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How Wise Are Crowd? A Comparative Study of Crowd and Institutions in Peer-to-Business Online Lending Markets

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Abstract

Funding small businesses used to be the exclusive domain of angel investors, venture capitalists, and banks. Crowds have only recently been recognized as an alternative source of financing. Whereas some have attributed great potential to the funding provided by crowds (?crowdfunding?), others have clearly been more skeptical. We join this debate by
examining the performance of crowds to screen the creditworthiness of small and medium sized enterprises (SMEs) compared with institutions in the context of new online peer-to-business lending markets. We exploit the randomized assignment of originated loans to institutions and crowds in the online peer-to-business platform of FundingCircle, and find that crowds underperform institutions in screening SMEs, thereby failing to lend at interest rates that adjust for the likelihood of defaulting on a loan. The interest rates set by crowds predict default 39% less accurately than institutions. Moreover, the underperformance gap of crowds compared with institutions widens with risky and small loans, suggesting that crowds lack the expertise to assess the risks or the incentive to expend resources to perform due diligence. Overall, our findings highlight when crowds face limitations in screening SMEs.

How Wise Are Crowds? A Comparative Study of Crowds and Institutions in Peer-to-Business Online Lending Markets

The losses on peer-to-peer lending which will emerge within the next five to ten years will make the worst bankers look like absolute lending geniuses.

Lord Adair Turner, Former Chairman of the Financial Services Authority[1]

1. Introduction

The majority of financing of small and innovative businesses was exclusively left to banks and venture capitalists. In each case, scholars have noted the organisational, informational, and agency constraints these organisations face (Kerr et al. 2014). For instance, the entrepreneurs funded by venture capitalists often share similar characteristics of their investors in terms of their educational, social, geographic, and professional characteristics (Rider, 2012). Although considerable funding has historically come from these incumbents, financial technologies ("Fintech") are disrupting the landscape of funding to entrepreneurs (Burtch, Ghose, Wattal, 2013, Lin, Prabhala, and Viswanathan,2013, Mollick, 2014). In particular, crowdfunding has emerged as a promising alternative source of financing, connecting directly a large number of entrepreneurs with many supporters and lenders. As a testimony to its growth, crowdfunding markets are estimated to have raised $140 billion in 2015, with over 200% annual growth rate (Rau, 2017). In turn, policy-makers extoll the virtues of crowdfunding, hoping that they will democratize access to entrepreneurial finance (Sorenson et al. 2016), especially for women and minority entrepreneurs, and that the firms crowdfunded will create jobs and economic growth (Mollick and Robb, 2016).

Among different models of crowdfunding, peer-to-peer lending had the largest global market share of about $133 billion (96% of total market). Within the lending-based crowdfunding, peer-to-business lending remains the largest category by volume in 2015 according to the report of Nesta[2], which investigates the online alternative finance market of the UK. Peer-to-business lending (excluding real estate lending) supplied the equivalent of

[1] https://www.theguardian.com/money/2016/feb/10/former-city-regulator-warns-peer-to-peer-lending-lord-turner

[2] https://www.nesta.org.uk/news/new-research-shows-uk-online-alternative-finance-market-grew-to-32-billion-in-2015/

13.9% of new bank loans to small businesses in the UK in 2015 (based on BBA's 2014 baseline figure of £6.34 billion).

Despite the expanding role played by crowds in funding entrepreneurs once left to professional investors, our knowledge is limited about how and when crowds and professional investors may differ in their ability to overcome (adverse selection) risks prevalent in financing markets. Indeed, there is debate about crowds' ability to select good investment opportunities, as the opening quote suggests. Below we offer the two following diverging perspectives of this debate.

On the one hand, the removal of formal intermediaries such as banks and venture capitalists, as a clear distinguishing feature of crowdfunding, leaves individual investors with direct exposure to adverse selection risks and moral hazard problems (Ahlers et al. 2015; Mohammadi and Shafi, 2017), which stem directly from prevalent information asymmetries in the markets of entrepreneurial financing (Gompers and Lerner 2004). Faced with these problems, individual investors may underperform because they have limited budget and resources including expertise and capabilities to perform due diligence (Freedman and Jin, 2011) as well as "limited" incentives due to low stake holding to expend effort in screening firms (Ahlers et al. 2015). This situation stands in contrast to the expected requirements governing the traditional intermediaries such as banks and venture capitalists, who are in possession of resources and capabilities both to alleviate adverse selection risks ex ante and to deter entrepreneurs' opportunistic behaviour ex post (Gompers and Lerner, 2004).

On the other hand, despite preceding limitations faced by individuals, a recent stream of literature argues that resorting to the wisdom of the crowds in crowdfunding markets helps improve the decision-making of the individuals (Iyer et al., 2016, Mollick and Nanda, 2016). The wisdom of crowd claims that mathematical or statistical aggregates (as measured by any form of central tendency) of the judgments of a group of individuals will be more accurate than those of the average individual by exploiting the benefit of error cancellation (Hogarth, 1978; Larrick and Soll, 2006). The necessary conditions for the formation of wisdom of crowd are that individuals in the crowd should be (1) knowledgeable about the subject, (2) motivated to be accurate, (3) independent, and (4) diverse. Therefore, under the preceding conditions, the deployment of wisdom of the crowd in crowdfunding markets is a source of performance advantage for individual investors.

This study examines two inter-related questions: (a) the degree to which crowds possess the ability to assess the risks of funding small business loans and (b) when crowds are susceptible to misjudging the risks. These questions are important for policies targeted at promotion of consumer protection in the Fintech sector. With more interest in regulating consumer financial products in the aftermath of financial crisis 2007–2008 (e.g., Campbell et al. 2011), Consumer Financial Protection Bureau was established in 2011 to monitor mostly mortgages, loans, and credit cards.[3] The basic aim of these regulations was to recover consumer confidence by imposing transparency, heightening awareness of risks, and appropriate handling of conflicts of interest. This paper offers insights into the functioning of the loan markets facilitated by online portals; more specifically, we highlight when less sophisticated consumers face limitations in assessing risks in these markets, and thereby, inform the evidence-based policy debate about requirements of risk disclosures and other legislative measures in protecting consumers in the direct to consumer platforms that are increasingly becoming important for all consumers to access FinTech products (FCA, 2017).

Several features of our research setting aim to address the extent of crowds' performance in assessing loans. First, we benchmark the performance of crowds against institutions (e.g. pension funds, insurance companies, family offices, and hedge funds) in screening SME borrowers in the peer-to-business lending market of FundingCircle.com. Institutional investors are referred to as "smart money" in the financial markets: they are supposedly expert and sophisticated in screening loans. Institutional investors are more likely to have considerable skin in the game because they purchase entire loans ("whole loans"), instead of pieces of loans that appeal to individual investors with more limited budgets. Practically, this comparison bears implications for stakeholders such as industry practitioners

[3] Taking cues from U.S. financial reform, in 2013, the European Commission proposed new consumer financial protection legislation to simplify disclosures and tighten guidance requirements related to financial products.

and legislators because the institutional demand – so-called "institutionalisation of crowdfunding" (Nesta, 2016) – has marked a pivot point for the growth of peer-to-peer lending industry. The fraction of institutional investors such as hedge funds and pension companies, or funds investing on behalf of individuals in peer-to-peer platforms, has skyrocketed since the creation of "whole loan" programs (Lin, Sias, and Wei, 2017), surpassing the share of individuals in the total loan volumes on platforms adopting this practice including market leaders such as LendingClub.com, Prosper.com, or FundingCircle.com. Second, both institutions and crowds participate in financing loans on the same platform, which removes the possibility for influence of confounding variables across settings. Third, the originated loans are randomly assigned to either institutions or crowds, removing ex ante selection bias.[4] Additionally, we have an objective and important sense of the long run success of the loans using default rates, which is difficult to obtain in other models of crowdfunding (Mollick and Nanda, 2016). Finally, lenders have primarily financial motivation to earn positive returns in lending to businesses (Pierrakis and Collins, 2013), removing potential influences associated with intrinsic or pro-social behaviours prevalent among other models of crowdfunding.

