ABSTRACT

Title of dissertation: ESSAYS ON MOTIVES AND MARKET OUTCOMES

Bryan Kaiser Stroube
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This dissertation examines the existence of heterogeneous motives in markets, particularly how a tension between profit motives and other utility can shape outcomes for organizations and individuals. I explore this tension in the context of biases, organizational identity, and investment behavior. Each of the three empirical chapters employs decision-level data from a different online crowdfunding platform.

Academic researchers and the general public are increasingly interested in the phenomenon of "crowdfunding." The term, however, encompasses an incredibly diverse set of activities—ranging from the facilitation of for-profit start-up investments to the charitable funding of medical procedures. This diversity can make it difficult to generalize research insights from studies of any particular instance of the phenomenon. In the introductory chapter I develop a general framework for understanding the source of observed behavior on crowdfunding platforms given some simple assumptions about platform policies. The goal is to provide context for the subsequent chapters of the dissertation.

The first empirical chapter examines biases against demographic groups, which are typically explained by one of two mechanisms: either decision makers have a taste for one demographic group over another, or demographics are employed as informational proxies for other unobserved but economically important traits. These mechanisms are difficult to empirically untangle despite the theoretical and practical importance of separating them. I attempt to do so in a Chinese peer-to-peer lending market by leveraging a loan guarantee policy that reduces the economic rationale for lenders to discriminate on borrower demographics such as gender and geography. Comparison of pre- and post-policy periods therefore provides a fruitful tool for measuring the degree of taste versus informational bias. I find that female borrowers appear to receive a preferential informational bias but a negative taste bias, while lenders' geographic bias toward borrowers located in the same province appears to be driven predominately by informational processes and not taste. These findings have implications for multiple sets of decision makers and underscore the theoretical importance of accounting for motives.

Chapter two examines the potentially conflicting investment motives found on a non-profit hybrid identity crowdfunding platform, where simultaneous market-like and charity-like motives may lead lenders to respond differently to funding requests from entrepreneurs who appear to have high economic ability and high personal need. I survey actual lenders on the platform to measure their stated preferences for borrowers who fit each of these categories. I find that 1) lenders vary in their preference for these categories and this preference is correlated with their demographics, and 2) past loans made by lenders with an above-average preference for both need and ability were funded faster than loans in other categories. These results highlight how actors' preferences are largely endogenous to the market in which they are observed.

In the final chapter I present the results of a simple online experiment conducted in conjunction with a peer-to-peer lending website. Potential lenders were presented randomized versions of the platform's lender registration web page. The content of the page varied in whether it promoted the potential social benefit of lending versus only the financial benefit. No difference was found between the treatment and control groups. The experiment provides some insight into how lenders self-select into crowdfunding activity and may serve as a model for similar experiments on other platforms.

ESSAYS ON MOTIVES AND MARKET OUTCOMES

by

Bryan Kaiser Stroube

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Advisory Committee:
Professor David M. Waguespack, Chair
Professor Rajshree Agarwal
Professor Wilbur Chung
Professor Brent Goldfarb
Professor Ginger Zhe Jin

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Chapter 0: Introduction: A Conceptual Framework for Analyzing Behavior on Crowdfunding Platforms

0.1 Introduction

There is growing interest in the phenomenon of crowdfunding from both the general public and academics. Figure 0.1 plots one measure of public popularity, the volume of worldwide Google searches for the term "crowdfunding" (Agrawal et al., 2013). Growth in popularity has been sustained since 2010. Along with this has come considerable academic interest. Recent conferences and conference sessions have focused exclusively on the topic (e.g., the Academy of Management's 2014 Annual Meeting[1], the Strategic Management Society's 2014 Annual International Conference[2], and multiple Berkeley symposia[3]). Despite crowdfunding having emerged as a popular social science and entrepreneurship research context, the diversity of crowdfunding platforms makes it difficult to generalize findings across

[1]For example, session 1106 "The Crowdfunding Phenomenon: Mapping Research and Data Opportunities" `http://program.aomonline.org/2014/submission.asp?mode=showsession&SessionID=150` and session 1462 "Crowdfunding State of the Union and the Related Research Horizon" `http://program.aomonline.org/2014/submission.asp?mode=showsession&SessionID=1097`

[2]SMS 2014 Conference Extension on "Crowdfunding and Entrepreneurship" in San Sebastian, Spain: `http://madrid.strategicmanagement.net/extensions/san-sebastian.php`

[3]UC Berkeley Fung Institute Academic Symposium on Crowdfunding, 2013, 2014: `http://www.funginstitute.berkeley.edu/event/academic-symposium-crowdfunding`

seemingly related crowdfunding studies.

The primary focus of most crowdfunding research is to understand why specific individuals, projects, or businesses achieve greater success in fundraising than others. The explanations may come from the behavior of the crowd (e.g., herding, social networks), the characteristics of the recipients themselves (e.g., attributes, resources), or some combination of the two (e.g., discrimination). Most of these studies employ a single context, so generalizing this research can be a challenge given the diversity of settings. "The Crowdfunding Canvas" presented by Gary Dushnitsky at the 2014 Academy of Management Annual Meeting highlights the range of platforms used for crowdfunding research.[4] Kickstarter appears to be the most frequent research context. However, it represents just a single platform of one specific type of crowdfunding model. How can researchers think about the generalizability of research conducted in such settings?

It may help to first isolate what makes crowdfunding unique, as the behaviors that crowdfunding facilitates are all found elsewhere to varying degrees. For example, banks make loans; charities support the arts; angel investors fund startups. It is the development of new mediating technology that now allows individuals to connect in what is typically termed "crowdfunding." Therefore, the specifics of a given crowdfunding platform have significant opportunities to define the dynamics of this new phenomenon.

A handful of existing studies analyze crowdfunding at this higher level as opposed to examining a specific platform. A working paper by Agrawal et al. (2013)

[4] http://www.dushnitsky.com/uploads/2/7/8/3/2783896/cf__canvas.pdf

outlines the "economics of crowdfunding," including the incentives and disincentives of the various participants understood through economic theory. It is more comprehensive than what I present below. Belleflamme et al. (2014) focus on the role of the platform directly by developing a model of two types of entrepreneurial crowdfunding activity—consumption through pre-order and profit-sharing through investments—and detail how "community benefit" provided by the activity can make those models more efficient than other fundraising channels.

This essay develops a general framework for thinking about how the structure of a platform influences the behavior of funders and the success or failure of specific projects. The goal is to broadly explain the success and failure of a project on a generic crowdfunding platform. To do so, I will attempt to explicate how the policies of the platform interact with the motives of the resource providers and the characteristics of the recipients to shape dynamics. How does a platform attract funders with the specific set of preferences that are ultimately observed? What mechanisms might allow for heterogeneity in funder preferences on a single platform? This can provide a framework for better interpreting research results produced from any one particular crowdfunding setting.

0.2 The framework

I begin by mapping the role of the three main actors in any crowdfunding context: the capital providers (funders), the capital recipients, and the platforms that facilitate the matching of funders and recipients. The focus of the framework is on how platform-level characteristics influence outcomes. The incentives in this framework are simpler than those outlined in Agrawal et al. (2013), because the focus is primarily on the platforms' policies. Also, I do not address the information asymmetry issues that become clear when the funds are primarily used for entrepreneurial activity.

In its most abstract form, crowdfunding involves the solicitation of funds from resource providers by resource seekers through an intermediate platform. This process unfolds as follows. A crowdfunding platform either solicits or screens applications from a self-selected pool of resource seekers at time $t-1$. At time t a separate self-selected group of resource providers makes decisions to invest in a resource seeker. Once resource seekers have received funds, they use the money for the desired activity at time $t+1$. The platform then typically facilities the transfer of either resources (money, products) or information from the recipients back to the funders at time $t+2$.

At each of these stages there is significant opportunity for a platform to influence the behavioral equilibria that will ultimately be observed by a researcher. Therefore, understanding the hard and soft policies that the platforms implement is crucial to understanding the behavior that takes place on a platform. Figure 0.2 sketches the general relationship between these actors. Each instance of the relationships depicted in Figure 0.2, however, is the result of an earlier process of self-selection between funders and platforms and to a lesser extent recipients and platforms. This ecosystem is illustrated in Figure 0.3. In the following sections I further develop the assumptions related to each set of actors.

0.2.1 Funders

Funders are the actors that provide the money. Depending on the context, they may be similar to traditional lenders, investors, donors, or customers. Some simple assumptions about their behavior are helpful to understand their role.

First, funders must have a motive for providing money. In this framework the motives of funders vary in the degree of *internal* versus *external* focus. Internally focused motives maximize the material returns to the funder. Internal motives can be further divided between *consumption*—which may include activities such as future delivery of products or even immediate entertainment—and *investment*—which takes the form of expected future financial gain. On the other hand, externally focused motives maximize the perceived benefit to the recipient—for example, an outright donation.

This is a useful distinction for crowdfunding analyses because it highlights what is often considered unique about the crowdfunding process. Traditional banks or charity organizations are typically thought of as maximizing exclusively on one of these dimensions. Concepts such as fiduciary responsibility and legal non-profit status enforce this approach. The "crowd," however, is often conceived of as having fewer restrictions when it comes to making funding decisions. An individual can freely mix and alternate between these motives even within a single funding decision. For example, lending to a local business might provide both internal and external utility.

Therefore, each capital provider i has a utility function that determines his or her desired ratio between seeking internal and external returns. The external utility is a function of recipient traits, and each funder has a preference for a specific set of recipient traits which maximize this social utility. Finally, funders incur a search cost in locating a specific recipient j on a specific platform k. It is assumed that this cost consists of two components: the cost of finding the platform and the cost of finding the project given the platform.

0.2.2 Fund seekers

Fund seekers are the potential recipients that pursue money through crowdfunding platforms. I assume the need for funds is exogenous; that is, the existence of the need is independent of the crowdfunding process itself. The main decision of a potential recipient then becomes which platform to choose.

This decision is based on a number of characteristics of the potential recipient. Each potential recipient j has a set of characteristics that include, 1) funding-use attributes related to how the funding will be employed (e.g., personal consumption, production, industry, time frame), and 2) personal attributes such as demographics (e.g., location, background, gender).

Given these characteristics, a fund seeker chooses a specific platform k to maximize his or her chance of receiving funding. This probability is determined by the perceived "fit" with a platform (the characteristics of the potential recipient interacted with a platform's policies), which will be elaborated later, and also the number of other funders and recipients using the platform.

0.2.3 Platforms

All crowdfunding platforms provide a similar set of basic services. Most visibly, they provide the technical infrastructure to host projects, accept payment from funders, and transfer that money to recipients.[5] Most also provide some form of screening of potential recipients to conduct quality control. Platforms are classic market makers with strong network effects. The more funders and recipients a platform can attract, the greater the value of the platform to any single participant. Therefore, the platform is also involved in the promotion of the platform to attract new funders and recipients. Finally, platforms must make money to sustain their function. Most do this through transaction fees.

I propose two main attributes that shape what might be considered the primary purpose and use of a given platform: its *structure* and its *identity*. It is the specific policies of the platform along these dimensions that define how it can be used and how it is actually used in practice. These elements are strategically determined by the platform managers through various hard and soft policies, which subsequently determine the behavior of actors on the platform.

Structure: Platforms are often grouped into four broad categories based on the type of structural relationship they facilitate between funders and recipients: debt, equity, rewards, and donation. "Debt" facilitates the lending of money to borrowers, often with interest. "Equity" involves purchasing partial ownership in a venture. "Rewards" involves purchasing a yet-to-be-produced good or service, often

[5] However, white label software solutions make it increasingly easy for anyone to run a crowdfunding website. So the purely technical value of a platform is arguably approaching zero.

without guarantee of delivery. "Donation" simply involves the transfer of money and does not involve any future material commitment from the recipient. These are somewhat loose categories and do not have fixed boundaries other than some legal constraints (mostly related to debt and equity, see e.g., Government Accountability Office, 2011). However, they can entail specific technical relationships between funder and recipient. For example, all platforms are assumed to have a mechanism to transfer money from funders to recipients (without which funding would not be possible). However, lending platforms must also have the ability to transfer money from recipients back to funders. Lending platforms may also have ancillary systems such as a collection mechanism to facilitate this repayment. A reward-based platform may have a system for contacting funders so products can be delivered, whereas other platforms might actively prevent interaction between funders and recipients outside of the platform.

This structure is also reflected in the platform's relationships with potential funders and recipients. For example, a lending website might check credit scores of potential recipients and verify other background information as part of due process, while a medical donation platform might completely source its recipients from trusted partners instead of allowing open application.

Identity: A softer version of this *structure* is found in a platform's *identity*, which allows a platform to specialize within the constraints of its *structure*. For example, a platform whose mission is to facilitate loans for business versus one that facilitates loans for education may be structurally similar but have different goals that are realized through additional mechanisms. This identity will be represented in the advertising, mission statement, and other "soft" elements of the platform. Screening of potential recipients will also be calibrated to match this identity.

Any given platform must choose how to set its *structure* and *identity*. It is assumed a platform's *structure* can take a number of discrete forms. For example, the four broad types of crowdfunding mentioned above represent one possible set of options: debt, equity, reward, or donation. These structures may be more or less fluid, but a platform initially sets its structure based on perceived market need when it is launched.

The platform then sets its *identity*, which for the sake of simplicity I assume varies on whether it emphasizes *external*, *internal*, or *mixed* returns for funders. Each identity represents the proposed benefit of the platform to potential funders. These identities can be adjusted without changing the fundamental *structure* of the platform. A platform also sets its identity based on perceived market need. For example, two lending platforms may have the same *structure* but different *identities* (e.g., one facilitates loans to businesses—an internal benefit—while the other facilitates low-interest loans to students at an alma mater—a mixed benefit).

It is assumed there is no gate keeping for potential funders—anyone who wants to provide money is able to do so.[6] The platform's *identity* is therefore enacted by the type of recipients actually available on the platform. Two gate-keeping policy variables, which are part of the recipient screening process, determine which potential recipients are allowed onto the platform.

[6] In practice this assumption should be amended with a "within legal limits" stipulation. Particularly for activity related to debt and equity, there may be securities laws related to who can become a potential funder.

The first is recipient *fit*, which varies based on how closely an applicant must match the predominant platform *identity*. The lower this value, the higher the diversity of projects posted on the platform. The second is a *quality* threshold, which further filters out potential recipients after they have met the *fit* requirements. This may range from a simple rule—for example, meeting a minimum credit score requirement in a borrowing context—to a more holistic evaluation of the potential recipient's quality.

Finally, in any given period t each platform k has a set of time variant attributes. These include the number of projects and the diversity of recipient types on the platform at time t.

0.2.4 Interaction between funders, platforms, and fund seekers

This simple framework can be used to analyze how dynamics might be expected to vary across platforms. For example, so-called "reward-based" crowdfunding platforms such as Kickstarter can be used for both purely internal and purely external motives, such as pre-selling or donating, respectively. Equity crowdfunding has certain legal boundaries attached to it, though can still allow for the expression of external rewards through, for example, the support of a local social enterprise.

The main unit of analysis is the decision of funders, as this ultimately defines performance of potential recipients. Each $decision_{i,j,k}$ is made by a funder i to a recipient j on a specific platform k. This decision is shaped ex-ante by the mechanisms discussed above. It is assumed that the platform is chosen first and then the recipient.[7]

In general, a platform seeks to appease existing funders on the platform by offering them projects that fit their aggregate preferences. A funder j then chooses between platforms in an attempt to maximize his or her expected utility. For example, if he or she is driven primarily by internal concerns then he or she will choose a platform with that identity. All else equal, lenders prefer a platform with more recipients, as it increases the likelihood of locating a recipient that maximizes utility.

The funder also incurs a number of search costs. First, the greater the number of platforms the higher the overall search cost. When evaluating a given platform, the lower the quality variance on the platform the lower the search cost. The more diverse the recipient characteristics are on a given platform, the higher the search cost of finding a suitable recipient on that platform.

0.2.5 Insights from the framework

If it is assumed that a platform receives its operating expenses from each transaction between funders and recipients, then a platform's overall goal is transaction growth. What is the optimal strategy to increase growth given that a platform is defined by its *structure*, *identity*, and gate keeping attributes of *fit* and *quality*? There is also a strong path dependency from its state at t to $t+1$.

Funders on a platform with an *internal* identity expect something in return for their money, which is costly for recipients. This means a platform with an *external*

[7] If the recipient is prominent enough to raise money on his or her own, it may be possible to bypass the need to use a platform to raise funds.

or *mixed* identity, all else equal, will draw more potential recipients because it allows them to potentially obtain cheaper capital. At the extreme, a pure *external* identity results in free donated capital for potential recipients. Therefore, I assume that all recipients prefer an *external* or *mixed* platform to an *internal* one.

While a pure donation may be the optimal scenario for potential recipients, it is unlikely that the characteristics of most recipients can generate enough external utility for funders to make pure donation a utility maximizing choice. Therefore, if a platform admits all of these potential recipients it will increase search costs for funders, which decreases the overall expected utility of the platform. This means that platforms with an *external* or *mixed* identity must restrict applicants to a greater degree than *internal* platforms. This will result in the need for a higher *quality* threshold at such platforms. Platforms will adjust their screening *fit* to ensure the recipients do not deviate too far from the platform *identity*. Otherwise, low quality recipients will increase the search costs for potential funders who, despite deriving value from more potential recipients, will face lower expected utility from using the platform. At the same time, there must be a sufficient number of funders with utility functions to support a particular identity.

This analysis also highlights that there is an incentive for platforms to find ways to increase the external utility they provide to funders. Increasing external utility will increase the number of applicants. This may be accomplished by attempting to shift the identity, perhaps through advertising. However, not all recipients will be able to generate enough external benefit for funders and these will resort to using platforms that promote internal benefit for funders.

Because of network effects, dominant platforms might be expected to eventually develop within each type of *structure*. The large number of recipients on these dominant platforms will increase the expected utility of funders during the first stage of selection. Within a platform of a given *structure* it is optimal to encompass as many different types of recipients as possible until marginal returns begin to diminish from the search costs incurred by funders.

Given these insights, the dynamics of the crowdfunding industry are likely similar to other settings. For example, the positional competition between crowdfunding platforms is in some ways similar to the role of standard-setting organizations (Lerner and Tirole, 2006; Chiao et al., 2007), in that each type of organization must strategically set policies to attract applicants while not diluting the overall value of the platform.

0.3 Application to existing crowdfunding research

Existing crowdfunding research is varied across a range of specific settings including but not limited to reward-based platforms (Greenberg and Mollick, 2014; Mollick, 2014; Marom et al., 2014; Burtch et al., 2015), for-profit lending (Duarte et al., 2012; Leung and Sharkey, 2013; Chen et al., 2014; Freedman and Jin, 2014), and non-profit lending (Burtch et al., 2014; Galak et al., 2011). The differences in these platforms' *structure* and *identity* are substantial. The interpretation of findings can vary based on assumptions about a platform's identity.

For example, if it appears that funders on a lending platform are not maximizing profits, it might be interpreted as unintentionally incurring losses. However, the same behavior may be utility maximizing if external motives are taken into account. This can require additional empirical strategies to untangle (e.g., Freedman and Jin, 2014).

Reward-based platforms such as Kickstarter highlight this issue even more starkly. For the same project a funder can 1) choose to give money and receive a reward, 2) donate money with no reward, or 3) choose to donate more money than is required for a specific reward. Depending on the ratio of the value of the expected reward to the amount of money the funder provided, this action could represent a range of purely external to purely internal motivation.

0.4 Conclusion and application to following chapters

This introductory essay has attempted to outline a simple framework for thinking about how crowdfunding platforms influence crowdfunding behavior. Each of the following three chapters empirically explores how the motives of funders have impacted the performance of loans on different peer-to-peer lending platforms. The platforms studied in this dissertation share a common *structure*, but draw on slightly different elements of the framework.

In the first chapter, I attempt to disentangle *external* rewards on a for-profit peer-to-peer lending platform between *consumption* and *investment* motives. Drawing on the distinction between taste-based and statistical discrimination (analogous to consumption and investment behavior, respectively), I attempt to disentangle the importance of these mechanisms for how lenders interpret gender and the location of borrowers. I find that gender decisions are driven by both consumption and investment concerns, while geography is primarily used in the course of investment decisions.

In the second chapter, I examine a tension that is derived from the hybrid *identity* of a non-profit microfinance lending platform. Do lenders prefer recipients who will be economically productive with their money or recipients who have the greatest personal need? The structure of the platform allows for both types of behavior. I employ an original survey and find diversity in this preference. Further, the preference appears correlated with funding performance for borrowers.

