Is the Crowd Wise Enough to Recognize Creditworthy Borrowers?

Hadar Gafni
Department of Industrial Economics and Management
KTH Royal Institute of Technology
gafni@kth.se, corresponding author

Lars Bo Jeppesen
Department of Strategy and Innovation
Copenhagen Business School
lbj.si@cbs.dk

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ABSTRACT

We study whether the crowd can apply its collective wisdom in the context of high information asymmetry—a crowdlending platform that matches lenders from the global north with borrowers from developing countries—and observe whether the lenders screen the borrowers correctly. We exploit interventions by a platform's administrators who cover for missing funding for campaigns to observe the counterfactual—repayment performance for loans that have not raised the required sums from the crowd of lenders. Our findings are threefold. First, we find that the crowd is able to screen creditworthy borrowers, but only when provided with financial information about the borrowers' businesses. In the latter case, the borrowers that the crowd alone chooses to fund are more likely to repay by 11 percentage points. Second, this ability to predict borrower repayment is lost once the loan offers a non-pecuniary, social return in addition to the monetary one. Third, financial experts among the crowd do not prove to have predictive ability that is significantly superior to that of amateur members. Since crowdlending platforms rely on the screening competency of their supply-side members to know a creditworthy borrower from one who is likely to default on one's loan, these results are important in order to reveal the conditions under which the crowd is able to prove its predictive power.

Keywords: Crowdfunding; Wisdom of the crowd; Peer-to-peer lending; Social loans.

1. Introduction

As crowdfunding has grown in importance, it has prompted a new line of research (Boudreau et al. 2021; Fleming & Sorenson 2016; Hildebrand et al. 2017; Mollick 2014; Schwienbacher & Larralde 2010; Younkin & Kuppuswamy 2018). The majority of such research has focused on understanding the factors involved in capitalizing crowdfunding projects using various financing models (Allison et al.

2013; Gafni et al. 2019; Lin et al. 2013; Lin & Viswanathan 2016; Mohammadi & Shafi 2018; Zhang & Liu 2012). Despite the growing role of crowds in making funding decisions, little is known about crowdfunders' ability to make "the right decisions"—that is, funding projects that deliver on their promises.

While crowdfunding has provided countless entrepreneurs and backers with opportunities that they might not have received otherwise from traditional financial institutions, its critics point out its possible fallacies. It is suggested that crowdfunding is merely a way to create false positives—providing funds to those rejected by better informed professional investors (Walthoff-Borm et al. 2018). Constrained by limited information and their lack of financial training, crowdfunders may simply lose their money and waste the time of the entrepreneurs they fund, thus reducing economic welfare (Agrawal et al. 2014). Moreover, these crowdfunders may be inclined to fund social applications that are not financially viable (Chen et al. 2019; Gafni et al. 2021), possibly doing more damage than good. Lastly, the above reasons may cause funders not only to fund businesses that should not be funded but also to miss worthy opportunities, thus creating false negatives as well. Stated differently, we know that crowdfunding works for fundraisers, yet we do not know whether the broader system of crowdfunding *works*.

Answering the latter question is notoriously challenging since the success of a given project is not easily measured, and even when it is, the outcomes of projects that were not funded are usually not observable. So far, less than a handful of studies provide insights into this matter. A recent study on reward-based crowdfunding suggests that crowdfunders differ little from experts in their evaluation of new opportunities (Mollick & Nanda 2016). In their study of a lending-based crowdfunding[1] setting, Iyer et al. (2016) find that the crowd screens borrowers better than credit scores and nearly as well as an econometrician's full and extensive information. An additional insight in the crowdlending context is that the available information, which is typically sparse for lenders compared with institutional investors, may put them at a disadvantage, thus playing a role in limiting lenders' ability to make the right decisions. Thus, changes in the availability of such information should be considered (Miller 2015).

In this paper, we study under which conditions the crowd can correctly assess the creditworthiness of borrowers in the context of crowdlending for small and medium-sized enterprises in the developing world, where the (typical western) lender's culture and ability to assess the quality of the business and its project are stressed. We analyze how the lenders' ability to determine which borrowers will fully

[1] Among the different crowdfunding models, the highest volume of funds is transacted through crowdlending (Massolution CL 2015), which is the model that we focus on in this paper. This category of crowdfunding has become the modus operandi for financing of individuals' and small businesses' capital needs, through loans provided via peer-to-peer lending platforms. This model competes with traditional financial products, as well as addresses under-served sectors.

repay their loans is affected by the availability of financial information, the prosocial loans offering non-pecuniary social returns, and financial expertise.

The setting that we study is the defunct platform MyC4, which connected lenders from the global north with small business owners in developing African countries. The platform was established in 2006 and intermediated funding of about 6,000 projects over 4 years. Researching the propriety data of this platform offers us several advantages: (1) It provides varying levels of information asymmetries between crowdfunders and borrowers given the distance contexts, which allows us to explore the effect of information. (2) The distance between lenders and borrowers makes the setting virtually clean of known biases in crowdfunding, such as home bias (Lin & Viswanathan 2016), ethnic bias (Chen et al. 2019), network effects (Lin et al. 2013), and support from families and friends (Agrawal et al. 2014). (3) The repayment rate is observable and stands at around 50%, making it a tough market for the crowd to test its screening abilities. (4) Most importantly, this setting allows us to observe repayment outcomes of loans that the crowd did not consider creditworthy. Such loans received last-minute support from the administrators of the platform itself to ensure that the loans would reach their funding goals and continue to the repayment stage. This allows us to observe not only true and false positives (full repayments of and defaults on loans funded by the crowd of lenders) but also whether the negatives were true or false (defaults on and repayments of loans that received help from the platform), in other words, the counterfactual.

The wisdom of the crowd theory asserts that the combined judgment of individuals leads to better estimations of true values, given that they have some relevant knowledge about the issue, incentivized to correctly predict the true value, and judgments are made without systematic errors (Larrick et al. 2011; Simmons et al. 2011). However, in our case, only some of these assumptions hold true. Studying the crowdlending platform Prosper, Iyer et al. (2016) find that lenders could predict defaults with 45% greater accuracy than credit scores, and they reached 87% of the predictive power of an econometrician who had access to far more financial information, thus harnessing the wisdom of crowds, even without satisfying all the conditions. Our setting differs from Prosper in the population of borrowers, who share very different levels of information about their business on the MyC4 platform, and it allows us to observe false negative decisions, both advantages to assist us in finding whether the crowd of lenders can still screen creditworthy borrowers.

Furthermore, to identify key conditions that are likely to affect the quality of prediction, we break down our analysis along two aspects: variations in loan features and variations in lender features (Lin & Viswanathan 2016; Miller 2015). One variation appears in the provided information in the campaign: about one-fifth of the listings provide financial information about the business. The appearance of this information is not likely to be the result of creditworthy borrowers choosing to present financial information since the decision is more likely to be made at the microfinance institution for the majority of the borrowers. In the setting of a western crowdlending marketplace, Miller (2015) finds that by having forced loan applicants to share more detailed credit information, the default rate of borrowers on the platform decreased by 17 percentage points among high-risk borrowers. Our conjecture is that providing relevant financial report about possible investments can reduce the information asymmetry low enough for the crowd to correctly assess the opportunity.

Beyond merely financial returns, some loans on MyC4 also offered non-pecuniary returns on investments since they aimed to deliver social returns, such as education, gender equality, poverty reduction, sustainability, and others. This setting allows us to observe whether the lenders' predictive power changes when they evaluate projects that display social aspects in addition to merely financial ones. The results from experiments suggest that lenders in such situations are driven by both financial returns and philanthropic motivations, and they are willing to incur greater risks if they can support social causes, to a certain degree (Chen et al. 2019). We can identify whether these social non-pecuniary returns affect the financial appraisal, and potentially, how they do so.

The entry of crowdfunding to the sphere of entrepreneurial finance has brought with it two main novelties. The first is the participation of amateur investors on the funding side, thus breaking the monopoly of institutional investors and accredited individual investors with high expertise. The second is that with the lower sums of individual funding, investment decisions are made quicker, often without any due diligence or direct contact with the fundraiser, and under high information asymmetry. The vast majority of crowdfunding research deals with the supply side as a whole, thus not separating the two elements. In this paper, we break down the notion of the *crowd*. The data allow us to observe the occupations of a considerably high proportion of lenders who comprise "the crowd" so that we can distinguish those with a professional background in investments from amateur investors. Specifically, we address the following questions: Do the experts outperform the amateurs in this context, even without having extensive knowledge about the business in question? Do experts improve the screening abilities on crowdfunding platforms? Should platforms strive to have more experts among the crowd?

We find that lenders are able to screen creditworthy borrowers, but only when provided with financial information about the borrowers' businesses, which help them to avoid false positive investments. This suggests that a prerequisite for the crowd's collective wisdom is the availability of relevant data that reduce information asymmetries. Furthermore, lenders do have a preference for investing in loans with a social value, but when these loans are up for auction, the lenders lose their predictive ability even when presented with the financial information. The preference for these loans might have created a systematic error, which reduces the crowd's ability to reach the correct aggregated estimate. Finally, we do not find any significant advantage of expert investors with a financial background over amateur investors, once they are presented with the same information. The experts' experience and knowledge may not show better results once they do not possess better information.

