Centre of Excellence
for Science and Innovation Studies

**CESIS** Electronic Working Paper Series

**Paper No. 450**

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

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March, 2017

**The Royal Institute of technology**
**Centre of Excellence for Science and Innovation Studies (CESIS)**
**http://www.cesis.se**

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

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Revised at Feb, 2017

See the latest revision at http://ssrn.com/abstract=2752085

**Abstract:** Funding small businesses used to be the exclusive domain of angel investors, venture capitalists, and banks. Crowd have only recently been recognized as an alternative source of financing. Whereas some have attributed great potential to the funding provided by crowd ("crowdfunding"), others have clearly been more skeptical. We join this debate by examining the performance of crowd 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. Exploiting the randomized assignment of originated loans to institutions and the crowd in the online peer-to-business platform of FundingCircle, we find that crowd underperform institutions in screening SMEs, thereby failing to lend at interest rates that adjust for the likelihood of defaulting on a loan. Moreover, the underperformance gap of crowd compared with institutions widens with risky and small loans, suggesting that crowd lack the expertise to assess the risks or the incentive to expend resources to perform due diligence. Overall, our findings highlight when crowd face limitations in screening SMEs.

**Keywords:** peer-to-peer lending, institutional investors, online loan market, SME, wisdom of the crowd

**JEL codes:** G11, G20, D80

We owe thanks to Massimo Colombo, Mingfeng Lin, Per Strömberg, Karl Wennberg and participants in 4th Crowdinvesting Symposium for helpful comments and discussions. All remaining errors are our own. Ali Mohammadi partly conducted this research while he has been visiting researcher in Swedish house of finance (Stockholm School of Economics).

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*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 (Ferrary and Granovetter, 2009; Kerr et al. 2014; Kortum and Lerner, 2000); for instance, the entrepreneurs funded by VCs often share similar characteristics of their investors in terms of their educational, social, geographic, and professional characteristics (Zacharakis and Meyer, 1998; Rider, 2012; Sorenson and Stuart, 2001; Shane and Stuart, 2002). Although considerable funding has historically come from these sources, crowdfunding has emerged as a promising alternative source of funding, 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 $16.2 billion in 2014, a 167% increase over the $6.1 billion raised in 2013 (Massolution Report, 2015). Among different models, lending-based crowdfunding – also known as peer-to-peer lending – had the largest global market share of about $11.08 billion in 2014 (it grew 223% from 2013). Within the lending-based crowdfunding, peer-to-business lending remains the largest model by volume in 2015 according to the latest report of Nesta (2016), which investigates the online alternative finance market of the UK. Peer-to-business lending (excluding real estate lending) supplied the equivalent of 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). 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, 2016).

Despite the growing role of crowds in funding entrepreneurs once left to professional investors, little is known about how and when crowd and professional investors may differ in

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

their ability to overcome adverse selection risks prevalent in entrepreneurial financing markets. Indeed, for crowds, at least, there is even considerable debate about their ability to select good investment opportunities, as the opening quote suggests. Two diverging perspectives are offered. 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, 2016), 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; Shafi and Sauermann, 2017). 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 (after the investment has been made) (Amit, Brander, & Zott, 1998; Baum & Silverman, 2004; Gompers & 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 crowd in crowdfunding markets helps improve the decision-making of the individuals (Mollick and Nanda, 2015). 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 & Soll, 2006; Makridakis & Winkler, 1983). 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.

Thus, we are interested in shedding light on two questions about the ability of crowd. First, we aim to provide an analysis of the degree to which crowd would assess the risks of funding small business loans. The second related question we seek to understand is when crowd is susceptible to misjudging the risks. The concerns related to questions like these have triggered drafting a series of regulations about crowdfunding (e.g. JOBS Act in the US or Prospectus Directive in the EU) that aim at protecting crowd investors. These regulations impose transparency requirements on companies intending to offer equity or debt to the public to publish a prospectus informing investors about the risks of purchasing these securities.

Several features of our research setting aim to address the extent of crowd performance in assessing loans. First, we benchmark the performance of the crowd 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": they are supposedly expert and sophisticated in screening loans as well as free of "limited" financial incentive faced by the crowd. Institutional investors 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 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 (Financial Times, 2013). 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, & Wein, 2015), 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 crowd participate in financing loans on the same platform, which removes the possibility for influence of cofounding variables across settings. Third, the originated loans are randomly assigned to either institutions or crowd, removing ex ante selection bias.

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, 2015). Finally, lenders have primarily financial motivation to earn positive returns (Pierrakis and Collins, 2013), removing potential influences associated with intrinsic or pro-social behaviours in other types of crowdfunding.

This study has two main findings. First, we document that crowd on average underperform institutional investors. Exploiting the randomized assignment of originated loans to either institutions or crowd[2] and after controlling for loan characteristics such as credit band, the crowd 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. Further support comes from a different identification strategy that analyses "recycled loans": loans left unfunded by the institutional investors (following random assignment) but later funded by the crowd; the nature of this rejection was unobservable to the crowd but observable to the econometricians. Employing a propensity-score matching method that matches each recycled loan with an institution-funded loan based on ex ante observable loan characteristics, we find that recycled loans underperform the 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[3]. 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 of the baseline finding of underperformance of the crowd compared with the institutions and are anchored in the crowd's limited expertise and incentive.

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

[3] 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-diff analysis are again consistent with the underperformance of the crowd compared with "fixed" interest rates.

We find that the underperformance gap of the crowd relative to the 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 crowd have limited expertise. Furthermore, the underperformance gap of the crowd relative to the 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. The incentive effect associated with larger loan size dominates the opposing effect associated with limited expertise, which would predict larger requested loans result in higher adverse selection risks and moral hazard problems that widen underperformance gap of the crowd relative to the institutions (borrowers with higher likelihood of default self-select into asking larger loans and subsequently, these borrowers have higher incentive to default) (Adams et al. 2009).

This paper contributes to two strands of literature. Our paper contributes to the literature on how crowdfunding investors make decisions (Colombo et al. 2015; Mohammadi and Shafi, 2016), especially the extent to which crowd's decisions are rationally made (Zhang and Liu, 2012) or congruent with those of experts (Mollick and Nanda, 2015). In contrast to these studies, we focus on the long-term and objective outcomes of the decisions by the crowd and document deficiencies in crowd's decisions relative to institutions. Furthermore, we reveal the role of cognitive or incentive limitations in the way crowd assess crowdfunding 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 the crowd to overcome adverse selection risks and moral hazard problems. The second contribution of our work is to the recent literature that examines the peer-to-peer lending markets (Morse, 2015). Much of this work has ignored the heterogeneity of lenders (and the ways these lenders may differ in drawing inferences about loans). 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. Therefore, examining lenders' heterogeneity can add to our knowledge of limitations and opportunities embedded in new online lending markets.

## 2. Theory

**2.1. Information Asymmetries in Markets for Entrepreneurial Financing.** SMEs are at a disadvantage in accessing external sources of financing compared with public or mature private enterprises and such lack of capital increases the risk of failure and limits the potential for growth of SMEs (Chemmanur, Krishnan, & Nandy, 2011). The source of difficulty in obtaining external financial resources is often attributed to extensive information asymmetry vis-à-vis prospective investors. SMEs tend to have limited histories and track records for informed assessments by prospective investors, lenders, and partners (Stuart et al. 1999; Ozmel, Robinson, & Stuart, 2013). Additionally, entrepreneurs have superior information about their intrinsic quality (Amit, Brander, & Zott, 1998), or conversely tend to be over-optimistic and have natural incentives to exaggerate their prospects, withhold or temper negative information, and overstate the potential value of their firm (Cooper, Woo, and Dunkelberg, 1988), which often is tied to growth expectations rather than tangible assets in place (Barzel, 1987; Shane and Cable, 2002; Shane and Stuart, 2002).

