_l + \varepsilon_l \tag{B.3}$$

Table B.16
Restricted sample II: Does social impact matter more when interest rates are the same?

	Baseline	Model 2	Model 3
Dependent Variable:	Invested (y/n)	Invested (y/n)	Invested (y/n)
Financial Return			
Interest Rate	0.283 (0.033)***	0.274 (0.034)***	0.283 (0.033)***
Loan Maturity (in Months)	-0.010 (0.001)***	-0.009 (0.001)***	-0.010 (0.001)***
Social Impact			
Female Borrower	0.016 (0.009)*	0.013 (0.008)	0.014 (0.009)
Employees	0.009 (0.010)	0.009 (0.010)	0.008 (0.010)
Beneficiaries	-0.009 (0.017)	-0.009 (0.018)	-0.007 (0.018)
Turnover (1000 EURO)	-0.003 (0.006)	-0.002 (0.005)	-0.003 (0.006)
Interact w. Same Interest			
Loan Maturity x Same Interest		-0.012 (0.002)***	
Female Borrower x Same Interest		0.042 (0.019)**	
Employees x Same Interest		0.003 (0.010)	
Beneficiaries x Same Interest		-0.011 (0.020)	
Turnover (1000 EURO) x Same Interest		-0.020 (0.013)	
Interact w. Same Interest, Maturity			
Female Borrower x Same Interest, Maturity			0.097 (0.035)**
Employees x Same Interest, Maturity			0.024 (0.019)
Beneficiaries x Same Interest, Maturity			-0.112 (0.047)**
Turnover (1000 EURO) x Same Interest, Maturity			-0.001 (0.019)
Sector (Base: Manufacturing)			

(*continued on next page*)

Table B.16 (*continued*)

	Baseline	Model 2	Model 3
Wholesale, Retail	-0.020 (0.017)	-0.021 (0.017)	-0.021 (0.018)
Agriculture	0.026 (0.019)	0.025 (0.019)	0.024 (0.019)
Services	-0.004 (0.014)	-0.003 (0.014)	-0.005 (0.015)
Processing	-0.001 (0.022)	-0.002 (0.022)	-0.002 (0.022)
Financial Services	-0.056 (0.119)	-0.055 (0.118)	-0.058 (0.120)
Sustainable Energy	-0.351 (0.100)***	-0.338 (0.098)***	-0.352 (0.100)***
Controls			
Loan Target (1000 EURO)	-0.009 (0.012)	-0.008 (0.012)	-0.009 (0.012)
Local Partner FE	yes	yes	yes
Investor-Day FE	yes	yes	yes
Dep. Variable, Unconditional Mean	0.2438	0.2438	0.2438
Joint F-Test, Social Variables	1.01	3.65	3.75
Joint F-Test, Interaction Terms		4	3.01
Adj. R^2	0.245	0.248	0.246
Num. obs.	25,304	25,304	25,304

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. The 25,304 choice sets are defined as the set of available loan applications to a given investor on a given day where they made an investment. The sample is restricted to exclude all choice sets where any direct loan was available. The dependent variable is coded as invested = yes if the specific loan was chosen in the given choice set. There are 3446 choice sets where all interest rates are the same (13.62%) and 1012 choice sets where all interest rates and all loan maturities are the same (4.00%). Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. All columns show results of linear probability models and estimation uses investor-day fixed effects, exploiting only variation within choice sets. Local partner fixed effects control for investment risk in all regressions. The F-Test on joint significance tests the unrestricted model against two restricted models, where (first) all four social impact variables are equal to zero or (second) all interaction terms with the same interest (or the same interest and same maturity) indicator are zero. Heteroskedasticity robust standard errors clustered at local partner and choice set level.

Table B.17
Restricted sample II, amount invested: Does social impact matter more when interest rates are the same?