Overall, our paper contributes to the discussion on whether the crowd funds the right entrepreneurs, projects, and companies (Iyer et al. 2016; Mollick and Nanda 2016), a central research discussion that is nevertheless in its infancy, by observing the outcomes of loans that the crowd chose not to fund. The discussion complements the large body of research on the determinants of success in reaching crowdfunding goals, by adding the perspective of whether crowdfunders screen campaigns that should be funded from those that should not. Specifically, our study contributes to the discussion about the predictive power of the crowd and how it is affected by information asymmetry and prosocial motivations in peer-to-peer lending on platforms' environments (Chen et al. 2019; Donovan 2021; Miller 2015). Our study also contributes to the discussion about the role of experts versus nonexpert crowdfunders (Budescu & Chen, 2015, Mohammadi & Shafi, 2020), by breaking down the definition of the crowd to understand it better. Our study is carried out in a funding setting relevant for development, where the social impact is also of importance, allowing us to contribute a perspective about the impact of social decisions on crowd prediction.

2. Theory and Literature

2.1. Do crowdlenders fund the right loans?

The theoretical framework of this paper is based on conceptual, mathematical, and empirical studies on the wisdom of the crowd, which asserts that the combined judgment of individuals can lead to more accurate estimations of true values. Academic attention to understanding this phenomenon dates back to the early works of Condorcet (1785/2014) and Galton (1907), and in recent decades, the phenomenon has regained interest with Surowiecki's (2004) book. While these publications provide cases where crowds correctly estimate certain values, there are plenty of examples where crowds fail to make accurate choices or predictions. Various attempts have been made to understand the conditions under which the crowd can apply its collective wisdom.

Simmons et al. (2011) and Larrick et al. (2011) outline these conditions: (1) Members of the crowd need to have some relevant knowledge about the issue at stake. (2) They need to be incentivized to be accurate in their judgment. (3) Their individual errors in making predictions should not be systematic. The last condition is believed to be achieved in two ways: by increasing diversity in group composition or views (Davis-Stober et al. 2014; Keuschnigg & Ganser 2017) and by ensuring that individual estimations are made independently (Hogarth 1978). It should be noted that many of the papers dealing with the topic discuss the wisdom of the crowd as an average of independent predictions of a quantitative true value, yet this phenomenon is observed in other contexts as well (Larrick et al. 2011).

In the context of crowdlending platforms, where potential lenders face decisions on whether to offer loans to borrowers, not all of the aforementioned conditions hold. On the one hand, with large numbers, crowds tend to be diverse; at least some members are likely to have knowledge about business administration and the business field in which they invest, and they are clearly incentivized by profit.

On the other hand, the independence of judgment condition is violated, since crowdlenders observe loan offers that were made or the absence of such offers prior to the crowdlenders' decision. It is of interest to know whether crowds can still make correct predictions even without satisfying this condition.

Few studies have tested the crowd's predictive power in peer-to-peer lending settings.[2] Iyer et al. (2016) discuss the question in the context of the peer-to-peer for-profit crowdlending platform *Prosper*, where they compare the lenders' ability to predict a borrower's likelihood of default with the borrower's (hidden) credit score and with an econometrician who has access to full data from the platform. They find that the lenders could predict defaults with 45% greater accuracy than the credit scores and reached 87% of the predictive power of the econometrician who had access to far more financial information, thus harnessing the wisdom of the crowd. Mohammadi and Shafi (2020) and Cummins et al. (2018) use a different benchmark. Taking advantage of the random allocation of loan applications to formal institutions and the crowd on the peer-to-peer crowdlending platform *FundingCircle*, they find that formal institutions outperformed the crowd in achieving lower interest rates that adjusted for the likelihood of default by small and medium businesses. These institutional investors set an interest rate that was approximately 22% more accurate in predicting defaults.

In the following subsections we discuss how the wisdom of the crowd in this context might be affected by variations in the information and the social orientation of the loans, as well as in the financial expertise level of the lenders.

2.2. Does information matter?

We also rely on theoretical models of information asymmetries in markets for entrepreneurial financing. These models propose that the inability to determine the true quality of a firm can cause over- or under-investments (Jaffee & Russell 1976; Stiglitz & Weiss 1981) as a result of the high adverse selection hazard faced by partially informed investors (Greenwald et al. 1984; Myers & Majluf 1984). In the context of an online platform with no direct contact between funders and businesses, this information asymmetry is likely to be larger than in traditional markets (Chemla & Tinn 2021) and cause worse lending decisions. Therefore, if fundraisers disclose more private information about their businesses, it is likely to improve the screening process. In particular, financial statements provide quantitative information regarding the revenues, costs, and profits of a business, which might improve the lenders' ability to evaluate its future performance and its likelihood to repay the loan (Donovan 2021). Indeed, Polzin et al. (2018) find that investors on debt and equity crowdfunding platforms who are not personally familiar with the entrepreneurs are more likely to rely on financial information when making decisions.

[2] Another stream of research focuses on the importance of crowd wisdom in stock predictions (Chen et al. 2014; Hong et al. 2020; Nofer & Hinz 2014).

In certain scenarios, the addition of financial information may decrease potential funders' will to invest in a business. One reason is that investors may deem the addition of voluntary and unaudited information as unreliable (Donovan 2021), which can create a moral hazard problem. Another reason is that it may crowd out the intrinsic motivation of funders in the context of financing ventures with a social value.

Two papers indicate the importance of financial information in the realm of crowdfunding. In the setting of a western crowdlending marketplace, Miller (2015) shows that a policy change that required borrowers to share more detailed credit information decreased the default rate of borrowers on the platform by 17 percentage points among high-risk borrowers. In the related context of an equity crowdfunding market, Donovan (2021) finds that startups that shared their financial reports were more likely to raise capital and that this capital was a mediating variable between financial reporting and performance of the startup. We seek to contribute to this research stream by observing directly whether the crowd's screening abilities are better than those of businesses that share financial information, *ceteris paribus*.

2.3. Do social projects matter?

Berns et al. (2020) find that on the interest-free crowdlending platform Kiva, loan campaigns that were associated with social microfinance institutions and the use of altruistic language were less favored by lenders. On the reward-based platform Kickstarter, Calic and Mosakowski (2016) find quite the opposite trend; technology projects that had a sustainability orientation were more likely to reach their funding goals. Calic and Mosakowski explain their finding by the 'loose ideology' shared by individuals on crowdfunding platforms, which enables social ventures to raise funds for their commercial ventures—a mission that they find particularly difficult (Austin et al. 2006).

These somewhat contradicting results suggest that opposite motives may be at play here. On one hand, prosocial and intrinsic motivations will cause crowdlenders to support social projects; on the other hand, financial incentives may discourage them, by crowding out the intrinsic motivations (Benabou and Tirole 2006; Frey 1997). In laboratory and online experiments, Chen et al. (2019) find that both financial return and philanthropic motivation affect the amount loaned and that lenders are willing to incur greater risks to help more needy borrowers but at a rate sensitive to their own degree of financial exposure.

A lender who is indeed willing to incur a risk in favor of supporting a socially beneficial venture is less concerned with profit making, which possibly reduces the lender's motivation to correctly predict the likelihood of repayment. If this occurs in a large enough number of cases, it violates the condition of the wisdom of the crowd, which states that the crowd members need to be motivated to predict the true outcome.

2.4. Do experts predict repayments better than amateurs do?

Few papers have compared the performance of experts with that of the crowd as a whole on crowdfunding platforms. When comparing the Kickstarter backers' choices of theater projects with those of a panel of experts who were presented the same information as was available on the platform, Mollick and Nanda (2016) find a high level of similarity between the two groups. Mohammadi and Shafi (2020) and Cummins et al. (2018) find that institutional investors outperformed crowdlenders by reaching lower interest rates and obtaining better default rates on the loans in which they invested.

On one hand, one may expect expert investors to outperform retail investors, since the former group has more training and experience in loans and investments, which allows it to screen loan candidates better.[3] On the other hand, in their day jobs, these experts rely on extensive information that is collected from applicant businesses, and they often meet each other personally. It is unclear whether their expertise can be put to use when the information asymmetry is very high.

3. Context and Data

According to the 2015 Massolution report, crowdlending platforms were estimated to account for approximately 25.1 billion dollars out of the total of 34.44 billion dollars that were forecasted to be raised in crowdfunding in 2015. These platforms match individual lenders and borrowers, which raise funds for the latter's businesses or for consumer objectives.

We answer the above-mentioned research questions using datasets of MyC4, a defunct online marketplace for crowdfunding microfinance that was active between 2007 and 2010. On MyC4, individual business owners from African countries posted proposals to request funding from individuals who signed up to be lenders on the platform. Lenders transferred a minimum amount of 15 euros to the platform, from which they chose a business opportunity to invest in, accepting full financial risk. During its activity, MyC4 attracted about 12,500 investors from more than 50 countries, mostly developed ones. The average amount of a bid on the platform was 27.8 euros (median = 10), and average interest rate was 15.1% (median = 15%). These lenders transferred over 10 million euros to almost 6,000 businesses, 86% of them in Kenya and Uganda. MyC4 was a signatory in the UN Global Compact, and its activities adhered to the compact's list of promises to respect societies and the environment.