The normative prescription of these information frictions is a market distortion in financing SMEs. Theoretical models suggest that difficulty in distinguishing between firms (e.g., borrowers) of different quality can have consequences varying from over-investment or under-investment relative to the optimum (De Meza and Webb, 1987; Stiglitz and Weiss, 1981; Jaffee and Russell, 1976). This is so because (hidden) information problems result in increased adverse selection risk for external investors (Myers and Majluf, 1984; Greenwald, Stiglitz, & Weiss, 1984). Additionally, hidden action problems result in increased moral hazard owing to agency issues after the investment (Jensen & Meckling, 1976; Grossman and Hart, 1982).

Financial intermediaries such as banks or venture capitalists are equipped with the relevant set of expertise and skills to overcome information problems prevalent in entrepreneurial financing markets. Take the case of venture capitalists that usually fund high-technology start-ups. These intermediaries rely on their expertise both to select promising start-ups and to devise mechanisms (e.g., staging, syndicating, using certain contractual covenants, and strong control rights exceeding cash flow rights) to deter entrepreneurs' opportunistic behaviour after the investment has been made (Amit et al., 1998; Lerner and Gompers, 2001; Baum and Silverman, 2004). VCs possess deep industry knowledge, have sophisticated mental schemas to detect signal from noise in decision making, and financial resources to perform due diligence. Overall, these intermediaries have organisational and informational advantages that helps them alleviate information asymmetries in these markets.

**2.2. The Role of Information in Online Lending Peer-to-Peer Markets.** The theoretical importance of asymmetric information and its potential for adverse selection risk is a cornerstone of studies in (consumer) credit markets (Berger and Udell; 1992; Ausubel, 1999; Karlan and Zinman, 2009). In credit markets, including peer-to-peer markets, lenders infer the creditworthiness of borrowers by observing both standard financial information (e.g., credit scores) and soft (non-verifiable in the sense of Stein (2002)) information about borrowers' quality (for a review of peer-to-peer literature, see Morse, 2015). Miller (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. Besides hard information such as credit score, soft information can reduce adverse selection risks. Few studies have shown how physical and demographical attributes of borrowers (e.g., beauty, age, and race) influence the peer-to-peer lending decisions (Duarte, Siegel, & Young, 2012; Pope & 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. As further evidence to the role of soft information, Iyer et al. (2016) show that the 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.

**2.3. Wisdom of the Crowd.** Crowdfunding markets facilitate pooling resources from a multitude of individuals, forming a crowd of investors. Hence, 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, 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 (Makridakis & Winkler, 1983). 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 (Larrick, Mannes, & Soll, 2011; Surowiecki, 2004), which either emphasize the quality of the signal or the nature of the noise in the individuals' judgment. First, crowd or at least some member of the crowd should have some relevant knowledge about the issue of judgment (Keuschnigg & 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 crowd judgment about the issue in question (Keuschnigg & Ganser, 2016; Larrick et al. 2011). Second, individual judgments should be formed independent of others (Hogarth, 1978; Sunstein, 2006). If the crowd 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 the crowd, we benchmark the lending decisions of the crowd against experts, i.e., 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 is not known or well defined ex ante (typical examples in prior research are the "cultural" markets of musical tastes (Salganik, Dodds, and Watts, 2006) or artistic projects (Nanda and Mollick, 2015), which renders the expert judgement the next best alternative. Second, research on other contexts has shown that at least some institutions such as mutual funds have (stock) selection ability and skill (as opposed to luck), evidenced by returns on investment above market indices (Grinblatt & Titman, 1989; Daniel, Grinblatt, Titman, & Wermers, 1997) (see Berk and van Binsbergen (2015) on managerial skill in the mutual fund industry). Overall, 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 (Gruber 1996, Zheng 1999).

**3.1. Does Crowd Perform Better than Institutions?** A few arguments cast doubt on the outperformance of the crowd compared with institutional investors. The first line of investigation scrutinizes the expertise of individual investors. Individuals underperform standard benchmarks (e.g., a low cost index fund) (Barber & Odean, 2013) and trading by individual investors produces economically large losses (Barber et al. 2009)[4]. Poor understanding of financial markets by individual investors leads to investment decisions that deviate from financial theories of wealth maximization (Calvet, Campbell, & Sodini, 2007).

[4] See also Schlarbaum, Lewellen, and Lease (1978a, 1978b); Odean (1999); Barber and Odean (2000, 2001); Grinblatt and Keloharju (2000); Goetzmann and Kumar (2008); and Linnainmaa (2003a, 2003b)).

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. Therefore, we propose the following hypothesis:

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

**3.2. Does Limited Expertise of the Crowd Contribute to Underperformance Gap?** In the subsequent hypotheses, we elaborate the boundary conditions of the underperformance of the crowd. 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 the crowd. We conjecture that that the extent of underperformance gap between crowd and institutions (a) increases with the expertise required to assess the riskiness of loans and (b) decreases with the incentives of the crowd 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. 2015). To specify our hypotheses linking loan risk and performance gap of crowd 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 & Mählmann, 2016). Accordingly, marginal value of expertise is higher among the risky investments. Fang et al. (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. Following a similar reasoning, if "returns to expertise" (skill or being informed) are smaller for less risky loans, then the gap between institutions and the crowd 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, & Uetake, 2014; Iyer et al. 2015), (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, Onishi, and Uetake (2014) show that borrowers in Prosper use low "maximum acceptable interest 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 alternate funding options. Therefore, lenders may infer borrowers as risky when they post a high reserve rate (Stiglitz and Weiss, 1981) – say, higher than the interest rates charged on average for similar credit bands. This is so because lenders may infer that this borrower faces difficulty from outside sources: Butler, Cornaggia, and Gurun (2017) find that borrowers who reside in areas with good access to bank finance request loans with lower reservation rates. In addition, Iyer et al. (2015) 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 measure of loan riskiness 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, & 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) (Etsy, 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 & Spencer, 1989).

Our last measure of loan riskiness 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 (Adams et al. 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 the crowd 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 the crowd 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 the crowd relative to the institutional investors in screening SMEs narrows with decreasing requested amount of borrowing.*

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

Investors will have an 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 crowd invests 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 venture capitalists participate intensively in screening and monitoring the management of their portfolio firms, 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 & Tirole, 1997). Investors would lack the incentive to produce an efficient level of creditworthiness information and monitoring when they would not receive the rewards from these activities. Take the case of loan sales by banks (or originate-to-distribute model of lending); by retaining a portion of the selling loan, the bank could reduce agency problems since it continues to face a partial incentive to maintain the loan's value. The greater the portion of the loan held by the bank, the greater will be its incentive to evaluate and monitor the borrower (Gorton & Pennacchi, 1995).

Larger requested amount of borrowing encourages greater incentive for production of accurate information for crowd. Larger requested amount of borrowing 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 foremost motivated financially (Pierrakis & Collins 2013) as opposed to pursuit of intrinsic, social motive, or desire for reward, which are common motivations in other types of crowdfunding and crowdsourcing (Jeppesen & Frederiksen, 2006; Afuah & Tucci, 2013). To extent to which the increase in intensity of screening with loan size for crowd is larger than institutions, we expect the underperformance gap to narrow. Our latter assumption claims that institutions benefit from and rely on standard routines and procedures of assessment that could be less subject to variations in the range of loan sizes offered in online platforms like ours. To the extent that this argument holds, we propose the following competing hypothesis:

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

**4. Institutional Context of FundingCircle.com**

Funding Circle established in 2010[5] is distinguishable from other players like Zopa (the first peer-to-peer platform in the world founded in the UK) by serving small and medium sized enterprises (SMEs) rather than individuals. 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 40,000 lenders invested around $1.5bn in 12,000 SMEs. SMEs that are looking for loans should usually have at least two years of operation, and a minimum turnover of £50k[6].

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[7]. The risk bands range from A+ to E, where A+ is 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.