This study has two main findings. First, we document that crowds on average underperform institutional investors. Exploiting the randomized assignment of originated loans to either institutions or crowds and after controlling for loan characteristics such as credit band, crowds compared with institutional investors earn about 40 basis points less interest return without significant decrease in the ex-post "hazard", or instantaneous probability, of default. We also show that the interest rates set by crowds predict default 39% less accurately than institutions. Further support comes from a different identification strategy that analyses "recycled loans": loans left unfunded by institutional investors (following random assignment) but later funded by crowds; the nature of this rejection was unobservable to crowds but observable to the econometricians. We employ a propensity-score matching

[4] https://support.fundingcircle.com/entries/56034068-How-will-you-decide-which-loans-will-be-whole-loans-

method that matches each recycled loan with an institution-funded loan based on observable loan characteristics, and we find that recycled loans underperform institution-funded loans of the matched control group by about 20 basis points return on interest rate, without ex-post significant changes in default rates.[5] These findings indicate that some of the conditions necessary to produce wisdom of the crowds are potentially violated. Our subsequent findings relate to two of these conditions and are anchored in the crowds' limited expertise and incentive.

We find that the underperformance gap of crowds relative to institutions narrows for loans with less risky borrowers: borrowers whose business is incorporated as unlimited company (relative to "limited" company), and borrowers who are willing to accept lower maximum interest rate within each credit band. Because riskier loans require greater expertise in their evaluation, our evidence suggests that crowds have limited expertise. Furthermore, the underperformance gap of crowds relative to institutions narrow for loans with larger requested amount of borrowing (loan size). Requested amount of borrowing for a loan listing likely increases the incentives to put more effort and produce accurate information because of higher payoffs in doing so.

2. Theory

2.1. The Role of Information in Online Lending Peer-to-Peer Markets. The relevance of asymmetric information and its potential for adverse selection risk is the theoretical cornerstone of studies in (consumer) credit markets (Karlan and Zinman, 2009). In credit markets, including peer-to-peer markets, lenders infer the creditworthiness of borrowers by observing both hard information (standard financial information such as credit scores) and soft information about borrowers' quality (for a review of peer-to-peer lending literature, see Morse, 2015). To show the role of hard information in influencing lenders' decisions, Miller

[5] In additional robustness checks, we leverage policy changes in the website of FundingCircle.com that switched the "auction-mechanism" of interest rate (the interest rate for a funded loan is determined through sequential bidding) for all loans to "fixed" interest rate (the interest rate for a loan is set by platform) at the end of September 2015. Before this change, only "property"-related loans had "fixed" interest rates. The results of diff-in-diffs analysis are again consistent with the underperformance of crowds compared with "fixed" interest rates.

(2015) exploits an unanticipated increase in borrowers' credit report details (visible to lenders) on Prosper.com and reports that allowing lenders to access more borrowers' credit information reduces default rates among high-risk borrowers because of improvement in lenders' selection ability. In addition to hard information, soft information can reduce adverse selection risks. Physical and demographical attributes of borrowers such as beauty, age, and race influence the peer-to-peer lending decisions (Duarte, Siegel, and Young, 2012; Pope and Sydnor, 2011; Ravina, 2012). Lin et al. (2013) show that friendship connections on Prosper.com help mitigate asymmetric information on the market by conveying costly and hard-to-imitate signals of borrowers' quality. Iyer et al. (2016) show that lenders in peer-to-peer markets substantially outperform the credit band (based on scoring technology) in terms of predicting loan default by decoding soft information such as maximum acceptable interest rate a borrower is willing to accept.

2.2. Wisdom of the Crowd. Crowdfunding markets facilitate pooling resources from a multitude of individuals, forming a group of investors where the decision of individuals is informed by and in turn influences others. The notion of "wisdom of crowd" characterizes the possibility that the aggregate of individual decisions outperforms each individual decision. More formally, the wisdom of crowd predicts that mathematical aggregation (such as averaging) of the individual's judgments can cancel out individual errors of judgment, leading to more accurate measures of true value (Larrick and Soll, 2006). In this sense, an individual's judgment comprises signal-plus-noise and averaging the judgments will cancel out the noise and extract the signal. The production of "wisdom of crowd" requires some conditions (for a review, see Larrick, Mannes, and Soll, 2011), which either emphasize the quality of the signal or the nature of the noise in the individuals' judgment. First, crowds or at least some member of the crowd should have some relevant knowledge about the issue of judgment (Keuschnigg and Ganser, 2016). This ability allows individual judgments to be informed and close to the true value. Second, Individuals should have the motivation or economic incentives to use their knowledge and expertise to achieve an accurate judgment (Simmons et al. , 2011). Finally, the individual errors should not be systematic. If all crowd's members make the same mistake, they are not able to cancel each other's errors and achieve more accurate judgment. Reduction of systematic errors is linked to two factors. First, there should be diversity in judgment of members in the crowd about the issue in question (Page, 2007; Hong and Page, 2008). Second, individual judgments should be formed independent of others (Sunstein, 2006). If crowds talk to one another and share their information, they will share the same errors (and same bias). The aggregation or averaging of such systematic errors is likely to impede the formation of the wisdom of the crowd. Indeed, group discussion can reinforce or even exacerbate individuals' biases (Sunstein, 2006). Social influence such as peer pressure toward conformity or group decision-making can bias the individual errors, and thus, undermine the production of wisdom of the crowd (Sunstein, 2006; Lorenz et al. 2011). In sum, given conditions of ability, incentive, diversity, and independence, when predicting an unknown outcome, the central tendency of individuals' judgements estimates the truth more closely than each individual judgement.

3. Hypothesis Development

To assess the performance of crowds, we benchmark the lending decisions of crowds against institutional investors, for the following reasons. First, an aggregate measure from a collection of individual judgments is said to be "wise" if it comes close to the true value. The true value however may not be known or well defined ex ante,[6] which renders the expert judgement the next best alternative. Second, institutional investors are referred to as "smart money" (Shleifer and Summers 1990) because they are sophisticated, informed, and expert in addition to well-capitalized players (Zheng, 1999). Research has shown that at least some institutions such as mutual funds have (stock) selection ability and skill (as opposed to luck) (Berk and van Binsbergen, 2015), evidenced by returns on investment above market indices (Daniel et al. , 1997).

3.1. Do Crowds Perform Better than Institutions? A few arguments cast doubt on the outperformance of crowds compared with institutional investors. The first one scrutinizes the

[6] Typical examples in prior research include the "cultural" markets of musical tastes (Salganik, Dodds, and Watts, 2006) or artistic projects (Nanda and Mollick, 2016).

expertise of individual investors. Individuals underperform standard benchmarks (e.g., a low cost index fund) (Barber and Odean, 2013) and trading by individual investors produces economically large losses (Barber et al. 2009; Grinblatt and Keloharju, 2000; Odean, 1998). Poor understanding of financial markets by individual investors leads to investment decisions that deviate from financial theories of wealth maximization (Calvet, Campbell, and Sodini, 2007). Field and Lowry (2009) show that individual investors make poor use of available information such as the reputation of the underwriters to make decisions under uncertainty about the quality of an IPO offering. Further evidence from behavioural finance suggests that individual investors tend to sell their winning stocks and keep the losing ones (Odean, 1998), contrary to the predictions of financial theories. In addition, the stocks individual investors buy underperform those they sell (Odean, 1999). Cohen, Gompers, and Vuolteenaho (2002) investigate how institutional and individual investors react to the news about future cash flows; institutions in response to positive (negative) cash-flow news, which signals potential future price growth, buy shares from (sell shares to) individuals. In the peer-to-peer lending market of Prosper, Freedman and Jin (2011) find evidence that lenders fund loans of low expected returns owing to lack of expertise in risk evaluation. Overall, individuals on average show limited financial expertise, as evidenced by their returns in other markets. Therefore, we propose the following hypothesis in the context of lending platforms:

> **Hypothesis 1**. *Crowds underperform institutional investors. That is, crowds compared with institutions request a lower interest rate on a given loan.*

3.2. Does Limited Expertise of Crowds Contribute to Underperformance Gap? In the subsequent hypotheses, we elaborate the boundary conditions of the underperformance of crowds relative to institutions. To do so, we explore when the assumptions behind the formation of “wisdom of crowd” are more likely to be violated. Two areas of interest relate to the expertise and the incentives of individuals in crowds. We conjecture that that the extent of underperformance gap between crowds and institutions (a) increases with the expertise required to assess the riskiness of loans and (b) decreases with the incentives of crowds for accurate production of information on loans.

Let us first focus on how the value of expertise in screening borrowers increases with risk. When the uncertainty about the borrowers' quality is higher, the production (and interpretation) of information is of greater importance (Miller, 2015). The expertise allows, for instance, inference from soft/nonstandard information when assessing worse quality borrowers (Iyer et al. 2016). To specify our hypotheses linking loan risk and performance gap of crowds relative to institutions, we draw on the idea that returns to expertise (skill) for riskier loans are larger. It is easier to detect the expertise of investors (or to distinguish between skilled/informed from unskilled/uninformed investors) in the riskier segment of markets (Liebscher and Mählmann, 2016). Accordingly, marginal value of expertise is higher among the risky investments. Fang, Tian and Tice (2014) show that the most skilled bond mutual fund managers are more likely to be assigned to the high yield bond market where returns to skill are arguably higher. Accordingly, if "returns to expertise" (skill or being informed) are smaller for less risky loans, then the gap between institutions and crowds should be narrower in screening these borrowers, ceteris paribus.