	Baseline	Model 2	Model 3
Dependent Variable:	Amount Invested	Amount Invested	Amount Invested
Financial Return			
Interest Rate	140.722 (14.798)***	136.401 (14.711)***	140.619 (14.817)***
Loan Maturity (in Months)	-4.722 (0.531)***	-4.480 (0.574)***	-4.729 (0.533)***
Social Impact			
Female Borrower	8.293 (4.670)*	6.551 (4.509)	7.452 (4.787)
Employees	3.306 (7.678)	2.905 (7.410)	2.353 (7.666)
Beneficiaries	-5.335 (8.354)	-4.816 (8.897)	-4.537 (8.573)
Turnover (1000 EURO)	-4.168 (3.285)	-4.385 (3.345)	-4.348 (3.355)
Interact w. Same Interest			
Loan Maturity x Same Interest		-5.364 (1.872)**	
Female Borrower x Same Interest		24.780 (9.331)**	
Employees x Same Interest		4.196 (7.241)	
Beneficiaries x Same Interest		-18.477 (14.503)	
Turnover (1000 EURO) x Same Interest		0.080 (8.332)	
Interact w. Same Interest, Maturity			
Female Borrower x Same Interest, Maturity			52.601 (26.635)*
Employees x Same Interest, Maturity			41.584 (21.619)*
Beneficiaries x Same Interest, Maturity			-64.411 (26.793)**
Turnover (1000 EURO) x Same Interest, Maturity			18.593 (11.121)
Sector (Base: Manufacturing)			
Wholesale, Retail	-13.061 (9.823)	-13.639 (10.060)	-13.683 (9.957)
Agriculture	12.472 (12.403)	11.750 (12.586)	11.424 (12.354)
Services	-1.592 (9.771)	-1.567 (9.831)	-1.900 (9.891)
Processing	-4.488 (13.900)	-5.469 (14.833)	-5.178 (14.061)
Financial Services	22.982 (34.264)	24.073 (34.414)	22.380 (34.656)
Sustainable Energy	-181.610 (50.535)***	-174.385 (50.005)***	-182.884 (51.006)***
Controls			
Loan Target (1000 EURO)	29.444 (10.121)**	29.909 (10.134)***	29.559 (10.091)**
Local Partner FE	yes	yes	yes
Investor-Day FE	yes	yes	yes
Joint F-Test, Social Variables	1.94	1.91	8.31
Joint F-Test, Interaction Terms		2.48	3.15
Adj. R^2	0.208	0.208	0.208
Num. obs.	25,304	25,304	25,304

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. The 25,304 choice sets are defined as the set of available loan applications to a given investor on a given day where they made an investment. The sample is restricted to exclude all choice sets where any direct loan was available. The dependent variable is the amount invested into a loan application in a given choice set. There are 3446 choice sets where all interest rates are the same (13.62%) and 1012 choice sets where all interest rates and all loan maturities are the same (4.00%). All columns show results of linear probability models, the dependent variable is if an investor chooses a loan application within a given choice set. Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. All columns use investor-day fixed effects, exploiting only variation within choice sets. Local partner fixed effects control for investment risk in all regressions. The F-Test on joint significance tests the unrestricted model against two restricted models, where (first) all four social impact variables are equal to zero or (second) all interaction terms with the same interest (or the same interest and same maturity) indicator are zero. Heteroskedasticity robust standard errors clustered at local partner and choice set level.

Table B.18
Restricted sample III: Heterogeneity in investment decisions by gender, age and nationality.