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[5] https://www.fundingcircle.com/uk/about-us/
[6] A step-by-step guide to borrowing, available at:
https://www.fundingcircle.com/uk/businesses/
[7] 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 bidding follows an open auction; everybody can 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 are bid down until the duration of the listing expires. Alternatively, as soon as a loan request is fully funded, the borrower can end a loan request (early) and accept the loan. All winning bidders receive 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. For instance, The Government-backed British Business Bank is lending through Funding Circle. In partial loan market, only individual investors can buy a part or whole of a loan. Loans are initially assigned randomly to each market[8]. 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 recycled loans[9] when funding these loans. This information is only visible on the loan book, accessible for download to investors 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 the crowd.

## 5. Methods

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

[9] "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/

## 5.1. Data

Our dataset includes all successful loan requests in the loan-book accessed at March of 2016 of FundingCircle.com. 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[10]. 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 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[11]. 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 1 reports the definition of variables used in this study.

*Insert Table 1 about here*

## 5.2. Results

*Basic framework*. As noted in the institutional setting of FundingCircle.com, loans are randomly assigned to two marketplaces of "whole loan" and the "partial loan" market. The randomization allows us to compare the loan performance of crowd compared with the institutions without sample selection concerns. The randomization

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

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

enables unbiased estimation of "crowd" performance. In an effort to avoid selection bias associated with recycled loans, we exclude them from this analysis. Table 1 presents the summary statistics of variables used.

Table 2 reports the regression results of basic framework that regresses the interest rate and hazard rate of loans on the funding by the crowd – our primary independent variable. Model 1 and 2 show the results of OLS regressions with *interest rate* as the dependent variable. The standard errors are robust to heteroskedasticity. The unit of observation is individual loan request. Model 1 is the baseline model with the control variables, explaining 86 percent of variance of the interest rate. Regarding the credit band, note that the coefficient of credit band of "E" is omitted to avoid singularity. The coefficients of credit bands therefore measure how the interest rate vary 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. Not only the coefficients of credit band are all statistically significant ($p<0.01$), combined they explain 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 the amount requested (it is log-transformed for concerns of skewness), consistent with the 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 ter ms reveal a positive and significant coefficient ($p<0.01$) (Term: 6-12 months is considered as omitted category). The coefficient on the 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 mulit-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.

The Model 2 of Table 3 reveals a negative and statistically significant relationship between crowd and interest rate. Funding by crowd relative to institutions is associated with a decrease of 40 basis points in interest rate. While this effect might not seem large, this is equal to 10% of monthly average salary in the UK (The UK average salary in 2014 was £26,500) considering the average amount requested is £57,000[12].

We now turn our 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)[13]. We use a Cox proportional hazard model. The model is convenient both because it allows for a flexible default pattern over time and because it allows us to work with our full sample of loans despite some observations being censored (a

[12] This amounts to over £9 million losses per year for all crowd investors assuming they are 40,000.

[13] 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.

lacuna for using probit specifications). We also check the proportionality hazard assumptions of Cox models on the basis of Schoenfeld residuals (and hence, exclude year dummies because they vary with time[14]). The Schoenfeld residuals test is analogous to testing whether the slope of scaled residuals on time is zero or not. We find the slope is not different from zero and 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 $p<0.05$). 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 actually randomly distributed as the ex post measure of quality of loans (default) is not different and (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 crowd requests a lower interest rate in spite of similar ex post hazard of default on loans.

*Insert, Table 1, and Table 2 about here*

*Propensity-Score matching of recycled loans.* Recycled loans refer to loans that are funded by the crowd but were initially left unfunded by the institutions. The econometrician only knows this information, meaning that individual investors during the loan listing are not informed about the nature of this rejection (unobserved to the crowd but observable to us, as researchers). We exploit an identification strategy

[14] Including year dummies does not change the insignificant coefficient of Crowd.

based on the exclusive availability of this information to the econometrician to test the performance of the crowd. To do so, for each recycled loan (treatment group), we match one loan among the loans funded by the institutions (control group) by employing propensity score matching method (PSM) (Rosenbaum & 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 the crowd. 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 the crowd) versus all loans that received funding from institutions. After verifying that covariates are balanced across recycled loans and the matched comparison groups (leading to disregarding recycled loans for which a match is not found[15]), we perform a multivariate analysis. In this analysis, the final sample size is 1,894.

Table 3 reports these results. In model 1 of Table 3, the estimation results of OLS models with robust standard errors show that recycled loans are associated with 20 basis points less interest rate. In model 2 of Table 3, the estimation results of Cox models with robust standard errors reveal positive yet not statistically significant coefficients of recycled loans. These results are in line with previous findings.

*Insert Table 3 about here*

*Moderators. "Normalized" maximum acceptable interest rate* and *limited company*: The previous models do not allow the performance of the crowd to depend on the characteristics of loans. We identify loans that are more subject to adverse

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[15] Matching is done by using all covariates reported in Table 2, model 1. The results of balance test are available upon request.

selection risk and moral hazard problems, and thus, require higher expertise for assessment. To explore the underperformance of crowd compared with institutions further, we introduce an interaction term between crowd indicator and various risk proxies of loans and report these results in Table 4.

The first measure of loan riskiness is the extent to which the maximum acceptable interest rate differs from the average interest rate in each risk band. We refer to this variable as "normalized" maximum acceptable interest rate. Model 1 presents OLS model of interest rate and reveal positive and significant coefficient on the normalized maximum acceptable interest rate ($p<0.01$); 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 ($p<0.01$) suggests that increase in the normalized maximum acceptable interest rate for the crowd is associated with reduction in interest rate.

The second measure of risk is whether a company is incorporated as "limited company". Model 3 presents OLS estimates of the interaction between limited company and crowd; the negative and statistically significant coefficient of this interaction term suggest that investing in limited companies for crowd is associated with reduction in interest rate.

The subsequent models (Model 5 to Model 7) present 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 lends empirical support to the choice of this variable as indicative of loan riskiness. Further models similarly show the interaction terms in Cox models between crowd and limited, and normalized maximum acceptable interest rate. For easier interpretation of the models with interaction terms, we plot these relationships in Figure 1 and Figure 2. These findings support Hypotheses 2 and 3.

*Insert Table 4, Figure 1, and Figure 2 about here*

*Amount requested*: The performance of the crowd is not only subject to expertise level, but is a function of the effort level in assessing the loan. We identify amount requested as a proxy of effort provision in Hypothesis 4b (and a proxy for loan riskiness in the competing Hypothesis 4a).

To test which of the preceding effects prevails, we interact *Crowd* and *Amount requested*. Model 4 of Table 4 presents the OLS estimates of interaction term. The positive coefficient on the interaction term ($p<0.01$) suggests that increase in the amount requested (logged) increases the interest rate for the crowd. The size of this effect is also shown in Figure 3. Interestingly, there is an almost negligible sensitivity of interest rates to the total requested amount of borrowing for institutions. Model 8 of Table 4 also present the Cox estimates of the interaction terms and Figure 3 plots the associated economic magnitude of hazard rate. These results favor Hypothesis 4b.

Overall, crowd respond to higher requested amount of borrowing by increasing the effort in risk assessment, and thus, request a higher interest rate in a way that recognizes the opportunity of adjusting the interest rate based on the probability of repaying a given loan (as institutions do).

*Insert Figure 3 about here*

### 5.3. Additional analysis[16]

*Diff-and-Diff Analysis.* We exploit a policy change in the platform of FundingCircle. At 28th of September 2015, FundingCircle switched the auction-

[16] The results of this section are not reported due to breivity.

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 diff-and-diff analysis and compare the performance of the crowd against the fixed interest rates (set by the platform). Note that the results from this analysis compare the performance of the crowd (treatment group) with the platform organizing and setting the interest rates (control group). For this analysis, the period of 4 months before and after the policy change is considered.