Before proceeding further, we identify risky loans using three proxies: (1) maximum interest rate a borrower is willing to pay – also known as reservation rate – in each credit band (Kawai, Onishi, and Uetake, 2014; Iyer et al. 2016), (2) the incorporation status of borrowers' business: limited or unlimited company (e.g. partnerships) and, (3) requested amount of borrowing (loan size). Below we describe in detail the logic related to our proxies of loan risk.

First, worse quality borrowers in each credit band are willing to accept higher interest rates to get funded. Kawai et al. (2014) show that borrowers in Prosper use low "maximum acceptable interest rate" (i.e. reservation rate) to signal higher creditworthiness; low reservation rate serves to separate good borrowers from the bad because (i) the cost of stating a low reservation rate is lower probability of the loan being funded, (ii) it is costlier for lower-quality borrowers to risk not having the loan funded as they have fewer alternative funding options. Therefore, lenders may infer borrowers as risky when they post a high reservation rate (Stiglitz and Weiss, 1981) – say, higher than the interest rates charged on average for similar credit bands. Butler, Cornaggia, and Gurun (2017) find that borrowers in peer-to-peer markets who reside in areas with good access to bank finance request loans with lower reservation rates. In addition, Iyer et al. (2016) find that among the soft/nonstandard variables, lenders infer the most from the maximum interest rate that a borrower posts she is willing to pay for the loan. Thus, the reservation rate likely serves as a credible signal conveying the borrowers' level of risk conditional on the credit band (Kawai et al. 2014).

The second proxy of risk is whether the business is incorporated as limited company relative to unlimited one (e.g. partnerships). Theoretically, the optimal exposure to risk of the limited liability firm is larger than full liability firm (Gollier, Koehl, and Rochet, 1997). Increased shareholder liability reduces risk taking by forcing shareholders to bear a greater proportion of the costs associated with negative outcomes. For example, in the late nineteenth and early twentieth centuries, American banks subject to stricter liability held a lower proportion of risky assets (and perhaps benefited from lower funding costs) (Esty, 1998; Grossman, 2001). Limited liability is similarly associated with agency problems of the moral hazard type (when the owner-manager's effort is private and cannot be observed by creditors) (Brander and Spencer, 1989).

Our last proxy for risk is the requested amount of borrowing (loan size). Both stories of moral hazard and adverse selection predict a positive correlation between loan size and default (see, Adams, Einav and Levin, 2009). Individual borrowers are more likely to default on larger loans because of higher incentives of the borrowers to default (moral hazard is the hidden action associated with the ex-post incentives to default). Adverse selection problems arise if borrowers at high risk of default also desire large loans, as might be expected given that they view repayment as less likely. Overall, larger requested amount of borrowing increases risk of default owing to increased payoff of behaving opportunistically.

Hypothesis 2. *The gap in underperformance of crowds relative to the institutional investors in screening SMEs narrows with decreasing the maximum accepted bid rate in each credit-band.*

Hypothesis 3. *The gap in underperformance of crowds relative to the institutional investors in screening SMEs narrows when the legal status of the borrower is unlimited company compared with limited company.*

> **Hypothesis 4a.** *The gap in underperformance of crowds relative to the institutional investors in screening SMEs narrows with decreasing requested amount of borrowing.*

3.3. Does Limited Incentive of Crowds Contribute to the Underperformance Gap?

Investors will have incentive to spend resources to process (new) asset value-relevant information if, and only if, they are compensated by higher expected returns (Grossman and Stiglitz, 1980). Based on this logic, we look for, and hypothesize that, requested amount of borrowing (loan size) is an input in the decision of how much crowds invest in screening and assessing information. This is consistent with the implications of model of Holmstrom and Tirole (1997, p. 686), which argue that the intensity of screening and monitoring is endogenous and positively related to the amount of capital that the intermediary has to put up. To illustrate, in the venture capital business because investors participate intensively in screening and monitoring the management of their portfolio ventures, they tend to hold large stake in the projects they finance. By contrast, commercial banks engage less intensively in screening and monitoring, which partly explains their high leverage of capital.

Diligent behaviour ensues from sufficient stake in the financial outcome (skin in the game) (Holmstrom and Tirole, 1997). Unless investors receive the rewards from producing an efficient level of information, they would not have enough incentive. Take the case of loan sales by banks (or originate-to-distribute model of lending); the banks could alleviate agency issues by keeping part of the loan they sell since they will have partial incentive to maintain the loan's value. The incentive to screen and monitor the borrower increases with the portion of the loan held by the bank (Gorton and Pennacchi, 1995).

Larger requested amount of borrowing encourages greater incentive for production of accurate information for crowds since it increases the financial payoffs associated with being correct (lenders are rewarded for production of reliable information). This is in line with survey evidence that show that peer-to-peer lenders are primarily motivated by financial returns (Pierrakis and Collins 2013) - pursuit of intrinsic, social motive, or desire for reward are among common motivations cited in other models of crowdfunding and crowdsourcing

(Jeppesen and Frederiksen, 2006; Afuah and Tucci, 2013). To extent that the increase in intensity of screening with loan size for crowds is larger than institutions, we expect the underperformance gap to narrow. Our latter assumption is based on the idea that institutions benefit from and rely on standard routines and procedures of assessment that are less subject to variations in the range of loan sizes offered in online platforms like ours. To the extent that this assumption holds,[7] we propose the following competing hypothesis:

Hypothesis 4b. *The gap in underperformance of crowds relative to the institutional investors in screening SMEs narrows with increasing requested amount of borrowing.*

4. Study context: FundingCircle.com

Funding Circle established in 2010 is distinguishable from other players like Zopa (the first peer-to-peer platform in the world founded in the UK) and Prosper.com by serving small and medium sized enterprises (SMEs) rather than individuals.[8] The company started its operations in the UK but over time has expanded to the USA, Germany, Spain, and the Netherlands. Since its establishment over 70,000 lenders invested around $3.4bn in 40,000 SMEs. SMEs that are looking for loans should usually have at least two years of operation, and a minimum turnover of £50k.[9]

The loan application is done through the platform. The Funding Circle team reviews loan applications in 2 days and decides whether the application is accepted, rejected, or needs additional documents. Funding Circle places a risk band on the business loan. The risk band depends on business credit score information, which Funding Circle sources from a wide range of sources including Experian; FundingCircle.com claims to incorporate many factors when assigning a credit band, including director's commercial track record, director's consumer scorecards, financial trend information, commercial invoice payment performance, county court judgments and bankruptcies (current and historical), latest management accounts, director's consumer information. The risk bands range from A+ to E, where A+ is

[7] We don't have data on contributions of individuals in the crowd. Therefore, our arguments further assume that the total sum of individual's effort is higher for larger loans.
[8] https://www.fundingcircle.com/uk/about-us/
[9] A step-by-step guide to borrowing, available at: https://www.fundingcircle.com/uk/businesses/

lowest risk. Borrowers only indicate the amount of loan and maximum interest rates that they are willing to pay (maximum acceptable interest rate).

Lenders can screen the listings and place one or several bids per business of at least £20 at any interest rate below or equal to the borrower's maximum rate. The maximum bid per business is £2,000, however investors can make multiple bids on the same loan request. Bids cannot be cancelled or withdrawn. Loan requests typically last between 7-14 days. Prior to September 28, 2015, the bidding followed an open auction; everybody could fully observe the amount and the interest rates of other bidders regardless of whether the aggregate borrower's demand is met or not. Lenders with highest interest rates were bid down until the duration of the listing expires. Alternatively, as soon as a loan request was fully funded, the borrower could end a loan request (early) and accept the loan. All winning bidders received the marginal interest rate.

Borrowers repay the loan in equal monthly instalments, which consists of interest payments and repayments of the outstanding principal of the loan. Each month the interest portion of the payment will typically go down and the principal portion will go up. The platform charges fees to borrowers and lenders once a listing becomes a loan. Lenders pay a 1% servicing fee deducted from monthly loan repayments.