In the final chapter, I present the results of an experiment where the *structure* of a crowdfunding platform remains fixed, but the platform's *identity* is experimentally manipulated. The ratio of proposed *internal* and *external* returns to funders is varied between the treatment and control groups. I measure whether this treatment influences the propensity of subjects to create an account on the platform, and find no difference between treatment and control. While the scope of this particular experiment is limited, the potential for similar randomized experimentation in crowdfunding contexts is significant.

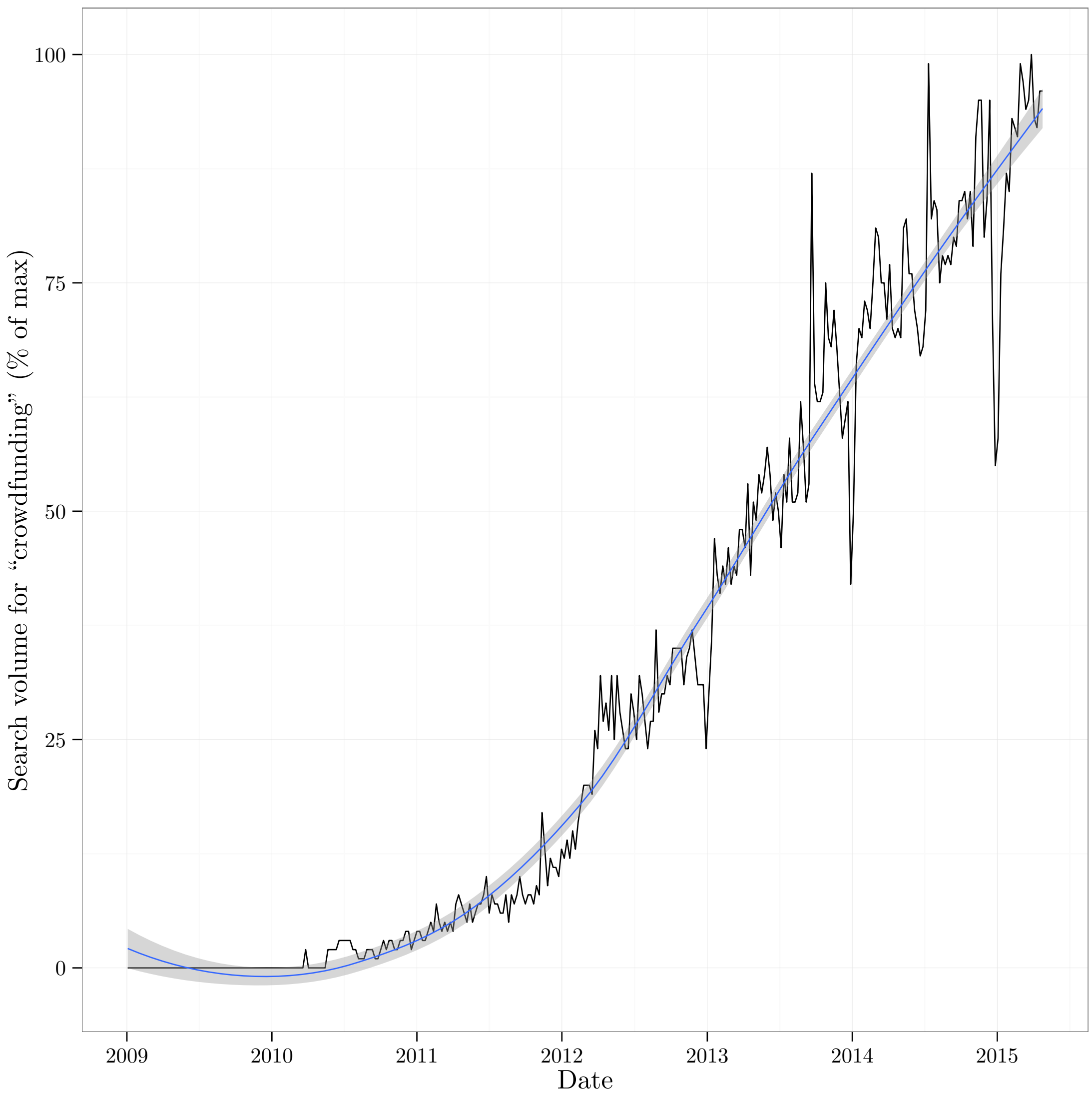


Figure 0.1: Google Trends data for the term "crowdfunding." Popularity as represented by worldwide search volume for the term has grown quickly since 2010. Plot updated since first appearing in Agrawal et al. (2013).

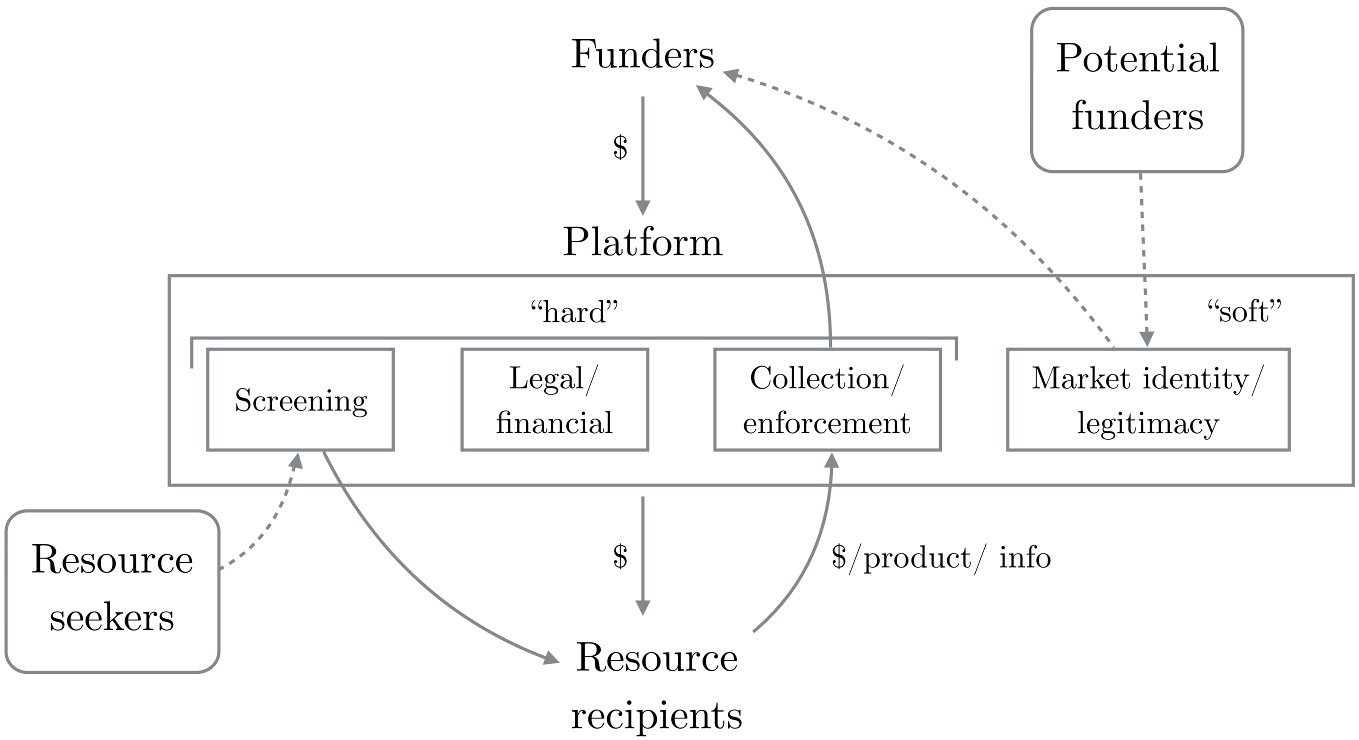


Figure 0.2: The role of the platform in mediating funder/recipient interaction.

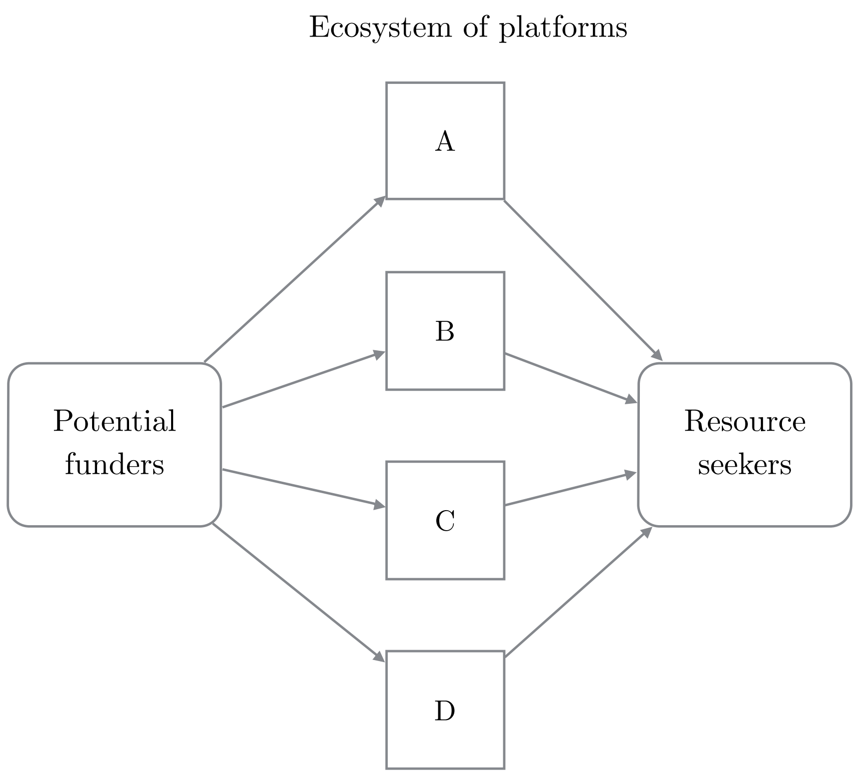


Figure 0.3: Potential funders choose crowdfunding platforms that maximize their utility. Likewise, resource recipients choose platforms that are most likely to successfully fulfill their request for capital.

Chapter 1: Biases in Peer-to-peer Lending Markets: Tastes vs. Information

1.1 Introduction

Researchers have demonstrated that audiences treat individuals and organizations differently based on a range of attributes such as race (e.g., Bertrand and Mullainathan, 2004), gender (e.g., Goldin and Rouse, 2000), and geographic location (e.g., McPherson et al., 2001), as well as status (e.g., Malter, 2014), category membership (e.g., Zuckerman, 1999), and network position (e.g., Podolny, 2001). Such research is frequently able to demonstrate the existence of disparate treatment based on such attributes, but less successful at locating the underlying mechanisms behind the treatment. This is critical because policy prescriptions at both the individual and organizational level hinge on the specific mechanisms that drive such results.

Demographic biases in particular have received significant attention by social scientists. Economists, sociologists, and psychologists have all addressed various aspects of the topic (for partial disciplinary reviews, see Charles and Guryan, 2011; Pager and Shepherd, 2008; Fiske, 2000). This is likely because demographic-based disparities are observed in a wide range of settings. Recent work by management researchers is diverse and has ranged from explaining the patent output disparity between male and female life scientists (Ding et al., 2006) to how the racial composition of employees is impacted by organizational hiring channels (Fernandez and Greenberg, 2013).

However, determining the precise mechanisms behind this disparate treatment has proven difficult for researchers. On the one hand, disparities may exist because decision makers have a "taste" for one group over another (Becker, 1957). On the other hand, demographics may be correlated with economic traits that would better explain the disparity if such information were readily observable—what economists term "statistical discrimination" because it is based on beliefs about the statistical correlation between the category and an important economic trait (Phelps, 1972; Arrow, 1973). This distinction regarding the source of bias is important because the appropriate strategic response is directly contingent on why the bias is occurring.

In this paper I investigate the importance of two specific demographics—gender and geography—in an online lending market. Employing data from a Chinese peer-to-peer lending platform, I examine the extent to which demographics influence the decisions of lenders and the motives for such behavior. For example, lenders may treat male and female borrowers differently because they believe that one gender will default on its loans less often than the other. Alternatively, or even simultaneously, lenders may have a non-economic preference for one gender over the other.

To disentangle these explanations, I leverage the implementation of a loan guarantee policy—what amounts to an insurance policy for lenders—to infer lender motivation by comparing pre- and post-policy time periods. The change in economic risk between the two periods alters the value of the demographic information itself and allows for a cleaner isolation of taste versus informational mechanisms in the interpretation of demographics. In the pre-policy period, lenders may use demographic information both as a proxy for unobserved economic traits and as a means to enact non-economic preferences. In the post-policy period, however, the nature of the demographic information has been altered so that it is less correlated with likelihood of repayment. The "taste" of lenders then becomes a more plausible explanation for disparities in borrower demographic outcomes.

Findings indicate a positive informational bias but negative taste bias for women. Lenders seem to believe that women repay at higher rates but prefer men when economic risks are equal. A "home bias" of lenders providing favorable treatment to borrowers located within the same province, however, appears to be driven primarily by informational bias and not taste. Disentangling these two mechanisms is important to individual and organizational strategy to the extent it determines the optimal response to such treatment. The policy prescription to address a taste bias may be very different from an informational one. Therefore, first-order knowledge that a disparate treatment exists is not sufficient; actors need to disentangle the mechanisms before crafting a strategy.

The paper proceeds as follows. I first outline the two major theories of demographic bias developed in the economics discipline and some recent empirical attempts to untangle them. I then turn to the emerging crowdfunding research, discuss the mechanisms of peer-to-peer lending, and introduce the specific Chinese context of this study. The data and empirical strategy are then presented along with the results. I conclude with a discussion of how disentangling taste and informational mechanisms can help advance a wider range of organizational research.

1.2 Theory

I first discuss the work by economists aimed at understanding the source of discrimination. This literature has historically been focused on how race and gender influence labor market outcomes. I then discuss how these theories apply to the more recent research on crowdfunding and peer-to-peer lending, and highlight the theoretical importance of disentangling the taste and informational mechanisms.

1.2.1 Economic explanations of demographic disparities

Economists have proposed two separate explanations for observed demographic disparities in markets. In the first, discrimination is a result of non-pecuniary utility and may exist in a market even with assumptions of perfect information. Becker (1957) developed this "tastes for discrimination" theory, where discrimination shifts the perceived price of a choice from p to $p(1+d_k)$. Given a decision maker's discrimination coefficient, d_k, he or she faces perceived prices that are either higher (positive d_k; for example sexism) or lower (negative d_k; for example nepotism) than the prices faced by actors with a zero discrimination coefficient. This type of discrimination is economically destructive but utility maximizing for the decision maker.

The second explanation for discrimination comes from the information-based models developed by Phelps (1972) and Arrow (1973), which demonstrate how certain discriminatory behavior may be rational and profit maximizing if a market exhibits imperfect information. In these models, decision makers act on beliefs about the statistical correlation between demographic categories and other outcomes if they are unable to observe the trait of interest directly. This "statistical discrimination" can be observed in the car insurance industry where rates are higher for younger male drivers than for older female drivers, because accidents have historically occurred at higher rates for the former group, and the insurer believes the correlation will exist into the future.[8] Rates would ideally be set based on a direct measure of cautious driving, but demographic traits are used in the absence of such information. Statistical discrimination is therefore profit maximizing for the decision maker assuming that his or her beliefs about the future correlation prove correct.[9]

The primacy of the demographic trait is therefore different between these two explanations. In the case of statistical discrimination, the decision maker is agnostic to the demographic trait and only employs it as a proxy for unobservables. The demographic trait would be readily ignored if better information were available. In the case of taste-based discrimination, however, it is the demographic factor itself that alters overall utility.

[8]For example, the website of Allstate Corporation's Esurance brand includes a section entitled "why women pay less for car insurance," which notes "There are 3 main categories that suggest women are safer drivers than men: accidents, speeding, and DUI convictions." This point is even constructed in the parlance of counterfactuals: "If you're a guy, all this really means is that a female clone of yourself would likely pay less for car insurance." See: `https://www.esurance.com/car-insurance-info/women-pay-less-for-car-insurance`

[9]This practice is not without debate. The Court of Justice of the European Union ruled gender-based price discrimination for insurance illegal beginning in December 2012. See: `http://ec.europa.eu/justice/gender-equality/files/unisex_insurance_en.pdf`

The difficulty of untangling these mechanisms in practice is that any single outcome may be driven by a combination of the two. As Fernandez and Greenberg (2013) recently noted, "Distinguishing between statistical and other forms of discrimination has been extremely difficult to accomplish." Nevertheless, a small body of research is aimed specifically at that goal. One strategy is to look for variance in the information available to decision makers, with an assumption that tastes are relatively consistent across time. If the visibility of core economic information changes across settings or time, then evidence for or against statistical or taste-based discrimination may be revealed by corresponding changes in demographic disparities. For example, Fernandez and Greenberg (2013) compare outcomes for job applicants received either via referred or non-referred channels at a single company and find that a racial gap for non-referred applicants disappears for referred applicants. They argue that the relatively information-rich referral channel overcomes the statistical discrimination against non-referred applicants. In another example, Siniver (2011) exploits the introduction of a certification examination to untangle the source of differential pay for immigrant versus native physicians in Israel. He finds that the availability of information on underlying quality revealed by the exam explains the previously identified pay gap (and thus supports a statistical discrimination interpretation).

In a lending context, lenders may use demographic attributes as proxies for other unobserved traits that they believe to be of primary economic interest. However, they may also exhibit taste-based favor or disfavor for a particular demographic. The "peer" aspect of peer-to-peer technologies makes this distinction even more salient. Strategies to untangle these in a crowdfunding context are discussed next.

1.2.2 Application to crowdfunding

The practice of crowdfunding involves a distributed set of individuals who provide funds for specific projects or loans. In the case of peer-to-peer lending, this involves matching individuals seeking loans to potential lenders. A number of researchers have explored the question of who gets funded in peer-to-peer lending. Pope and Sydnor (2011) and a working paper by Ravina (2012) both examine issues similar to this research in the context of the Prosper.com marketplace—a U.S. based peer-to-peer lending website. Both papers are concerned with the likelihood of borrowers receiving a loan, the favorability of loan terms (a feature of the Prosper marketplace), and the average financial performance of different demographic groups. A mismatch between how lenders treat the demographic category and that demographic category's future economic performance is interpreted as evidence of taste-based discrimination. The difficulty with this approach is that it requires assumptions about lender knowledge at the time of decision. Lender beliefs may be incorrect and lenders may misestimate the correlation between demographics and future repayment. Any number of mechanisms could cause this misestimation, including a lack of lender expertise or a change in underlying market characteristics.

Without a change in information regimes it is difficult to untangle misconception by lenders from taste-based discrimination. Did lenders miss-price loans based on incorrect beliefs (failed statistical discrimination), or did they intentionally choose an under-performing loan based on other characteristics (successful taste-based discrimination)? Both scenarios may appear the same in the data to an external researcher.

When assessing the importance of a trustworthy physical appearance in borrower photographs, Duarte et al. (2012) conclude that "lenders do not fully account for the lower probability of default among trustworthy borrowers and mistakenly charge them interest rates that are too high." A taste-based interpretation is also consistent with the data though seemingly non-intuitive in that case (it would require lenders to have a taste for people that look untrustworthy). This issue is more strongly highlighted in the Pope and Sydnor (2011) finding that the higher rates charged to black borrowers do not fully offset the higher default rates of the same borrowers once the loans mature (similar to the Theseira (2009) finding that "the market appears to possess an inefficient degree of statistical discrimination"). They note that "The problem, of course, is that once one allows for the possibility of inaccurate beliefs, results from other studies that find evidence of taste-based or accurate statistical discrimination come into question. Thus, the results from this study suggest caution when interpreting evidence in favor of one theory of discrimination versus another" (see Pope and Sydnor, 2011, p. 90 for full discussion). This quote highlights the theoretical importance of beliefs in theories of discrimination. Lender *beliefs* about future performance should be of more empirical interest than their actual ability to predict loan performance.

Finally, the availability of lender demographic data is typically constrained in peer-to-peer lending studies. The scope of most extant research has been on borrower demographics, with some exceptions, such as Ravina (2012) who leverages demographics for the sub-sample of lenders that have also registered as borrowers. If taste-based preferences do exist in a market, then explaining their ultimate source is complicated and beyond the scope of this paper (hence "tastes" as a catch-all term). However, sociologists have produced a large body of literature documenting the positive correlations between network ties and demographic similarity (McPherson et al., 2001), and psychologists have conducted extensive research on ingroup psychological processes related to prejudices, stereotypes, and discrimination (Fiske, 2000).