In the diff-and-diff 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 of September 2015. In this analysis the treatment effect is 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) – it is noteworthy to mention that baseline in this regression is not institutions but the platform setting the interest rates. The coefficient of interaction term in the hazard model shows a large negative and statistically significant value. The reason is that not enough time has passed for loans to fail at the time of access to the loan-book on March of 2016 (less than 10 loans have failed).

The preceding diff-and-diff 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 (2013). First, we repeat analysis on the sample of pre policy change and included interaction terms of all periods (4 periods) prior to policy change. The results show there are no statistically significant differences between the predicted slope for treated and control group prior to policy change (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, 2013: 529). The result shows that effect of pre-policy change is statistically indistinguishable from zero while effect after policy change is statistically different than zero. Finally, we have done another falsification test by repeating our diff-and-diff analysis on sample of loans that has been closed in 8 months prior to policy change. We assume the middle of the period as the time the fake policy change happened (after-fake). We would expect not to observe similar effects as real policy change in our analysis. The result shows while the coefficient is negative (the real effect was positive), it is not statistically significant from zero.

*Observables or Unobservables.* We set out to understand whether institutional investors provide the effort of acquiring new sources of information that are private (e.g., obtained from interactions with business owners) and not already captured by the controlled covariates in our analysis. This information channel might explain some of the underperformance gap and is distinguishable from the institutional investors' capability and ability to use the available information efficiently for better selection. While the former is about new sources of information to make better decisions, the latter corresponds to the capability and know-how for efficient use of the same set of information. The current literature is ignorant of this theoretical distinction, failing specially to recognize its practical value to the design of crowdfunding markets in terms of transparency and disclosure requirements aimed at increasing market efficiency.

To test this, following Iyer et al. (2016) we measure the inference drawn from uncoded information by computing this inference as a “residual,” that is, the variation of interest rates that remains after controlling for a very flexible functional form of all coded information. This strategy considers a role for the non-traditional and soft information, to predict default and goes beyond the ability of lenders to use listing information (observables).

First, we find that the market interest rate on loans explains more variation in ex post default than other covariates such as the credit band (Iyer et al. 2016) – from examining the $R^2$. Second, although the coefficient on the interaction of interest rate and crowd is significant in the regression of ex post default rate, the marginal effects don't show differences between the crowd and institutions. Furthermore, the marginal effects of “residuals” separated by investor type are also non-significant. These results show that the crowd as compared with institutions is not able to make use of all readily available information (i.e., observable characteristics of the loan) in their decisions to set risk-adjusted interest rates *ex ante* in a way that predicts the default probability on a loan *ex post*.

**6. Discussion**

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 (von Hippel 2005; Terwiesch and Ulrich 2009; Afuah and Tucci 2012) and scientific research (Franzoni and Sauermann, 2014). With increasing interest from scholars in understanding crowd behaviour (Zhang and Liu, 2012; Colombo et al. 2015; Surowiecki, 2004) and the limitations and opportunities facing markets based on crowd, we investigate the performance of crowd judgement in crowdfunding markets and when and whether it can be relied on (Magnussen, Wastlund, and Netz, 2014;

Poetz and Schreier, 2012). In fact, the future growth and sustainability of crowdfunding markets as a viable source of entrepreneurial financing rests on understanding the conditions under which the wisdom of the crowd is deployed. To address this question, we compare the performance of crowd, relative to institutions, in assessing loans in the online peer-to-business lending of FundingCircle.com. We find that relative to institutions, the crowd earns between 20 to 40 basis points lower interest rate on loans without differences in ex post borrower's probability of default. As our further tests show this underperformance gap stems from the limited expertise and the capability of crowd to process riskier loans or their limited incentive to perform screening owing to insufficient skin in the game.

Even though our results show performance gap of the crowd relative to institutions, the magnitude of these effects are not so large to suggest madness of crowd; Rather, our results to some extent conform to prior findings that collective intelligence compare favourably to those from experts (e.g., Galton 1907; Shankland 2003; Antweiler and Frank 2004; Lemos 2004; Surowiecki, 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 the crowd 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 (Van Rooij, Lusardi, and Alessie, 2011). Relatedly, crowd funders 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 (Cyert & March, 1963; Simon, 1955; Williamson, 2002). However, when the crowd 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 (e.g. the bids in the competitor platform of ThinCats can be made in £1,000 increments).

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 industry needs more regulation (from regulatory agencies such as Financial Conduct Authority). First, our results suggested that the major component of underperformance of crowd relative to institutions is unrelated to the loans rejected by institutions but funded by crowd (our analysis including and excluding the recycled loans show no substantial differences in terms of performance gap). Such evidence disagrees with negative comments like the opening quote. 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 that we find that customers in lower credit scores (subprime customers) are not the primary category of loans rejected by institutions (at least on observables Table A11), we lack evidence that loans in crowdfunding markets are sub-prime and the crowd are naïve lenders being taken advantage of. Second, default rates of loans on FundingCircle are generally low, further indicating that selection procedures of platforms can play strong gate-keeping roles.

Our paper also provides evidence of the role of crowdfunding in democratizing access to funding for firms that institutions have rejected to lend to. We further show that viewed from businesses' perspective, this funding source is a cheaper source of capital than institutions provide in these markets. However, 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), raising the question of the extent to which our findings can be generalized to other types of crowdfunding models such as equity crowdfunding. Future research may profitably explore how crowd relative to venture capitalists or business angels perform when choosing their equity investments. 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. Take the assumption of independence that is debated in the crowdfunding literature by observations of herding behavior, see Colombo, Franzoni, & Rossi-Lamastra, 2015; Burtch, Ghose, & Wattal, 2013; Zhang & Liu, 2012). Decision making in crowdfunding markets are susceptible to social influence. Under conditions of uncertainty and sequential decisions, individuals are unlikely to arrive at their decisions independently. Instead, they are likely to observe others' actions and update their private beliefs (in a Bayesian manner). This observational learning might engender informational cascades or herding (Celen & Kariv, 2004), in which individuals ignore their private beliefs or overweight the information learned from the actions of others – people may suspect that others have better information (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992). 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, & Andrews, 2011). This re-enforcing dynamic associated with herding in crowdfunding (Colombo, Franzoni, & Rossi-Lamastra, 2015; Zhang & Liu, 2012; Burtch, Ghose, & Wattal, 2013) likely undermines production of wisdom of the crowd by violating independence of individual judgments. Although theory lacks clear predictions about the performance outcome of such complex social and informational interactions (Lorenz et al. 2011), Zhang & Liu (2012) show empirically that lenders arrive at good decisions because they are rational observers and able to aggregate information on borrower creditworthiness from observing prior lenders.

To illustrate how 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, default rate) will tend to converge to the actual outcome (conditional on independence of judgments). It becomes less and less likely that, by chance, actual outcomes will deviate from expected outcomes. This intuition is formalized in Condorcet Jury Theorem: where a group votes on two alternatives, one of which is correct, and the members of the group are even slightly more likely to be right than wrong, then as the number of members in the group increases, the probability that a majority vote of the group is correct tends towards certainty. Furthermore, increasing the diversity in judgements can compensate the lack of expertise or low incentive to be accurate, which are necessary in the production of the wisdom of the crowd. Keuschnigg and Ganser (2016) find that diversity and ability can substitute each other to some degree in production of the wisdom of the 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 production of the wisdom of the crowd. This explanation further lends support to Hypothesis 4b. Therefore, even though an ideal setting would allow us to tease out which assumptions behind wisdom of crowd are violated, our data don't allow us to do so.

In terms of managerial implications, as small business owners are increasingly turning to this alternative source of money to fund their businesses, policy makers may wish to keep a close eye on both levels and terms of such lending. Because such loans require less paperwork than traditional loans, they may be considered relatively attractive. It is unlikely that current practices in terms of screening in these markets are doomed. The many funding opportunities available from these markets in addition to their use by UK government in targeting underfunded regions show the potential for these markets in filling the seed and early stage gap. However, more research is required to understand the long-term impact of such loans on the longevity of the firm and more education to potential borrowers is likely in order.