The loans will be posted randomly on two marketplaces: one for whole loans and another one for partial loans. In the whole loan market, only institutional investors (such as pension funds, insurance companies, family offices and hedge funds) can invest in the whole loan. In partial loan market, only individual investors can buy a part or whole of a loan. Loans are initially assigned randomly to each market.[10] This randomization assures individual investors that there is no cherry picking in which best loans are allocated to institutional investors, leaving "lemons" for individual investors. The loans that are not funded by institutional investors after a pre-set duration on the platform will recycle into partial loan market. Individual investors do not know that institutional investors have rejected this set of

[10] https://www.fundingcircle.com/blog/2014/04/introducing-whole-loans/

recycled loans when funding these loans.[11] This information is only visible on the loan book, accessible to investors for download after the completion of funding. Investors are also able to sell or buy loan parts in a secondary market. Figure 1 plots the growth of loan volume in British Pounds in FundingCircle for institutional investors relative to crowds.

5. Methods

5.1. Data

Our dataset includes all successful loan requests in the loan-book accessed at March of 2016 of FundingCircle.com.[12] Our communications with FundingCircle platform in the UK indicate that no loans were left unfunded on the platform. We keep loans funded after May 6, 2014 and before September 28, 2015. At May 6, 2014, institutional investors began investing in the platform.[13] Prior to September 28, 2015, interest rates on loans were set according to the auction process described above. As of September 28, 2015, however, FundingCircle changed its business model so that interest rates are determined by a formula that evaluates a borrower's credit risk, so called "fixed interest rate" model. In addition, FundingCircle's new business model removes the opportunity for borrowers to declare maximum acceptable interest rate, which is a necessary variable for us to operationalize one of our risk proxies. We also drop loans in the industry category of "property and construction" because they were subject to the "fixed interest rate" model prior to September 28, 2015.[14] Applying these filters leaves us with 6,947 loan requests, which we use for our main tests.

The dataset includes information about the borrowers' business characteristics (e.g., Industry of business, regional location of business, type of business) and the loans (e.g., interest rate, default, duration of loan, repayment amount, loan purpose, and maximum accepted interest rate). Table A1 reports the definition of variables used in this study.

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[11] "no one is able to pick more attractive loans. They are allocated either as a partial or whole loan on a completely random basis." https://www.fundingcircle.com/blog/2014/12/funding-circle-announces-groundbreaking-132-million-investment-british-small-businesses/

[12] We updated our data about the loan failures in November 2017. The results are very robust and available upon request.

[13] The data is available to registered users at https://www.fundingcircle.com/loanbook

[14] Per our communications with FundingCircle.com, "property and construction" related loans are marked by security type of either "First charge" or "Second charge".

5.2. Results

5.2.1. Do crowds underperform institutions in screening loans? Evidence from random assignment of loans

As noted in the institutional setting of FundingCircle.com, loans are randomly assigned to two marketplaces of "whole loan" and the "partial loan" market. Such randomization allows us to compare the loan performance of crowds with that of institutions without concerns over sample selection. To avoid selection bias associated with recycled loans, we exclude them from this analysis. Table 1 presents the summary statistics of variables used.[15] We perform t-tests and find no differences in the two sample means for control variables in addition to the interest rates across institutions and crowds. While we expected control variables not to differ but dependent variables such as interest rates to differ, the test shows lack of difference on interest rates across institutions and crowds. This result may be related to not controlling for many factors influencing interest rates. Thus, we perform multivariate analysis.

Table 2 reports the regression results that regress the interest rate and hazard rate of default on the funding by crowds – our primary independent variables. Model (1) and (2) show the results of OLS regressions with *Interest rate* as the dependent variable. The standard errors are robust to heteroskedasticity. Model (1) is the baseline model with the control variables, explaining 87 percent of variance of the interest rate. Note that the coefficient of *credit band E* is omitted to avoid singularity. The coefficients of credit bands therefore measure how the interest rate varies as a given credit band moves from "*E*" to the credit band in question. The coefficient on the *credit band A+* suggests that the interest rate reduces by -10.37 percent relative to the *credit band E*. The interest rate predicted at the *credit band A+* (A) is 7.96 (9.15) percent. The coefficients of credit band are all statistically significant ($p<0.01$), altogether explaining 85 percent of the variance (the largest portion of the variance among the set of covariates as expected). There is furthermore a positive coefficient ($p<0.01$) for *Amount requested* (it is log-transformed for concerns of skewness), consistent with the

[15] Figure A.1 shows the (Epanechnikov) kernel density estimates of interest rates separated by investor type.

findings of Adams et al. (2009) in consumer credit markets. Doubling the amount requested would increase the interest rate by about 17 basis points. The purpose of loan and whether the borrowing business is limited company or not are not statistically significant in predicting interest rate at conventional confidence intervals. The coefficients of loan terms reveal a positive and significant coefficient ($p<0.01$) (*Term: 6-12 months* is omitted category). The coefficient on *Term: 24-36 months* suggests that the interest rate increases by 15 basis points for loans with the maturity in the interval of 24 and 36 months relative to the interval of 6 and 12 months. This effect becomes larger for loans in the interval of 48-60 months. Given that it is likely that loans with larger amount requested also have longer terms, we tested for possible multi-collinearity issues by checking variance inflation factors. The average VIF in Model 1 is 5.79. In addition, while *Term: 48-60 months* is positively correlated with *Amount requested* (0.19, $p<0.01$), *Term: 24-36 months* is negatively correlated with *Amount requested* (-0.13, $p<0.01$). We also control for location and industry of business, and year of loan origination.

Next, we include *Crowd* in Model (2) of Table 2. The estimate reveals a negative and statistically significant relationship between *Crowd* and *Interest rate*. Funding by crowds relative to institutions is associated with a decrease of 40 basis points in interest rate (equivalent of 22.3% of standard deviation of interest rate). While this effect might not seem large, this is equal to 10% of monthly average salary in the UK (The average salary in 2014 was £26,500 in UK and the average amount of loan requested is £57,000).

We now turn attention to loan repayment, or default behavior. The dependent variable is the number of months between origination and the earliest date the loan's status becomes "loan: defaulted". For loans that borrowers pay off in full, on time, or late, the dependent variable is right-censored at the number of months between origination and that event (maturity of the loan, or the last recorded payment).[16] We use a Cox proportional hazard model. We also check the proportionality hazard assumptions of Cox models based on

[16] The results are robust to other definitions; (1) we also include "late" in the group of default; or (2) Lin et al. (2013) consider a loan as defaulted if a payment is late by at least two months.

Schoenfeld residuals (and hence, exclude year dummies because they vary with time).[17] The Schoenfeld residuals tests whether the slope of scaled residuals on time is zero or not. We find the slope is not different from zero, thus, the proportional hazard assumption has not been violated. Model (3) and Model (4) in Table 2 present the coefficients of the estimates (and not hazard ratios). Although all the coefficients of credit bands are negative, only credit bands of A+, A, and B are statistically significant (respectively $p<0.01$, $p<0.01$, and $p<0.05$). As these estimates indicate credit score is a good predictor of default (Adams et al. 2009; Einav et al. 2013); for example, there is a 94% reduction in default risk associated with the *credit band A+* relative to *E*. In Model (4), the coefficient of *Crowd* is not statistically different from zero. This non-result indicates that (1) loans were randomly distributed as the ex post measure of quality of loans (i.e., default) is not different; (2) the higher interest rate on the loans of the institutions is not causing moral hazard ex post (the higher requested interest rate does *not* increase borrowers' incentive to default ex post). In sum, we find support for Hypothesis 1 that crowds request a lower interest rate compared with institutions despite similar ex post hazard of default on loans.

Insert Table 1, and Table 2 about here

5.2.2. Do crowds underperform institutions in screening loans? evidence from recycled loans

In the previous analysis, we excluded recycled loans, which are the set of loans funded by crowds but were initially left unfunded by institutions. We now turn attention to recycled loans. Individual investors during the loan listing are not informed about the nature of this rejection from institutions (this information is unobserved by crowds but known to us, as researchers). We exploit an identification strategy based on the exclusive availability of this information to the econometrician to test the performance of crowds. To do so, for each recycled loan (treatment group), we match one loan among the loans funded by institutions

[17] Including year dummies does not change the conclusions such as insignificant coefficient of *Crowd* on the hazard of default.

(control group) by employing propensity score matching method (PSM) (Rosenbaum and Rubin, 1983) without replacement.