To obtain loans on the MyC4 platform, business owners first applied to local credit providers, typically a local microfinance institution (MFI) partnered with MyC4, where they would undergo an initial screening. Fund seekers posted pictures and descriptions of their businesses, of themselves, and of the intended use of the requested funds, as well as specified their desired loan amount at the highest interest they could tolerate (hereafter, maximum interest rate) and the time they would require for repayment

[3] This may be compared with investments in the stock market, where there is evidence of higher profits made by institutional investors compared with retail investors (Barber et al. 2008; Cohen et al. 2002).

(see examples in Figures 1 and 2). Prospective investors reviewed the proposals on the website and made bids on those in which they would like to invest. These bids included a sum of money that was equal to or lower than the total loan amount, as well as an interest rate that was equal to or lower than 50%. The auction continued until the deadline or until the loan amount was reached, with a total weighted average that was equal to or lower than the maximum interest rate ('Dutch auction'). At the end of the auction, the bids with the lowest interest rates were declared as winners until the sum of the loan was reached. A loan campaign was considered failed if either the sum of the loan was not reached or it was reached with a weighted interest that was higher than the maximum interest rate. It should be noted that bidders could set bids with interests that were higher than the maximum interest rate; if there were enough amounts from other bids with low rates, then they could offset the higher bids in the calculation of the final weighted interest.

[Insert Figure 1 about here]

[Insert Figure 2 about here]

The aforementioned investors were not the only ones bidding on the loans in the marketplace; the platform's administrators participated in bidding as well. Bids by MyC4 were made extensively on the majority of the auctions on the website, especially on the campaigns that needed a boost of activity. At times, the bids were made to fill a missing amount with a low enough interest on the closing hours of the auction in order to ensure that the loan would not end up unfunded.

After a campaign was successfully completed, the raised money was transferred to the borrower. The money was invested in the business, and the borrower started repaying the outstanding principal and the interest in monthly instalments. The money was then transferred to the MFI, which transferred it to the platform, which in turn returned it to the lenders. Both the MFI and the platform charged fees for their services.

The aforementioned intervention by the platform's administrators allows us to observe the counterfactual—the loans that were not favored by the crowd but were still funded and continued to the repayment stage. Investigating MyC4 offers additional advantages: we observe the full bidding history with exact timestamps, and we access information about the lenders. Since the lenders and the borrowers came from different continents, they were not likely to know each other; therefore, we do not expect to find any bias to support families and friends, home bias (Lin & Viswanathan 2016), ethnic bias (Chen et al. 2019), network effects (Lin et al. 2013), or similar biases that are found in various crowdfunding platforms.

Table 1 provides the summary statistics for both the universe of loan campaigns that were either repaid or defaulted and the set of loans that were repaid. Only 46.8% of the loans in the sample were fully repaid; the rest were defaulted. The average loan amount was 1,828 euros, but only 1,211 euros among the loans that were repaid. The maximum interest rate that the borrowers set was 13.85%, but the interest rate that eventually resulted from the bids was 11.29% on average—and 10.96% for the loans that were later repaid. Women comprised more than 51% of the borrowers in the sample, and they were over-represented among the borrowers who repaid the loan, at 55.7%. Approximately 87% of the loans in the sample were taken for businesses in retail and service industries.

[Insert Table 1 about here]

4. Methodology

4.1. Do crowdlenders fund the "right" loans?

In our empirical strategy, we compare the repayment rates of the loans that the crowd favored with the repayment rates of the loans that would not have been funded if the platform's administrators had not intervened. Initially, we assume that lenders wish to maximize the returns on their loans, an assumption that we will relax later.

Dependent variable: Repaid. This is a binary variable that is equal to 1 if the loan was fully repaid and 0 if the borrower defaulted on it. Approximately 46.8% of the loans in the sample were fully repaid, making this setting particularly appealing for research, since 'lucky guesses' are less likely. The loans that were not funded by the end of their campaigns are not considered in the analysis, which may create a sample selection bias. However, only 91 loan campaigns did not reach their goals, less than 2% of the sample. Another group of loans that is not included in the analysis comprised loans that were in the process of repayment when the data were retrieved. To decrease a potential bias, we exclude any campaign that was created from September 2009 onward. Approximately 10% of the sample were funded projects that by the time of the data retrieval were neither repaid nor defaulted. The results are not likely to be biased by sample selection, since these proportions are small enough. We address this potential bias in the analysis.

Independent variable: MyC4 Intervention. For this analysis, we include either the loans that were funded (almost) solely by the lenders of the platform or the loans that would not have reached their funding goals if the platform's administrators had not made additional bids (hereafter, bids by MyC4). The assumption is that the loans that did not need the intervention of MyC4 were more attractive to lenders, *ceteris paribus*.

We employ two definitions of loan campaigns where MyC4 did not intervene. The first and the stricter definition considers only the loans that did not include any winning bids by MyC4 at the end of the auction (hereafter, *Definition A1*). It should be mentioned that these campaigns may include bids by MyC4, but with interests that were too high to eventually win the auction and enter into the loan in question. Although these losing bids may seem to be a form of intervention in itself, the fact that enough lenders chose to outbid MyC4 shows how attractive the loan was for them. The second definition allows for MyC4 bids in the final winning group of bids—up to 5% of the total requested sum of the loan (*Definition A2*). The data reveal that at times, MyC4 covered for a missing small sum before the end of the auction, outbidding bids for sums larger than needed, yet the final weighted interest would not be too high even with the first losing loan.

We also identify campaigns that would have failed without the platform's intervention (*Definition B*). These campaigns received a MyC4 winning bid up to 48 hours before the deadline, and without the bids by the platform, each campaign would not have reached either the requested sum or the required maximum interest rate.

The restrictive Definitions A1-B give values to 1,377 observations out of the 4,584 in the sample, with 22.7% that are considered loans that would not have been funded without the platform's intervention. The less restrictive Definitions A2-B expands the number of loans that are considered funded without the platform's help, and in this definition, the rate of intervened loans decreases to 11.9%. Only four campaigns are at the intersection of Definitions A2 and B, and they are attached to the latter group. Moreover, 1,353 campaigns do not fit any of the definitions since they include a winning MyC4 bid that came early. We are unable to claim with sufficient certainty that the campaigns would have been funded without these bids, nor can we state that they would have failed. These loans are not included in the analysis.

Equation 1 presents the regression model for this analysis:

$$(1)\ \ Prob(Repaid = 1) = \alpha + \beta MyC4Int + \gamma LoanAmount + \lambda MaxR + \phi X + \eta_t + \varepsilon\ ,$$

where $MyC4Int$ stands for *MyC4 Intervention*, $MaxR$ denotes the highest acceptable interest rate that the borrower is willing to pay, and $LoanAmount$ signifies the requested amount of the loan (log-transformed to avoid concerns of skewness). The latter two variables are likely to be correlated with the riskiness and the attractiveness of the loan to lenders and its repayment rate (Adams et al. 2009; Iyer et al. 2016; Kawai et al. 2014; Stiglitz & Weiss 1981). The vector X adds several covariates: the sector of activity (Gafni et al. 2020); the planned repayment term (measured in months); a dummy for adding detailed financial information about the business, typically income statements and Excel files on business plans[4] (Miller 2015); dummies for the MFIs; and the gender of the borrower (Gafni et al. 2021), determined using the database of genderize.io based on his or her first name. The variable η_t denotes year dummies.

The model is estimated using a probit analysis with robust standard errors. A negative β would indicate that the loans that required interventions would be less likely to be repaid and that the crowd's judgment was correct in choosing not to lend money to the borrowers. To test whether the crowd's judgment

[4] The decision the decision is more likely to be made as a general rule at the microfinance institution: almost all of these institutions have close to 100% of their borrowers sharing information – or close to 0%. In all loan level specification we control of the microfinance institution.

would be improved when the borrower provided financial information, we interact the variable *MyC4 Intervention* with the dummy of having financial information.

4.2. Do social projects matter?

For this part of the analysis, we define social loans. The investment objective of every project was described on the website in a couple of sentences. We identify all the loans that cited a benefit to society—either to reduce poverty, contribute to developing rural areas, support orphans, build water supply infrastructure, contribute to sustainable consumption, or increase educational or health capacity—or to assist in overcoming hardships of the borrowers themselves (those who suffered violence, handicapped borrowers, or borrowers whose families depended on them). These loans comprised approximately 11% of all the loans that were either repaid or defaulted. Moreover, female borrowers pledged payments for approximately 51% of the loans, and supporting them might hold an additional social value of gender equality. We examine these loans either separately or together with the socially oriented loans.

Before checking whether lenders make right financial choices by lending to borrowers whose loans have social values, we would like to find out if they have a preference for these loans. We do so by running two models, which set two different indicators of the success of the campaigns. The first indicator is the ratio of the weighted average of non-MyC4 bids divided by the maximum interest set by the borrower. The lower the ratio is, the more attractive the loan is, relative to the belief of the borrower. The second indicator is a dummy that indicates whether the campaign needed the assistance of MyC4 to be funded, by using Definitions A2-B from the previous subsection. In both models, the dependent variables are regressed over dummies of the loans, being social, women-led, or either of them, and the same covariates as those included in the first analysis.