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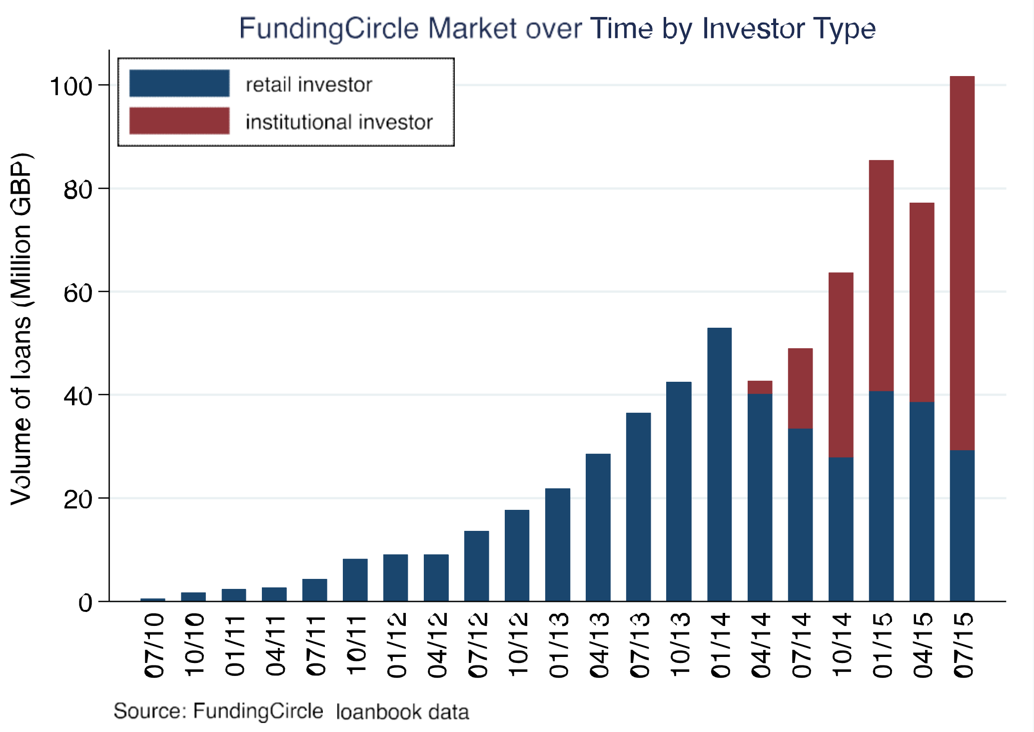