	Baseline	Same Interest	Baseline	Same Interest
Dependent Variable:	Invested (y/n)	Invested (y/n)	Amount Invested	Amount Invested
Financial Return				
Interest Rate	0.289 (0.032)***	0.281 (0.032)***	135.075 (17.609)***	131.644 (17.292)***
Loan Maturity (in Months)	-0.009 (0.001)***	-0.008 (0.001)***	-3.419 (0.612)***	-3.023 (0.585)***
Social Impact				
Female Borrower	0.015 (0.029)	0.010 (0.029)	24.028 (12.309)*	18.396 (11.541)
Employees	0.010 (0.017)	0.005 (0.017)	3.510 (11.089)	1.349 (11.025)
Beneficiaries	-0.017 (0.019)	-0.017 (0.018)	-2.600 (8.242)	-3.880 (9.273)
Turnover (1000 EURO)	0.002 (0.009)	0.006 (0.008)	-5.846 (5.215)	-5.061 (5.426)
Female Investors				
Interest Rate x Female Investor	-0.011 (0.006)	-0.011 (0.006)	4.308 (6.489)	4.369 (6.513)
Loan Maturity x Female Investor	0.000 (0.000)	0.000 (0.000)	-0.634 (0.312)*	-0.624 (0.330)*
Female Borrower x Female Investor	0.028 (0.007)***	0.030 (0.007)***	1.849 (5.157)	2.586 (4.827)
Employees x Female Investor	-0.000 (0.004)	-0.002 (0.004)	3.885 (3.159)	2.806 (3.425)
Beneficiaries x Female Investor	0.007 (0.007)	0.008 (0.007)	-5.008 (6.227)	-4.492 (6.607)
Turnover (1000 EURO) x Female Investor	0.005 (0.003)*	0.006 (0.003)*	0.445 (2.481)	0.774 (2.614)
Young Investors				
Interest Rate x Young Investor	-0.004 (0.006)	-0.003 (0.006)	-68.739 (6.621)***	-68.655 (6.589)***
Loan Maturity x Young Investor	-0.001 (0.001)**	-0.001 (0.000)**	1.118 (0.289)***	1.063 (0.301)***
Female Borrower x Young Investor	-0.013 (0.007)*	-0.012 (0.007)	-8.039 (4.229)*	-5.773 (4.230)
Employees x Young Investor	0.002 (0.003)	0.003 (0.004)	-9.160 (2.850)***	-9.121 (3.458)**
Beneficiaries x Young Investor	0.000 (0.006)	-0.001 (0.005)	-7.928 (3.700)**	-8.836 (4.442)*
Turnover (1000 EURO) x Young Investor	-0.000 (0.004)	-0.001 (0.004)	3.226 (2.408)	3.870 (2.522)
Dutch Investors				
Interest Rate x Dutch Investor	-0.001 (0.009)	-0.002 (0.008)	20.076 (11.309)*	19.256 (11.505)
Loan Maturity x Dutch Investor	-0.001 (0.001)*	-0.001 (0.001)*	-1.483 (0.477)***	-1.637 (0.427)***
Female Borrower x Dutch Investor	-0.003 (0.024)	-0.001 (0.025)	-14.863 (11.191)	-11.462 (10.674)
Employees x Dutch Investor	-0.000 (0.009)	0.005 (0.010)	1.081 (7.517)	3.146 (7.254)
Beneficiaries x Dutch Investor	0.006 (0.010)	0.006 (0.010)	0.532 (10.791)	2.580 (11.201)
Turnover (1000 EURO) x Dutch Investor	-0.007 (0.006)	-0.009 (0.005)*	0.220 (4.791)	-0.981 (5.179)
Interact w. Same Interest				
Loan Maturity x Same Interest		-0.018 (0.007)**		-11.401 (4.891)**
Female Borrower x Same Interest		-0.010 (0.087)		16.940 (43.397)
Employees x Same Interest		0.099 (0.042)**		50.800 (35.637)
Beneficiaries x Same Interest		-0.069 (0.065)		-29.207 (56.330)
Turnover (1000 EURO) x Same Interest		-0.026 (0.031)		-5.463 (25.171)
Same Interest w. Female				
Loan Maturity x Female Investor x Same Interest		0.002 (0.002)		-1.738 (1.662)
Female Borrower x Female Investor x Same Interest		-0.033 (0.021)		-23.634 (21.069)
Employees x Female Investor x Same Interest		0.021 (0.014)		18.182 (9.689)*
Beneficiaries x Female Investor x Same Interest		-0.013 (0.021)		-15.547 (24.359)
Turnover (1000 EURO) x Female Investor x Same Interest		-0.009 (0.016)		-5.010 (10.570)
Same Interest w. Young				
Loan Maturity x Young Investor x Same Interest		-0.001 (0.003)		1.838 (2.378)
Female Borrower x Young Investor x Same Interest		0.002 (0.017)		-29.571 (9.803)***
Employees x Young Investor x Same Interest		-0.017 (0.019)		-0.811 (9.848)
Beneficiaries x Young Investor x Same Interest		0.014 (0.030)		26.961 (21.740)
Turnover (1000 EURO) x Young Investor x Same Interest		-0.003 (0.013)		-15.077 (9.544)
Same Interest w. Dutch				
Loan Maturity x Dutch Investor x Same Interest		0.006 (0.007)		6.196 (4.717)
Female Borrower x Dutch Investor x Same Interest		0.059 (0.081)		17.910 (42.789)
Employees x Dutch Investor x Same Interest		-0.099 (0.037)**		-51.172 (34.097)
Beneficiaries x Dutch Investor x Same Interest		0.059 (0.059)		6.230 (45.254)
Turnover (1000 EURO) x Dutch Investor x Same Interest		0.007 (0.032)		9.479 (24.544)
Sector (Base: Manufacturing)				
Wholesale, Retail	-0.020 (0.018)	-0.020 (0.018)	-12.829 (9.904)	-13.539 (10.141)
Agriculture	0.025 (0.019)	0.024 (0.020)	12.408 (12.589)	11.522 (12.762)
Services	-0.005 (0.015)	-0.004 (0.015)	-2.025 (9.703)	-2.095 (9.743)
Processing	-0.002 (0.023)	-0.003 (0.023)	-5.185 (14.544)	-6.312 (15.511)
Financial Services	-0.057 (0.120)	-0.056 (0.118)	25.854 (35.060)	26.448 (35.469)
Sustainable Energy	-0.348 (0.100)***	-0.334 (0.099)***	-180.455 (49.415)***	-171.934 (48.963)***
Controls				
Loan Target (1000 EURO)	-0.009 (0.012)	-0.008 (0.012)	30.364 (10.073)***	30.869 (10.048)***
Local Partner FE	yes	yes	yes	yes
Investor-Day FE	yes	yes	yes	yes
Dep. Variable, Unconditional Mean	0.2438	0.2438		
Adj. R^2	0.249	0.251	0.211	0.211
Num. obs.	25,304	25,304	25,304	25,304