Next, we aim to know if the lenders' screening ability is affected by non-pecuniary social returns offered by a loan. We split the sample into social loans (including those by women) and loans by men or without any non-pecuniary element to them, and we rerun the regression model of Equation 1 on each of them (with and without the interaction with financial information). This allows us to observe whether the results of previous estimations hold in both of these contexts.

4.3. Do experts predict repayments better than amateurs do?

In contrast to the previous analyses that are performed at the loan level, the unit of this analysis is the bid. The initial sample includes every bid made on every loan, winning or losing, with information about the amount and the interest rate bid. In the analysis, we keep only those bids on loans that were eventually either repaid or defaulted (making it our dependent variable), as well as categorized occupations, as described in the following paragraph.

Explanatory variable. Lenders on the platform have the option to specify their occupations on their personal page, and 43% of them do so in an open text form. We categorize these lenders as *Financial experts, Amateurs*, or neither, according to their jobs. Lenders whose occupations require knowledge in assessing financial situations of businesses, such as investor, chief financial officer, banker, and auditor, are categorized as *Financial experts*. They comprise 1.5% of the registered users on the platform. Lenders whose jobs clearly do not relate to finance, such as teacher, engineer, doctor, and nurse, are considered *Amateurs* (11.6% of the users). Job titles that do not fit perfectly in one of these categories are not considered in this analysis (e.g., chief executive officer, manager, or missing entries). Neither are the users who are the administrators of the platform considered. We do not expect any sample selection with regard to users who choose to share their occupations on the platform.

Equation 2 presents the probit model analysis:

$$(2)\quad Prob(Repaid_i = 1) = \alpha + \beta FinanceExpert_l + \gamma LoanAmount_i + \lambda MaxR_i + \rho X_i + \theta BidNum_{ib} + \kappa NumPrevExpertBids_{ib} + \eta_t + \varepsilon_{ilb}$$

A positive and significant β coefficient would suggest that financial experts would be more likely to make bids on loans that would eventually be repaid. We consider both winning and losing bids, since their campaign outcomes also depend on other bidders. Beyond the previously mentioned covariates, we also control for the ordinal number of the bid within the auction to account for herding effects (Åstebro et al. 2019; Herzenstein et al. 2011; Zhang & Liu 2012), noted as $BidNum$, and for the number of bids by financial experts that were made in the specific auction before the observed bid, noted by $NumPrevExpertBid$. The latter accounts for the possibility that bidders would base their bidding decisions on others' past activities that are believed to have better information (Banerjee 1992; Bikhchandani et al. 1992). Standard errors are clustered at the lender level and robust to heteroscedasticity.

Making bids on the platform is essentially costless; anyone can bid a small sum with a high interest that is not likely to win. If the bid wins the auction, then the bidder has a relatively high expected return; if the bid loses, no costs are incurred by the bidder. Therefore, high-interest bids might not reflect the bidders' true belief that the loan would likely be repaid. To eliminate this concern, we rerun the specification of Equation 2 over a subsample of bids with interests that are lower than the interest level that the borrower set as the maximum. This means that these bidders believed that the loans that they bid on were even safer than what the borrower believed, thus also offering a stronger signal of prediction by the lenders that the loan would be repaid.

The aforementioned analyses do not consider the size of the bids—a bidder who believes that a loan will likely be repaid will bid with not only a lower interest but also a larger sum of money. For each classified lender, we compute the mean sum of his or her bids, as long as they are equal to or lower than the borrower's maximum interest rate. We then subtract the mean sum of the bids on the loans that were eventually repaid from those on which the borrowers defaulted. Finally, we compare the deltas of the financial experts and the amateurs.

5. Results

We first examine whether the crowd can pick the loans that end up being repaid by looking for an empirical association between the loans that are funded without external intervention by MyC4's administrators and the repayment of the loans. We also check whether their ability to pick the right loans changes once the applicant presents financial information about the business. Next, we check whether lenders have a preference to invest in social loans and whether it is the financially correct decision to make. Finally, we observe whether financial experts predict quality loans better than amateur investors do.

5.1. Do crowdlenders fund the right loans?

Table 2 presents the results of the first analysis, with a dummy for complete loan repayment as the dependent variable. Column 1 is the baseline model with the control variables. Columns 2 and 3 use Definitions A1-B for the *MyC4 Intervention* variable. Columns 4 and 5 use Definitions A2-B, which are less restrictive, with a larger number of observations.

The association between the variable *MyC4 Intervention* is found to be statistically insignificant in both definitions ($p = .439$ in Column 2; $p = .389$ in Column 4), suggesting that lenders are unable to tell high-quality loans from low-quality ones. However, when we interact the variable *MyC4 Intervention* with the dummy of financial information for both definitions (Columns 3 and 5), we find a negative association for the interaction ($p = .039$ in Column 3; $p = .047$ in Column 5). This result suggests that lenders do choose the right loans, as long as they are provided with financial information about the business. In terms of economic magnitude, loan campaigns that need no assistance from MyC4 to reach their goals and that share their financial information are more likely to fully repay the loan by 11 percentage points (calculated over the specification of Column 5), making the repayment likelihood on 36% for campaigns that required assistance from the platform. Panels A and C of Figure 3 show that the values of the interactions of Columns 3 and 5, respectively, are negative for all values, and Panels B and D show their significance at the 5% levels in all but extreme values. Since the results using the two definitions are essentially similar, we proceed with Definitions A2-B for later analyses, to obtain greater statistical power.

[Insert Table 2 about here]

[Insert Figure 3 about here]

Computing the sensitivity and the specificity rates of the prediction of the crowd, we get further insights into the aforementioned results. Over the sample, the crowd reaches sensitivity of 92.3%, meaning that lenders did fully fund most of the loan campaigns that eventually repaid, yet reached only 15.7%, suffering from a high number of false positives – funding loans that eventually defaulted. Limiting the sample to campaigns which provided additional financial information, the sensitivity rate increases slightly to 93.4%, yet the specificity rate almost doubles to 30.5%. This suggests that the improved screening of the lenders is achieved by using the additional information to find hazards in the financial reports, and avoid investing in business which do not repay the loans. These results are visualized in Figure 4.

[Insert Figure 4 about here]

Observing the coefficients of the covariates in Table 2, we can see that as expected, the larger the loan is, the less likely it is to be repaid and likewise with the payback period. The positive coefficient of the maximum interest rate is less expected. Possible explanations are the rather realistic expectations by the borrowers, which may be correlated with better management or may represent riskier projects that eventually gain high profits.

An alternative explanation for the higher default rates on the loans that need the platform's help is that it is a consequence of the auction process itself. The platform's administrators have to make their bids due to the low demand for the loans, which is reflected in their higher interest rates. The burden of these higher interest rates might cause the borrowers to default on their loans (Stiglitz & Weiss 1981). Indeed, the mean final interest rate for the loans that receive help from the platform is higher by 2.5 percentage points than those that do not (by Definition A2). To test this explanation, we regress the repayment of a loan on the final interest rate, the sum of the loan, year, and industry, in an unreported regression. The coefficient of the interest variable is small and statistically insignificant (*-.005*, *p = .53*).[5]

5.2. Do social projects matter?

In this subsection we learn where whether the prediction ability of the crowd is affected once project offer a social value – and start with two tests that aim to answer whether women-led and social loans are more attractive to lenders than other loans. Columns 1 to 3 of Table 3 use the ratio between the weighted average interest (without the MyC4 bids) and the maximum interest set by the borrower. The negative results of Columns 2 and 3 show that these loans are indeed preferred by the lenders, *ceteris paribus*. The second test, presented in Column 4, observes which types of projects require intervention from the platform's administrators. Social and female-led loans are found to be less likely to need extra bids beyond those of the crowd in comparison to loans without a clear non-pecuniary return or led by

[5] This result is in line with the findings of Iyer et al. (2016) and Mohammadi and Shafi (2020), who also do not find a causal effect of the interest rate on default in Prosper and FundingCircle, respectively.

male entrepreneurs. This result is in line with the results of Columns 2 and 3 of Table 3. Overall, the results suggest that lenders do have a preference for loans that provide a non-pecuniary return or are pledged by female entrepreneurs.

[Insert Table 3 about here]

Next, we aim to discover whether lenders make the right financial choice by funding these social and female-led loans. A subsample that features these loans is the context of Column 1 of Table 4, while loans that are either led by men or are not social comprise the subsample in Column 2. The lenders' tendency to correctly screen borrowers who share their financial information, which is found in the previous subsection, holds only in the latter group, with the interaction being negative and statistically significant (see Panels C and D of Figure 5). It appears that lenders do not effectively screen the creditworthy loans (Panel B of Figure 5). Taken together with the results that lenders prefer social loans, it suggests that this bias towards this kind of loan is the systematic error that prevents them from applying their collective wisdom and reaching the correct aggregated estimate.

[Insert Table 4 about here]

[Insert Figure 5 about here]

The same results emerge when we compute the sensitivity and the specificity of the prediction of the crowd for social and non-social loans. The sensitivity of the prediction is as high as 97.0% for the non-social loans, while it is only 91.5% for the social ones (while both provide additional financial information). The gap between the specificity rates is higher, 39.6% when the loans do not have a social cause, and 22.8% when they do. When it comes to non-social loans, lenders fully-fund more loans overall, including many which end up defaulting. These results are visualized in Figure 4.