**Figure 1. FundingCircle Market over Time by Investor Type**

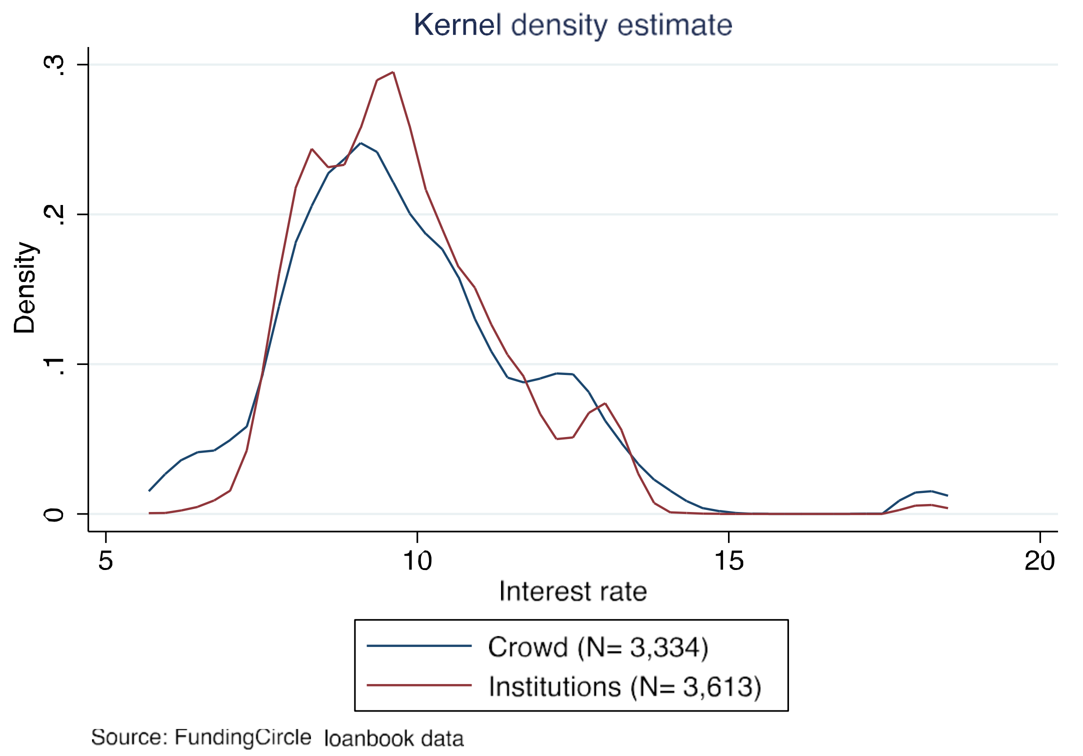


**Figure 2. Kernel density estimates of interest rate separated by investor type.**

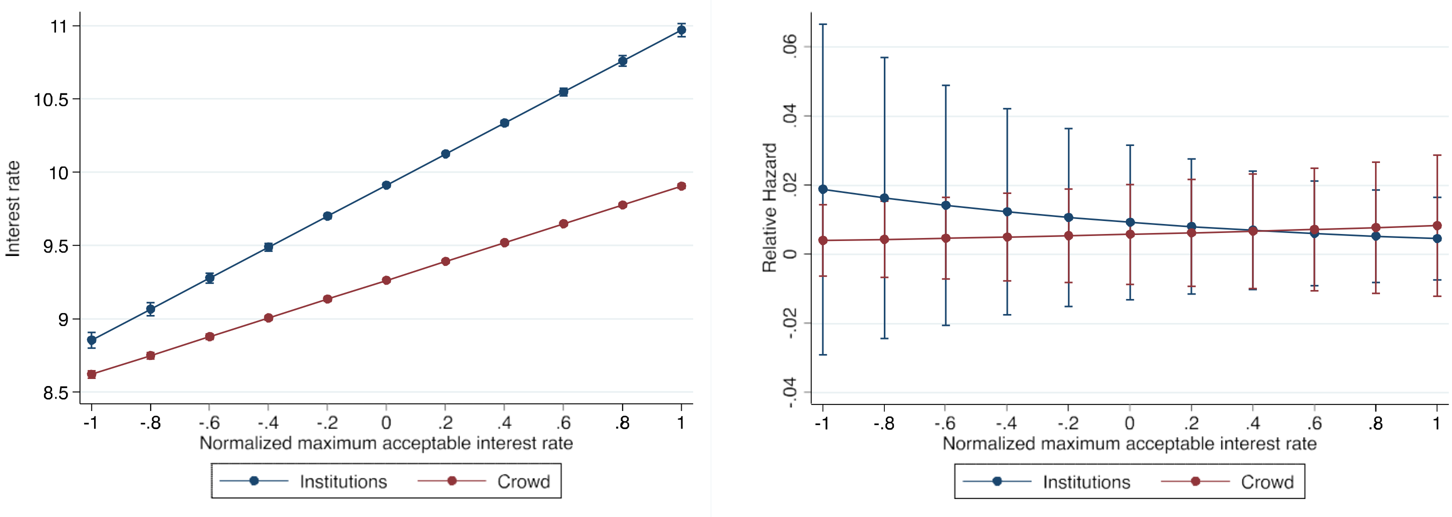


**Figure 3. Boundary Condition: Normalized maximum acceptable interest rate**

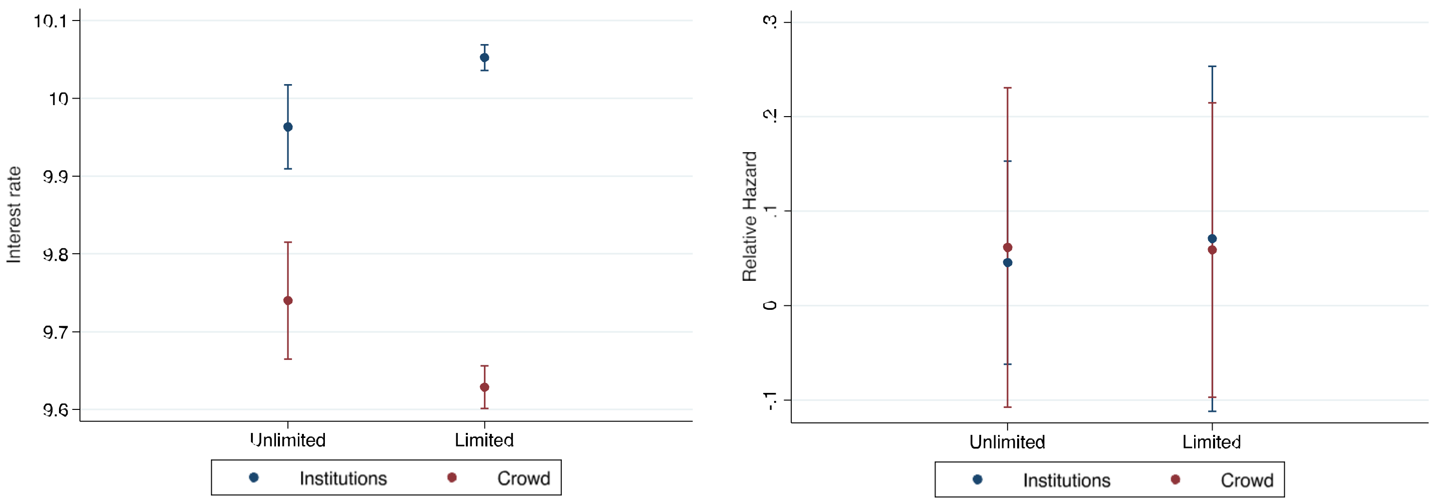


**Figure 4. Boundary Condition: Limited company**

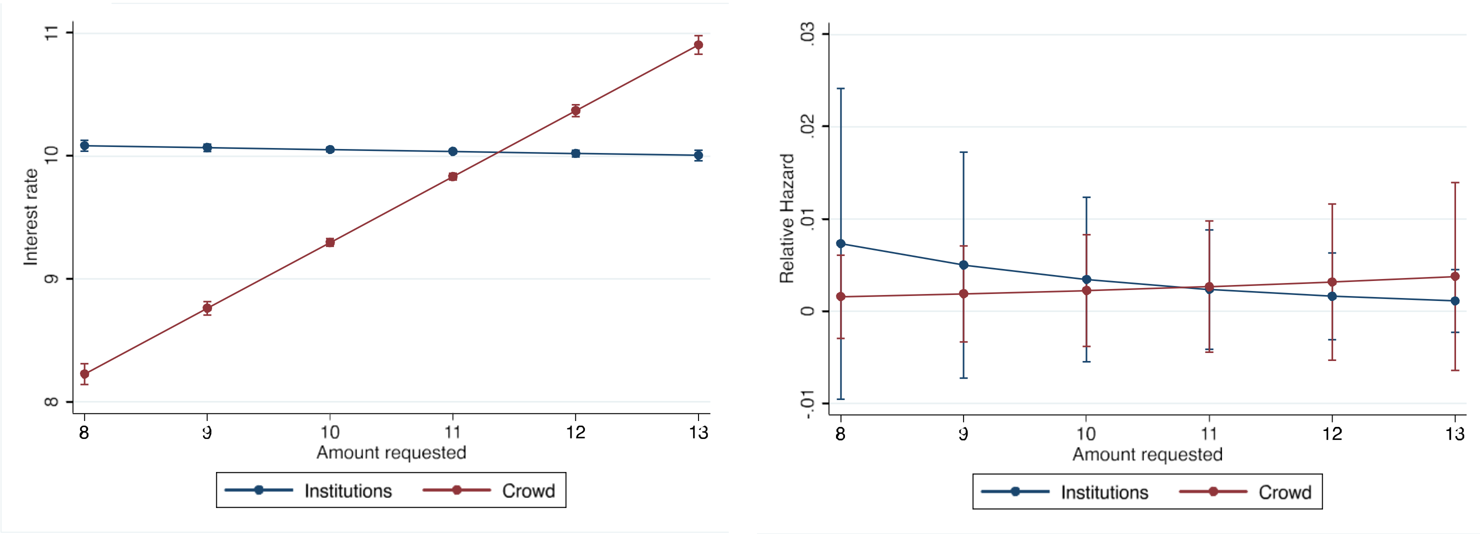


**Figure 5. Boundary Condition: Amount requested**

**Table 1. Variable Definitions**

| Variable | Definition |
|---|---|
| Amount requested | The amount in British Pound requested by the borrower in the listing (This variable is logged in the regressions). |
| Credit band (dummy) | Each borrower is assigned a credit band: A+, A, B, C, D, E (dummy). A+ designates the lowest risk, E the highest. "E" is the reference in our analysis. |
| Purpose (dummy) | It is a dummy variable indicating the purpose of loan. These include Asset financing, Expansion, Working capital, and Other purposes. |
| Crowd (dummy) | This variable is set to one if the crowd finances a loan, otherwise zero. To identify loans financed by crowd, the number of loan parts is above one. This is so because institutions purchase the whole of the loan and thus the number of loan parts equals by definition one. |
| Limited company (dummy) | If the borrower's business is incorporated as "limited company", this dummy variable is set to one, otherwise zero. Unlimited companies also include partnerships. |
| Term (dummy) | This is a dummy variable indicating the maturity of loans. The three categories for loan terms are 6-12 months, 24-36 months, 48-60 months. |
| Normalized maximum acceptable interest rate | This variable is calculated by taking the difference of maximum interest rate the borrower is willing to pay when applying for a loan on FundingCircle and the monthly average interest rate for each credit-band. |
| Interest rate | This is the marginal interest rate on the loan. |
| Defaulted (dummy) | We coded a loan as defaulted if the status of the loan in the loan book is "defaulted". The time to default is one month after last payment recorded. |
| After (dummy) | This is a dummy variable indicating the period after 30$^{th}$ September of 2015, when FundingCircle switched from auction-mechanism interest rate to fixed interest rate. |
| Sector other than property and construction (dummy) | This is a dummy variable that indicates loans not belonging to the categories of property and construction. The sector of property and construction had fixed interest rate even prior to 30$^{th}$ September of 2015. |
| Industry sectors (dummy) | The industries are Agriculture, Arts & Entertainment, Automotive, Consumer Services, Education & Training, Finance, Healthcare, IT and Telecommunications, Leisure & Hospitality, Manufacturing and Engineering, Other, Professional and Business Support, Property and Construction, Retail, Transport and Logistics, Wholesale. |
| Geographical region (dummy) | These regions are East Anglia, London, Midlands, North East, North West, Northern Ireland, Scotland, South East, South West, and Wales (omitted category). |