PSM attempts to estimate the performance effect of recycled loans (treatment effect) by accounting for the covariates that predict recycled loan funding by crowds. This method then reduces the bias due to confounding variables that could be found in an estimate of recycled loans obtained from simply comparing the outcomes among recycled loans (funded by crowds) versus all loans that received funding from institutions. Matching is done by using all variables reported in Model (1) of Table 2. In the process of matching, recycled loans without a match (out of support) are discarded. After verifying that covariates are balanced across recycled loans and the matched comparison groups (the results of balance test are available upon request), we perform multivariate analysis and present the results in Table 3. In this analysis, the final sample size is 1,894.

Table 3 reports these results with PSM sample in Model (1) and (2) and without PSM sample in Model (3) and (4). Model (1) shows that that recycled loans are associated with 20 basis points less interest rate. Model (2) reveals positive yet not statistically significant coefficient of recycled loans. These results are in line with previous findings. We repeated the same analysis without PSM in subsequent models (3) and (4). Results remain similar.

Insert Table 3 about here

5.2.3. Does underperformance gap of crowds relative to institutions vary with loan characteristics?

The previous models do not allow the performance of crowds to depend on the characteristics of loans. We first identify loans that are more subject to adverse selection risk and moral hazard problems, and thus, require higher expertise for assessment. As discussed previously, these proxies include: (i) borrower has higher reservation rates (*Normalized maximum acceptable interest rate*), (ii) the borrower's business is incorporated as *Limited*, and (iii) borrower's *Amount requested*. Additionally, we explore whether the increased incentive associated with the *Amount requested* improves the screening performance of crowds. To explore the performance gap of crowds compared with institutions, we introduce an interaction term between *Crowd* and the preceding moderating variables and report these results in Table 4.

Insert Table 4 about here

Normalized maximum acceptable interest rate: this proxy is defined as the difference between the maximum acceptable interest rate and the average interest rate in each risk band. Model (1) in Table 4 reveals positive and significant coefficient ($p<0.01$); one standard deviation increase in the *Normalized maximum acceptable interest rate* is associated with 60 basis points increase in interest rate. Model (2) shows the OLS estimates of interaction terms between *Normalized maximum acceptable interest rate* and *Crowd*. The negative coefficient on the interaction term ($p<0.01$) suggests that increase in the *Normalized maximum acceptable interest rate* for crowds is associated with reduction in interest rate.

Model (5) and (6) in Table 4 present the corresponding Cox models. In Model (5), the coefficient of *Normalized maximum acceptable interest rate* is positive ($p<0.01$) and one standard deviation increase in this variable increases the default by 34 percent. This result empirically supports our choice of this proxy to measure loan risk. In Model (6), the interaction between *Crowd* and *Normalized maximum acceptable interest rate* is positive ($p<0.05$); however, in non-linear specifications, the interaction terms is not equal to the cross-partial derivative of the interacting terms (Norton and Ai, 2003). Therefore, for easier interpretation of the models with interaction terms, we plot the hazard as a function of the *Normalized maximum acceptable interest rate* (In appendix: Figure A2). As the figure suggests, across a range of *Normalized maximum acceptable interest rate*, the hazard for both groups is not significantly different from each other. These results provide support for Hypothesis 2.

Limited company: This proxy of risk is a dummy variable and defined as whether a company is incorporated as limited company or not (i.e. unlimited company). Model (3) presents OLS estimates of the interaction between limited company and crowds; the negative and statistically significant coefficient of this interaction term suggests that investing in limited companies for crowds is associated with reduction in interest rate. Model (6) presents the corresponding Cox estimates of the interaction between *Crowd* and *Limited company*; The interaction coefficient is not statistically significant (In appendix: Figure A3). These estimates provide support for Hypothesis 3.

Amount requested: To test the two competing Hypotheses 4a and 4b, we interact *Crowd* and *Amount requested* and present the results in Model (4) and Model (8) in Table 4. The positive coefficient on the interaction term in Model (4) ($p<0.01$) suggests that increase in the amount requested (logged) increases the interest rate for crowds. Interestingly, for institutional investors there is an almost negligible sensitivity of interest rates to the total requested amount of borrowing, whereas for crowd investors this slope is positive (In appendix: Figure A4). Model (8) in Table 4 also presents the Cox estimates of the interaction terms (in appendix: Figure A4) plots the associated economic magnitude of hazard rate. These results appear to favor Hypothesis 4b over Hypothesis 4a. Overall, crowds seem to respond to higher requested amount of borrowing by requesting a higher interest rate, and in doing so, close the performance gap.

5.3. Do Institutions Have Better Screening Performance Compared with Crowds? Evidence from Observable Covariates

We have so far shown how crowds fail to request higher interest rates while considering the likelihood of defaulting on a loan. In this section, we evaluate the screening power of crowds relative to institutional investors and further ask whether the greater accuracy of institutional investors' judgement relies upon observable covariates of loan considered in this study or other unobservable factors. To answer this question, we follow the approach proposed by Iyer et al. (2016) and use the area under a "receiver operating characteristic" (ROC) curve that measures the quality of a screening method and commonly used in commercial financial banking markets. The ROC curve provides an estimate of screening performance in a setting with a continuous predictor (e.g., interest rate) for a binary outcome (e.g., default). This method identifies, given above the threshold value for the interest rate, how many observations are correctly classified as default and how many observations are incorrectly classified as default. The ratio of observations correctly classified as default relative to all default realizations is called true positive rate (TPR). Similarly, the ratio of observations incorrectly classified as default relative to all default realizations is called false positive rate (FPR). The ROC curve plot the TPR on y-axis against FPR on the x-axis as the threshold value of interest rate is reduced. The area under the ROC curve (AUC) quantifies the accuracy of screening. We estimate the AUCs and show the ROC curves in Figure 2 and Figure 3 separated by investor type. AUC for crowds and institutional investors is 0.632 and 0.683, respectively. In sum, AUC shows that the interest rate set by crowds predicts default 39% less accurately than the interest rate set by institutional investors.[18]

Next we set out to understand whether institutional investors can use the available and coded information (e.g. those observable covariates) more efficiently than crowds. We follow Iyer et al. (2016) and calculate the AUC using predicted interest rate based on estimated regression of interest rate and actual observable covariates.[19] This measures the inference drawn from coded information by lenders when setting the interest rate. As shown in Table 5, AUC calculated by predicted interest shows institutional investors outperform crowds by 75%. In sum, the quality of inference by crowds is lower than institutions and the difference largely due to variation in inferences from coded (observable) information.

Insert Table 5 about here

5.4. Do Crowds Underperform Rates Set by the Platform? Evidence from a policy change

We exploit a policy change in the platform of FundingCircle. At 28th of September 2015, FundingCircle switched the auction-mechanism of interest rate for all loans to fixed interest rate. Before this change, only "property"-related loans had fixed interest rates. This allows us to use a difference-in-differences (DiD) analysis and compare the performance of crowds against the fixed interest rates (set by the platform). Note that this analysis compares the

[18] We calculate the percentage difference as (0.683 – 0.5) / (0.632 – 0.5) = 1.386, where 0.5 is subtracted from the interest rate AUC because 0.5 is the AUC under a noninformative (random) scoring system (Iyer et al. 2016). If we also consider the recycled loans in the sample, the AUC for *Crowd* will be 0.636.

[19] This is estimated from an OLS regression which include all control variables as independent variables and interest rate as dependent variable.

performance of crowds (treatment group) with the platform setting the interest rates (control group). For this analysis, the period of 4 months before and after the policy change is considered.

Table 6 reports the results of our analysis. The non-treatment group is the sector of property and construction. The dummy variable *after* equals one when the platform switches from an auction-based interest rate for loans in the treatment group to the fixed interest rate on 28th September, 2015. In Model (1) of Table 6, we present the treatment effect: the coefficient of interaction term between *after* and the *sector other than property and construction*. The treatment effect is 31 basis points, showing that policy change in the platform increased the interest rate on loans (and hence, it was beneficial for lenders). In Model (2) of Table 6, the coefficient of interaction term in the hazard model shows there is no statistically differences before and after policy change in hazard of default.