Gender in crowdfunding has drawn specific research interest given what some see as the potential of the technology to help women better access financing (e.g., see working papers by Marom et al., 2014; Greenberg and Mollick, 2014). Greenberg and Mollick (2014) demonstrate that choice homophily is an important element of understanding gender disparities on Kickstarter, and the effect (what they term "activist homophily") is even responsible for providing women a relative advantage in categories where women are under represented (e.g., technology). Similarly, the role of geography in peer-to-peer marketplaces has produced considerable research interest given the ability of the technology to dramatically alter geographic search costs (e.g., see working papers by Agrawal et al., 2011; Lin and Viswanathan, 2013). This interest is grounded in the finance literature which has a long history of researching the role of geography in influencing investment decisions. Individuals and to a lesser extent institutional investors exhibit a "home bias" when they disproportionately invest in nearby firms (Grinblatt and Keloharju, 2001). Even before the rise of peer-to-peer lending technology, the increasing availability of information meant that the average distance between small businesses and their lenders was increasing (Petersen and Rajan, 2002). Therefore, it is clear that both gender and geographic biases may be influenced by both taste and informational mechanisms.

1.3 Empirical setting

The lending and borrowing of money is one of the most basic features of an economy, but technological advancements have significantly altered the transaction costs and market frictions of the process. Individual borrowers and lenders can now directly participate in debt financing through mediated online platforms. In some regards, these new developments still mirror the basic processes found in centuries-old person-to-person kinship and village-based lending networks. In other elements, the geographically decentralized and relatively anonymous nature of the markets allows for the formation of lending ties across a much greater span of demographics than would otherwise be possible. This study examines peer-to-peer lending, one element of this broader shift.

In a stylized version of peer-to-peer lending, a mediating "platform" accepts applications from potential borrowers, screens them, posts them on a website for lenders to peruse and select from, and then facilitates the transfer of money from lenders to borrowers and borrowers back to lenders. Loan requests are fulfilled in a piecemeal fashion, where many lenders each contribute a portion of a given borrower's total loan request. Once the full loan request is met, the loan is closed and the platform facilitates the transfer of funds from the lenders to the borrower. The platform then facilitates the collection of loans and periodic borrower repayments. In addition to the studies mentioned above, a broader body of work has begun to explore the range and scope of behavior on such platforms (e.g., Agrawal et al., 2011; Freedman and Jin, 2011; Lin et al., 2013; Mollick, 2014; Zhang and Liu, 2012).

The prototypical and earliest peer-to-peer lending platforms in the United States were Propser.com, Lending Club, and the 501(c)(3) platform Kiva.org, which is designed for non-profit lending. Prosper and Kiva were both founded in late 2005, however for-profit lending is not yet legal in all states.[10] A handful of other platforms cater to niche markets such as student loans or medical procedures.[11]

This study takes place in the context of an online for-profit peer-to-peer lending platform in China. Chinese peer-to-peer ("个人对个人" or "individual to individual") lending differs from the American context in a number of ways. This is partly due to differences in the historical development of the financial services industry in China and partly from looser present-day regulatory constraints. In the United States, peer-to-peer lending companies rely on existing credit scores to screen potential borrowers.[12] China lacks an extensive national credit scoring system such as the FICO score, so the role of peer-to-peer lending companies is broader than in the United States and includes more intensive verification of borrower backgrounds.

[10]For example, as of June 2014 twenty states still did not allow lending on Prosper.com.

[11]The Government Accountability Office (2011) provides an overview of the history and evolving regulatory environment of the American peer-to-peer lending industry.

[12]For example, as of June 2014, "A new Prosper borrower must be a U.S. resident in a state where Prosper loans are available, and must have a bank account, a Social Security number, and a credit score of at least 640. Prosper uses Experian to obtain credit scores." Source: `https://www.prosper.com/help/borrowing/`

The most obvious industry difference between the United States and China is the existence of both online and offline peer-to-peer lending. Offline lending consists of either visiting physical offices to borrow and lend money or the use of a field sales force (offline lending is not examined in this study).

American peer-to-peer lenders technically invest in promissory notes sold by the peer-to-peer platforms, which are tied to the repayment of specific loans that are issued by a bank.[13] In China, however, the platforms more directly facilitate the transfer of money between lender and borrower. In theory, this results in less regulation since it amounts to activity outside of traditional banking institutions. This is observable in company names. For example, Ppdai, one of the first peer-to-peer lending platforms in China, is registered as Shanghai Ppdai Financial Information Service Co., Ltd.[14] The business name of the company in this study includes "commercial advising." Therefore, at the time of the study the industry still occupied an uncertain space in the broader scope of Chinese financial services with most platforms functioning as some form of financial information or advising company.

The number of online Chinese peer-to-peer platforms increased rapidly from just nine in 2009 to 132 in the first quarter of 2013 (Li, 2013). Some media reports put the value of peer-to-peer loans issued in China at US$11 billion, an almost threefold increase over the previous year (Zhu, 2014). Despite this rapid development, the Chinese context has been employed in few studies (for an exception, see Xu et

[13]Both Propser and LendingClub use WebBank, an FDIC-insured institution. Kiva loans are distributed and collected through partner microfinance institutions.

[14]"上海拍拍贷金融信息服务有限公司" Source: Shanghai Administration of Industry and Commerce using Ppdai's company registration number: 310115001783417
`http://www.sgs.gov.cn/lz/etpsInfo.do?method=index`

al., 2011; Chen et al., 2014). Regulatory constraints typically limit the operations of such firms to national borders meaning there is no international competition. A tradition of heavy state involvement in the Chinese financial system increased the attractiveness of these companies to both lenders and borrowers. State-owned banks both offered low interest rates to investors and preferential lending to state-owned enterprises, making it difficult for individuals and small businesses to procure bank loans. This drove overall demand for financial innovations such as peer-to-peer lending. It is against this institutional backdrop that this study takes place.

Data for this study was collected from a platform that began offering peer-to-peer lending services in 2010. At its founding, loans were not guaranteed and functioned similar to US-based platforms such as Prosper.com (although to my knowledge never featured competitive bidding on interest rates). It first implemented a loan repayment guarantee policy in the first half of 2011 when total loan volume was still low. In early January 2012 the company updated its loan guarantee policy to cover loans of all credit rating levels. These types of loan guarantee policies were common in the industry as a way to assuage fears about repayment and attract new lenders. For example, competitor Ppdai began offering a principle guarantee in July of 2011.[15] Because of the lack of a comprehensive national credit scoring system, lenders have always had to place trust in the peer-to-peer companies to perform proper due diligence on potential borrowers. Therefore, the guarantees acted as a mechanism to demonstrate that the companies' incentive to

[15]Source: `http://help.ppdai.com/helpdetail/335`, "本金保障计划是拍拍贷于 2011 年 7 月发起的，旨在促使借出者分散投资，保障投资收益。"

perform adequate due diligence on borrowers was aligned with that of lenders.

1.4 Empirical strategy

1.4.1 Data

The dataset consists of all investment decisions made on the platform along with demographic characteristics of both borrowers and lenders. The unit of analysis is the lender-borrower dyad. Each dyad represents a decision by a specific lender to loan to a specific borrower and includes the date and time the investment was made and the size of the investment. Investment decisions are only possible for loans that have not already been fully funded. According to the company, borrower data is typically verified (and visible to lenders to use while making decisions) while lender data is self-reported. This results in more complete demographic data for borrowers than lenders, but nevertheless provides significant visibility to the demographics on both sides of the dyad.

1.4.1.1 Dependent variable

The main outcome of interest is the amount a lender decided to lend to a specific loan request. This decision is contingent on a lender first having the ability to loan to a specific borrower (i.e., a loan request has not already been filled) and then deciding whether and at what amount to make a loan to the borrower. If a lender invested in the same loan more than once, the total amount invested in that loan by the lender is aggregated for purposes of analysis.[16] By using the loan size decision instead of other outcomes such as the overall choice of borrower, it is largely possible to sidestep the selection and timing effects that are difficult to control for using a one-sided matching model. Further, the speed at which borrowers are funded and the relatively constrained supply of borrowers in this particular context make the loan size decision a more practical metric. If anything, this should understate actual biases, as very biased lenders may choose to avoid certain borrowers altogether.

1.4.1.2 Independent variables

I explore the role of two demographic variables in this paper: gender and geography. These particular traits were chosen because they speak to current management and organizational research on inequality in markets. The gender analysis consists of borrower gender and borrower gender interacted with lender gender. The geographic analysis examines the possibility of "home bias"—a differential treatment of borrowers located in the same location as a lender. I construct a binary variable of *Geographic Overlap* that equals one if the lender shared the borrower's province (i.e., the lender's work or home province overlaps with the publicly visible borrower's work province). I interact these demographic variables with a binary variable equal to one in the post-policy period to untangle the taste and informational biases.

[16]This occurs with some frequency in the data. An employee of the company indicated that because loans are sometimes funded almost instantaneously, a prospective lender may first attempt a smaller sized investment than his/her actual target and then repeat the process until they have either invested their desired amount in the loan or other lenders have already fully satisfied the loan request. Lenders may even use third-party software tools for this purpose, though this is discouraged by the company.

1.4.2 Research design

The goal of this study is to disentangle the degree to which taste and informational mechanisms drive biased behavior in this market. In most settings these two mechanisms are confounded, meaning that even experimental evidence that audiences impart disparate treatment based on an attribute does not necessarily explain *why* audiences respond to that attribute. What is required to disentangle the mechanisms is a change in environments: from a confounded environment where either or both mechanisms may be driving an observed disparity, to an environment where only a single mechanism is plausibly present. A difference-in-differences between two such environments can then be employed to separate each mechanism. Conceptually, this second environment should alter the economic cost of employing an attribute in a decision to be either infinitely small or infinitely large. If the economic cost of using an attribute approaches zero, then any remaining disparate treatment can be interpreted as the result of a taste mechanism, because the potential economic differences are now normalized to zero. Likewise, if the economic cost of using an attribute approaches infinity, then the cost of exerting tastes becomes prohibitive, and disparate treatment will be the result of information mechanisms.

This study employs the first of these environments, a setting where the cost of employing specific attributes in a decision is normalized to zero. In early January 2012 the company updated its loan principle repayment guarantee policy. For practical purposes, this guarantee amounted to an insurance policy for lenders. Unlike an existing policy implemented in the first half of 2011, this new policy covered every loan on the platform (the previous policy did not cover HR loans). It was funded by assessing service fees on loans ranging from 0% to 5% depending on the company-assigned credit rating of the loan. Assuming lenders believed the guarantee, it largely removed the economic rationale for lending to one borrower over another.[17] Therefore, statistical and taste-based discrimination are confounded in the pre-policy period, but biases should be primarily driven by taste-based considerations in the post-policy period. That is, in the pre-policy period, the decision size of lender i to borrower j is a function of both the lender's personal expectations about that borrower's repayment at a future date $t + k$ and the lender's time invariant tastes:

$$Decision_{i,j,t} = f(E(repayment_{j,t+k}), taste_i) \tag{1.1}$$

In the post-policy period, decision size is no longer a function of expected repayment.

$$Decision_{i,j,t} = f(taste_i) \tag{1.2}$$

A difference-in-differences design using 30-day windows on either side of the policy is implemented to measure the change between pre- and post-period biases. The demographic disparity in the post-policy period will be interpreted as the level of taste-based bias. The difference in the disparities between each of the two periods

[17] It is worth noting that loan collection outside of the platform was never practically feasible. Therefore, even in the pre-policy period lenders had to trust that the company was honest and would be able to collect repayments over the life of the loan.

(the difference-in-differences) will be interpreted as the level of informational bias. This research design is summarized in Table 1.1.

Employing limited 30-day windows on either side of the policy change strengthens the identification in two ways. First, it limits the potential influence of other concurrent events in the firm, industry, or broader economy. Second, it limits the potential for lender learning, which should theoretically alter informational biasing behaviors. Prior studies have noted such learning processes (e.g., Altonji and Pierret, 2001; Freedman and Jin, 2011), but lenders must wait extended periods of time to observe loan performance. After the policy change, lenders should still be influenced by two readily observable but easily controlled-for economic traits: the interest rate of the loan and the loan repayment term. The decision size may also be influenced by the total amount of money requested for the loan (i.e., for larger loans there is a higher ceiling on the decision, lowering the possibility of right-truncation).

1.4.3 Methods

Crosstab averages of pre- and post-policy average decision sizes for each gender and the presence of geographic similarity are first calculated. A set of OLS models is then developed to complement these simple averages. Equations 1.3 and 1.4 represent the general form of these models, where $DecisionSize_{ij}$ is the amount of money that lender i loaned to borrower j, $Gender_j$ is whether borrower j is female, $GeoOverlap_{i,j}$ is whether lender i and borrower j share geographic overlap, $Policy_{\{0,1\}}$ is a dummy variable for whether the decision was made during the post-policy period, and X_j is observable characteristics of the pertinent loan: the interest rate, term of the loan, size of the requested loan, and credit rating category. X_j is later expanded during additional empirical tests.

$$DecisionSize_{ij} = Policy + Gender_j + Policy * Gender_j + X_j \tag{1.3}$$

$$DecisionSize_{ij} = Policy + GeoOverlap + Policy * GeoOverlap + X_j \tag{1.4}$$

1.4.4 Descriptive statistics

Lenders made 25,440 decisions to lend across 558 loans. Approximately 8% of these decisions shared geographic overlap and 14% of the loans were female. Table 1.2 summarizes the 25,440 lender decisions across the two 30-day periods (10,975 in the pre-policy period and 14,465 in the post-policy period). Figure 1.1 summarizes the dependent variable by plotting the average size of investment decisions and the total number of investment decisions over the course of the window analyzed for the policy change. There is not a clear trend in terms of the average loan size. The average investment size is 882 RMB in the 30 days before compared to 865 RMB in the 30 days after. However, Figure 1.1 shows that the absolute number of decisions is greater in the second period and highlights the volatility in loan supply, with some days where no loans were made at all. Table 1.3 employs an OLS regression to summarize the impact of the policy on lenders' loan decision sizes accounting for available control information. The lack of significance on the policy coefficient in most models indicates the policy itself had limited impact on the size of lenders' investment decisions during the study period.

Table 1.4 summarizes the 558 individual loans in the windows (317 in the pre-policy period and 241 in the post-policy period). The overall loan interest rates varied from 6.1% to 24.4% with the most common categories of 13% and 15%. Loan sizes also varied greatly, from 3,000 to 500,000 RMB, however the majority of loans were small and fell into either the 3,000 or 5,000 RMB categories (approximately $480 and $800, respectively). The loan terms ranged from three to twenty-four months, with the majority being three or six month loans. Most loans were funded very quickly, with an average of just over eight hours. This statistic combined with an average of just over nine available loans per day indicates that lenders did not have a substantial opportunity to actively choose between many borrowers at the time of their decisions.

Tables 1.5 through 1.7 provide additional information on the 558 loans that were open for lending at some point during the experimental window. Table 1.5 shows that only 25 of the total 558 loans ended up as "bad debt". Table 1.6 lists the purposes of the loans, the majority of which were used for short-term turnover. Table 1.7 shows the distribution of the company-assigned credit rating ranging from AA (highest quality) to HR (high risk) along with summarized loan characteristics for each category. The pool of loans grows progressively larger as the quality decreases, and as expected, so does the average interest rate.

Table 1.8 summarizes the number of lenders that were active in both periods versus only the pre- or post-policy window. It is conceivable that the set of lenders may be different in each period because of the policy. A reasonable model of lender behavior is a two stage choice, where a lender first decides if he or she wants to lend through a specific platform and then decides the details of the actual investment decision. Therefore, the study needs to be cognizant of lender self-selection effects at the platform level. Table 1.8 indicates that the number of new users increased following the policy change (see table footnote), however, this increase is surely confounded with the natural platform growth process.

1.5 Results

1.5.1 Gender

Table 1.9 presents a crosstab summary of average decision sizes to male and female borrowers in the pre- and post-policy periods. Table 1.10 further divides the data by the gender of the lender. From Tables 1.9 and 1.10 it is clear that the majority of lenders and borrowers are male, and the average investment size is greater for women in the pre-policy period but slightly greater for men in the post-policy period.

Table 1.11 represents different versions of the OLS model detailed in Equation 1.3. Model 1 reproduces the crosstab calculations from Table 1.9. The coefficients on the interaction terms can be used to shed light on the relative amounts of statistical and taste-based bias in the market. From theory, the taste-based component can be interpreted as the difference between women and men when the policy is in place. In Model 1 of Table 1.11, this is equal to the sum of the gender coefficient *Borrower sex (female)* and the coefficient on the *Borrower sex * policy* interaction term. This -150 RMB (272 minus 422) indicates that women are negatively discriminated against when there are no economic repercussions for doing so. To infer the level of informational bias, I examine the inverse of the coefficient on the interaction term. This positive 422 RMB indicates that lenders believe women borrowers to be preferable to men when economic risks are present. It is worth noting that this coefficient is larger than the 272 RMB (1103 minus 831 RMB) preference that might be inferred from simply comparing female and male borrowers' averages in the pre-policy period from Table 1.9. Model 2 adds the economic controls, which reduce the economic significance but do not change the overall direction of the result. Model 3 incorporates the gender of the lender and indicates that female lenders make smaller decisions after the policy, but otherwise the differences observed in Table 1.10 are not statistically meaningful.

Lenders appear to believe that women repay at higher rates than men, but nevertheless hold some form of taste-based bias against them. This is consistent with the traditional microfinance narrative of women being economically superior borrowers to men despite cultural discrimination against them (Roodman, 2012). It is interesting to note that in this context the profit maximizing bias *for* women appears to overwhelm the taste-based bias *against* women. Further, without this deliberate attempt to untangle the two mechanisms, there is no ex-ante reason to believe that taste-based bias exists in the market.

The relatively low default rate of the sample prevents fully implementing the statistical approach of the studies mentioned previously, where loan decisions are correlated with future defaults to infer economic rationality. However, the data from default rates does not refute the interpretation that lenders are indeed economically "correct" in their positive informational bias for women. From Table 1.5, only one of the 25 borrowers that eventually defaulted was a woman.

1.5.2 Geography

Lenders and borrowers share geography in around 8–9% percent of investment decisions. Table 1.12 tabulates the basic pre- and post-policy decision size averages when such geographic overlap occurs and shows that the average investment size is 80% larger when such overlap exists in the pre-policy period but only 5% larger in the post-policy period. This indicates significant informational bias but limited taste bias.

Different versions of the OLS model detailed in Equation 1.4 regressing geographic overlap on decision size are reported in Table 1.13. Model 1 replicates the crosstabs of Table 1.12 and indicates that in the pre-policy period lenders made on average 644 RMB (80%) larger loans to borrowers that shared their geography (the coefficient on *Geographic overlap*). The coefficient on the difference-in-differences between the two periods of -600 RMB indicates that the impact of geography greatly decreased with the implementation of the policy. The inverse of this coefficient (positive 600 RMB) represents the level of informational bias. The imputed level of taste-based local bias is therefore just 44 RMB (644 minus 600). Most of the pre-policy positive geographic bias therefore appears to be from informational processes and not taste, and indicates that "home bias" is driven by beliefs about better repayment prospects rather than some type of social homophily. This general result holds when controls are introduced in Models 2 and 3, though the taste component actually becomes slightly negative.

1.6 Additional empirical tests

1.6.1 Model specification

A fundamental challenge in studies of demographic disparities is understanding what exactly a demographic attribute represents. Even variables such as race present serious taxonomical challenges, where definitions change over time and it is not always apparent what category membership entails or how the information is interpreted (Charles and Guryan, 2011). To further complicate matters, most demographics are heavily confounded with other demographics: e.g., if lenders prefer people with short hair it might show up as gender discrimination even though gender is not what is directly being acted upon. Therefore, it is impossible to ever be certain how lenders fully interpret such demographic information. These issues are important because they influence what an "ideal" model specification should look like.

In the preceding sections I separately analyzed each of the demographic traits of interest. I next construct a model with nearly all of the available information simultaneously included. Table 1.14 presents these results. Both sets of coefficients on the gender and geography variables are consistent with the prior results.