*** $p < .01$; ** $p < .05$; * $p < .1$. The 25,304 choice sets are defined as the set of available loan applications to a given investor on a given day where they made an investment. The sample is restricted to exclude all choice sets where any direct loan was available. Among the available loan applications, loans that were chosen by the given investor are coded as invested = yes (dependent variable Column 1 and 2) and the investment amount is recorded (dependent variable Column 3 and 4). There are 3446 choice sets where all interest rates are the same (13.62%) and 1012 choice sets where all interest rates and all loan maturities are the same (4.00%). Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. All columns use investor-day fixed effects, exploiting only variation within choice sets. Local partner fixed effects control for investment risk in all regressions. Young investors are defined as those born in or after 1980. The same interest interactions set apart choice sets where the interest rate for all available loan applications was the same. Heteroskedasticity robust standard errors clustered at local partner and choice set level.

Table B.19
Heterogeneity in investment decisions by nationality.

	Model 1	Model 2
Dependent Variable:	Invested (y/n)	Amount Invested
Financial Return		
Interest Rate	0.242 (0.033)***	122.907 (16.713)***
Loan Maturity (in Months)	-0.007 (0.001)***	-2.112 (0.508)***
Social Impact		
Female Borrower	0.021 (0.020)	17.500 (8.315)**
Employees	0.014 (0.009)	4.567 (6.632)
Beneficiaries	-0.000 (0.011)	1.643 (6.948)
Turnover (1000 EURO)	-0.015 (0.005)***	-9.366 (3.942)**
Dutch Investors		
Interest Rate x Dutch Investor	-0.000 (0.006)	9.696 (7.608)
Loan Maturity x Dutch Investor	-0.001 (0.001)*	-1.965 (0.475)***
Female Borrower x Dutch Investor	-0.016 (0.015)	-13.428 (6.720)*
Employees x Dutch Investor	-0.007 (0.005)	1.224 (4.880)
Beneficiaries x Dutch Investor	-0.004 (0.005)	-5.945 (4.927)
Turnover (1000 EURO) x Dutch Investor	0.005 (0.003)	-0.870 (3.338)
Sector (Base: Manufacturing)		
Wholesale, Retail	-0.009 (0.014)	-3.200 (7.035)
Agriculture	0.024 (0.014)	12.387 (8.266)
Services	-0.008 (0.012)	-2.324 (7.525)
Processing	0.015 (0.020)	2.725 (12.901)
Financial Services	-0.091 (0.115)	16.426 (40.349)
Sustainable Energy	-0.224 (0.036)***	-145.098 (20.666)***
Controls		
Loan Target (1000 EURO)	-0.010 (0.010)	26.963 (8.479)***
Direct Loan	-0.033 (0.050)	49.394 (56.966)
Interaction with Investor Age and Gender	omitted	omitted
Local Partner FE	yes	yes
Investor-Day FE	yes	yes
Dep. Variable, Unconditional Mean	0.246	
Adj. R^2	0.251	0.186
Num. obs.	45,370	45,370

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. The 45,370 choice sets are defined as the set of available loan applications to a given investor on a given day where they made an investment. Within each choice set, loans that were chosen by the given investor are coded as invested = yes (dependent variable Column 1) and the investment amount is recorded (dependent variable Column 2). Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. All columns use investor-day fixed effects, exploiting only variation within choice sets. Local partner fixed effects control for investment risk in all regressions. Heteroskedasticity robust standard errors clustered at local partner and choice set level.