The question that remains is whether lenders treat these pro-social loans as charity rather than true investments, that is, money that they do not expect to receive back with interest. We observe the statistics that may help us answer this question. The first is the average interest rate for these loans; if the lenders' motivation is strongly pro-social, then they would offer very low interest rates with their bids. The results shown in Table 3 prove that indeed, the interest rates for these loans are lower, yet in terms of magnitude, the mean interest rate bid on social and female-led loans is 96% of the mean interest rate on non-social and male-led loans. Furthermore, one would expect lower sums of money to be invested in donation-like financing. In an unreported regression, we find that loans that have social value or are pledged by females receive higher bids, controlling for the usual covariates. These findings lead us to believe that lenders do treat these loans as business opportunities, yet the social added value could have distorted the cold financial judgment.

5.3. Do experts predict repayments better than amateurs do?

As mentioned earlier, the *crowd* does not mean the same as the *amateurs*, since the crowd includes lenders who are experts in the fields of investments and business auditing. Before learning whether the financial experts (hereafter, experts) make smarter investment choices than the amateurs, we compare their investment patterns. On average, bids by experts are 8.47 euros higher than bids by amateurs ($p = .000$), while the distribution of the bids between the industries is very similar.

Additionally, we would like to know the experts' opinions about the issue of social versus non-social loans investigated in the previous analysis. Column 1 of Table 5 regresses a dummy that indicates if the lender is an expert, on the variable of the loan being social or pledged by a female borrower. We find a negative correlation between the two variables (Column 1, $p = .024$). Limiting the sample to bids that feature lower interest rates than the highest accepted rate (Column 2), the results are essentially the same—financial experts prefer to bid on loans that neither have a clear social value nor are pledged by women.

[Insert Table 5 about here]

A possible explanation for the results regarding social loans suggests that the experts are driven by different motivations than the amateurs, who may be more pro-social. To investigate if this explanation holds, we compare the mean interest rates bid by the experts and the amateurs. A lender who is driven by pro-social motives will bid with a lower interest rate, which will make it financially easier for the borrower. We find that in the sample of bids, the interest rates on bids by financial experts are 0.54% lower than those on bids by amateurs ($p = .000$, using a t-test). Thus, we can rule out the possibility that experts are less likely to bid on social loans because of different motivations.

The next step would be to observe directly whether financial experts predict repayments better than amateurs do. The results presented in Table 6 suggest that this is not the case. The coefficient of the financial experts is positive yet statistically insignificant ($p = .201$, Column 1). In Column 2, we try to check whether experts can apply their knowledge when provided with financial information about the business, yet the interaction between the two variables is insignificant as well. Limiting the sample to bids with interest rates equal to or lower than the maximum interest rate, the results remain similar, with the exception of the coefficient of the financial experts being marginally significant only in the specification of Column 3 ($p = .085$). Overall, the results suggest no clear differences between the experts and the amateurs.[6] Observing the differences between the mean sums invested in repaid and defaulted loans, we do not find any significant difference between the experts and the amateurs,

[6] A similar statistically insignificant difference between the performance of the two groups is found when calculating the area under the receiver operator characteristic (ROC) curve (AUC), with or without financial information.

although the experts performed somewhat better. The same outcome appears again when considering the proportion of the money invested in repaid loans out of the total amount bid on the platform.

[Insert Table 6 about here]

We add another test to verify the validity of the aforementioned results, this time analyzing the sample at the level of the single lender. The dependent variable of the regressions presented in Table 7 divides the number of bids on loans that are successfully repaid by the total number of bids on loans that are either repaid or defaulted. We add the controls of the lender's gender, age, and country. The coefficients of the lender being a financial expert are insignificantly different from zero, supporting the result that in this setting, financial experts do not hold an advantage over amateur investors.

[Insert Table 7 about here]

Lastly, the crowd has a significantly larger number of amateur lenders than experts, which may give the amateurs a certain advantage in this aspect: Condorcet's jury theorem asserts that increasing the number of agents who make decisions will increase the probability of reaching the true value (as long as each agent has a probability of over 0.5 in choosing the right loan application). Rerunning the specifications in Table 5 on a sample of the same expert lenders and a subsample of randomly chosen amateurs of the same size still produces insignificant results.

6. Conclusion

As the interest in impact investing in developing countries has continued to grow, crowdfunding has emerged as an alternative that allows individuals from developed countries a nearly direct channel to support and invest in people and organizations. However, these individuals also bear the responsibility to fund and support only those who can use the infused capital wisely in order to improve their lives and those of the people around them. In particular, in the context of crowdlending to developing countries, this means funding only the entrepreneurs that will invest these funds in a way that will allow them to return the principal and the interest without falling into over-indebtedness. Therefore, these entrepreneurs must be wisely screened, and when pooling its resources on a crowdlending platform, the crowd should apply its collective wisdom. Thus, in this paper, we study whether the crowd is wise in this setting, and we identify the determinants that cause it to make better or worse investments.

This study's results show that crowdlenders have no clear ability to predict which borrowers would repay their loans, but once financial information is added to the loan application, correct prediction rates increase by 11 percentage points. This is achieved mainly by increasing the specificity rates of the prediction: the financial information allowed lenders to tell which loans were going to default, and then avoided investing in them. Theories about the wisdom of the crowd in entrepreneurial finance should include the level of information about the business as a necessary condition. At the same time, crowdfunding never satisfies all of the (current) conditions for the wisdom of the crowd, since contributions and bids are usually made sequentially and not independently—yet we observe incidents where the crowd performs well, with different benchmarks (Iyer et al. 2016; Mollick & Nanda 2016; this study). A theoretical discussion may reconsider the conditions for the wisdom of the crowd to be factors with a high level of one factor able to compensate for the lack of others.

This study's identification methods provide substantial support to earlier papers that highlight the role of information in crowdfunding and in entrepreneurial finance in general (Donovan 2021; Miller 2015). Platform owners would benefit from increasing the level of information that fundraisers share about their businesses—this information is required for the screening process by the crowd, which in turn is essential for the platform's sustainability.

To further learn about what causes predictions to be more or less accurate, we observe that the crowd is no longer likely to make correct predictions about social impact loans, even when presented with financial information about the ventures. Since we also find that lenders actually prefer bidding on these loans, we interpret it as a systematic error that is large enough to bias the predictions. Nonetheless, the question remains whether this is intentional—whether the crowd pays to be social. If they do, then they are willing to lose money or donate it to a social project, which decreases the factor of the crowd's motivation to make correct estimations (or violates the corresponding condition). Although we cannot definitively answer this question, the fact that lenders bid with large sums and high interest rates suggests that they do not treat these loans as donations but as business opportunities. Since these choices do not provide lenders with the best outcomes, it is of interest to know whether these are results of non-pecuniary returns, the belief that social impact loans are likely to perform better, or the taste-based restraint from other loan campaigns. We leave further investigations of the drivers of this behavior for future research.

Finally, we find that expert lenders do not screen loans significantly better than amateur members of the crowd without a financial background, in this setting where they are presented with the same information. The experts' experience and knowledge may not show better results once they do not possess better information. Our study contributes to the literature that studies the effectiveness of experts' business evaluations (see Scott et al. 2020), as well as to the literature that compares the performance of experts with those of non-experts (Mollick & Nanda 2016). Although we do not aim to thoroughly answer the question of whether the information is more important than the evaluator, our findings point to the former and suggest that information may be a condition for experts to apply their expertise. Although they do not outperform the crowd of amateurs, we still hope to bring a more nuanced approach to the crowdfunding literature, to consider more heterogeneity among the crowd, and in this case, their level of expertise.

Although this paper contributes to the scarce literature that observes crowdfunding outcomes beyond the fundraising stage, it is important to remember that repayment is only one step forward, and it does not necessarily mean success. It is possible that funds were repaid without having a meaningful impact on the business that borrowed them, or worse, that it only worsened the situation, even losing money on the interest. Future research might take another step by investigating later stages of the crowdfunding process and observing business outcomes.

In our setting, as in virtually all research about crowdfunded microfinance, the borrowers undergo the initial process of screening by microfinance organizations, before being screened again on the crowdfunding platform. Future research will gain advantage from observing whether crowdlenders can efficiently screen microentrepreneurs of developing countries, even without having them preselected.