1.6.2 Policy treatment specifications

Because policy changes such as the one in this study are not experimentally exogenous, I also construct and test two "placebo" policy dates. The first placebo test sets the treatment date one month before the actual date and compares the 30-day windows on either side; the actual pre-policy period becomes the post-placebo period in this design. The second placebo treatment employs the same approach but moves the treatment date to one month after the actual date, so that the actual post-policy period becomes a pre-placebo period. This design is summarized in Figure 1.2. The more fully specified model detailed above in Section 1.6.1 is replicated for each of the placebo tests, and these results are presented in Tables 1.15 and 1.16. Only one or two coefficients remain significant in each of the two placebo periods, reducing the likelihood that the original results presented in Table 1.14 were the result of a spurious process.

I next investigate whether the credit rating of the loans influences the results, given that the updated guarantee policy covered loans with an HR ("high risk") credit rating while the previous policy did not. To test for this, I split the the sample into two separate groups: 1) loans with a credit rating of AA through E, and 2) loans with a credit rating of HR. Table 1.17 presents this analysis. The non-HR subset maintains the same general pattern of the previous results, while the subset of HR-only loans does not generate significant coefficients. However, the HR subset may present sample size challenges. For example, only 317 of the total 3,755 HR decisions were from lenders lending to borrowers in the same province. Also, the HR loans may not contain the same variance on other dimensions (e.g., loan size; see Table 1.7). If the effect is heterogeneous across other loan attributes then this may also be contributing to this result.

1.6.3 Behavioral change versus selection

The preceding analysis indicates that borrowers face different conditions before and after the policy introduction. This effect could be driven by multiple scenarios. One possibility is that a fixed group of lenders changed its behavior based on the policy. A second possibility is that the policy itself attracted or repelled specific lenders with a different set of preferences. Table 1.8 indicates about half of all unique lenders active during the study period made loans both pre- and post-policy. Therefore, it is also possible that both scenarios are occurring simultaneously.

Lender fixed effects are employed to approach this question. The main challenge to employing lender fixed effects in this context is the extent to which it restricts the sample. Even when analyzing gender and geography separately, a lender must have made at least four loans to possess enough variance across the independent variables. For gender this comprises at least one decision to a man and one decision to a woman in both the pre- and post-policy periods. Limiting the data to such lenders results in 405 lenders who make 11,874 total decisions across the span of the two windows (less than 50% of the original sample). The average number of decisions for these lenders to each gender in each period is calculated in Table 1.18. The previous gender regression is then rerun (excluding lender gender which is collinear with a lender fixed effect) using this subsample and reported in

Table 1.19. The effects are the same direction, but the interaction term is no longer statistically significant. This seems to indicate that at least some of the disparity is generated by a change in behavior for the specific lenders that are active in both periods.

I repeat this process for the geographic analysis by limiting the dataset to lenders that have made loans to at least one person in their same province and one person in a different province in both the pre- and post-policy periods. This greatly reduces the sample to just 219 lenders who made a total of 7,190 decisions across the span of the two windows. The average number of decisions for these lenders is calculated in Table 1.20, and the regression results are presented in Table 1.21. Neither the subsample itself (Model 1) nor the subsample with fixed effects (Model 2) has significant coefficients, even though the direction remains the same. Thus, the data are unable to provide a conclusive answer to the amount of selection versus treatment effect from the policy.

1.6.4 Sample heterogeneity

It is plausible that the measured effect is not observed equally across the range of decisions. To test for this, I exclude small loans and small decisions from the analysis with the assumption that the bias effect may not be present for situations where limited cognitive effort is exerted or the economic stakes are exceedingly low. Table 1.22 details the results when only analyzing decisions equal to or greater than 100 RMB and loans equal to or greater than 20,000 RMB; this results in around 16,000 decisions. Although the statistical significance of the pre-policy positive bias is lower in the models without controls, the magnitudes of the previously observed effects are in general larger for this subset. This indicates the effect is more pronounced at the higher end of the decision distribution.

1.7 Discussion

It is often easier to demonstrate the existence of disparities than it is to substantiate the specific mechanisms that produce such outcomes. These mechanisms, however, play a critical role in both theory and practice and were the impetus for this paper. An understanding of why disparate treatment exists allows members of an affected group to strategically react to knowledge about disparities that affect them. It also provides direction to organizational managers and policy makers regarding what specific strategies would be most effective for altering such biases.

In this study I examined the role of lender motives in producing demographic disparities for borrowers by leveraging a change in the economic value of demographic information. This approach requires fewer ex-ante assumptions about decision maker beliefs than would be the case without an information change. Findings indicate that lenders in this context are indeed cognizant of borrower demographic traits and employ demographics both as informational signals about the economic favorability of borrowers and to express taste-based preferences. This research design strategy may be applicable to a wider range of settings where a change in the economic value of the demographic information itself allows a researcher to infer motives that are otherwise unobservable. Any setting where a policy normalizes risks at an individual level is a potential candidate for this approach.

This study also speaks to current challenges in the literatures studying status, categories, and networks, where similar underlying informational and taste mechanisms may also drive results and therefore moderate the importance of such topics as standalone theories. For example, status rankings may simply serve as proxies for unobserved quality that would be ignored if better information were available. On the other hand, audiences may derive direct utility from interacting with high status actors. Malter (2014) attempts to isolate how status matters in the wine industry by separating product quality from brand status. He notes of the Podolny (1993) view of status, "audiences would not have to rely on status to infer quality if quality were perfectly observable" (Malter, 2014, p. 276), while he empirically demonstrates that conspicuous consumption clearly matters and status—at least in the wine industry—matters in its own right.

The categories literature faces a similar challenge, where category membership can either serve as a fundamental trait itself—for example, by creating an illegitimacy discount from not belonging to an established category (Zuckerman, 1999)—or is simply used as a shortcut for quality; perhaps because low-quality actors have difficulty positioning themselves in certain categories. Recent work by Pontikes (2012) demonstrates how venture capitalists prefer more ambiguous classification, while consumers prefer less ambiguous classification. Classification appears to serve as a signal that can be used toward different ends by different audiences and therefore may be a strong informational mechanism.

Finally, the networks literature highlights how network position can serve as a quality signal—the "prism" element of networks, where "a tie between two market actors is an informational cue on which others rely to make inferences about the underlying quality of one or both of the market actors" (Podolny, 2001, p. 34). At the same time, popularity (as represented by metrics such as centrality) might be valued for popularity's sake alone. The positive relationship on Twitter between message dissemination and number of followers might be one such example (Suh et al., 2010). Therefore, one direction for future work in the status, categories, and networks literatures is to more explicitly separate the informational and taste aspects of these theories. Such separation will improve the ability of these theories to make appropriate policy prescriptions.

Finally, managers of many organizations encounter issues of bias within their ranks, and this study highlights the practical importance of locating its cause before designing an organizational remedy. Any managerial attempt to promote diversity or limit biases, such as the types of interventions studied by Kalev et al. (2006), needs to account for the distinction between informational and taste mechanisms. For example, informational biases may be best overcome by increasing the availability of underlying quality information, while taste bias likely requires a fundamentally different type of educational program to alter preferences. The finding by Kalev et al. (2006) that the diversity training programs they analyzed were largely ineffective is also consistent with an environment where managers or trainers did not properly identify the sources of employee bias before enacting a solution. At an individual or entrepreneur level, this might include attempting to alter the manner in which one's demographic information is portrayed or actively avoiding or seeking out particular markets based on the mechanisms at work in those markets. This research provides guidance in developing such strategies.

1.7.1 Limitations

While this study sheds light on the importance of disentangling taste and informational mechanisms, it does not make detailed predictions about which mechanism will necessarily dominate ex-ante. However, it does highlight some elements of this question that may guide future research. In settings where a decision maker is not constrained by strong economic penalties, one can expect taste to play a larger role than would otherwise be expected.

Caution should be taken when attempting to generalize these direct results to other settings, as these empirical results represent just one particular setting. There are reasons to believe that the cultural context, industry dynamics, and other factors should influence the specific ratio or existence of each of these mechanisms. The approach to separate them, however, is likely generalizable to a wide range of settings.

Finally, this study treats taste and information as additive, though recent work in behavioral economics indicates that this is not strictly true for all economic and social decisions. For example, Gneezy and Rustichini (2000) show that a monetary fine imposed for late pickups at a childcare center actually increases the occurrence of late pickup. One explanation is that the imposition of an economic cost reshaped the informal social contract that existed in the absence of a fine; it reduced the guilt associated with a late pickups. Such research violates the assumption of this and other studies that taste is constant and not instantaneously manipulable. While the policy change leveraged in this study seems unlikely to fundamentally alter tastes in this way, researchers should nevertheless be cognizant of this possibility.

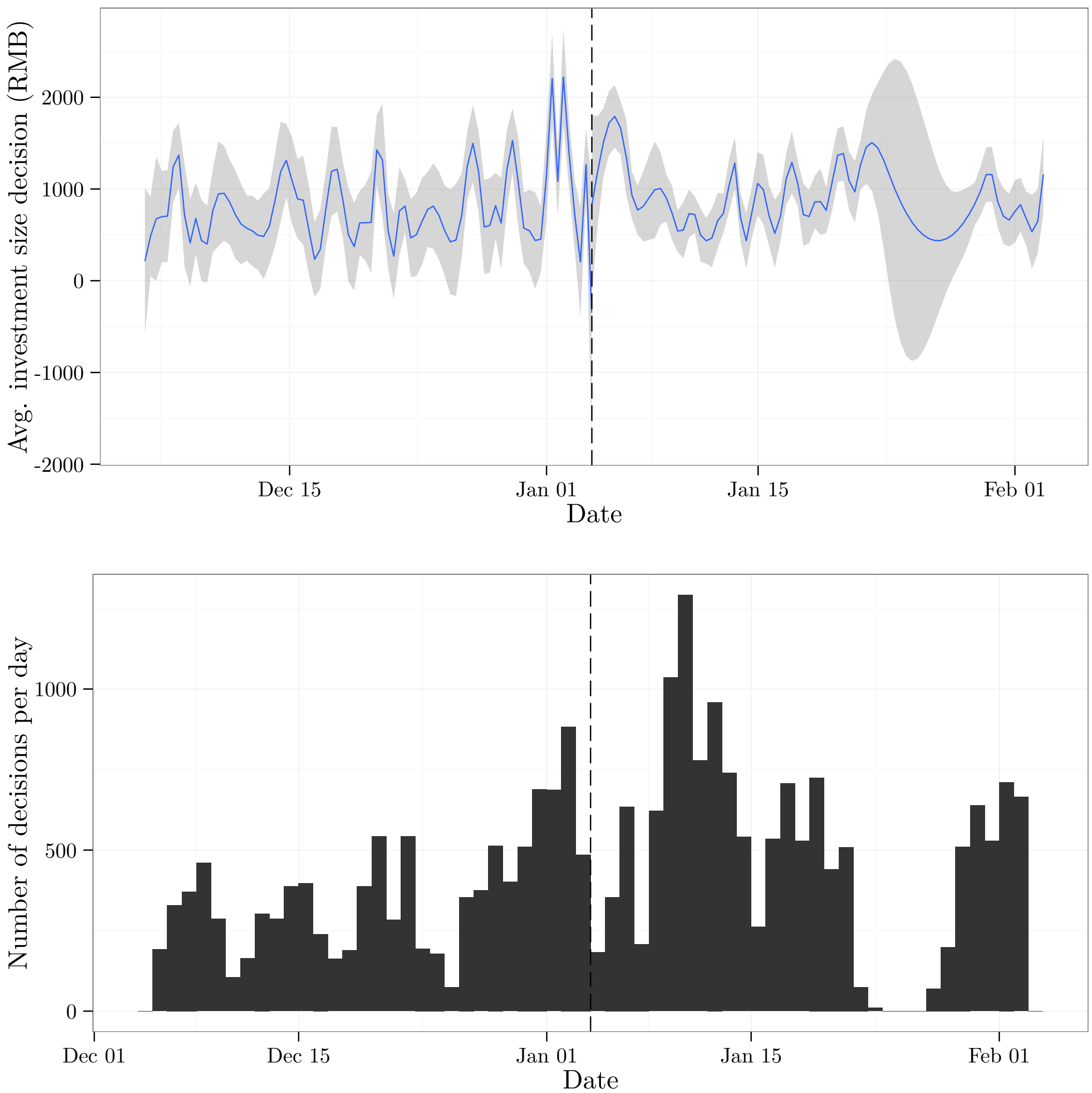


Figure 1.1: Temporal descriptive stats for the 30 days +/- the policy change. Smoothed with generalized additive models using basis dimension $k = 50$. Histogram using $binwidth = 1$ day.

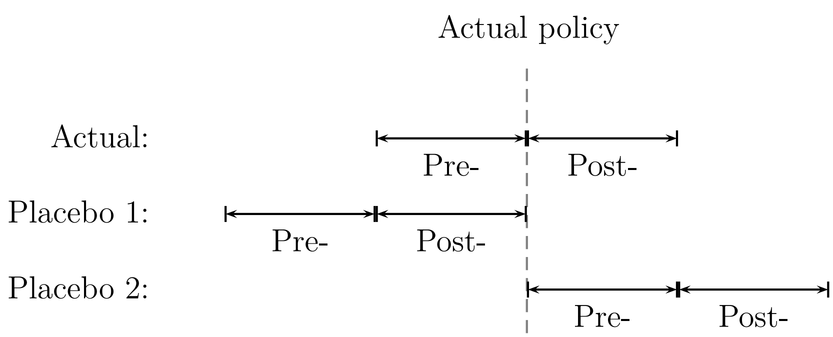


Figure 1.2: Summary of the two placebo treatment robustness tests in relation to the main research design. Placebo 1 shifts the treatment date to one month earlier than the actual date. Placebo 2 shifts the treatment date to one month later. The subsequent regression results of this design are presented in Tables 1.15 and 1.16.

Table 1.1: Research design employing 30-day pre- and post-policy windows to isolate levels of taste-based versus informational biases.

	Average size of lenders' investment decisions	
	t_1: pre-policy	t_2: post-policy
Demographic category A	A_1	A_2
Demographic category B	B_1	B_2
Taste-based bias for A =		$A_2 - B_2$
Information bias for A =	$(A_1 - B_1) - (A_2 - B_2)$	

Table 1.2: Summary of lender decisions in the pre- and post-policy windows

	Pre-policy period	Post-policy period	Both periods
Number of decisions	10975	14465	25440
Avg investment size	882	865	872
Max investment size	1e+05	8e+04	1e+05
Min investment size	50	50	50
Stdev investment size	3220	2979	3085
Unique lenders in window	2090	2521	3087
Unique loans in window	319	241	558
Avg. int. rate	13.9	14.3	14.1
Avg. loan term (months)	8.1	9.3	8.8
% same geography	9.0	7.6	8.2

Table 1.3: Descriptive regressions of loan guarantee, borrower characteristics, and lender characteristics on investment decision size

	DV: decision size (Chinese RMB)			
	(1)	(2)	(3)	(4)
Guarantee policy (true)	−17.2	−64.5	−121.3**	−6.7
	(39.1)	(40.5)	(58.7)	(69.9)
Loan int rate		41.5***	38.4**	29.9*
		(12.0)	(15.0)	(17.9)
Loan term (months)		15.2**	7.2	8.4
		(5.9)	(7.6)	(9.0)
Loan size		0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)
Constant	882.1***	920.0**	1,341.6	−603.4
	(29.5)	(438.1)	(1,068.1)	(1,320.9)
Credit rating controls§	No	Yes	Yes	Yes
Loan purpose controls	No	No	Yes	Yes
Borrower demographics†	No	No	Yes	Yes
Lender demographics‡	No	No	No	Yes
Observations	25,440	25,440	24,212	15,268
R^2	0.000	0.01	0.01	0.04
Adjusted R^2	-0.000	0.01	0.01	0.03

Note: *p<0.1; **p<0.05; ***p<0.01

§One of seven company-assigned credit rating categories: AA, A, B, C, D, E, or HR.

†Borrower demographics include gender, age, marital status, work province, academic achievement, office cateogry (type, size, and industry), salary range, loan purpose category, ownership of car and house, children.

‡Lender demographics include gender, age, marriage status, work province, and academic achievement. Missing self-reported lender data results in the reduction of observations.

Table 1.4: Overall loan-level summaries of the pre- and post-policy windows

	Pre-policy period	Post-policy period	Both periods
Number of loans	317	241	558
Number of unique borrowers	242	214	420
% loans male	86.4	85.9	86.2
% loans female	13.6	14.1	13.8
Avg. int. rate	14.3	14.3	14.3
Avg. loan term (months)	6.7	7.6	7.0
Avg. total loan size (RMB)	30542	51918	39774
Max total loan size (RMB)	500000	500000	500000
Min total loan size (RMB)	3000	3000	3000
Avg. borrower age	32.3	35.1	33.5
Avg. fund time (hours)	6.4	10.5	8.2
Avg. unique lenders / loan	34.6	60.0	45.6

Table 1.5: Loan outcomes as of August 2013

Category	...	Loan count	Male %	Female %
已结标	Already complete (success)	524	85.9	14.1
坏账	Bad debt	25	96.0	4.0
还款中	In repayment	8	75.0	25.0
逾期	Overdue	1	100.0	0.0

Table 1.6: Distribution of loan use categories

Category	Loan count	Pre-policy	Post-policy
Short-term turnover	259	97	162
Personal consumption	155	145	10
Other	75	47	28
Startup investment	55	23	32
Redecoration	6	2	4
Wedding preparations	3	2	1
Education/training	2	1	1
Automobile	2	0	2
Housing	1	0	1

Table 1.7: Statistics on credit rating categories

Credit rating	Number of loans	Int rate %	Loan term	Loan size
AA	3	6.9	3.0	4,333
A	2	13.0	9.0	42,500
B	65	11.4	7.4	31,708
C	87	13.3	7.4	43,393
D	119	13.7	7.5	67,159
E	135	14.9	7.4	40,273
HR	147	16.2	6.0	19,259

Table 1.8: Number of unique active lenders in respective windows
Note: does not account for activity that is outside the experimental window. A lender who is active just before the policy and then again at $window + 1$ will be counted above as active pre-policy only.

Period of activity	Lender count	Avg. age	% lenders female
Pre-policy window only	566	33.5	21.4
Both pre and post windows	1,524	33.8	22.5
Post-policy window only	997	32.7	28.6

Table 1.9: Basic exposition of gender effects not accounting for lender gender

Borrower	Post-policy	Avg. investment	Decision count
M	FALSE	831.2	8,917
M	TRUE	884.1	12,621
F	FALSE	1,103.0	2,058
F	TRUE	733.7	1,844

Table 1.10: Basic exposition of gender effects accounting for lender gender

Lender	Borrower	Post-policy	Avg. investment	Decision count
M	M	FALSE	815.4	7,042
M	M	TRUE	939.4	9,596
M	F	FALSE	1,127.2	1,613
M	F	TRUE	803.2	1,398
F	M	FALSE	890.5	1,875
F	M	TRUE	708.9	3,025
F	F	FALSE	1,015.2	445
F	F	TRUE	515.9	446

Table 1.11: Regression of loan policy and gender on investment size decision

	DV: decision size (Chinese RMB)		
	(1)	(2)	(3)
Guarantee policy (true)	53.0	−20.8	48.2
	(42.7)	(45.0)	(50.4)
Borrower sex (female)	271.8***	184.9**	227.7***
	(75.4)	(76.5)	(85.9)
Borrower sex * policy	−422.3***	−221.9**	−258.9**
	(107.7)	(110.6)	(124.9)
Lender sex (female)			71.9
			(79.8)
Lender sex * policy			−293.9***
			(102.2)
Lender sex * borrower sex			−199.8
			(182.6)
Lender sex * borrower sex * policy			178.3
			(255.5)
Loan interest rate		42.1***	41.1***
		(12.1)	(12.1)
Loan term		13.6**	13.3**
		(6.0)	(6.0)
Loan size		0.002***	0.002***
		(0.000)	(0.000)
Constant	831.2***	882.2**	883.8**
	(32.7)	(438.3)	(438.8)
Controls for credit rating	No	Yes	Yes
Observations	25,440	25,440	25,440
R^2	0.001	0.01	0.01
Adjusted R^2	0.001	0.01	0.01
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 1.12: Crosstabs of geographic overlap, policy change, and investment size

Geographic overlap	Post-policy	Avg investment size	Decision count
FALSE	FALSE	824.4	9,991
TRUE	FALSE	1,468.8	984
FALSE	TRUE	861.6	13,359
TRUE	TRUE	905.6	1,106

Table 1.13: Regression of policy and geographic overlap on investment size decision

	DV: decision size (Chinese RMB)		
	(1)	(2)	(3)
Guarantee policy (true)	37.2	-10.4	1.9
	(40.8)	(42.1)	(42.1)
Geo. overlap (true)	644.4***	616.5***	440.4***
	(103.0)	(102.5)	(101.2)
Geo. overlap * policy	-600.4***	-623.5***	-484.6***
	(141.1)	(140.4)	(138.7)
Loan int. rate		42.2***	36.8***
		(12.0)	(11.9)
Loan term		15.4***	16.9***
		(5.9)	(5.9)
Loan size		0.002***	0.002***
		(0.000)	(0.000)
Constant	824.4***	856.0*	907.8**
	(30.8)	(437.9)	(440.7)
Controls for credit rating	No	Yes	Yes
Lender's work province	No	No	Yes
Observations	25,440	25,440	24,322
R^2	0.002	0.01	0.03
Adjusted R^2	0.001	0.01	0.02

Note: *p<0.1; **p<0.05; ***p<0.01
Lenders without geographic information counted as no overlap.