Table B.20
Heterogeneity in crowding out: gender, age, nationality.

	Model 1	Model 2
Dependent Variable:	Invested (y/n)	Amount Invested
Financial Return		
Interest Rate	0.235 (0.032)***	119.805 (16.628)***
Loan Maturity (in Months)	-0.007 (0.001)***	-1.887 (0.507)***
Social Impact		
Female Borrower	0.019 (0.020)	14.424 (7.950)*
Employees	0.013 (0.009)	4.053 (6.708)
Beneficiaries	-0.001 (0.011)	0.979 (7.445)
Turnover (1000 EURO)	-0.014 (0.004)***	-9.312 (4.026)**
Female Investors		
Interest Rate x Female Investor	-0.003 (0.005)	-3.387 (3.748)
Loan Maturity x Female Investor	0.000 (0.000)	-0.389 (0.255)
Female Borrower x Female Investor	0.019 (0.006)***	-0.620 (4.260)
Employees x Female Investor	-0.002 (0.002)	-1.827 (2.429)
Beneficiaries x Female Investor	0.010 (0.004)**	-1.377 (2.956)
Turnover (1000 EURO) x Female Investor	0.005 (0.002)**	3.659 (1.910)*
Young Investors		
Interest Rate x Young Investor	0.009 (0.006)	-44.694 (6.719)***
Loan Maturity x Young Investor	-0.001 (0.000)*	1.091 (0.361)***
Female Borrower x Young Investor	-0.016 (0.006)**	-7.584 (4.123)*
Employees x Young Investor	-0.003 (0.004)	-13.753 (3.062)***
Beneficiaries x Young Investor	0.005 (0.003)	9.447 (3.377)***
Turnover (1000 EURO) x Young Investor	-0.001 (0.002)	5.309 (2.433)**
Dutch Investors		

(*continued on next page*)

Table B.20 (*continued*)

	Model 1	Model 2
Interest Rate x Dutch Investor	-0.001 (0.006)	9.107 (7.707)
Loan Maturity x Dutch Investor	-0.001 (0.001)*	-1.978 (0.476)***
Female Borrower x Dutch Investor	-0.015 (0.015)	-11.612 (6.433)*
Employees x Dutch Investor	-0.006 (0.005)	1.905 (4.865)
Beneficiaries x Dutch Investor	-0.004 (0.005)	-5.551 (5.145)
Turnover (1000 EURO) x Dutch Investor	0.004 (0.003)	-0.861 (3.352)
Interact w. Same Interest		
Loan Maturity x Same Interest	-0.016 (0.005)***	-6.945 (3.769)*
Female Borrower x Same Interest	-0.014 (0.075)	46.579 (39.582)
Employees x Same Interest	0.076 (0.047)	39.398 (33.745)
Beneficiaries x Same Interest	-0.043 (0.066)	-9.283 (50.462)
Turnover (1000 EURO) x Same Interest	0.003 (0.030)	13.286 (21.833)
Same Interest w. Female		
Loan Maturity x Female Investor x Same Interest	0.001 (0.002)	-0.699 (1.700)
Female Borrower x Female Investor x Same Interest	-0.023 (0.021)	-17.617 (21.642)
Employees x Female Investor x Same Interest	0.022 (0.011)*	18.888 (8.485)**
Beneficiaries x Female Investor x Same Interest	-0.016 (0.019)	-11.023 (21.655)
Turnover (1000 EURO) x Female Investor x Same Interest	-0.008 (0.014)	-1.786 (9.709)
Same Interest w. Young		
Loan Maturity x Young Investor x Same Interest	-0.002 (0.002)	3.441 (2.317)
Female Borrower x Young Investor x Same Interest	0.005 (0.015)	-23.835 (9.787)**
Employees x Young Investor x Same Interest	-0.012 (0.018)	0.182 (9.463)
Beneficiaries x Young Investor x Same Interest	0.013 (0.031)	16.612 (20.438)
Turnover (1000 EURO) x Young Investor x Same Interest	-0.002 (0.011)	-9.065 (9.715)
Same Interest w. Dutch		
Loan Maturity x Dutch Investor x Same Interest	0.003 (0.005)	0.240 (3.989)
Female Borrower x Dutch Investor x Same Interest	0.064 (0.071)	-15.642 (39.589)
Employees x Dutch Investor x Same Interest	-0.076 (0.041)*	-38.443 (32.390)
Beneficiaries x Dutch Investor x Same Interest	0.038 (0.061)	-12.269 (43.578)
Turnover (1000 EURO) x Dutch Investor x Same Interest	-0.018 (0.028)	-13.071 (20.912)
Sector (Base: Manufacturing)		
Wholesale, Retail	-0.010 (0.014)	-3.708 (7.118)
Agriculture	0.023 (0.014)	11.959 (8.399)
Services	-0.008 (0.012)	-2.556 (7.441)
Processing	0.014 (0.021)	1.771 (13.534)
Financial Services	-0.087 (0.113)	18.063 (40.111)
Sustainable Energy	-0.217 (0.036)***	-141.993 (20.545)***
Controls		
Direct Loan	-0.017 (0.047)	55.497 (57.473)
Loan Target (1000 EURO)	-0.010 (0.010)	27.093 (8.568)***
Local Partner FE	yes	yes
Investor-Day FE	yes	yes
Dep. Variable, Unconditional Mean	0.246	
Adj. R^2	0.253	0.186
Num. obs.	45,370	45,370