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Tables

Table 1. Descriptive Statistics

	All loans			Repaid loans		
Variable	Observations	Mean	Standard Deviation	Observations	Mean	Standard Deviation
Loan repaid	4,584	0.468	0.499	2,146	1	0
Loan amount (in thousand euros)	4,584	1.828	2.614	2,146	1.211	1.321
Maximum interest rate	4,584	13.850	2.349	2,146	13.824	2`.327
Final weighted interest rate	4,584	11.294	2.348	2,146	10.963	2.959
Female borrower	4,268	0.515	0.500	2,019	0.557	0.497
Financial information	4,580	0.218	0.413	2,142	0.153	0.360
Number of employees	2,110	3.248	1.323	978	3.281	1.392
Social loans	4,584	0.112	0.316	2,146	0.091	0.287
MyC4 Intervention Definitions A1-B	1,377	0.227	0.419	719	0.136	0.343
MyC4 Intervention Definitions A2-B	2,632	0.119	0.323	1,272	0.077	0.267
Import	4,296	0.000	0.015	2,030	0.000	0.022
Extraction	4,296	0.033	0.178	2,030	0.032	0.176
Manufacturing	4,296	0.087	0.281	2,030	0.088	0.284
Retail	4,296	0.557	0.497	2,030	0.567	0.496
Services	4,296	0.316	0.465	2,030	0.301	0.459
Wholesale	4,296	0.005	0.070	2,030	0.010	0.099
Other	4,296	0.003	0.055	2,030	0.001	0.038
Year = 2007	4,584	0.115	0.319	2,146	0.185	0.388
Year = 2008	4,584	0.692	0.462	2,146	0.697	0.460
Year = 2009	4,584	0.193	0.395	2,146	0.118	0.323

Notes. In *Repaid loans* we include only fully repaid loans, and these are a subsample of the left panel of all the loans. *Maximum interest rate* is the highest weighted average interest rate of the winning bids that the borrowers is willing to pay. *Definitions A1-B* include the campaigns that did not include any winning bids by MyC4 at the end of the auction and campaigns that would have failed without the platform's intervention. *Definitions A2-B* include the campaigns that had the share of the final sum by MyC4 is 5% or less and campaigns that would have failed without the platform's intervention.

Table 2. Loan Performance and Interventions by the Platform

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Repaid = 1				
		Definitions A1-B		Definitions A2-B	
MyC4 Intervention		0.094	0.190	0.100	0.189
		(0.121)	(0.133)	(0.115)	(0.126)
Intervention X Financial information			-0.628**		-0.589**
			(0.304)		(0.296)
log(Loan amount)	-0.051	-0.202***	-0.199**	-0.097*	-0.100*
	(0.042)	(0.078)	(0.079)	(0.055)	(0.055)
Maximum interest rate	-0.004	0.060**	0.063**	0.009	0.009
	(0.012)	(0.029)	(0.029)	(0.018)	(0.018)
Payback period	-0.165***	-0.145***	-0.149***	-0.169***	-0.170***
	(0.013)	(0.026)	(0.026)	(0.018)	(0.018)
Financial information	-0.153**	-0.016	0.085	-0.143	-0.093
	(0.071)	(0.133)	(0.143)	(0.098)	(0.101)
Female borrower	-0.003	-0.051	-0.044	-0.108*	-0.106*
	(0.049)	(0.087)	(0.087)	(0.064)	(0.064)
Constant	2.955***	2.830***	2.801***	3.059***	3.072***
	(0.532)	(0.601)	(0.601)	(0.385)	(0.386)
Industry, MFI, year dummies	Yes	Yes	Yes	Yes	Yes
Observations	3,969	1,118	1,118	2,166	2,166

Notes. Column 1 is a baseline specification. The dependent variable is equal to 1 if the loan was fully repaid and 0 if the borrower defaulted on it. Columns 2 and 3 use Definitions A1-B for the explanatory variable *MyC4 Intervention*, and Columns 4 and 5 use Definitions A2-B. An intervention of the platform, which is a proxy for a preference of the crowd not to fund the campaign, is not significantly correlated with loan performance (Columns 2 and 4). The platform's intervention is only correlated with a higher likelihood to of default when interacted with the availability of financial information about the business. Panels A and C of Figure 3 show that the values of the interactions of Columns 3 and 5, respectively. Dummies for industries, microfinance institutions, and years are included in all specifications. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 3. Attractiveness of social and female-led projects

	(1)	(2)	(3)	(4)
	DV: Non-MYC4 weighted average interest / max interest			DV: MyC4 intervention
Social project		-0.040***		
		(0.011)		
Female borrower		-0.022***		
		(0.007)		
Social project or female borrower			-0.024***	-0.175**
			(0.007)	(0.072)
log(Loan amount)	0.023***	0.019***	0.022***	0.484***
	(0.006)	(0.007)	(0.006)	(0.072)
Maximum interest rate				-0.124***
				(0.031)
Financial information	-0.040***	-0.037***	-0.039***	0.131
	(0.011)	(0.011)	(0.011)	(0.122)
Payback period	0.001	0.002	0.001	0.029**
	(0.001)	(0.001)	(0.001)	(0.013)
Constant	0.594***	0.648***	0.628***	-3.176***
	(0.042)	(0.046)	(0.043)	(0.437)
Industry, MFI, year dummies	Yes	Yes	Yes	Yes
Observations	4,292	4,002	4,292	2,406
R-squared	0.044	0.052	0.046	

Notes. The dependent variable of Columns 1 to 3 is a ratio of the weighted average of non-MyC4 bids divided by the maximum interest set by the borrower, with a lower ratio suggesting greater demand for the project. The dependent variable of the specification of Colum 4 is a dummy that equals to one if the campaign required the administrators of the platform to reach its goal, according to *Definitions A2-B*. Column 1 is a baseline specification with only controls, and the specification of Column 3 aggregates the explanatory variables *Social project* and *Female borrower* of Column 2. The results of Columns 2 to 4 suggest that social and female-led campaigns had greater success. Dummies for industries, microfinance institutions, and years are included in all specifications. **Significant at 5%, ***significant at 1%.

Table 4. Loan Performance and social and female-led projects.

	(1)	(2)
	Dependent Variable: Repaid = 1	
	Social / Female	Male and not social
MyC4 Intervention	0.211	0.157
	(0.175)	(0.179)
Financial information	-0.179	0.081
	(0.124)	(0.160)
Intervention X Financial information	-0.226	-1.610**
	(0.344)	(0.641)
log(Loan amount)	-0.102	-0.086
	(0.065)	(0.086)
Maximum investment rate	0.025	-0.013
	(0.022)	(0.029)
Payback period	-0.182***	-0.153***
	(0.022)	(0.027)
Constant	2.942***	3.290***
	(0.468)	(0.580)
Industry, MFI, year dummies	Yes	Yes
Observations	1,423	856

Notes. The sample of Column 1 consists of loans that are either social or pledged by female borrowers, and the sample of Column 2 consists of loans that are non-social and pledged by men. The dependent variable is equal to 1 if the loan was fully repaid and 0 if the borrower defaulted on it. The crowd reached correct predictions only when having access to financial information – and only when the projects did not have a social aspect to them. Visualization of the interaction terms is available in Figure 5. Dummies for industries, microfinance institutions, and years are included in all specifications. **Significant at 5%, ***significant at 1%.

Table 5. Financial experts and social projects.

	(1)	(2)
	DV: Bidder is a finance expert	
		r < max r
Social project or female borrower	-0.053**	-0.063***
	(0.024)	(0.024)
log(Loan amount)	-0.037	-0.088
	(0.064)	(0.078)
Maximum interest rate	-0.041***	-0.042***
	(0.015)	(0.014)
Bid number	-0.000**	-0.000
	(0.000)	(0.000)
Number of previous bids by experts	-0.044	-0.064
	(0.097)	(0.091)
Financial information	0.054	0.062
	(0.044)	(0.049)
Payback period	0.007	0.005
	(0.006)	(0.007)
Constant	0.216	0.239
	(0.562)	(0.743)
Industry, MFI, year dummies	Yes	Yes
Observations	49,541	32,136

Notes. The dependent variable is equal to 1 when the lender's occupation is in the realm of finance and auditing of businesses, and 0 when the lender occupation is clearly out of that realm. The unit of analysis is now the single bid, either winning or losing, yet only by lenders who were classified as experts or amateurs. The specification of Column 2 is run over a subsample of the sample of Column 1, limited to only bid which featured interest rates that were lower than the borrower's highest acceptable interest rate. Projects that had a social aspect and/or pledged by women were negatively correlated with the lender being an expert, suggest experts had no preference for this type of loans. Dummies for industries, microfinance institutions, and years are included in all specifications. **Significant at 5%, ***significant at 1%.

Table 6. Loan performance and type of lenders.

	(1)	(2)	(3)	(4)
	DV: Repaid = 1			
			Interest rate below the maximum	
Financial expert	0.059	0.076	0.074*	0.077
	(0.046)	(0.051)	(0.043)	(0.047)
Financial information	-0.296***	-0.280***	-0.288***	-0.286***
	(0.032)	(0.033)	(0.043)	(0.046)
Expert X Financial information		-0.096		-0.013
		(0.074)		(0.076)
log(Loan amount)	0.045**	0.045**	0.021	0.021
	(0.018)	(0.018)	(0.022)	(0.022)
Maximum interest rate	-0.042***	-0.042***	-0.042***	-0.042***
	(0.008)	(0.008)	(0.008)	(0.008)
Payback period	-0.172***	-0.172***	-0.171***	-0.171***
	(0.006)	(0.006)	(0.007)	(0.007)
Social project	-0.036	-0.037	-0.049	-0.050
	(0.028)	(0.028)	(0.038)	(0.038)
Female borrower	-0.009	-0.009	-0.036	-0.036
	(0.018)	(0.018)	(0.023)	(0.023)
Bid number	-0.001***	-0.001***	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Number of previous bids by experts	0.008	0.008	0.003	0.003
	(0.008)	(0.008)	(0.010)	(0.010)
Constant	2.713***	2.710***	2.867***	2.866***
	(0.145)	(0.145)	(0.191)	(0.191)
Industry, MFI, year dummies	Yes	Yes	Yes	Yes
Observations	44,876	44,876	24,294	24,294

Notes. The dependent variable is equal to 1 when the lender's occupation is in the realm of finance and auditing of businesses, and 0 when the lender occupation is clearly out of that realm. The unit of analysis is the single bid, either winning or losing, yet only by lenders who were classified as experts or amateurs. The specifications of Column 3 and 4 are run over a subsample of the sample of Columns 1 and 2, limited to only bid which featured interest rates that were lower than the borrower's highest acceptable interest rate. Overall, being a financial expert is not associated with statistically significant better prediction over the loan outcomes. Dummies for industries, microfinance institutions, and years are included in all specifications. *Significant at 10%, **significant at 5%, ***significant at 1%.