Table 1.14: More fully specified model regressing policy and demographics on investment size decision

	DV: decision size (Chinese RMB)	
	(1)	(2)
Guarantee policy (true)	6.5	11.2
	(65.9)	(65.6)
Borrower sex (female)	205.5**	226.2**
	(90.4)	(88.5)
Borrower sex * policy	−346.1**	−402.2***
	(144.3)	(144.1)
Geographic overlap (true)	630.3***	439.7***
	(105.9)	(104.7)
Geo. overlap * policy	−656.9***	−498.9***
	(143.8)	(142.2)
Loan interest rate	36.9**	32.9**
	(15.0)	(14.9)
Loan term	5.8	5.9
	(7.6)	(7.5)
Loan size	0.002***	0.002***
	(0.000)	(0.000)
Constant	1,288.7	1,505.9
	(1,064.7)	(1,048.3)
Controls for credit rating	Yes	Yes
Borrower characteristics†	Yes	Yes
Borrower work province	Yes	Yes
Lender work province	No	Yes
Observations	24,212	23,108
R^2	0.02	0.03
Adjusted R^2	0.01	0.02
Note:	*p<0.1; **p<0.05; ***p<0.01 †In addition to gender, borrower characteristics include level of academic degree, age, loan purpose, salary range, office characteristics (type, size, and industry), and the existence of a car, house, or children.	

Table 1.15: More fully specified model regressing 30 days prior placebo policy and demographics on investment size decision

	DV: decision size (Chinese RMB)		
	(1)	(2)	(3)
Placebo policy (true)	-209.9^{***}	-230.6^{***}	-196.4^{***}
	(57.4)	(65.7)	(65.6)
Borrower sex (female)	4.5	-26.8	-15.8
	(114.0)	(134.2)	(133.6)
Borrower sex * policy	64.1	94.4	100.7
	(139.1)	(159.7)	(158.9)
Geographic overlap (true)		163.8	41.7
		(128.4)	(128.9)
Geo. overlap * placebo policy		427.9^{**}	372.9^{**}
		(168.0)	(168.0)
Loan interest rate	25.9^{*}	26.9^{*}	23.2
	(14.3)	(16.2)	(16.2)
Loan term	9.5	11.7	13.7^{*}
	(7.4)	(8.1)	(8.1)
Loan size	0.003^{***}	0.003^{***}	0.003^{***}
	(0.000)	(0.000)	(0.000)
Constant	382.3	853.1	976.6
	(490.5)	(1,083.8)	(1,079.5)
Controls for credit rating	Yes	Yes	Yes
Borrower characteristics†	Yes	Yes	Yes
Borrower work province	No	Yes	Yes
Lender work province	No	No	Yes
Observations	17,432	16,908	16,866
R^2	0.03	0.03	0.04
Adjusted R^2	0.03	0.03	0.04
Note:	*p<0.1; **p<0.05; ***p<0.01		
	†In addition to gender, borrower characteristics include level of academic degree, age, loan purpose, salary range, office characteristics (type, size, and industry), and the existence of a car, house, or children.		

Table 1.16: More fully specified model regressing 30 days after placebo policy and demographics on investment size decision

	DV: decision size (Chinese RMB)		
	(1)	(2)	(3)
Placebo policy (true)	−210.1***	−227.9***	−209.6***
	(35.0)	(41.1)	(44.4)
Borrower sex (female)	−173.6**	−195.7**	−205.2**
	(72.0)	(83.4)	(88.9)
Borrower sex * policy	155.2*	152.9	175.8
	(90.5)	(101.4)	(109.4)
Geographic overlap (true)		27.5	14.2
		(82.3)	(85.8)
Geo. overlap * placebo policy		75.6	49.3
		(109.3)	(113.4)
Loan interest rate	40.9***	43.2***	39.2***
	(12.0)	(13.3)	(14.3)
Loan term	5.0	5.1	8.5
	(5.9)	(7.0)	(7.5)
Loan size	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Constant	375.9	477.6	632.3
	(601.4)	(643.2)	(677.2)
Controls for credit rating	Yes	Yes	Yes
Borrower characteristics†	Yes	Yes	Yes
Borrower work province	No	Yes	Yes
Lender work province	No	No	Yes
Observations	35,576	34,548	30,037
R^2	0.01	0.01	0.02
Adjusted R^2	0.01	0.01	0.02

Note: *p<0.1; **p<0.05; ***p<0.01

†In addition to gender, borrower characteristics include level of academic degree, age, loan purpose, salary range, office characteristics (type, size, and industry), and the existence of a car, house, or children.

Table 1.17: Comparison of HR and non-HR rated loans in a more fully specified model regressing policy and demographics on investment size decision

	DV: decision size (Chinese RMB)			
	Non-HR	HR only	Non-HR	HR only
	(1)	(2)	(3)	(4)
Guarantee policy (true)	27.8	13.7	52.3	6.5
	(77.1)	(289.1)	(78.0)	(257.6)
Borrower sex (female)	61.7	367.6	88.1	381.4
	(105.3)	(280.7)	(104.7)	(248.7)
Borrower sex * policy	-369.6^{**}	-239.9	-484.3^{***}	-266.3
	(182.9)	(426.2)	(186.2)	(380.2)
Geographic overlap (true)	698.8^{***}	194.6	517.4^{***}	-18.1
	(114.4)	(287.8)	(114.8)	(257.1)
Geo. overlap * policy	-724.5^{***}	-216.4	-592.9^{***}	105.0
	(157.0)	(367.9)	(157.5)	(330.8)
Loan interest rate	51.8^{***}	-14.1	44.5^{**}	-20.9
	(19.8)	(38.5)	(20.1)	(34.1)
Loan term	1.1	5.1	2.0	7.2
	(8.5)	(31.2)	(8.5)	(27.9)
Loan size	0.002^{***}	0.001	0.002^{***}	0.001
	(0.000)	(0.001)	(0.000)	(0.001)
Constant	$1,400.4^{**}$	-106.2	$1,355.4^{**}$	414.6
	(621.9)	(1,750.2)	(631.8)	(1,571.3)
Controls for credit rating	Yes	No	Yes	No
Borrower characteristics†	Yes	Yes	Yes	Yes
Borrower work province	Yes	Yes	Yes	Yes
Lender work province	No	No	Yes	Yes
Observations	20,644	3,568	19,713	3,395
R^2	0.02	0.02	0.03	0.05
Adjusted R^2	0.01	0.004	0.02	0.02

Note: *p<0.1; **p<0.05; ***p<0.01

†In addition to gender, borrower characteristics include level of academic degree, age, loan purpose, salary range, office characteristics (type, size, and industry), and the existence of a car, house, or children.

Table 1.18: Summary of decision counts at the lender level for the sample used for gender regressions with lender fixed effects. To be included in the sample, a lender must make at least one loan to a man and one to a woman in both periods; 405 lenders meet this criteria.

Statistic	Mean	St. Dev.	Min	Max
Decisions to women, pre-policy	2.9	2.3	1	16
Decisions to women, post-policy	2.3	2.0	1	16
Decisions to men, pre-policy	11.5	11.5	1	83
Decisions to men, post-policy	12.7	11.6	1	96

Table 1.19: Lender fixed effects OLS regression of loan policy and gender on investment size decision

	DV: decision size (Chinese RMB)	
	(1)	(2)
Guarantee policy (true)	−50.4	41.4
	(69.9)	(64.5)
Borrower sex (female)	121.7	210.8**
	(110.1)	(96.9)
Borrower sex * policy	−169.7	−202.8
	(162.6)	(143.0)
Loan interest rate	33.5*	34.6**
	(17.9)	(17.0)
Loan term	20.7**	−2.8
	(9.1)	(8.5)
Loan size	0.003***	0.003***
	(0.000)	(0.000)
Constant	977.0	768.7
	(621.0)	(698.5)
Controls for credit rating	Yes	Yes
Lender fixed effects	No	Yes
Observations	11,874	11,874
R^2	0.02	0.3
Adjusted R^2	0.02	0.3
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 1.20: Summary of decision counts at the lender level for the sample used for geography regressions with lender fixed effects. To be included in the sample, a lender must make at least one loan to a borrower in the same province and one loan to a borrower in a different province in both periods; 219 lenders meet this criteria.

Statistic	Mean	St. Dev.	Min	Max
Decisions to same province, pre-policy	2.5	2.4	1	18
Decisions to same province, post-policy	2.2	2.2	1	18
Decisions to other province, pre-policy	14.1	13.9	1	84
Decisions to other province, post-policy	14.1	12.5	1	91

Table 1.21: Lender fixed effects OLS regression of policy and geographic overlap on investment size decision

	DV: decision size (Chinese RMB)	
	(1)	(2)
Guarantee policy (true)	−68.2	47.7
	(105.0)	(96.5)
Geo. overlap (true)	177.3	94.1
	(185.9)	(163.4)
Geo. overlap * policy	−410.4	−242.9
	(268.5)	(235.2)
Loan int. rate	37.0	52.0**
	(26.8)	(25.4)
Loan term	35.8**	−12.6
	(14.1)	(13.0)
Loan size	0.004***	0.005***
	(0.000)	(0.000)
Constant	988.6	688.2
	(1,016.7)	(1,036.0)
Controls for credit rating	Yes	Yes
Lender fixed effects	No	Yes
Observations	7,190	7,190
R^2	0.03	0.3
Adjusted R^2	0.02	0.3
Note:	*p<0.1; **p<0.05; ***p<0.01 Lenders without geographic information counted as no overlap.	

Table 1.22: Tests for sample heterogeneity: more fully specified model regressing policy and demographics on investment size decision for loans equal to or larger than 20000 RMB and decisions equal to or greater than 100 RMB.

	DV: decision size (Chinese RMB)		
	(1)	(2)	(3)
Guarantee policy (true)	−163.7	−53.2	−79.4
	(103.2)	(122.8)	(122.7)
Borrower sex (female)	198.0	233.1	258.4*
	(140.1)	(156.3)	(153.5)
Borrower sex * policy	−392.7*	−482.9*	−549.9**
	(207.1)	(265.5)	(265.7)
Geographic overlap (true)		989.8***	708.5***
		(167.6)	(166.2)
Geo. overlap * policy		−1,062.2***	−801.2***
		(216.4)	(214.2)
Loan interest rate	138.4***	149.5***	168.8***
	(40.5)	(48.1)	(48.1)
Loan term	−5.7	−10.2	−7.2
	(15.8)	(18.5)	(18.5)
Loan size	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
Constant	2,442.2**	2,844.6	3,351.9*
	(1,245.2)	(1,808.0)	(1,806.3)
Controls for credit rating	Yes	Yes	Yes
Borrower characteristics†	Yes	Yes	Yes
Borrower work province	No	Yes	Yes
Lender work province	No	No	Yes
Observations	15,992	15,822	15,024
R^2	0.01	0.02	0.03
Adjusted R^2	0.01	0.01	0.03
Note:	*p<0.1; **p<0.05; ***p<0.01		
	†In addition to gender, borrower characteristics include level of academic degree, age, loan purpose, salary range, office characteristics (type, size, and industry), and the existence of a car, house, or children.		

Chapter 2: Heterogeneous Motives in Lending Markets: the Influence of Market Identity

2.1 Introduction

Producers in a market face performance implications based on their adherence to established market categories (Zuckerman, 1999). However, the different audiences that evaluate these producers are unlikely to value the same categories at exactly the same levels (Pontikes, 2012).[18] Category performance is therefore a function of audience preferences. Most studies, however, do not directly measure audience preferences and instead rely on decision-level data that may or may not accurately represent underlying motives. How important are motives to understanding market behavior, and where might these motives come from?

This paper argues that audience motives are largely endogenous to a given market. A market's identity attracts participants with specific preferences, and these actors then behave in a manner consistent with the market's identity. While variance in motives is most likely greatest between audiences in separate markets, it may also exist within a single market. Markets with so-called "hybrid identities" may be at greatest risk in this regard. This study examines one such market, where the

[18]This is true for products as well. In the extreme, "one man's trash is another man's treasure."

audience (lenders) evaluates candidates (borrowers) in a market that was explicitly designed to promote both economic and social goals.

In general, social entrepreneurs are characterized by a need to "simultaneously demonstrate their social and economic competence" (Dacin et al., 2011, p. 1207). This hybrid identity presents a puzzle for fundraising efforts. Emphasizing the "business" side of an enterprise will attract traditional investors, emphasizing the "social" side of an enterprise will attract social investors, but emphasizing both elements simultaneously has more ambiguous performance implications. I examine funding decisions in a single market—Kiva, a charitable lending microfinance organization—to inductively theorize about this nexus between organizational identity and investor preferences.

A social enterprise is a type of hybrid-identity organization—an organization "whose identity is composed of two or more types that would not normally be expected to go together" (Albert and Whetten, 1985, p. 270). A subset of research on organizational identity addresses the relationship between stakeholders and organizational identity (e.g., Brickson, 2005; Scott and Lane, 2000). However, development of an empirical understanding of the functioning of such organizations has often proved challenging (e.g., Foreman and Whetten, 2002).

The Kiva empirical context draws on strong themes from both charity and business activity. I propose that lender motives mirror the market identity, so that individual lenders evaluate entrepreneurs based on two underlying dimensions: perceived economic ability (corresponding to the market's business identity) and perceived personal need (corresponding to its charity identity). This study is designed to measure distributions of these motives and the subsequent performance implications for entrepreneurs.

I extend Albert and Whetten's original conception of holographic and ideographic forms of internal organizational duality to external stakeholders and test which of these forms is present in the non-profit peer-to-peer lending website examined in this study. A theory of the relationship between external stakeholder identification and organizational identity is developed. Interpreted within the burgeoning scholarship on social entrepreneurship, this work may contribute insights about how such contexts differ from conventional markets.

Results from an original survey indicate that lender motives are indeed consistent with the market's identity and are moderately dominated by a preference for perceived need. These preferences are also correlated with lender demographics. Further, variance in preferences matters for borrowers on the platform. Loans made by lenders with a high preference for both of the dimensions were funded fastest, while loans made by lenders with a low preference for these categories were funded slowest. The importance of these categories appears to decrease over time as the market matures, which may be an indication of a shift from an ideographic to a holographic configuration. These results contribute to an understanding of the role of external stakeholders in the maintenance and support of hybrid-identity organizations. The remainder of the paper is organized as follows: 1) theoretical discussion of hybrid-identity organizations, 2) introduction to the empirical setting, 3) methods, and 4) results.

2.2 Theory

The concept of a hybrid-identity organization was first popularized by Albert and Whetten (1985, p. 270), who defined it as "an organization whose identity is composed of two or more types that would not normally be expected to go together." The organizational example they proposed was the university. Universities employ both utilitarian and normative constructs that are exemplified in business-like and church-like behavior. Therefore, a university can be conceptualized in terms of its two components, each of which contributes to its overall functioning. Additional studies have highlighted that hybrid organizations can be found in many sectors of the economy, such as rural co-ops (Foreman and Whetten, 2002), law firms, and beverage producers (Brickson, 2005).

Included in the original discussion of hybrid-identity organizations was a proposal for two potential structural forms of duality within an organization: holographic and ideographic. Holographic refers to an organization where "each internal unit exhibits the properties of the organization as a whole," and ideographic (or specialized) refers to the case where "each internal unit exhibits only one identity—the multiple identities of the organization being represented by different units" (Albert and Whetten, 1985, p. 271). Universities, for example, are structurally divided between faculty and administrators who support the organization's normative and utilitarian functions, respectively.

I propose that the holographic and ideographic concepts originally developed for internal organizational arrangements may also exist for external stakeholders such as customers and investors. In a holographic arrangement, these stakeholders may all identify with the single hybrid identity of the organization. In the ideographic arrangement, separate subsets of stakeholders may identify with one or the other element of the organization's identity. Therefore, the organization may maintain its hybrid-identity as a result of either multiple types of stakeholders or one single type. These configurations are summarized in Figure 2.1.

Implicit in this discussion is the fact that organizational identity is the result of both managers and stakeholders. As Scott and Lane (2000, p. 44) argue, "organizational identity is best understood as contested and negotiated through iterative interactions between mangers and stakeholders." The organizational founder, therefore, sets an initial identity for the organization at its time of conception. Potential stakeholders then respond to this identity by deciding whether and in what capacity to interact with the organization. If there is a discrepancy between how the organization sees itself and how stakeholders conceive of it, the organization may be forced to update its identity to satisfy stakeholder conceptions. This process is ongoing over the life of the organization. Stakeholder configurations may be distinct in both theory and practice from internal forms of organizational duality. For example, a hybrid organization could be internally heterogeneous (i.e., ideographic), but attract homogeneous stakeholders (i.e., holographic). Or the hybrid organization could be homogeneous in its internal units (i.e., holographic) but attract discrete sets of stakeholders (i.e., ideographic) which separately identify with different elements of its hybrid identity.

A number of implications regarding the long-term sustainability of an organization can be conjectured given this theoretical relationship between stakeholder forms and organizational unit forms. It is conceivable that the (in)stability of organizational forms is fundamentally linked to how external stakeholders identify with the organization. The four potential configurations of internal unit and external stakeholder configurations are explored in Tables 2.1 and 2.2 along with conjectures regarding the potential consequences for the organization. While these cannot be directly tested in this paper, they will help frame the discussion of empirical results.

2.2.1 The empirical setting

Brickson (2005, p. 582) notes that, "though some preliminary antecedents of hybrids have been offered, little empirical work addresses them." Kiva represents an ideal setting to study a hybrid market comprised of actors with potentially heterogeneous motives. The wealth of empirical data generated by the Kiva context also addresses the growing interest in organizational research on sustainable industries such as microfinance (Khavul, 2010).

Kiva is self-described as "a non-profit organization with a mission to connect people through lending to alleviate poverty."[19] Kiva acts as an intermediary between individual lenders typically in higher-income economies and microfinance institutions (MFIs) typically in lower-income economies that directly distribute and manage the loans of individual entrepreneurs. Kiva manages its public website,

[19] Quote accessed June 16, 2015 at the Kiva "About" webpage (`http://www.kiva.org/about`). Kiva held a very similar mission statement for most of its history. Historical versions were accessed at the Internet Archive [link]. Hyperlinks are included in the PDF version:

May 14, 2008 [link]: "Kiva's mission is to connect people through lending for the sake of alleviating poverty."

Kiva.org, where it posts individual borrower profiles provided by the MFIs. Anyone from the public can register for a Kiva account and then loan money to specific borrowers. Fundraising is performed in a piecemeal fashion ($25 increments); a borrower's public loan page states the total amount of funds requested and the amount of money currently raised from other individual lenders. Once the aggregate contributions from lenders equal the entrepreneur's requested amount, the loan is considered fully funded and removed from the Kiva website. Loan repayment occurs on a predetermined schedule. However, Kiva lenders never receive interest on their loans. While there is no potential for profits, lenders do incur some economic risk.[20]

Early in the organization's history, Kiva co-founder Matt Flannery detailed five elements of Kiva's product philosophy. Included in his list was "Emphasize Progress Over Poverty" (Flannery, 2007, p. 40). In Flannery's conception, "Business is a universal language that can appeal to people of almost every background. This can lead to partnerships rather than benefactor relationships. We appeal to people's interests, not their compassion." The idea that people could be open to lending money as a charitable act is now well supported by the growth of the broader microfinance movement (Khavul, 2010). However, the phenomena of charity and lending are not obviously related on a theoretical level: the act of lending is centrally concerned with the economically productive use of capital within a market, while charity is focused on helping others through benevolent actions—often ad-

[20]For a discussion of economic risk at different levels of the Kiva system (borrower, field partner, country), see: `http://www.kiva.org/about/risk`

dressing a perceived market failure. One way to interpret the enormous popularity of Muhammad Yunus—founder of Grameen Bank and often considered the "father of microfinance"—is that the concept of applying market-based business principles to poverty alleviation problems was so novel and innovative as to warrant the awarding of a Nobel Peace Prize—surely the first for a financial innovation. Studies such as Battilana and Dorado (2010) have explicitly examined how this hybrid tension plays out within commercial microfinance organizations (see also Kent and Dacin (2013) for an analysis of the two dominant logics in the broader microfinance industry).