*** $p < .01$; ** $p < .05$; * $p < .1$. The 45,370 choice sets are defined as the set of available loan applications to a given investor on a given day where they made an investment. Among the available loan applications, loans that were chosen by the given investor are coded as invested = yes (dependent variable Column 1) and the investment amount is recorded (dependent variable Column 2). There are 3697 choice sets where all interest rates are the same (8.15%) and 1022 choice sets where all interest rates and all loan maturities are the same (2.25%). Number of Employees, Number of Beneficiaries, Turnover and Loan Target are log transformed. All columns use investor-day fixed effects, exploiting only variation within choice sets. Local partner fixed effects control for investment risk in all regressions. Young investors are defined as those born in or after 1980. The same interest interactions set apart choice sets where the interest rate for all available loan applications was the same. Heteroskedasticity robust standard errors clustered at local partner and choice set level.

Table B.21
Robustness IV - Active steering of competition.

	Competition (Start - End)	Competition (Average - End)
(Intercept)	-0.138 (0.080)*	0.232 (0.043)***
log(Funding Duration)	0.049 (0.029)*	-0.019 (0.017)
R^2	0.001	0.001
Num. obs.	2114	2114

*** $p < .01$; ** $p < .05$; * $p < .1$. The unit of observation is one loan application. The competition difference outcome variable is the difference between the competition at the start of the funding campaign (Column 1), or average competition throughout the funding campaign (Column 2) and the competition at the end of the funding campaign. Funding duration is log transformed. Both models are estimated with linear-log least squares regressions, with heteroskedasticity robust standard errors.

If competition is actively reduced towards the end of the funding period to benefit long funding projects, $\hat{\beta}_1$ should be negative (since a high value for funding should mean more competition at the beginning than at the end). Instead, Table B.21 shows that the correlation between funding duration and the change in the competition is not significantly different from zero. Column 1 estimates Eq. B.3. The estimate for β_1 is not significant at the five percent level and positive. Additionally, there is no significant effect when considering the difference between average competition and competition at the end (Column 2).

Appendix C. Survey Appendix

The following appendix describes the design, implementation and results of a survey among 200 Lendahand investors. The survey was administered specifically for the purpose of this study and with support from Lendahand staff. The aim of the survey is to better understand how investors perceive loan applications on the Lendahand platform along a financial return, social impact and risk dimension. While it is quite straightforward to understand which characteristics determine the attractiveness with respect to financial return (interest rate and loan maturity), it is less obvious what characteristics investors consider when forming an opinion about the expected social impact and about the risk of a loan.

Survey design The survey was designed in Dutch and English, with Dutch being the default language. However, respondents could switch languages at any point without loosing the progress they had made.[38] The survey was introduced by the following message:

Dear Lender,

nice that you want to participate. We will show you 4 projects and ask you consequently for your impression. With the results we will be able to improve the information about the projects on our website.