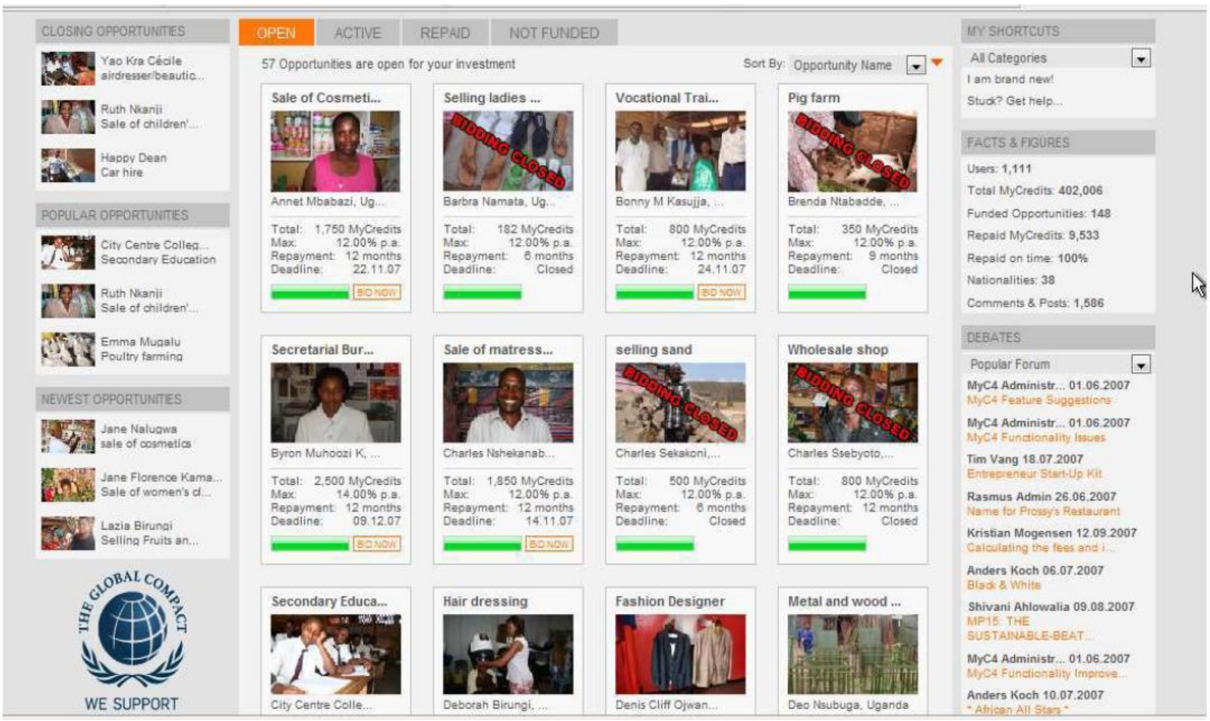
Table 7. Success Rates of Lenders.

	(1)	(2)	(3)
	DV: Lender's success rate		
Financial expert	0.001	-0.010	-0.053
	(0.021)	(0.032)	(0.073)
Age		-0.000	-0.001
		(0.001)	(0.002)
Male lender			0.011
			(0.051)
Constant	0.375***	0.331***	0.180**
	(0.007)	(0.075)	(0.070)
Country dummies	No	Yes	Yes
Observations	1,688	954	283
R^2	0.000	0.034	0.096

Notes. The dependent variable divides the number of bids on loans that are successfully repaid by the total number of bids on loans that are either repaid or defaulted. We add the controls of the lender's age, gender, and country. The coefficients of the lender being a financial expert are insignificantly different from zero, supporting the result that in this setting, financial experts do not hold an advantage over amateur investors. **Significant at 5%, ***significant at 1%.

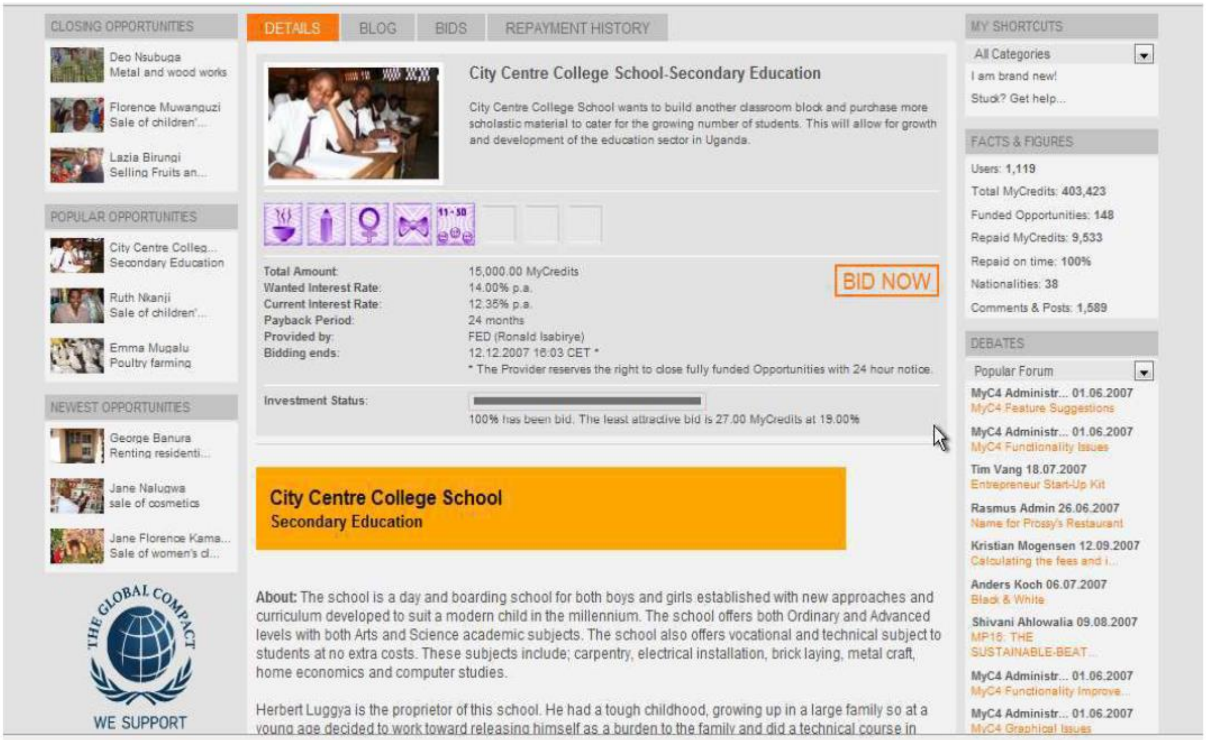
Figures

Figure 1. Screenshot of loans menu.



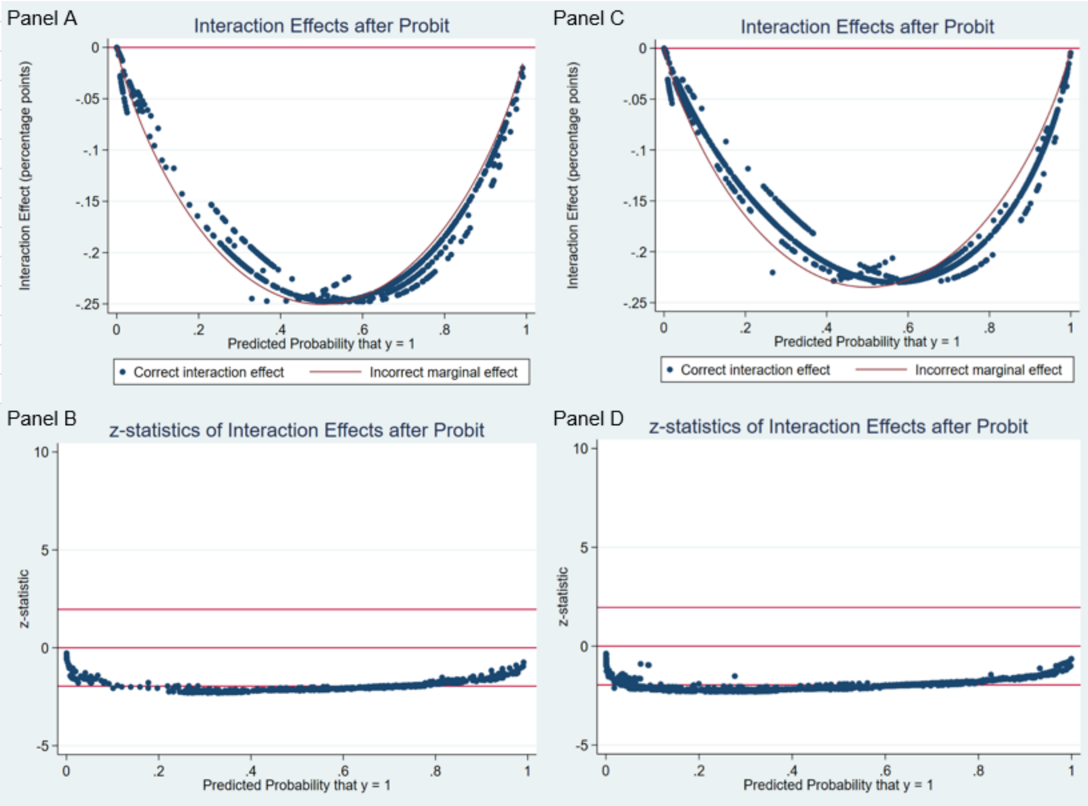
Notes. A screenshot of a projects menu page on the website of MyC4. Potential lenders could browse through the projects and choose which auctions they bid on.