Insert Table 6 about here

The preceding DiD analysis relies on parallel trend assumption in the pre-treatment period. We verify this assumption by conducting three sets of analysis recommended by Roberts and Whited (2006). First, we repeat analysis on the sample of pre-policy change and included interaction terms of all periods (4 periods) prior to policy change. There are no statistically significant differences between the predicted slope for treated and control group prior to policy change (In appendix: Table A3, all interactions are statistically insignificant). Second, we repeated analysis by considering one- and two-month pre-policy change. "The estimated treatment effect on pre-policy change should be statistically indistinguishable from zero to ensure that the observed change is more likely due to the treatment, as opposed to some alternative force" (Roberts and Whited, 2006: 529). The results (In Appendix: Table A4) show that effect of pre-policy change is statistically indistinguishable from zero while the effect after policy change is statistically different than zero. Finally, we have performed another falsification test by repeating our diff-in-diffs analysis on the sample of loans during the 8 months prior to policy change (during this period, there is no policy change, hence, we expect not to observe similar treatment effect in this period). We create the variable *After-fake* that is a dummy variable that is equal 1 during the last 4 months prior to policy change. We would expect to not observe similar effects as the real policy change. This test ensures the observed treatment effect is due to policy change and no other trends in other time periods. These falsification results (In appendix: Table A5) suggest that other periods other than the 28th September, 2015 are not associated with interest rate change across treatment groups. Finally, we don't find any treatment effect in the sample of loans funded by institutional investors (In Appendix: Table A6).

5.5. Additional tests

We perform a series of tests to check the robustness of our results. First, instead of Cox proportional hazard models, we employ a probit model to predict the likelihood of default. The results are similar and available upon request from authors. Second, we repeated our analysis using propensity score matching on all covariates reported in Model (1) of Table 3. The results reported (In appendix: Table A2) are again consistent with those reported in Table 3. Finally, we calculate rate of investment for a loan (ROI) that allows us to combine information on interest rate and the cash flow payments for a given loan. Results presented (In appendix: Table A7 and A8) support our previous conclusions and shows crowd's ROI is lower than institutional investors.

6. Contribution, Discussion, and Conclusion

Enabled by technological advances, crowds participate more and more in decision-making in areas ranging from provision of funding to entrepreneurship or other resources such as product ideas and solutions to corporations (Lukyanenko, Parsons, Wiersma, 2014; Girotra, Terwiesch and Ulrich, 2010; Afuah and Tucci 2013) and scientific research (Franzoni and Sauermann, 2014). With increasing interest from scholars in understanding crowd behaviour and the limitations and opportunities facing markets based on crowds (Magnusson, Wastlund, and Netz, 2016; Poetz and Schreier, 2012; Budescu and Chen, 2015), we investigate the performance of crowd judgement in crowdfunding markets (see also Mollick and Nanda, 2016). In fact, the future growth and sustainability of crowdfunding markets as a viable source of financing rests on understanding the conditions under which the wisdom of the crowd is deployed. To address this question, we compare the performance of crowds, relative to institutions, in assessing loans in the online peer-to-business lending of FundingCircle.com. We find that relative to institutions, crowds earn between 20 to 40 basis points lower interest rate on loans without differences in ex post borrower's probability of default. Further evidence shows this underperformance gap stems from the limited expertise and the capability of crowds to assess loans or their limited incentive to perform screening owing to insufficient skin in the game.

Although our results show performance gap of crowds relative to institutions, the magnitude of these effects are not so large to suggest madness of crowds; Rather, our results to some extent conform to prior findings that collective intelligence compare favourably to those from experts (Mollick and Nanda, 2016; Antweiler and Frank, 2004). Furthermore, by exploring the conditions necessary for formation of "wisdom of crowd", we underline when the collective intelligence improves (with respect to experts). Our findings imply that limited expertise or incentives of crowds might hamper effective participation of the individuals. Such evidence is consistent with prior work that highlights the relevance of financial literacy in the stock market participation of households (e.g., Van Rooij, Lusardi, and Alessie, 2011). Relatedly, crowdfunders may use shortcuts and heuristics to save cognitive effort. The decision makers' limitations including cognitive, resource, information, and time put bounds on the information they can access, process, or store, imposing constraints on their evaluations. However, when crowds have enough skin in the game, they have more incentives to put effort for the gain in accuracy (Payne, 1982). Consistent with this notion, some platforms active in the same area have large minimum bids; the competitor platform of ThinCats offers bids only in £1,000 increments.

This paper contributes to two strands of literature. Our paper contributes to the literature on how crowd investors make decisions in crowdfunding markets (Colombo et al. 2015; Mohammadi and Shafi, 2017; Agrawal, Catalini, Goldfarb, 2015; Wei and Lin 2017; Zhang and Liu 2012, Lin et al. 2013; Iyer et al. 2016; Lin and Viswanathan 2016), especially the extent to which crowds' decisions are rationally made (Zhang and Liu, 2012) or congruent with those of experts (Mollick and Nanda, 2016). In contrast to these studies, we focus on the long-term and objective outcomes of the decisions by crowds and manage to document crowds' underperformance relative to institutions. Furthermore, we reveal the role of cognitive or incentive limitations in the way crowds evaluate projects. Overall, our contribution bears important implications for the long-run sustainability of crowdfunding, as an alternative source of business financing, that partially hinges on the ability of crowds to overcome adverse selection risks and moral hazard problems (Agrawal, Catalini, Goldfarb, 2015). The second contribution of our work is to the recent literature that examines the peer-to-peer lending markets (for a review, see Morse, 2015). Much of this work has ignored the heterogeneity of lenders (and the ways these lenders may differ in drawing inferences about loans; for an exception see Lin, Sias and Wei, 2017). Accordingly, our study complements prior research in other markets of financing of SMEs that have associated some characteristics of banks or venture capitalists with their screening abilities; size of banks influences the acquisition of (soft) information for lending to SMEs (Berger et al. 2005), or the investment experience of venture capitalists fosters their selection capabilities (Sorensen, 2007). Therefore, examining lenders' heterogeneity can add to our knowledge of limitations and opportunities embedded in new online lending markets.

A discussion of few interrelated issues about the functioning of the crowdfunding are in order because they have implications for informing the debate about whether the peer to peer platforms, or more broadly platforms that offer access to investment products through an online portal, need more legislative measures (from regulatory agencies such as Financial Conduct Authority in the UK or Consumer Financial Protection Bureau in the USA) or other measures such as publishing general guidance, or proposing enhanced industry self-regulation. To start thinking about these issues, it is imperative to understand whether platform customers are able to make informed choices (FCA, 2017). Given the limitations faced by crowds in evaluating loans, platforms can actively help investors make investment decisions by offering tools through which they can find investment products. Among these tools, robo-advisors have the potential to help investors in areas that retail investors may not have sufficient expertise. Second, there has been some concern that platforms may not offer investors value for money by taking advantage of their unsophisticated consumers. First, in the context of FundingCircle, the major component of underperformance of crowds relative to institutions is unrelated to the loans rejected by institutions but funded by crowds (our unreported analysis including and excluding the recycled loans show no substantial differences in terms of performance gap). Such evidence casts doubt on pessimistic views expressed in the opening quote on the consumers' ability to fund loans in peer-to-peer markets. Additionally, Rhydian Lewis, chief executive of Ratesetter, has commented that "It's a pernicious assumption that our lending is just for the bank rejects, I genuinely say that's not the case. It's convenient for the banks to say that, but we're now beyond that and definitely competing for borrowers with the banks – in many situations undercutting the banks and offering borrowers better deals." Given the role of institutions and their growing demand in these markets, and given that customers in lower credit scores (subprime customers) are not the primary category of loans rejected by institutions (based on unreported analysis of observable characteristics), we lack strong evidence that loans in crowdfunding markets are sub-prime and crowds are naïve lenders being taken advantage of. Second, default rates of loans on FundingCircle are generally low, further indicating that platforms play strong gate-keeping roles in the well-functioning of these online markets. Finally, we highlighted how the switch in interest rate setting by the platform improved consumers' returns.

Our study also highlights the role of crowdfunding in democratizing access to funding for firms that institutions have rejected to lend to. We further show that this funding source can be a more attractive source of capital than institutions provide in these markets. However, as evidenced by higher rates for larger loan sizes, the capacity of crowdfunding to complement other sources of financing, at least with a competitive price, remains limited at its current development status, although promising in its momentum.

Our study's limitations present several avenues for future research. One is linked to the drawbacks of our research setting for one type of crowdfunding model (i.e. peer-to-business lending), leaving questions around whether our findings can be generalized to other types of crowdfunding models such as equity and reward based crowdfunding (Roma, Gal-or, and Chen, 2018). For instance, future research may explore how crowds relative to venture capitalists or business angels perform when choosing their equity investments. Second, we acknowledge that there is an alternative, plausible mechanism for the observed underperformance gap. It is possible that institutional side of the market ("whole loan" market) offers lower competition than the *crowd* side of the market, and this may result in performance gap reported in this study. While we don't have bid-level data or the number of investors active in each side of the market to empirically rule out this alternative explanation, it is unlikely that different levels of competition across markets generate predictions consistent with moderating factors related to expertise and incentive, highlighted in this study.