The above quote from Flannery, however, compliments and contrasts with Kiva's objective status as a 501(c)(3) non-profit and its mission "to connect people through lending to alleviate poverty." The fact that lenders are never paid interest on their loans results in a de facto selection bias of lenders to the Kiva platform, as participants have an ex-ante understanding that the purpose of their lending is not to make a profit. At the same time, lenders likely do expect their loans to be repaid (historical repayment rates are around 98%) and explicitly choose to use Kiva instead of more traditional charity outlets that would allow them to conduct outright donations. Critical to this research approach is the acknowledgement that stakeholders deliberately self select into relations with particular organizations such as Kiva. Therefore, lenders are drawn to the Kiva platform at least in part by its ability to combine elements of charity and business activity into a single service. Any empirical observations are a direct result of this latent choice process, even though I cannot map the entire ecosystem (e.g., the choice set might contain a wide range of other charities, investment opportunities, etc.). In short, the preferences of actors in the market are at least partly endogenous to the market's identity.

I propose that understanding lender motives is critical on at least two theoretical dimensions. First, it represents a clear instantiation of the organization's hybrid-identity at the external stakeholder level: if the behavior of lenders is not consistent with the organization's identity, the identity would be temporally unsustainable. Therefore, the question becomes how exactly lenders support this identity. Second, for borrowers and market managers, understanding the distribution of lender motives may shape how they choose to position themselves within the market.

A handful of recent studies have also employed Kiva as a research context. A number of these studies corroborate Flannery's observations. Some have demonstrated that the language used in loan descriptions influences fundraising performance (Allison et al., 2013, 2015; Moss et al., 2015). Others have demonstrated a homophily effect between lenders and borrowers (Burtch et al., 2014; Desai and Kharas, 2013; Galak et al., 2011). These studies provide strong evidence that Kiva is a unique context where lenders may be expected to reward borrower characteristics in ways that differ from both for-profit lending and pure charity. I extend these studies to the extent that I directly measure lender motives.

2.2.2 Lender preferences

Individual lenders make choices about where to direct their capital, and the entrepreneurs that best match preferences receive funding faster than others. Similar to a traditional lending setting, there is evidence that choices are nonrandom.

However, unlike banking or venture capital settings, the market identity is expected to attract different types of lenders. Matt Flannery, the co-founder, commented on this relatively soon after Kiva's founding: "Lenders showed unambiguous preferences according to region, gender, and business type: Africans first, women first, and agriculture first. A female African fruit seller? Funded in hours. Nicaraguan retail stand? Funded in days. A Bulgarian Taxi Driver? Funded in weeks" (Flannery, 2007, p. 50). But where did these preferences come from? The question of whether this hybrid logic takes the structure of a homogeneous adoption across lenders (i.e., holographic: all lenders have the same hybrid preference) or a heterogeneous combination of business and charity logics (i.e., ideographic: subsets of lenders have different preferences and are motivated by different elements of Kiva) is an empirical one that has yet to be fully explored in the literature on dual identity organizations.

Because lenders self-select into Kiva usage—and have ex-ante awareness of Kiva's identity—the framework for thinking about Kiva's hybridity can be extended to lender motives for lending. These motives ultimately influence a lender's lending decisions. This is similar to the importance of members' identification with multiple-identity organizations (Foreman and Whetten, 2002). Therefore, the organizational identity of Kiva shapes both the attraction and subsequent behavior of stakeholders. Average lender preference for each dimension of the market identity should therefore be high.

In the case of Kiva, I suggest that lenders classify borrowers along two specific dimensions that correlate with the platform's charity-like and business-like identity:

the borrower's perceived level of personal need and perceived level of economic ability. If true, lenders will rate these dimensions as independently important. However, this alone does not provide insight into the configuration of preferences.

The two potential forms of lender configurations were depicted earlier in Figure 2.1. In the holographic scenario, all lenders directly employ a hybrid preference for borrower need and ability. In the ideographic scenario, two subsets of lenders each employ separate preferences that then on average combine to produce the observed hybrid identity. The configuration of the market can therefore be revealed by asking lenders to choose between the separate dimensions. If there is a preference for each category independently, but no preference between the two categories, then the market is more holographic than ideographic.

This may be important because if subgroups of stakeholders prefer different aspects of the identity, then the hybrid organization may benefit from strategically promoting the stability of that distribution. If not, the organization's identity may be challenged. If all stakeholders employ a single hybrid preference, however, the organization's hybrid identity may be at less risk of external challenges. Because lenders are external stakeholders instead of internal units, these predictions are theoretically distinct from those made by Albert and Whetten (1985) regarding potential consequences of each of the two internal forms.

2.2.3 The impact of lender preferences on borrowers

The variance in the preference for perceived economic ability and personal need of borrowers should shape lenders' choices. Loans that most closely satisfy each lender preference will be funded fastest. The more a borrower appears to be in personal need, the more clearly he or she will satisfy a lender's charity motive. The more a borrower appears to have economic ability, the more likely he or she will satisfy the business motive. A continuum is proposed for each category, because "category members fall within fuzzy boundaries, so it is not always clear which instances belong in that category" (Fiske and Taylor, 2008, p. 94).

From the above discussion, two hypotheses are proposed regarding an individual loan's performance given how closely it matches the motives of lenders.

Hypothesis 1: Loans made by lenders with a high preference for *economic ability* will be funded faster than loans made by lenders with a low preference for *economic ability*.

Hypothesis 2: Loans made by lenders with a high preference for *personal need* will be funded faster than loans made by lenders with a low preference for *personal need*.

The optimal configuration is for a borrower to appear to have high personal need and high economic ability. The least optimal configuration for a borrower is to communicate low personal need and low economic ability. Table 2.3 summarizes the main hypotheses regarding speed of funding in relation to each combination of these categories.

The previous hypotheses relate to the aggregated performance of individual loans. However, there may be temporal implications of category membership. It is possible that the importance of separate categories may dissipate over time as what once once a novel combination slowly becomes more accepted.

> **Hypothesis 3**: The performance differential between the ability and need categories will converge over time as the market matures.

2.3 Methodology

The challenge of indirectly inferring motives from decision-level data is that actors may make the same decisions for a multitude of reasons. Any attempt by a researcher to assign borrower characteristics to categories would thus involve a high degree of subjectivity. For example, if a lender preference for female borrowers is observed, it might be that lenders believe women to have greater ability or greater need. Both are plausible interpretations from the microfinance literature (Roodman, 2012).

To resolve this issue, I survey a subset of actual Kiva lenders on their motives for lending and then compare this to their loan portfolios. First, a random sample of lenders is directly surveyed on the importance of the two categories previously outlined. Each respondent's survey data is then matched to the loans in his or her historical portfolio. This portfolio is comprised of each loan to which the lender has lent using Kiva. These data are then used to calculate borrower-level performance effects of appealing to different lender motives.

This approach has a number of limitations. First, because it is guided by apriori theory, it does not allow for the emergence of other motives. For example, prior research has identified a range of overall motives for lending on Kiva, some related to this framework and some not (Liu et al., 2012). The result is that this process will not be able to exhaustively explain lender motives. However, it is efficient for testing the link between market identity, motives, and loan category performance, which is the focus of this paper.

2.4 Data

The primary loan and lending decision data were collated from the public data set provided by the company. To my knowledge, this consists of data on every loan from Kiva's founding until February 9th, 2015, as well as all public lenders and lending decisions.[21] I designed a separate survey to determine the motives of lenders along the two theoretical dimensions discussed above. These two data sources were then matched when possible. I next present descriptive statistics on each of these data sources.

2.4.1 The full population of Kiva data

2.4.1.1 Lenders

The platform had 1,599,750 registered users, of which 1,023,885 had made at least one publicly visible loan. These lenders have made in total 16,018,887 lending decisions, an average of 16 loans per active user. An individual historical lending

[21] The majority of lending on the platform is public, though a lender can choose to lend anonymously if they wish. If a lender lends anonymously I would not be able to see the activity.

portfolio can be constructed for each lender based on these data. While complete statistics on the location of lenders are not available, the majority of those that self-report say that they are from the United States (65%).

2.4.1.2 Borrowers

A total of 835,330 individual loans had been posted on the platform for fundraising since its founding. These loans were administered by 381 different field partners. Figure 2.2 plots the growth in the number of new loans posted across the history of the platform, and Figure 2.3 plots the cumulative dollar sum lent, which is now in excess of $600 million. Because Kiva screens new loans and actively manages relationships with field partners, it has some degree of control over the supply of loans. During this growth, loan supply and demand appear to be fairly well matched, though the supply to demand ratio has increased slightly in recent years. Figure 2.4 shows the current status of every loan request in the platform's history. The vast majority of loans were successfully paid off or (for recent loans) are currently in repayment. Nearly every loan request was successfully funded until 2012, when about five percent of loan requests expired.[22] The default rate incurred by lenders has remained in the very low single digits.

Table 2.4 details loan-level statistics. The average loan has a 13 month repayment term and requested $841. About 74% of borrowers are women. About 14% of loans are "group loans," meaning the loan will be divided between a collection of

[22] For a discussion of expiring loans, see a 2012 Kiva blog post: http://www.kiva.org/updates/kiva/2012/08/13/qa-expiring-loans-credit-limits-and-the-evolution-of-kiva.html

individuals.

Loans are requested for a variety of purposes and are categorized by use into sectors and further subdivided into more granular activities. Table 2.5 details the distribution of loans across the 15 sectors (food-related business is the most frequent), and Table 2.6 shows the distribution by popular sub-activities (retail general store is the most frequent). Table 2.7 lists the most prevalent countries in terms of number of loan requests. There is no dominant world region; the three most frequent countries are the Philippines, Kenya, and Peru.

2.4.2 The survey

2.4.2.1 Design of the survey

A brief online survey was designed to directly solicit lending motives from actual Kiva lenders. The primary question used for this study consisted of, "When you personally choose a borrower to lend to using Kiva...", 1) "...how important is it to you that the borrower has the potential to be economically productive with a loan? (for example, it appears a loan would allow the borrower to make significant economic profits)" and 2) "...how important is it to you that the borrower appears to have a strong personal need for a loan? (for example, it appears that a loan would significantly improve the borrower's life)" Each of these two questions was followed with a nine point Likert scale ranging from "Not at all important" to "Extremely important."[23]

[23]These questions were presented in a randomized order on the same page. Each of the following questions—or set of questions—were presented on independent pages.

To account for respondents that may have ranked the two similarly, the subsequent question asked for the dominant preference: “Thinking back on the loans you have already made using Kiva, which of the following was more important to you?” 1) “that the borrower appeared to have economic ability” or 2) “that the borrower appeared to have personal need”. It is possible that a lender might diversify his or her portfolio across these dimensions, so a followup question was designed to understand how consistent this preference had been: “Did you always prefer a borrower with [personal need / economic ability] over a borrower with [economic ability / personal need]?” “Yes, always,” “Yes, mostly,” or “No.” If “No,” “Please explain how your decision changed across loans.” A final question about organizational similarity to a bank and to a charity was also included, as well as fields for respondent gender, country location, estimated number of loans made, and lender ID.

2.4.2.2 Description of survey data

A link to the online survey was distributed by Kiva via email to 10,000 active users on March 11, 2015 and was open for one month.[24] The recruitment emails were sent by Kiva, and I ran the survey independently through the Qualtrics survey platform.[25] By completing the survey, respondents were entered into a raffle for

[24] Kiva randomly selected these 10,000 users from a pool consisting of all users that 1) were active—had either logged into the website or received a repayment within the prior six months, 2) had not previously opted out of Kiva email newsletters, and 3) were not part of a previous smaller pilot survey in this study.

[25] The same link was distributed to all email addresses, meaning participants could have forwarded it to others if desired, though they were not explicitly asked to do so. The text of the recruitment email was as follows:
Subject: Kiva wants to hear from you!
Greetings! The Kiva Research Team has partnered with researchers at the University of Maryland who are interested in studying the different motivations of Kiva lenders. They’ve put together a short survey that will take approximately 2 minutes to complete.

a \$25 Kiva gift card. This resulted in 1,509 completed responses. Figures 2.5, 2.6, and 2.7 present a summary of the raw main results. Table 2.8 shows that the vast majority of respondents are in the United States. Figure 2.8 indicates that self-reported past experience of the lenders (number of loans made) is fairly well distributed and most are female (59%).

909 responses could be successfully matched to lender usernames in the main Kiva data. The respondents that could not be matched either provided an incorrect version of their Kiva username or chose to lend anonymously, and therefore their lending activity is not publicly observable. This process resulted in the creation of a historical loan portfolio for the survey respondents consisting of all loans to which at least one respondent had lent. There were two survey respondents that were outliers in the number of loans they had made (one more than ten thousand loans and one more than a thousand loans; the next highest was less than four hundred loans). Therefore, the loans from these two respondents were removed to prevent their loan portfolios from overwhelming the other respondents in the data. The remaining respondents' collective historical loan portfolio consisted of 36,263 unique loans. At least one lender to each of these loans was a survey respondent.

From the overlaid histogram in Figure 2.2, this portfolio of loans does not perfectly mirror the distribution of the full population. However, neither is it heavily skewed toward more recent loans which could be a risk of running the survey at only one point in time. Figure 2.9 also indicates that the respondents fairly closely match

Click here to learn more about the project and to take the survey on the University of Maryland's site.
Thanks so much!
The Kiva Research Team

the full lender population in terms of when they first began using Kiva. It therefore appears that the survey respondents are a fairly good representation of Kiva lenders.

The relevant survey responses were next assigned to each of these 36,263 loans. If multiple survey respondents lent to the same loan, then the survey responses were averaged for that loan (approximately 6.5% of these loans were invested in by more than one respondent).

Two categorical variables were then created for each loan. The first leverages the individual Likert scale responses regarding the importance of economic ability and personal need. *High need* and *high ability* are defined as having above average need and ability scores, respectively. This average value is calculated from the full completed survey respondent pool, as opposed to the loan pool or only respondents that were matched to loans. Each loan falls into one of the four combinations of these variables: high-high, high-low, low-high, and low-low.

For the second variable, *loan category*, each loan was assigned to one of three categories: need, ability, or mixed. I do this by leveraging the survey question that forced a preference between need and ability (see Figure 2.6). If a respondent subsequently answered that they always or mostly held that preference, then the loan is assigned to that category. If the respondent replied that they did not always hold the preference, then it is assigned to a "mixed" category. If two lenders shared a loan in their portfolios, but had different answers to the preference question, it was also assigned to the mixed category.

2.4.3 Outcome variables

The main outcome variables are the lender preferences measured in the survey. Analyses of their distributions will provide the primary insight into the configuration of market preferences. The impact of these preferences on borrowers is measured by comparing these surveyed preferences with the characteristics of the loans actually made by survey respondents.

The primary borrower variable is the amount of time required for a successful loan to be fully funded. This is calculated as the time between when a loan was posted on the website for funding and the time the loan was fully funded. The average funded loan required 143 hours to reach the requested amount, with a median of 31 hours. Figure 2.10 plots this variable across the history of the platform. The value has been steadily increasing which supports the interpretation that the supply has increased slightly faster than demand. The prior tables (Tables 2.5, 2.6, and 2.7) also include average times required to fulfill loan requests by categories, and it is clear that the speed at which loans are funded varies significantly depending on the attributes of the borrower.

2.5 Results

2.5.1 Lender preferences

The main survey results in Figure 2.5 indicate the majority of respondents believed both ability and need to be independently important. The average score on the 1–9 scale for economic ability was 6.6 and for personal need was 7.4. The high preferences for each of these categories indicate that motives do parallel the broader market identity. Figure 2.6 shows that one of the two categories was typically more important than the other to most respondents, indicating an ideographic distribution of motives: 35% always or mostly preferred economic ability, 42% always or mostly preferred personal need, and 23% did not have a consistent preference between the two.

These preferences also appear correlated with respondent demographics. Tables 2.9 and 2.10 detail the gender and geographic differences between respondents with preferences for different categories of respondents. Tests of statistical significance between the categories were performed with either pairwise comparisons using Tukey's method for continuous variables (e.g., fund time) or pairwise comparisons of proportions with Holm corrections for binary variables (e.g., gender). The percentage of female respondents was significantly higher for need than ability (63% versus 53%). This difference was largest between high ability/low need respondents (48% female) and low ability/high need respondents (65% female). A preference for higher ability borrowers appears more common in the United States than in other countries. For example, only 52% of the low ability/high need respondents were from the United States, compared to 62% of the high ability/low need category and 66% of the high ability/high need. However this geographic distinction was not statistically significant for the ability, need, and mixed categories.

The above statistics are also tabulated in Table 2.11 for the subsample of respondents that were matched to lending data. Two additional statistics can be calculated on this sample: the number of loans made and the average date that a lender joined Kiva. These values do not appear to significantly vary by category, as the average join date is very similar and the number of loans made is not statistically distinguishable.

2.5.2 The impact of lender preferences on borrowers

Table 2.12 summarizes the characteristics of the borrowers in each of the categories. “Mixed” is funded slower than need and ability and are larger loans on average. The percentage of female borrowers is slightly higher for need (73%) than ability (71%) and mixed (69%)—compared to a population average of 71%.

To test the loan performance hypotheses, I leverage the independent ability and need ratings in conjunction with the time required for a loan to be funded. Table 2.13 presents this two-by-two using the separate scores, and shows that loans rated both high on ability and high on need were funded the fastest (requiring 88% of average time of a low/low loan). Low/low was the slowest, with low/high and high/low in between. These results support hypotheses 1 and 2 which predicted that loans that demonstrate more need and ability would be funded faster.

To test Hypothesis 3—whether these performance effects dissipate as the market matures—I plot the performance by category over time. Figures 2.11 and 2.12 plot this relationship. It does appear that the performance differential between categories is smaller for more recent loans, lending support to Hypothesis 3.

2.6 Discussion and conclusion

This study begins to explore a number of questions regarding the relationship between organizational identity, external stakeholders, and organizations. It does so in the context of the emerging charitable microfinance industry. The findings indicate that lenders appear to participate in the market using motives consistent with both charity and business contexts. This is important for borrowers to the extent that it influences their funding performance.

This research contributes to the hybrid-identity literature by beginning to untangle the potentially unique role of stakeholders in such organizations. The Kiva market represents a kind of "bridging institutional entrepreneurship" (Tracey et al., 2011), where the market is a novel combination of two separate forms. This study therefore provides evidence for the micro-foundation of such markets, and the methodology may apply to other cases of novel institutions.

It also contributes to the emerging research on prosocial lending (Allison et al., 2013, 2015; Burtch et al., 2014; Galak et al., 2011; Moss et al., 2015). As the broader crowdfunding industry continues to develop it is likely that new forms of yet-to-be-imagined platforms will be created. This research may help provide insight into what that process might look like by providing individual-level behavioral analysis of why people participate.

There are a number of limitations to the study. First, it does not measure organizational identity change. Therefore, any conclusions about how stakeholders may influence organizational identity over the long run cannot be empirically explored.

Second, the survey may suffer from retrospective bias. The survey was worded to avoid this, but it is nevertheless possible that lenders were unable to accurately recount their historical motives for lending. Third, the Kiva context may generalize well to settings where the relationship between the organization and the external stakeholders is comprised of discrete interactions (e.g., consumer products, other investing contexts). However, other relationships between external stakeholders and organizations may be significantly more complex. Therefore, the frameworks presented in this paper may serve as a starting point for thinking about future research in such contexts.

Finally, traditional streams of management research such as the Resource-based View (Barney, 1991; Dierickx and Cool, 1989; Wernerfelt, 1984) attempt to define critical firm attributes, but if investors evaluating these attributes have heterogeneous motives, then it can say little about the performance implications across settings. Firms that most closely match investor preferences should perform well in capital acquisition. This may also reshape some theorizing in the categories literature. For example, any "illegitimacy discount" or legitimacy premium exists only to the extent that the audience being studied has a preference for specific categories. As this study highlights, heterogeneity in underlying motives can indeed influence performance in some markets.