Figure 2. Screenshot of a project's details.



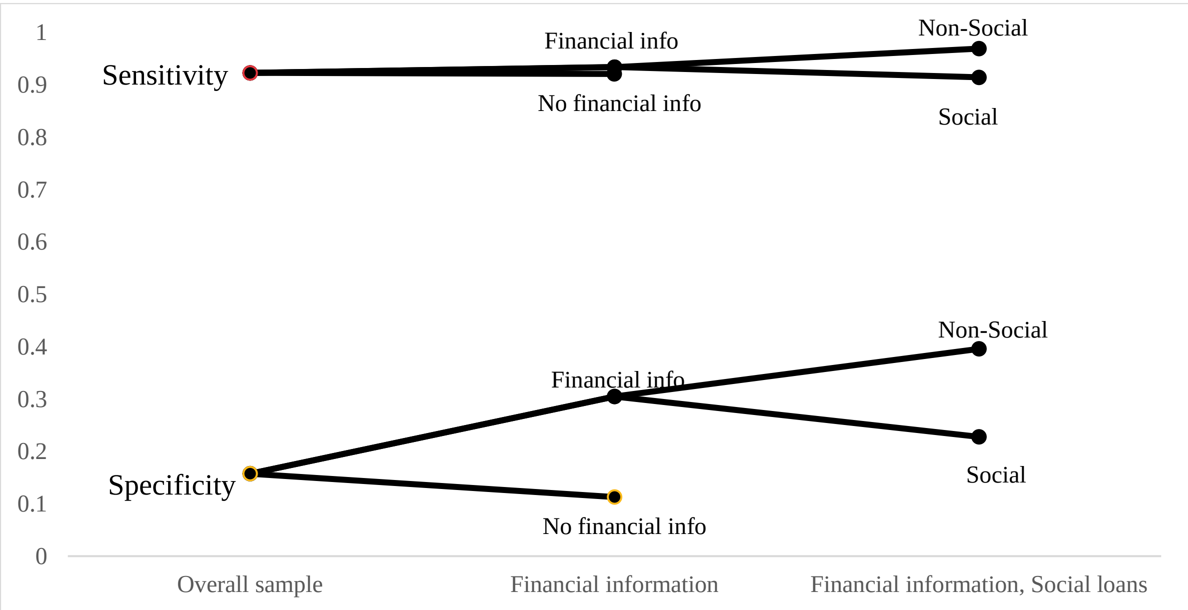
Notes. A screenshot of a project page on the website of MyC4. It includes a description of the project, a picture, and details about the requested loans and the current state of the auction.

Figure 3. Interaction Effects after Probit and z-statistics of the Interaction Effects of Table 2



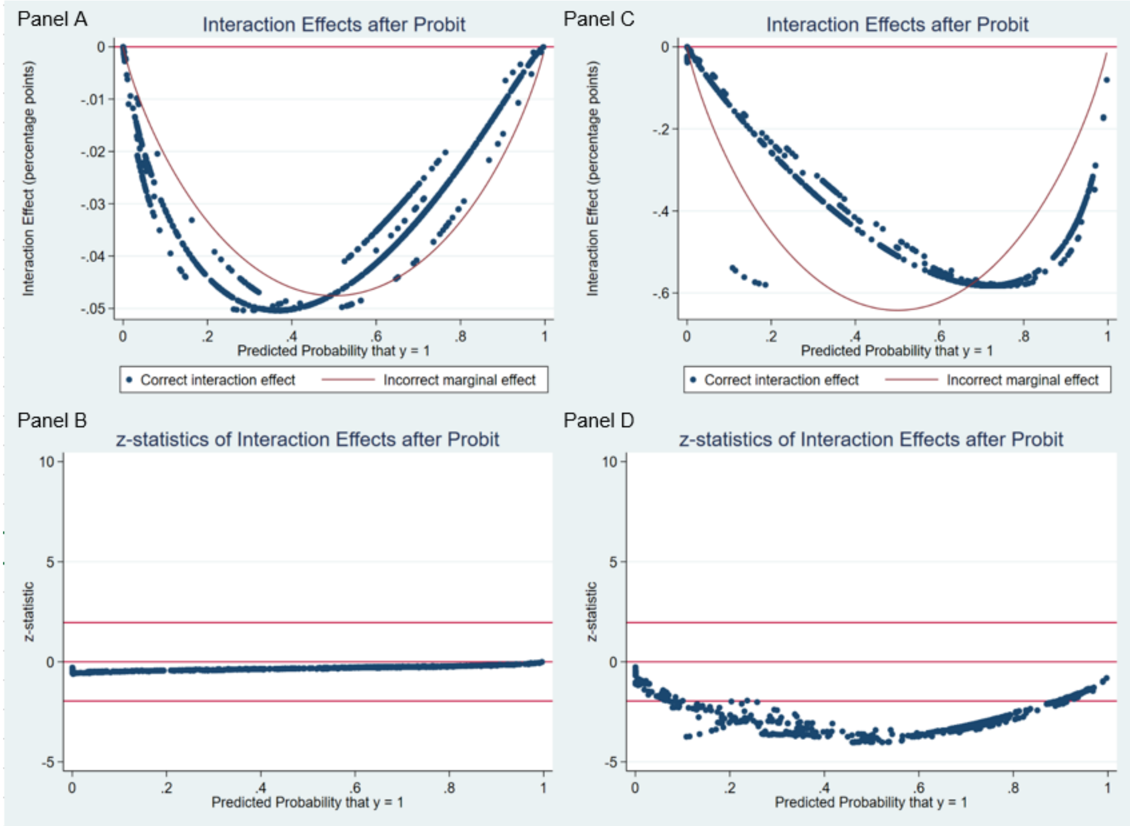
Notes. Panels A and B relate to the interaction term of specification of Column 3 of Table 2, and Panels C and D relate to specification of Column 5 of the same table. The value of the interaction are negative throughout, and mostly significantly different from zero.

Figure 4. Sensitivity and Specificity of the Screening



Notes. Both the sensitivity and sensitivity of the screening are higher when financial information is added, and even higher in cases that the loan is not socially-motivated. The differences are higher when concerning the specificity. The central column ("Financial information") divides the left overall sample of the left column to observation with and without financial information about the business.

Figure 5. Interaction Effects after Probit and z-statistics of the Interaction Effects of Table 4



Notes. Panels A and B relate to the interaction term of specification of Column 1 of Table 4, and Panels C and D relate to specification of Column 2 of the same table. The values of the interaction between the intervention and the financial information are statistically insignificant different from zero when it comes to social and female-led projects (Panel B), but largely significantly negative for non-social and male-led projects (Panel D).

Appendix 1 – Description of variables.

Variable	**Description**
Repaid	1 = The principal and interest of the loans were fully repaid, 0 if not.
MyC4 Intervention	1 = The loan would not have been funded if it was not for an intervention of the platform that covered for the missing funds. 0 = Either no support at all from the platform (*Definition A1*) or a minor support (*Definition A2*).
Financial information	A dummy for adding detailed financial information about the business, typically income statements and Excel files on business plans.
Loan amount	The total requested amount. The sum of the bids of the lenders much reach this amount for the campaign to be successful.
Maximum investment rate	The highest acceptable interest rate that the borrower is willing to pay. This is set prior to the start of the bidding. The loan is funded only if the weighted average of the bids with the lowest interest is lower or equal to this rate.
Payback period	The planned duration of the payback period. This is set prior to the start of the bidding.
MFI	Microfinance institution which intermediates the loan.
Social loan	Loans that cited a benefit to society (regarding poverty, education, health, sustainability, etc), assist in overcoming hardships of the borrowers themselves.
Financial Expert	1 = Lenders whose occupations require knowledge in assessing financial situations of businesses. 0 = Lenders whose jobs clearly do not relate to finance.
Bid number	The sequential number of the bid in the auction.
Number of previous bids by experts	Number of previous bids by experts in that same auction.