Finally, an additional drawback of research data is that we cannot directly test other assumptions behind formation of "wisdom of crowd": independence in judgements or the diversity in the opinions of individuals. First, take the assumption of independence that is debated in the crowdfunding literature by observations of herding behavior (Colombo, Franzoni, and Rossi-Lamastra, 2015; Burtch et al. , 2013; Zhang and Liu, 2012). Because in crowdfunding both the timing and the amount of other participants' prior contributions are often published for all to see, social influence can generate informational cascades and herding, meaning that supports gravitate towards projects with large numbers of early supporters (Herzenstein, Dholakia, and Andrews, 2011). Although theory lacks clear predictions about the performance outcome of such complex social and informational interactions (Lorenz et al. 2011), Zhang and Liu (2012) show empirically that lenders in peer-to-peer markets arrive at good decisions because they are rational observers and able to aggregate information on borrower creditworthiness from observing prior lenders. Therefore, although it is tempting to consider herding to be a potential factor contributing to underperformance, empirical evidence of Zhang and Liu (2012) in a platform similar in functioning to the one studied here suggests otherwise.

To illustrate how the assumption of diversity may influence our results, consider that larger loans are on average financed by more crowd lenders (to help with risk diversification). The best-known mechanisms of collective wisdom rest on the statistical principle known as the law of large numbers: As the number of lenders increases, the estimates of the unknown outcome (here, interest rate) will tend to converge to the actual outcome (conditional on independence of judgments). Condorcet Jury Theorem formalizes this intuition that as the number of individuals in the crowd increases, the probability of a majority vote of crowds is correct is higher when crowds vote on two alternatives that one of which is slightly more likely to be right than wrong. Furthermore, increasing the diversity in judgements can compensate the lack of expertise. Keuschnigg and Ganser (2016) find that diversity and ability can substitute each other to some degree in the production of "wisdom of crowd"; Homogeneous crowds can only be accurate if they contain extremely expert individuals, and groups of naive individuals can only be collectively accurate if they possess great diversity (Page, 2007; Hong and Page, 2008). Overall, increased number of lenders, even though they have limited expertise, can generate diversity, which is a condition as important as competence in producing "wisdom of crowd". To the extent that larger loans are funded by more lenders, the requested loan size decreases the underperformance gap of crowds relative to institutions, a prediction that is supported in our data. In sum, given the limitations of secondary data used here, we encourage further research that explores whether certain conditions behind wisdom of crowd are more important than others and possible substitutions of those conditions.

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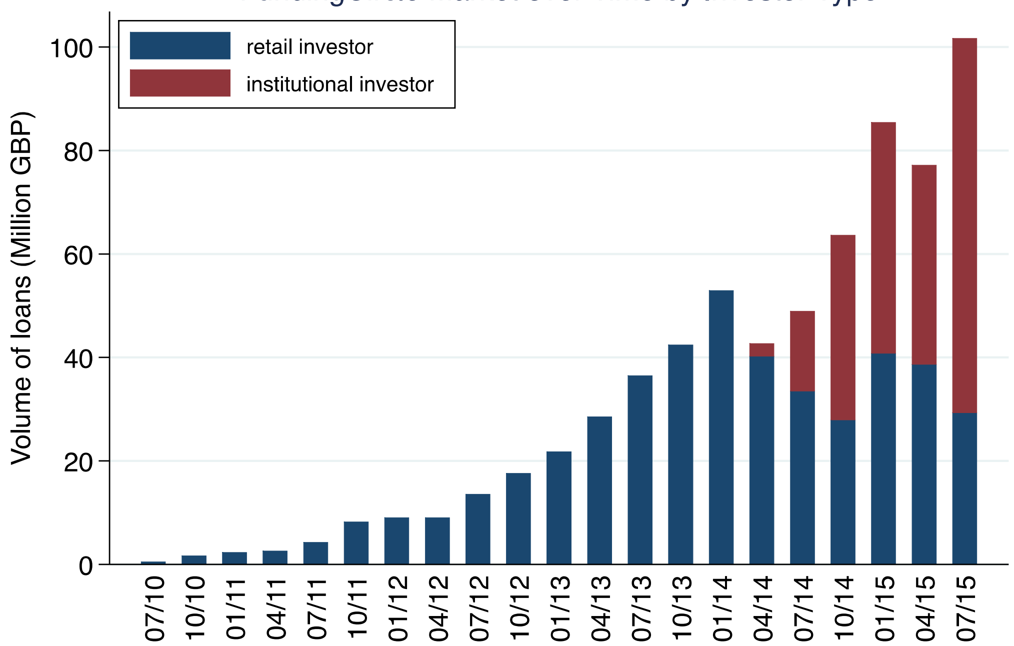
FundingCircle Market over Time by Investor Type



Source: FundingCircle loanbook data

Figure 1. FundingCircle Market over Time by Investor Type

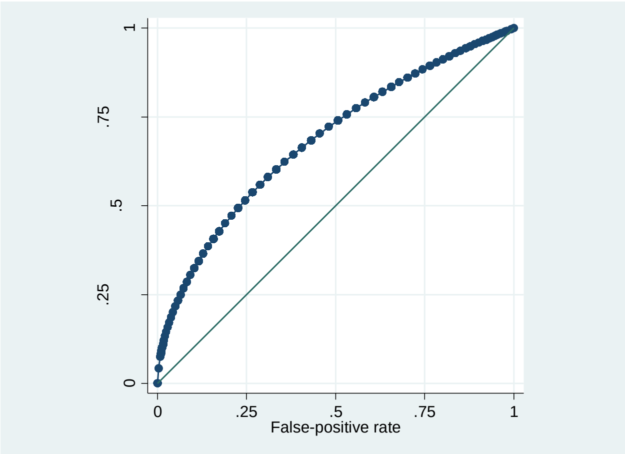


Figure 2. Crowd - Area under ROC curve = 0.632

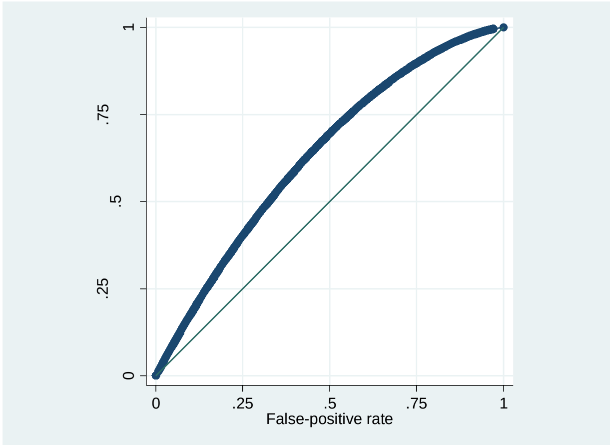


Figure 3. Institutional investors - Area under ROC curve = 0.683)

Table 1. Descriptive Statistics of Loans by Investor Type

	Crowd			Institution		
	N	**Mean**	**S.D.**	**N**	**Mean**	S.D.
Panel A: Loan characteristics						
Interest rate	**3,334**	**9.854**	**2.006**	**3,613**	**9.850**	**1.577**
Amount requested (£1,000's)	**3,334**	**57.314**	**47.805**	**3,613**	**57.411**	**49.988**
Normalized maximum acceptable interest rate	**3,334**	**0.630**	**1.239**	**3,613**	**0.104**	**0.268**
Limited company	**3,334**	**0.890**	—	**3,613**	**0.924**	—
Defaulted dummy	**3,334**	**0.021**	—	**3,613**	**0.018**	—
Panel B: Distribution of loan term						
Term: 6-12 months	**180**			**227**		
Term: 24-36 months	**1,125**			**1,333**		
Term: 48-60 months	**2,029**			**2,053**		
Panel C: Distribution of credit band						
A+	**982**			**952**		
A	**633**			**1,069**		
B	**755**			**775**		
C	**562**			**530**		
D	**353**			**270**		
E	**49**			**17**		
Panel D: Distribution of loan purpose						
Asset financing	**165**			**170**		
Expansion	**1,646**			**1,940**		
Working capital	**1,274**			**1,252**		
Other purposes	**249**			**251**		
Total	3,334			3,613		

Note: t-test differences in mean are shown in Panel A, Normalized maximum acceptable interest rate and limited are significantly different ($p<0.001$) for crowd and Institution. There is no statistically significant differences between other variables.