A number of recommendations can potentially be made to practitioners based on the study's findings. Organizations that have hybrid identities need to consider how the stakeholders with which they interact view the organization. In the case of a financial market like Kiva, the success of borrowers can depend on understanding this relationship. Managers of hybrid-identity organizations might be well served to note not only how their internal units contribute to their organization's identity, but also the nature of the relationships that their organization maintain with external stakeholders. As theorized, there may be strategic implications for the firm depending on these configurations.

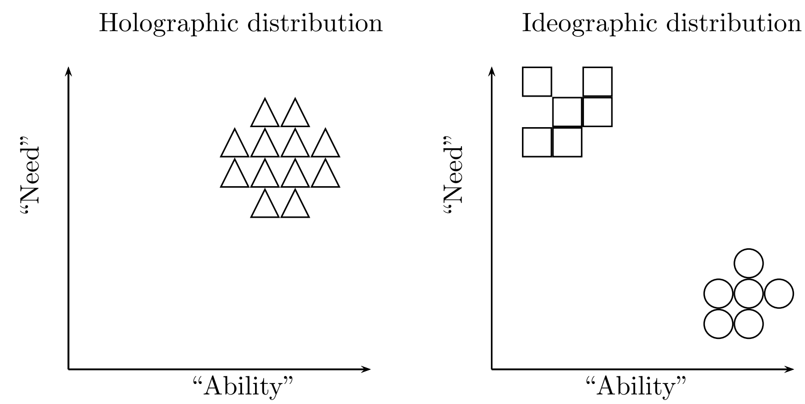


Figure 2.1: The two potential forms of lender preferences: holographic and ideographic structures of duality. Left: holographic distribution of lender portfolios where lenders all prefer a mixed category. Right: ideographic distribution where subsets of lenders have heterogeneous preferences.

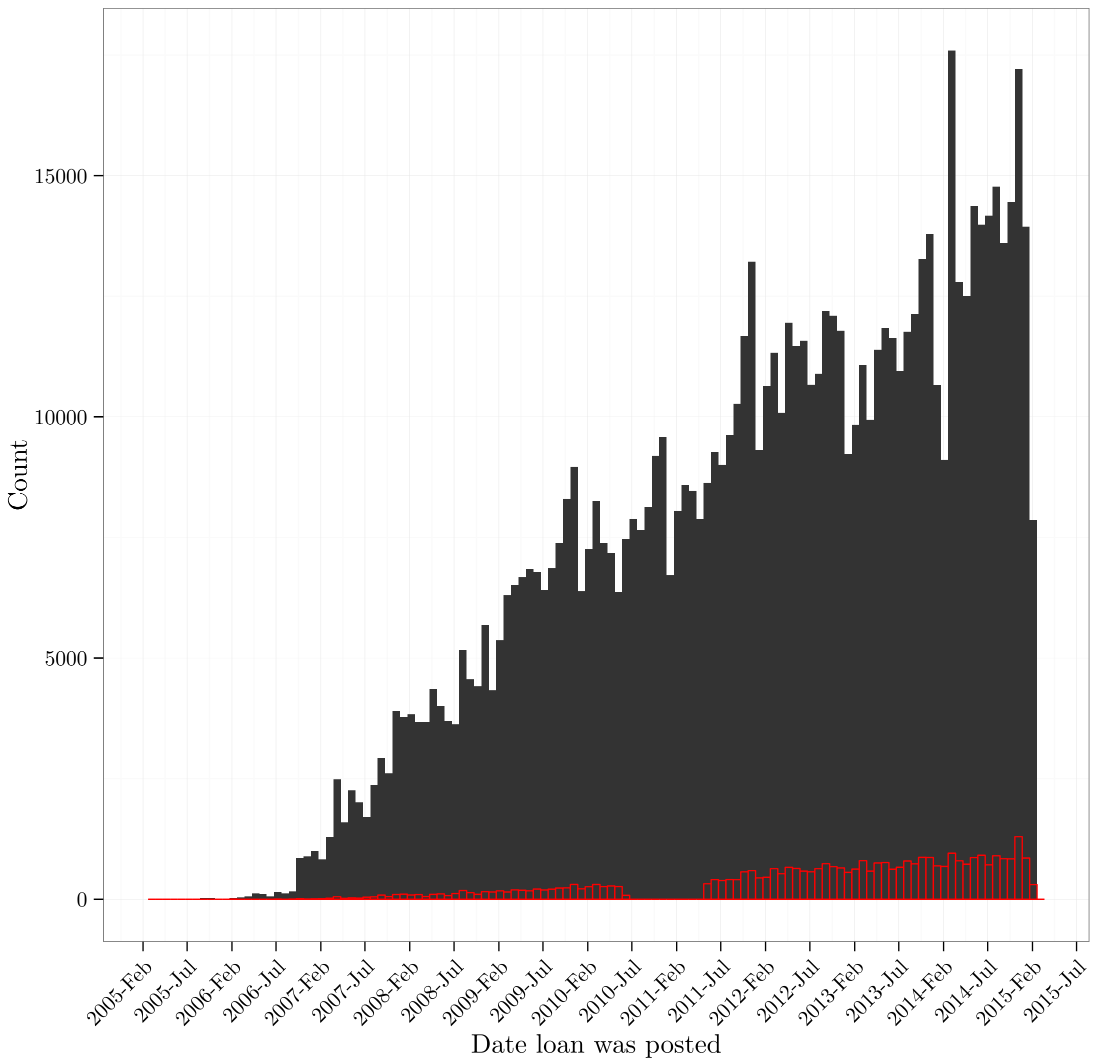


Figure 2.2: Number of loans posted on the Kiva platform by month. Separate histogram of survey respondent portfolio loans overlaid in red.

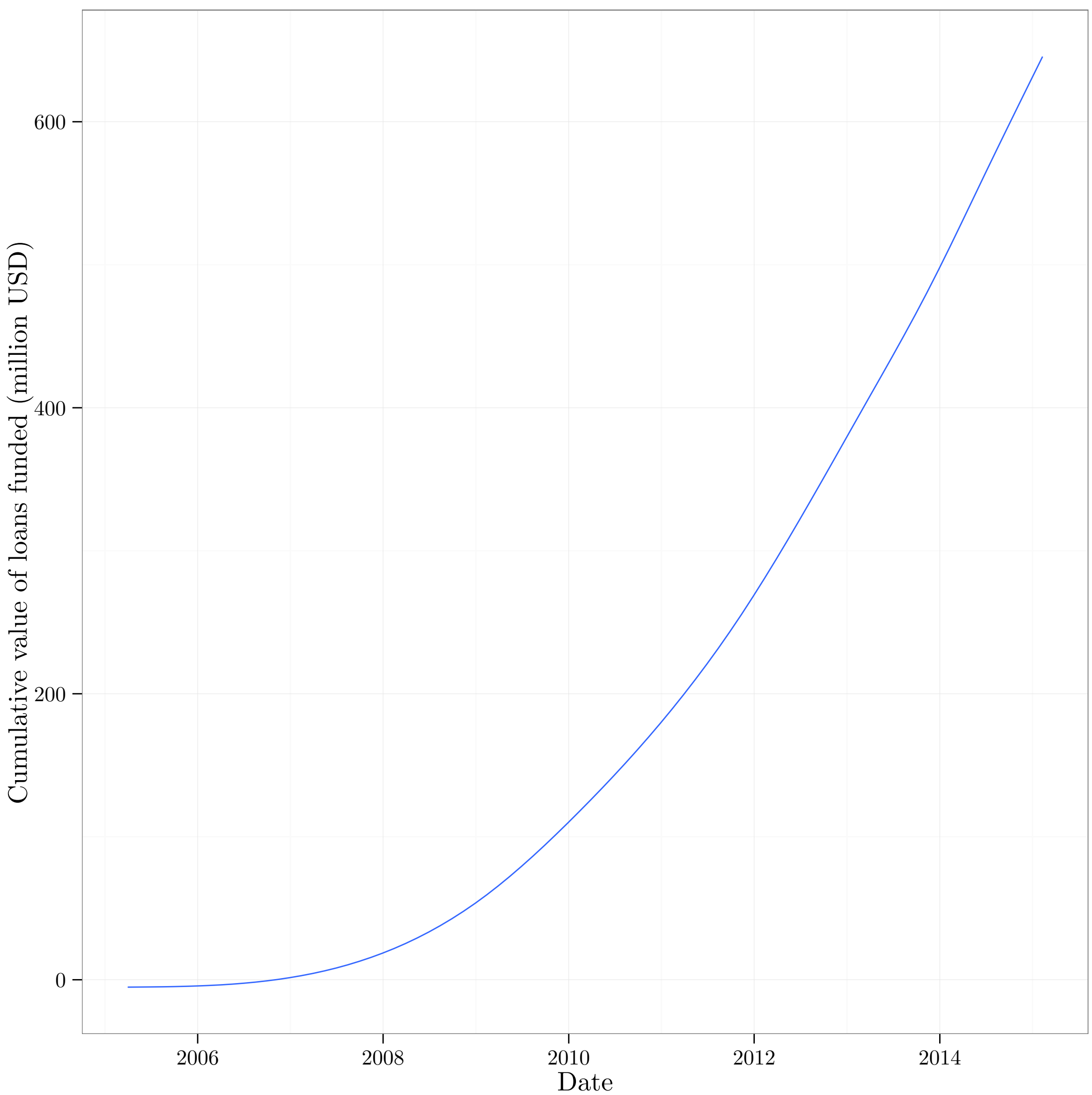


Figure 2.3: Growth of loan volume on the platform in USD.

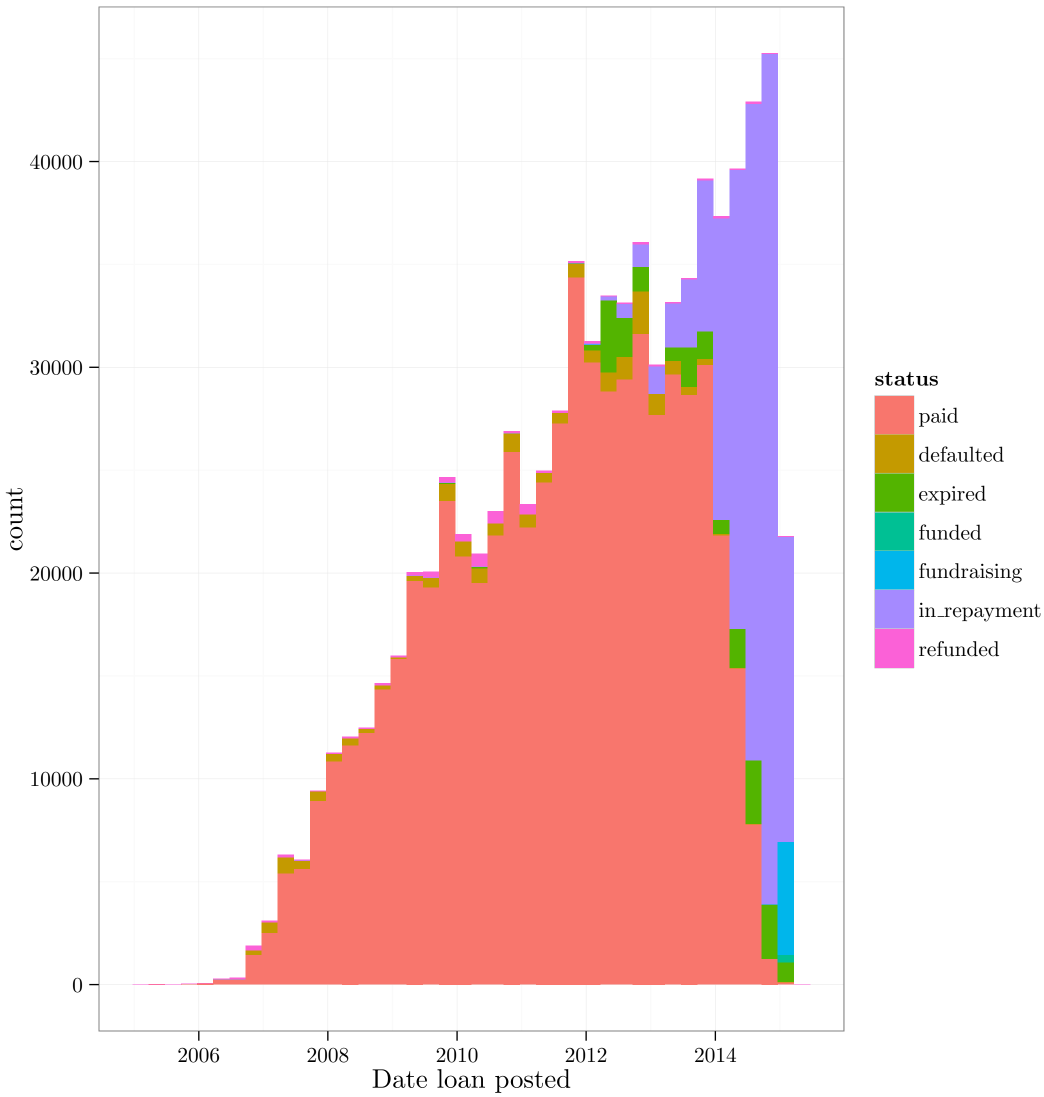


Figure 2.4: Stacked bar histogram of the status of every loan on Kiva over time. Binwidth equals one quarter of a year.

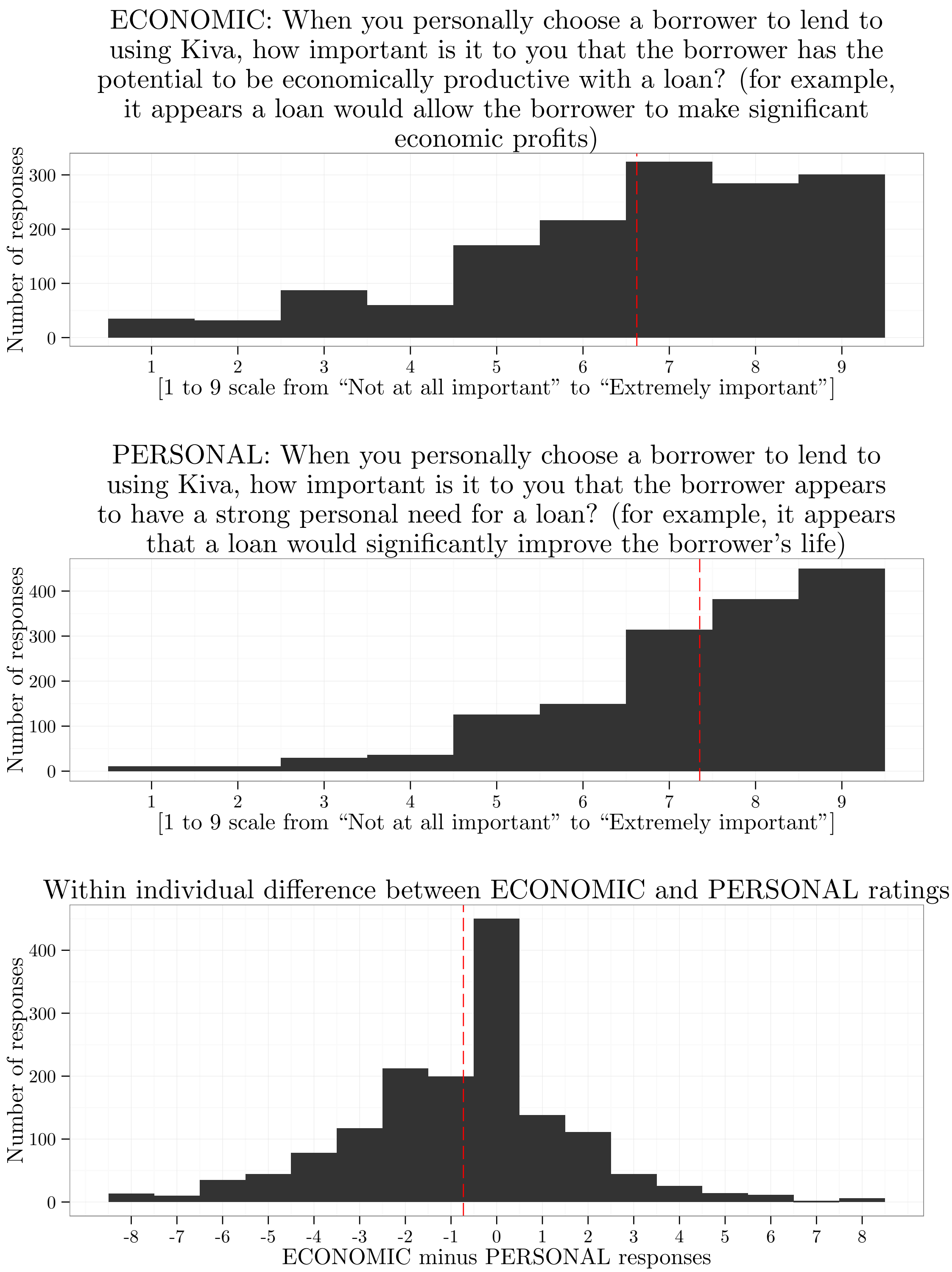


Figure 2.5: Survey responses regarding preferences for borrower economic productivity and personal need. Dashed vertical lines are the average responses. Includes data from all 1,509 completed responses.

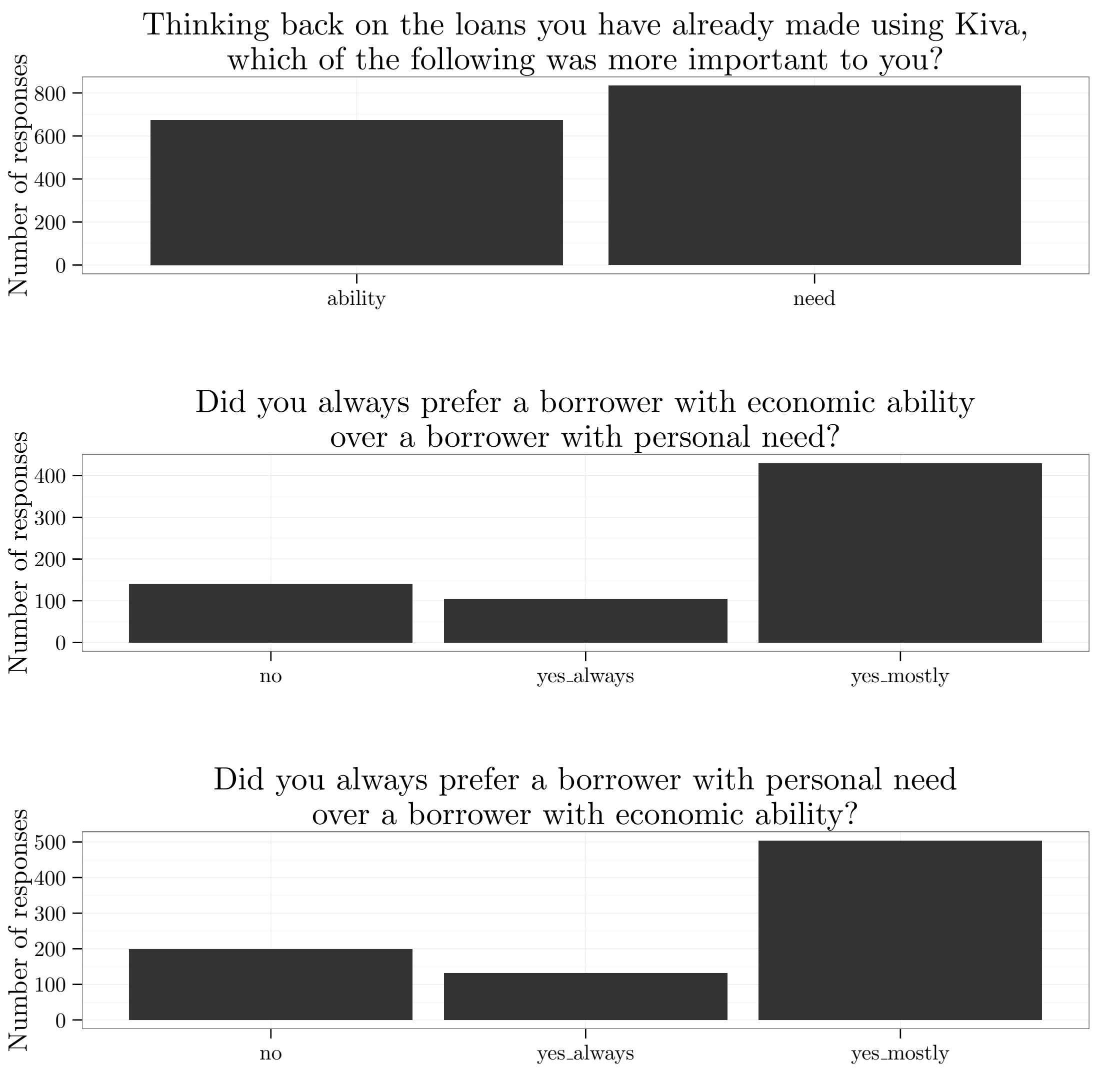


Figure 2.6: Survey responses regarding individual loan portfolio diversification preferences. Depending on the answer to the top question, the respondent was asked the appropriate followup about either need or ability. A followup prompt was requested if they answered no to these: "If no, please explain how your decision varied across loans." Includes data from all 1,509 completed responses.