**Table 2. Descriptive Statistics of Loans by Investor Type**

| | Crowd | | | Institution | | |
|---|---|---|---|---|---|---|
| | **N** | **Mean** | **S.D.** | **N** | **Mean** | S.D. |
| **Panel A: Loan characteristics** | | | | | | |
| 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** |
| Interest rate | **3,334** | **9.854** | **2.006** | **3,613** | **9.850** | **1.577** |
| Limited company | **3,334** | **0.890** | — | **3,613** | **0.924** | — |
| Defaulted | **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 | | |

**Table 3. Regression Results of Basic Framework (Interest Rate and Time-to-Default of Crowd)**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Interest Rate | | Hazard | |
| **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) |
| **Crowd** | | -0.405*** | | -0.141 |
| | | (0.016) | | (0.177) |
| **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 4. Regressions related to the Propensity Score Matching of Recycled Loans**

| | (1)<br>Interest Rate | (2)<br>Hazard |
|---|---|---|
| **Recycled loans** | -0.202*** | 0.334 |
| | (0.032) | (0.278) |
| **Amount requested** | 0.295*** | 0.029 |
| | (0.023) | (0.158) |
| **Limited company** | 0.007 | 0.655 |
| | (0.060) | (0.563) |
| **Purpose: asset finance** | -0.024 | -0.717 |
| | (0.081) | (0.742) |
| **Purpose: expansion** | 0.060* | -0.467 |
| | (0.034) | (0.292) |
| **Purpose: other** | 0.051 | -0.765 |
| | (0.066) | (0.602) |
| **Term: 24-36 months** | 0.066 | -0.798 |
| | (0.117) | (0.684) |
| **Term: 48-60 months** | 0.234** | -1.115* |
| | (0.115) | (0.675) |
| **Credit band: A+** | -10.339*** | -2.497*** |
| | (0.072) | (0.926) |
| **Credit band: A** | -9.162*** | -1.955** |
| | (0.065) | (0.826) |
| **Credit band: B** | -8.089*** | -1.797** |
| | (0.069) | (0.847) |
| **Credit band: C** | -6.919*** | -0.961 |
| | (0.072) | (0.797) |
| **Credit band: D** | -5.414*** | -1.386 |
| | (0.070) | (0.872) |
| **Constant** | 15.229*** | |
| | (0.332) | |
| **Year dummies** | Y | N |
| **Industry dummies** | Y | Y |
| **Region dummies** | Y | Y |
| **N** | 1,894 | 1,894 |
| **Specification** | OLS | Cox model |
| **R-squared** | 0.869 | |
| **Chi-squared** | | 4,2030.173 |
| **Pseudo-R-squared** | | 0.069 |

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

**Table 5. Boundary Conditions of Basic Framework**

| | (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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

**Table 6. Diff-in-Diff Analysis for crowd**

| | (1) Interest Rate | (2) Hazard |
|---|---|---|
| **Sector other than property and construction** | -0.340*** | -26.548*** |
| | (0.085) | (1.511) |
| **After** | 0.111** | -1.127 |
| | (0.056) | (1.100) |
| **Sector other than property and construction × After** | 0.310*** | -39.636*** |
| | (0.065) | (1.348) |
| **Amount requested** | 0.274*** | -1.127*** |
| | (0.018) | (0.242) |
| **Limited company** | -0.155*** | 0.183 |
| | (0.052) | (1.479) |
| **Purpose: asset finance** | 0.005 | -43.042*** |
| | (0.081) | (0.966) |
| **Purpose: expansion** | 0.023 | -1.718 |
| | (0.033) | (1.116) |
| **Purpose: other** | 0.084 | 1.244 |
| | (0.052) | (1.381) |
| **Term: 24-36 months** | 0.190*** | 1.469** |
| | (0.070) | (0.690) |
| **Term: 48-60 months** | 0.499*** | 1.519 |
| | (0.073) | (1.171) |
| **Credit band: A+** | -10.344*** | -2.793 |
| | (0.060) | (2.004) |
| **Credit band: A** | -8.926*** | -0.410 |
| | (0.058) | (1.366) |
| **Credit band: B** | -7.967*** | 0.591 |
| | (0.058) | (1.513) |
| **Credit band: C** | -6.767*** | -43.001*** |
| | (0.064) | (1.409) |
| **Credit band: D** | -4.746*** | 0.865 |
| | (0.070) | (0.962) |
| **Constant** | 14.905*** | |
| | (0.224) | |
| **Month dummies** | Y | N |
| **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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

**APPENDICES**

**Appendix 1- Result of Table 3 after propensity score matching**

| | **(1) Interest rate** | **(2) Hazard** |
|---|---|---|
| **Crowd** | -0.402*** | -0.178 |
| | (0.017) | (0.188) |
| **Credit band: A+** | -10.257*** | -3.772*** |
| | (0.065) | (0.831) |
| **Credit band: A** | -9.031*** | -2.655*** |
| | (0.064) | (0.748) |
| **Credit band: B** | -8.042*** | -2.227*** |
| | (0.064) | (0.753) |
| **Credit band: C** | -6.900*** | -1.748** |
| | (0.065) | (0.754) |
| **Credit band: D** | -5.218*** | -1.796** |
| | (0.066) | (0.772) |
| **Amount requested** | 0.263*** | -0.136 |
| | (0.012) | (0.097) |
| **Limited Company** | -0.003 | 0.603 |
| | (0.029) | (0.439) |
| **Purpose: asset finance** | -0.084** | -1.017* |
| | (0.042) | (0.591) |
| **Purpose: expansion** | -0.017 | -0.739*** |
| | (0.019) | (0.201) |
| **Purpose: other** | -0.044 | -0.347 |
| | (0.033) | (0.398) |
| **Term: 24-36 months** | 0.168*** | 0.574 |
| | (0.045) | (0.544) |
| **Term: 48-60 months** | 0.274*** | 0.402 |
| | (0.045) | (0.547) |
| **Constant** | 15.429*** | |
| | (0.152) | |
| **Year dummies** | Y | N |
| **Industry dummies** | Y | Y |
| **Region dummies** | Y | Y |
| **N** | 5,814 | 5,814 |
| **Specification** | OLS | Cox model |
| **R-squared** | 0.856 | |
| **Chi-squared** | | 87.508 |
| **Pseudo-R-squared** | | 0.046 |

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

**Appendix 2- Result of Table 4 without propensity score matching**

| | (1) Interest rate | (2) Hazard |
|---|---|---|
| **Recycled loans** | -0.163*** | 0.414** |
| | (0.030) | (0.210) |
| **Credit band: A+** | -10.232*** | -2.314*** |
| | (0.034) | (0.852) |
| **Credit band: A** | -9.069*** | -1.618** |
| | (0.032) | (0.788) |
| **Credit band: B** | -8.074*** | -1.052 |
| | (0.034) | (0.777) |
| **Credit band: C** | -6.930*** | -0.445 |
| | (0.036) | (0.767) |
| **Credit band: D** | -5.354*** | -0.528 |
| | (0.035) | (0.782) |
| **Amount requested** | 0.115*** | -0.130 |
| | (0.011) | (0.097) |
| **Limited Company** | 0.009 | 0.451 |
| | (0.035) | (0.358) |
| **Purpose: asset finance** | -0.028 | -0.666 |
| | (0.043) | (0.518) |
| **Purpose: expansion** | 0.002 | -0.654*** |
| | (0.018) | (0.207) |
| **Purpose: other** | 0.015 | -0.656 |
| | (0.037) | (0.436) |
| **Term: 24-36 months** | -0.012 | -0.103 |
| | (0.040) | (0.497) |
| **Term: 48-60 months** | 0.099** | -0.150 |
| | (0.039) | (0.502) |
| **Constant** | 17.107*** | |
| | (0.143) | |
| **Year dummies** | Y | N |
| **Industry dummies** | Y | Y |
| **Region dummies** | Y | Y |
| **N** | 4,715 | 4,715 |
| **Specification** | OLS | Cox model |
| **R-squared** | 0.894 | |
| **Chi-squared** | | 66,045.969 |
| **Pseudo-R-squared** | | 0.047 |