Table 2. Regression results related to performance of crowd

	(1)	(2)	(3)	(4)
	Interest Rate		Hazard	
Crowd		-0.405***		-0.141
		(0.016)		(0.177)
Credit band: A+	-10.375***	-10.531***	-2.760***	-2.812***
	(0.033)	(0.041)	(0.702)	(0.712)
Credit band: A	-9.189***	-9.319***	-1.608***	-1.652***
	(0.030)	(0.039)	(0.612)	(0.621)
Credit band: B	-8.206***	-8.331***	-1.200**	-1.242**
	(0.031)	(0.039)	(0.612)	(0.618)
Credit band: C	-7.074***	-7.194***	-0.823	-0.863
	(0.033)	(0.041)	(0.619)	(0.624)
Credit band: D	-5.432***	-5.532***	-0.697	-0.731
	(0.033)	(0.041)	(0.630)	(0.636)
Amount requested	0.241***	0.242***	-0.109	-0.109
	(0.011)	(0.010)	(0.092)	(0.092)
Limited company	0.007	-0.024	0.147	0.138
	(0.027)	(0.027)	(0.303)	(0.303)
Purpose: asset finance	-0.064	-0.067*	-1.140*	-1.142*
	(0.041)	(0.037)	(0.596)	(0.594)
Purpose: expansion	-0.002	-0.017	-0.613***	-0.619***
	(0.017)	(0.017)	(0.183)	(0.184)
Purpose: other	-0.028	-0.033	-0.277	-0.278
	(0.033)	(0.030)	(0.360)	(0.360)
Term: 24-36 months	0.149***	0.153***	0.449	0.450
	(0.045)	(0.040)	(0.497)	(0.498)
Term: 48-60 months	0.221***	0.246***	0.299	0.309
	(0.044)	(0.040)	(0.493)	(0.494)
Constant	15.511***	15.821***		
	(0.138)	(0.133)		
Year dummies	Y	Y	N	N
Industry dummies	Y	Y	Y	Y
Region dummies	Y	Y	Y	Y
N	6,947	6,947	6,947	6,947
Specification	OLS	OLS	Cox Model	Cox Model
R-squared	0.869	0.881		
Chi-squared			77.028	78.328
Pseudo-R-squared			0.033	0.033

Note. Robust standard errors appear in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 3. Regression results of recycled loans (referred to loans funded by crowd but initially rejected by institutional investors)

	(1)	(2)	(3)	(4)
	PSM sample		Without PSM sample	
	Interest Rate	**Hazard**	**Interest rate**	**Hazard**
Recycled loans	-0.202***	0.334	-0.163***	0.414**
	(0.032)	(0.278)	(0.030)	(0.210)
Amount requested	0.295***	0.029	0.115***	-0.130
	(0.023)	(0.158)	(0.011)	(0.097)
Limited company	0.007	0.655	0.009	0.451
	(0.060)	(0.563)	(0.035)	(0.358)
Purpose: asset finance	-0.024	-0.717	-0.028	-0.666
	(0.081)	(0.742)	(0.043)	(0.518)
Purpose: expansion	0.060*	-0.467	0.002	-0.654***
	(0.034)	(0.292)	(0.018)	(0.207)
Purpose: other	0.051	-0.765	0.015	-0.656
	(0.066)	(0.602)	(0.037)	(0.436)
Term: 24-36 months	0.066	-0.798	-0.012	-0.103
	(0.117)	(0.684)	(0.040)	(0.497)
Term: 48-60 months	0.234**	-1.115*	0.099**	-0.150
	(0.115)	(0.675)	(0.039)	(0.502)
Credit band: A+	-10.339***	-2.497***	-10.232***	-2.314***
	(0.072)	(0.926)	(0.034)	(0.852)
Credit band: A	-9.162***	-1.955**	-9.069***	-1.618**
	(0.065)	(0.826)	(0.032)	(0.788)
Credit band: B	-8.089***	-1.797**	-8.074***	-1.052
	(0.069)	(0.847)	(0.034)	(0.777)
Credit band: C	-6.919***	-0.961	-6.930***	-0.445
	(0.072)	(0.797)	(0.036)	(0.767)
Credit band: D	-5.414***	-1.386	-5.354***	-0.528
	(0.070)	(0.872)	(0.035)	(0.782)
Constant	15.229***		17.107***	
	(0.332)		(0.143)	
Year dummies	Y	N	Y	N
Industry dummies	Y	Y	Y	Y
Region dummies	Y	Y	Y	Y
N	1,894	1,894	4,715	4,715
Specification	OLS	Cox model	OLS	Cox model
R-squared	0.869		0.894	
Chi-squared		4,2030.173		66,045.969
Pseudo-R-squared		0.069		0.047

Note. Robust standard errors appear in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table 4. Regression results related to moderating factors of crowd performance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Interest Rate				Hazard			
Amount requested	-0.010*	0.003	0.242***	-0.016*	-0.235**	-0.256***	-0.109	-0.380***
	(0.006)	(0.006)	(0.010)	(0.008)	(0.094)	(0.096)	(0.092)	(0.109)
Crowd	-0.718***	-0.663***	-0.223***	-6.272***	-0.350*	-0.470**	0.304	-5.972***
	(0.008)	(0.008)	(0.046)	(0.184)	(0.187)	(0.197)	(0.613)	(1.965)
Limited company	-0.002	-0.010	0.089***	-0.022	0.142	0.161	0.444	0.129
	(0.015)	(0.014)	(0.029)	(0.026)	(0.304)	(0.303)	(0.537)	(0.303)
Normalized maximum acceptable interest rate	0.659***	1.072***			0.321***	-0.707		
	(0.008)	(0.024)			(0.072)	(0.466)		
Crowd × Normalized maximum acceptable interest rate		-0.439***				1.067**		
		(0.025)				(0.475)		
Crowd × Limited company			-0.200***				-0.488	
			(0.048)				(0.638)	
Crowd × Amount requested				0.552***				0.554***
				(0.017)				(0.185)
Constant	18.880***	18.659***	15.731***	18.672***				
	(0.082)	(0.081)	(0.129)	(0.121)				
Risk band dummies	Y	Y	Y	Y	Y	Y	Y	Y
Loan purpose dummies	Y	Y	Y	Y	Y	Y	Y	Y
Term dummies	Y	Y	Y	Y	Y	Y	Y	Y
Year dummies	Y	Y	Y	Y	N	N	N	N
Industry dummies	Y	Y	Y	Y	Y	Y	Y	Y
Region dummies	Y	Y	Y	Y	Y	Y	Y	Y
N	6,947	6,947	6,947	6,947	6,947	6,947	6,947	6,947
Specification	OLS	OLS	OLS	OLS	Cox Model	Cox Model	Cox Model	Cox Model
R-squared	0.967	0.969	0.882	0.897				
Chi-squared					97.596	117.014	78.468	92.489
Pseudo-R-squared					0.038	0.040	0.033	0.036

Note. Robust standard errors appear in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.0$

Table 5. Area under the curve for crowd and institutional investors based on predicted interest rate (based on observable covariates) and residuals of interest rate (unobservable).

Crowd		Institutional investors	
Observables	**Unobservable**	**Observables**	**Unobservable**
AUC= 0.630**	AUC= 0.620***	AUC= 0.705***	AUC= 0.483***

Table 6. Regression results related to difference-in-differences

	(1) **Interest Rate**	**(2)** **Hazard**
Sector other than property and construction	-0.340*** (0.085)	-0.234 (0.496)
After	0.111** (0.056)	0.070 (0.371)
Sector other than property and construction × After	0.310*** (0.065)	-0.236 (0.441)
Amount requested	0.274*** (0.018)	-0.081 (0.113)
Limited company	-0.155*** (0.052)	0.629* (0.375)
Purpose: asset finance	0.005 (0.081)	-1.548 (1.013)
Purpose: expansion	0.023 (0.033)	0.226 (0.220)
Purpose: other	0.084 (0.052)	-0.251 (0.412)
Term: 24-36 months	0.190*** (0.070)	-0.972** (0.386)
Term: 48-60 months	0.499*** (0.073)	-0.965** (0.375)
Credit band: A+	-10.344*** (0.060)	-1.984*** (0.517)
Credit band: A	-8.926*** (0.058)	-0.422 (0.388)
Credit band: B	-7.967*** (0.058)	-0.156 (0.396)
Credit band: C	-6.767*** (0.064)	-0.137 (0.421)
Credit band: D	-4.746*** (0.070)	0.086 (0.447)
Industry dummies	Y	Y
Region dummies	Y	Y
N	1,788	1,788
Specification	OLS	Cox Model
R-squared	0.947	
Pseudo-R-squared		0.418

Note. Robust standard errors appear in parenthesis. * p<0.10, ** p<0.05, *** p<0.01