There may be something else in it for you! Among all participants we give away 4 WakaWaka Lights worth 2995 euro. Therefore do not forget to fill out your email address after the last question. Just click next to start the survey.

With kind regards,
Team Lendahand

On the next pages of the survey respondents saw screenshots of firms that had raised loans on the Lendahand platform in the past. The questions and introductory text was the same for each screenshot. The questions were introduced by the sentence: *Please take a look at the project as if you would consider funding this entrepreneur and answer the questions at the bottom.* This was followed by a screenshot of borrower profile page, similar to the one shown in Fig. A.6. At the bottom of the page respondents were asked a number of questions:

1. *Have you seen this project before on the Lendahand website?* – yes / no
   (a) if yes: *Did you lent to this entrepreneur?* – yes / no
   (b) if no: *Based on the project page above, would you lend to this entrepreneur?* – yes / no
2. *Please rate the attractiveness of this project based on the social impact you expect this project to generate* – 1 (lowest) to 10 (highest)
3. *Please rate the attractiveness of this project based on your personal financial return from this project* – 1 (lowest) to 10 (highest)
4. *Imagine you would lend to this entrepreneur, how would you rate the risk of your investment?* – 1 (very high risk) to 4 (very low risk) or "no answer"

Answering these questions was mandatory and once respondents had answered them, they were shown the next screenshot.

In total, each respondent saw four screenshots. The first screenshot was the *vignette profile* which was identical for everyone. This vignette profile was chosen to be relatively representative for the average interest rate, loan maturity and employment creation for borrowers on the Lendahand platform. The next three screenshots were randomly assigned out of a total of sixty options. In order to assure that the profiles that were shown represented enough variation in financial and social impact characteristics, I used stratified randomization in the procedure to assign profiles to respondents. The sixty profiles were divided into three groups: Group 1 contained twenty borrowers that were a priori identified as relatively high financial return and low social impact. Group 2 contained twenty borrowers with low financial return but high social impact. Group 3 contained ten borrowers with high financial and social returns and ten borrowers with low financial and social returns.[39] Within each of the three groups, profiles were chosen to assure that the firms included in the survey sample were balanced along country, sector and applicants' gender. Each respondent was randomly shown one profile from each group. The order in which the profiles from group 1 and group 2 were shown was again randomized. The selected profile from group 3 was shown last.[40]

After respondents had answered the questions described above for each of the four borrowers, they were given one last set of questions. These questions asked respondents directly to reflect on the characteristics that were important in their judgment. They were introduced by the sentence: *We are almost there. Lastly, we would like to ask you which factors were most important in the answers that you gave for the 4 projects.*

1. *Which 3 characteristics were most important to judge the social impact of the projects that you have seen?*
2. *Which 3 characteristics were most important to judge the financial return of the projects that you have seen?*
3. *Which 3 characteristics were most important to judge the risk of investment of the projects that you have seen?*

The questions were multiple choice and for each of the three questions, respondents were asked to check at most three of the following possible answers:

Interest Rate, Maturity, Redemption Schedule, Partner Organisation, Country, Sector, Turnover, Number of Employees, Number of New Jobs, Gender of Entrepreneur, Type of Investment (direct vs. indirect), Other.

Whenever respondents answered *Partner Organisation* or *Other* a field appeared, asking respondents to specify the answer further.

Survey Implementation The survey was designed using the tool Limesurvey and was hosted on the Lendahand servers. The link to

[38] This appendix presents the English version of the survey, the Dutch version is available upon request.

[39] The classification into high or low financial return was based on interest rate and loan maturity. The classification into high or low social impact was based on the number of jobs created and the number of employees. In general, borrowers were categorized as high financial return and low social impact when they paid an interest rate of four percent or more and had a maturity of less than three years. Additionally they had to create at most one job and have not more than two employees. Borrowers that were categorized as low financial return and high social impact paid interest rates of no more than 3.5 percent and matured after two years or more. Additionally they created more than two jobs and had more than three employees. Borrowers with high financial and high social returns or low financial and low social returns were categorized accordingly.

[40] The reason is that some screenshots o borrowers in group 3 were significantly longer than those from group 1 or group 2. In order to not discourage respondents early during the survey, screenshots from group 3 were shown last.

Table C.22
The influence of loan characteristics on perceived financial returns, social impact and risk.