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

**Appendix 3- Test of parallel trend prior to switch to fixed interest rate (period 4 is omitted category)**

| | (1) Interest rate |
|---|---|
| **Sector other than property and construction** | 0.045 |
| | (0.136) |
| **Period 1** | 0.089 |
| | (0.119) |
| **Sector other than property and construction × Period 1** | -0.203 |
| | (0.137) |
| **Period 2** | 0.206* |
| | (0.108) |
| **Sector other than property and construction× Period 2** | -0.211 |
| | (0.134) |
| **Period 3** | 0.070 |
| | (0.118) |
| **Sector other than property and construction × Period 3** | 0.006 |
| | (0.155) |
| **Constant** | 12.891*** |
| | (0.378) |
| **Controls** | Y |
| **Year dummies** | Y |
| **Industry dummies** | Y |
| **Region dummies** | Y |
| N | 860 |
| **R-squared** | 0.945 |

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

**Appendix 4- Falsification of effect of pre-treatment period**

| | (1) Interest rate |
|---|---|
| **Sector other than property and construction** | -0.397*** |
| | (0.097) |
| **Period 3** | -0.019 |
| | (0.114) |
| **Sector other than property and construction× Period 3** | 0.179 |
| | (0.145) |
| **Period 4** | -0.056 |
| | (0.102) |
| **Sector other than property and construction× Period 4** | 0.119 |
| | (0.123) |
| **After** | 0.092 |
| | (0.072) |
| **Sector other than property and construction× after** | 0.370*** |
| | (0.081) |
| **Constant** | 14.932*** |
| | (0.224) |
| **Controls** | Y |
| **Year dummies** | Y |
| **Industry dummies** | Y |
| **Region dummies** | Y |
| **N** | 1,788 |
| **R-squared** | 0.947 |

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

**Appendix 5- Falsification on sample of observations 8 months prior to policy change. The after-fake is the middle point of period.**

| | (1) |
|---|---|
| | **Interest rate** |
| **Sector other than property and construction** | 0.189 |
| | (0.155) |
| **After-fake** | -0.031 |
| | (0.164) |
| **Sector other than property and construction× after-fake** | -0.221 |
| | (0.153) |
| **Constant** | 7.411*** |
| | (0.357) |
| **Controls** | Y |
| **Year dummies** | Y |
| **Industry dummies** | Y |
| **Region dummies** | Y |
| **N** | 1,858 |
| **R-squared** | 0.832 |

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

**Appendix 6- Diff-in-Diff Analysis for institutional investors**

| | (1) Interest rate | (2) Hazard |
|---|---|---|
| **Sector other than property and construction** | -0.009 | -0.829 |
| | (0.038) | (1.118) |
| **After** | 0.043 | -21.876*** |
| | (0.032) | (0.591) |
| **Sector other than property and construction × After** | -0.037 | 20.921 |
| | (0.035) | (19.911) |
| **Constant** | 17.265*** | |
| | (0.115) | |
| **Controls** | Y | Y |
| **Month dummies** | Y | N |
| **Industry dummies** | Y | Y |
| **Region dummies** | Y | Y |
| **N** | 3,334 | 3,334 |
| **Specification** | OLS | Cox Model |
| **R-squared** | 0.967 | - |
| **Pseudo-R-squared** | - | 0.102 |

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

**Appendix 7- Descriptive analysis of recycled loans and Loans accepted by institutional investors.**

| | Recycled loans | | | Institution | | |
|---|---|---|---|---|---|---|
| | **N** | **Mean** | **S.D.** | **N** | **Mean** | S.D. |
| **Panel A: Loan characteristics** | | | | | | |
| Amount requested (£1,000's) | **1,102** | **61.523** | **52.636** | **3,613** | **57.411** | **49.988** |
| Normalized maximum acceptable interest rate | **1,102** | **0.994** | **1.341** | **3,613** | **0.104** | **0.268** |
| Interest rate | **1,102** | **10.389** | **2.132** | **3,613** | **9.850** | **1.577** |
| Limited company | **1,102** | **0.880** | — | **3,613** | **0.924** | — |
| Defaulted | **1,102** | **0.040** | — | **3,613** | **0.018** | — |
| **Panel B: Distribution of loan term** | | | | | | |
| Term: 6-12 months | **26** | | | **227** | | |
| Term: 24-36 months | **289** | | | **1,333** | | |
| Term: 48-60 months | **787** | | | **2,053** | | |
| **Panel C: Distribution of credit band** | | | | | | |
| A+ | **166** | | | **952** | | |
| A | **314** | | | **1,069** | | |
| B | **259** | | | **775** | | |
| C | **208** | | | **530** | | |
| D | **131** | | | **270** | | |
| E | **24** | | | **17** | | |
| **Panel D: Distribution of loan purpose** | | | | | | |
| Asset financing | **56** | | | **170** | | |
| Expansion | **548** | | | **1,940** | | |
| Working capital | **413** | | | **1,252** | | |
| Other purposes | **85** | | | **251** | | |
| Total | 1,102 | | | 3,613 | | |

**Appendix 8- Probit regression model predicting the probability a loan being rejected by institutional investors**

| | (1)<br>Recycled loans |
|---|---|
| **Credit band: A+** | -1.608*** |
| | (0.220) |
| **Credit band: A** | -1.414*** |
| | (0.217) |
| **Credit band: B** | -1.363*** |
| | (0.218) |
| **Credit band: C** | -1.363*** |
| | (0.219) |
| **Credit band: D** | -1.189*** |
| | (0.224) |
| **Amount requested** | 0.028 |
| | (0.030) |
| **Limited Company** | -0.095 |
| | (0.076) |
| **Purpose: asset finance** | -0.099 |
| | (0.106) |
| **Purpose: expansion** | -0.095** |
| | (0.048) |
| **Purpose: other** | 0.016 |
| | (0.092) |
| **Term: 24-36 months** | 0.341*** |
| | (0.129) |
| **Term: 48-60 months** | 0.821*** |
| | (0.127) |
| **Constant** | -0.731* |
| | (0.431) |
| **Year dummies** | Y |
| **Industry dummies** | Y |
| **Region dummies** | Y |
| **N** | 4,715 |
| **Chi-squared** | 770.320 |
| **Pseudo-R-squared** | 0.182 |

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

**Appendix 9- Test of differences of return on investment between crowd and Institutional investors**

| | Crowd | | | Institution | | |
|---|---|---|---|---|---|---|
| | N | Mean | S.D. | N | Mean | S.D. |
| **ROI** | **3,334** | **7.573** | **2.208** | **3,613** | **7.877*** ** | **1.833** |

**Appendix 10-Regression Results of Basic Framework using return on Investment (ROI)**

| | (1) ROI |
|---|---|
| **Crowd** | -0.412*** |
| | (0.048) |
| **Credit band: A+** | -2.527*** |
| | (0.366) |
| **Credit band: A** | -2.181*** |
| | (0.367) |
| **Credit band: B** | -1.974*** |
| | (0.368) |
| **Credit band: C** | -1.771*** |
| | (0.372) |
| **Credit band: D** | -1.689*** |
| | (0.384) |
| **Amount requested** | 0.241*** |
| | (0.028) |
| **Limited Company** | 0.027 |
| | (0.093) |
| **Purpose: asset finance** | 0.175* |
| | (0.098) |
| **Purpose: expansion** | 0.069 |
| | (0.053) |
| **Purpose: other** | -0.019 |
| | (0.105) |
| **Term: 24-36 months** | -1.260*** |
| | (0.109) |
| **Term: 48-60 months** | -1.202*** |
| | (0.106) |
| **Year dummies** | Y |
| **Industry dummies** | Y |
| **Region dummies** | Y |
| **Constant** | 8.532*** |
| | (0.530) |
| **N** | 6,947 |
| **R-squared** | 0.064 |

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