	Model 1	Model 2	Model 3
Dependent Variable:	Financial Score	Social Score	Risk Score
Financial Return			
Interest Rate	0.662 (0.153)***	-0.279 (0.159)*	0.174 (0.099)*
Loan Maturity (in Months)	0.004 (0.009)	0.011 (0.009)	-0.006 (0.006)
Social Impact			
Female Borrower	0.085 (0.113)	0.196 (0.118)*	-0.051 (0.073)
Employees	0.030 (0.100)	-0.067 (0.104)	0.073 (0.065)
Beneficiaries	-0.222 (0.129)*	0.302 (0.135)**	0.035 (0.083)
Turnover (1000 EURO)	0.108 (0.064)*	0.067 (0.067)	-0.038 (0.041)
Local Partner FE	yes	yes	yes
Joint F-Test Financial Variables	17.221***	1.536	1.54
Joint F-Test Social Impact Variables	2.103*	2.932**	1.028
Joint F-Test Local Partner Dummies	0.881	2.368**	4.463***
Adj. R^2	0.153	0.182	0.107
Num. obs.	679	679	676

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$. The unit of observation is a survey response by one of 197 respondents who each rated one to four out of a total 53 loan applications. All models are estimated with random effects at the respondent level, the p-values for a Hausman test comparing fixed effects with random effects are 0.996, 0.985, 0.237 for Model 1, 2 and 3 respectively. Number of Employees, Number of Beneficiaries and Turnover are log transformed. The F-Test on joint significance tests the unrestricted model against the restricted model, where the two financial, the four social impact or all local partner dummies are restricted to equal zero.

the survey was send out on June 28th 2017 as part of the monthly newsletter to all registered investors on the platform. In total the newsletter was send to 3065 newsletter subscribers of which 44% opened the email. In the end, the survey generated 247 responses of which 184 completed the whole survey. The dataset used to analyze the survey results contains responses from 200 investors (184 who completed the whole survey plus 16 who answered questions about at least one screenshot). The dataset contains 766 investor-borrower pairs, because not all of the 200 respondents completed the whole survey. The responses were exported on July 25th 2017 and the survey was deactivated on that date.

Survey Responses Of the 766 investor-borrower pairs, 92 investors had seen the assigned profile page in the past, when it was actively seeking funding on the Lendahand website. Of these investors, 39 (42%) had invested into the firm. The 674 respondents who had never seen the assigned profile before were asked if they would invest, given the information in the screenshot. 416 (64%) answered that they would lend to the firm in question. In the main part of the survey, individuals were asked to rate profiles on a financial return, social impact and risk dimension. The average financial score is 6.28 (one a 1–10 scale) with a standard deviation of 1.61. The average social impact score is 6.58 with standard deviation 1.58. On the risk dimension the average score is 1.59 (on a 1–4 scale, where one is the lowest risk) with standard deviation 0.95. When asked which characteristics determine the different ratings, respondents named the variables that would be expected. To rate the financial return of loans, 76% of respondents named the interest rate and 64% the loan maturity among the most important characteristics. All other characteristics are mentioned far less often. With respect to the expected social impact of the loans, the number of new jobs (71%) – which is used to construct the number of beneficiaries variable –, the sector (50%), country (40%) and number of employees (35%) are mentioned as the most important characteristics. In order to judge the risk of the loan, respondents mention the type of the loan (indirect vs. direct, 55%) and the local partner (45%) as the most important determinants.

There is considerable heterogeneity in the level of individuals ratings. On the vignette profile, the responses for financial and social ratings range from two to nine. Recall that this vignette profile was the same for everyone, so while this heterogeneity might reflect genuinely different opinions about the profile, it most likely reflects differences in respondents overall level of ratings. I therefore exploit the panel structure of the survey responses to estimate how within-respondent variation in ratings relates to observable characteristics of the loan.

Survey Results The subjective financial, social and risk scores can be used to validate the use of the gender of the borrower, the number of employees and beneficiaries and the turnover of the firm as proxies for expected social impact. Table C.22, Model 2 shows that the number of beneficiaries and the gender of the borrower indeed positively influence the respondents perception of the loans social impact. The four social impact variables are also jointly significant. Model 3 shows that except for the interest rate, none of the financial or social impact variables significantly influence the perceived investment risk. Instead, the F Test on join significance of the local partner dummies shows that survey respondents (correctly) identify the local partner as determining the investment risk, and not the individual loan application.

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