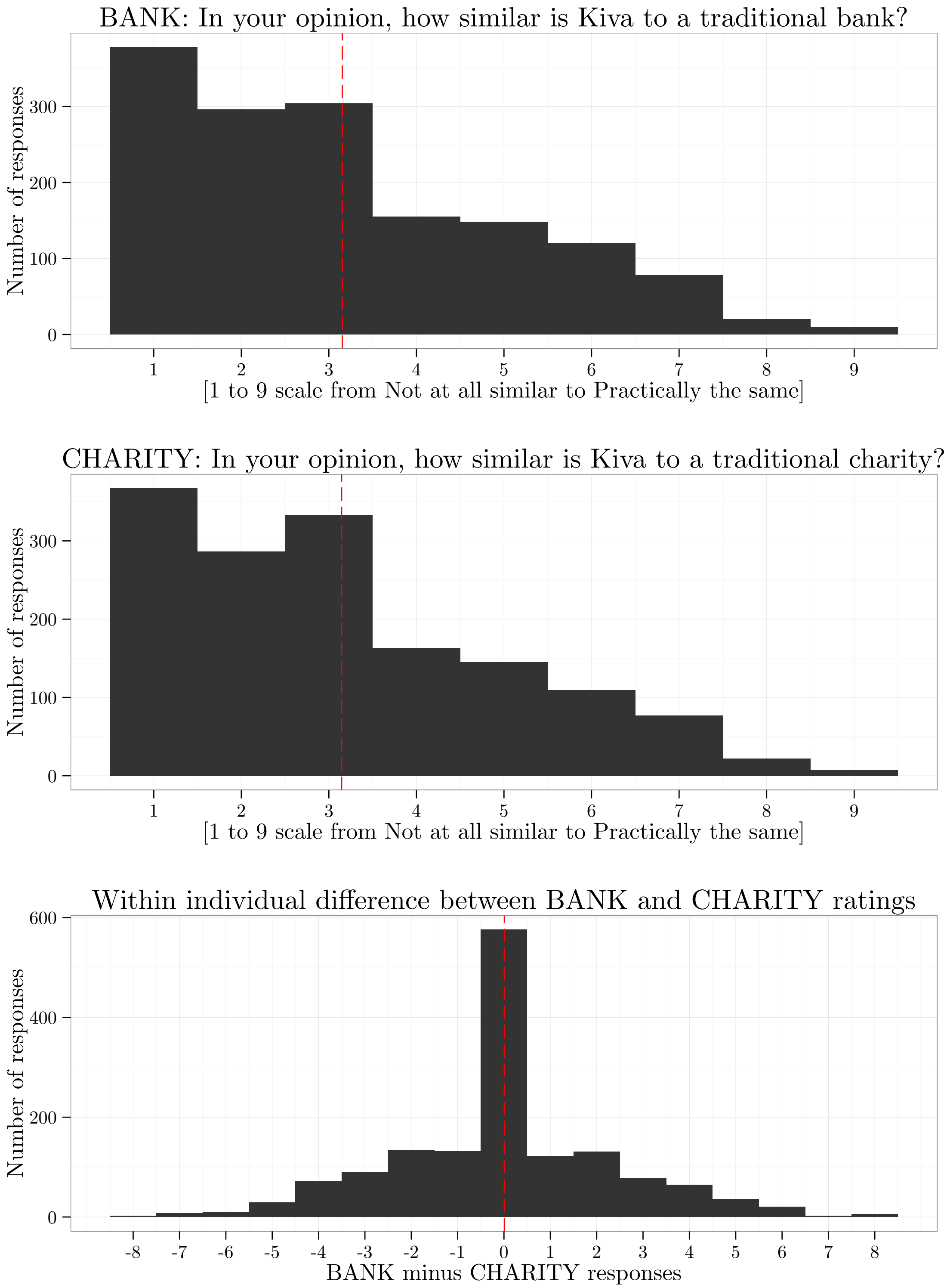


Figure 2.7: Survey responses regarding perceived similarity of the platform to a bank and to a charity. Dashed vertical lines are the average responses. Includes data from all 1,509 completed responses.

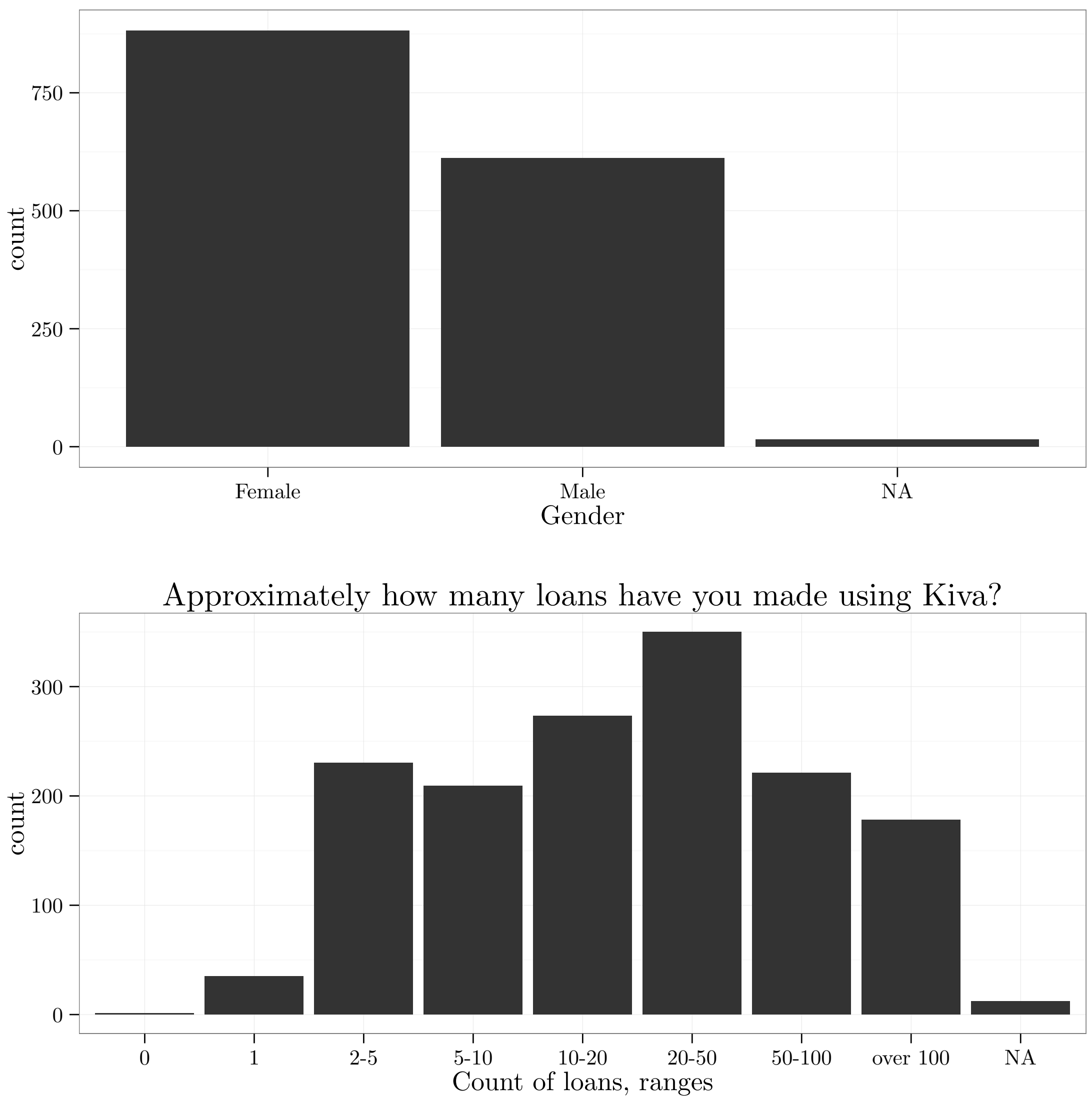
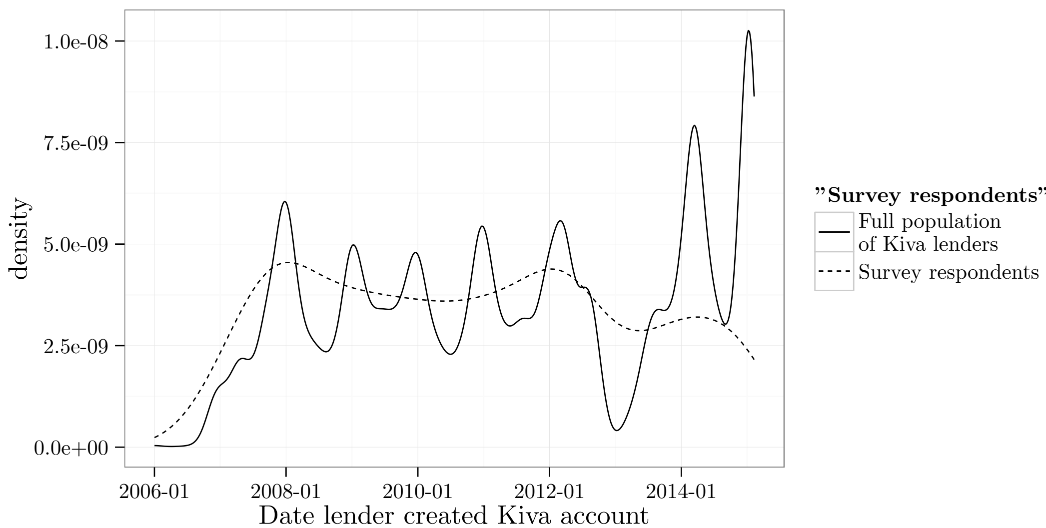


Figure 2.8: Self-reported survey respondent demographics. Includes data from all 1,509 completed responses.



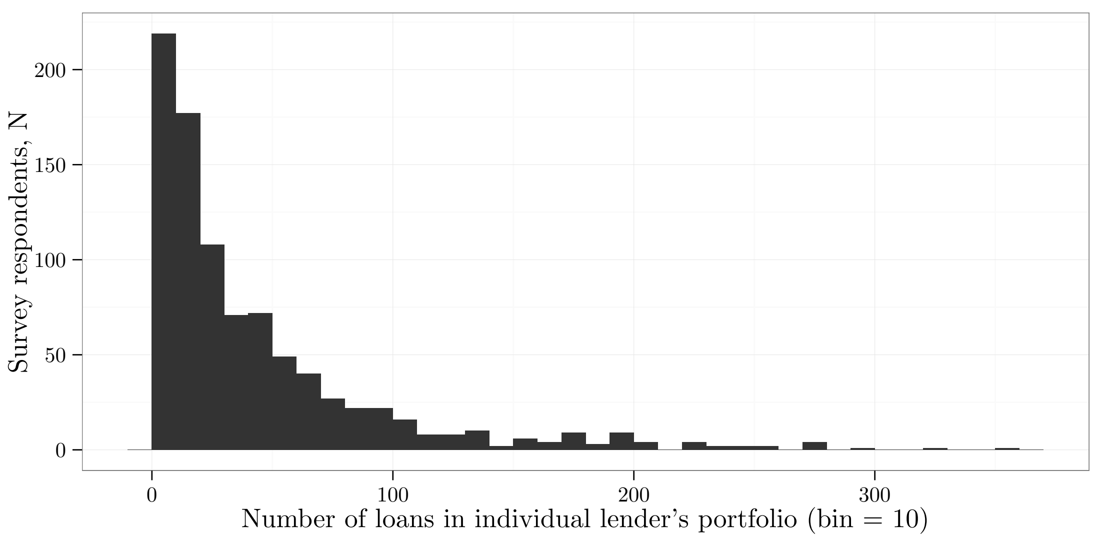


Figure 2.9: Descriptive statistics of the 909 survey respondents that could be matched to loan data.

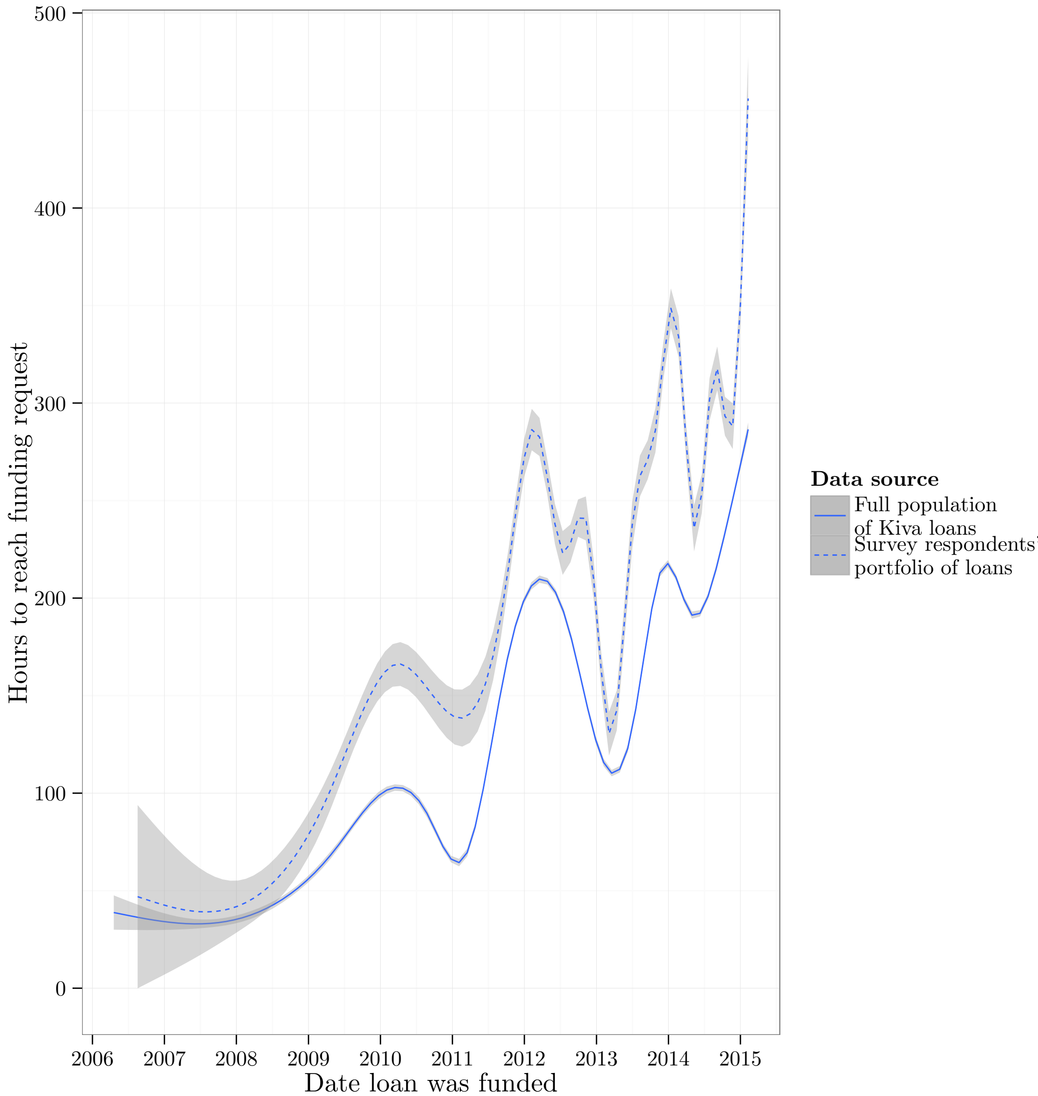


Figure 2.10: Average time (hours) required for a loan to be fully funded.

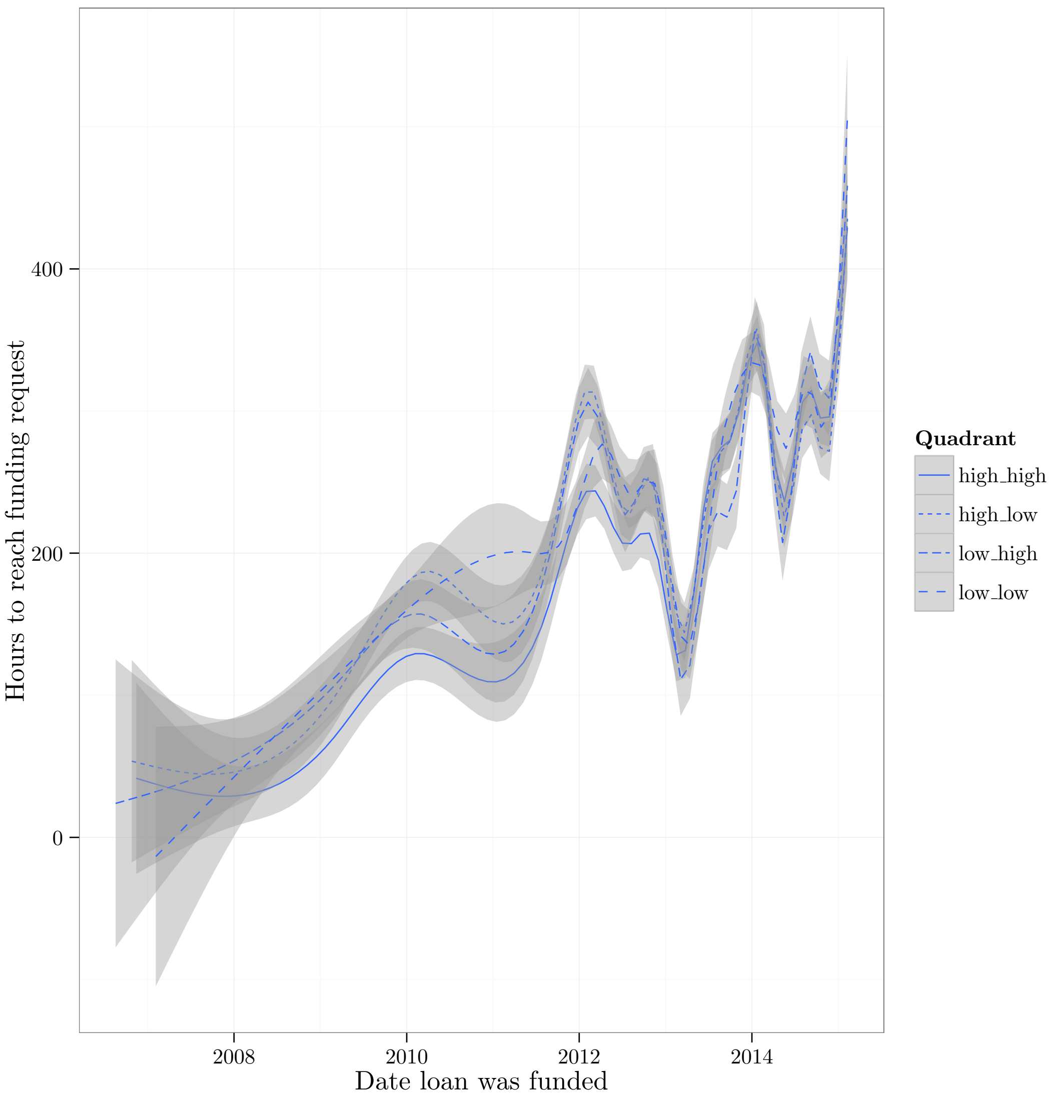


Figure 2.11: Changes over time in loan category performance for loans in survey respondents' portfolios. The performance appears to converge as the platform matures. Quadrant names represent: economic ability, personal need.

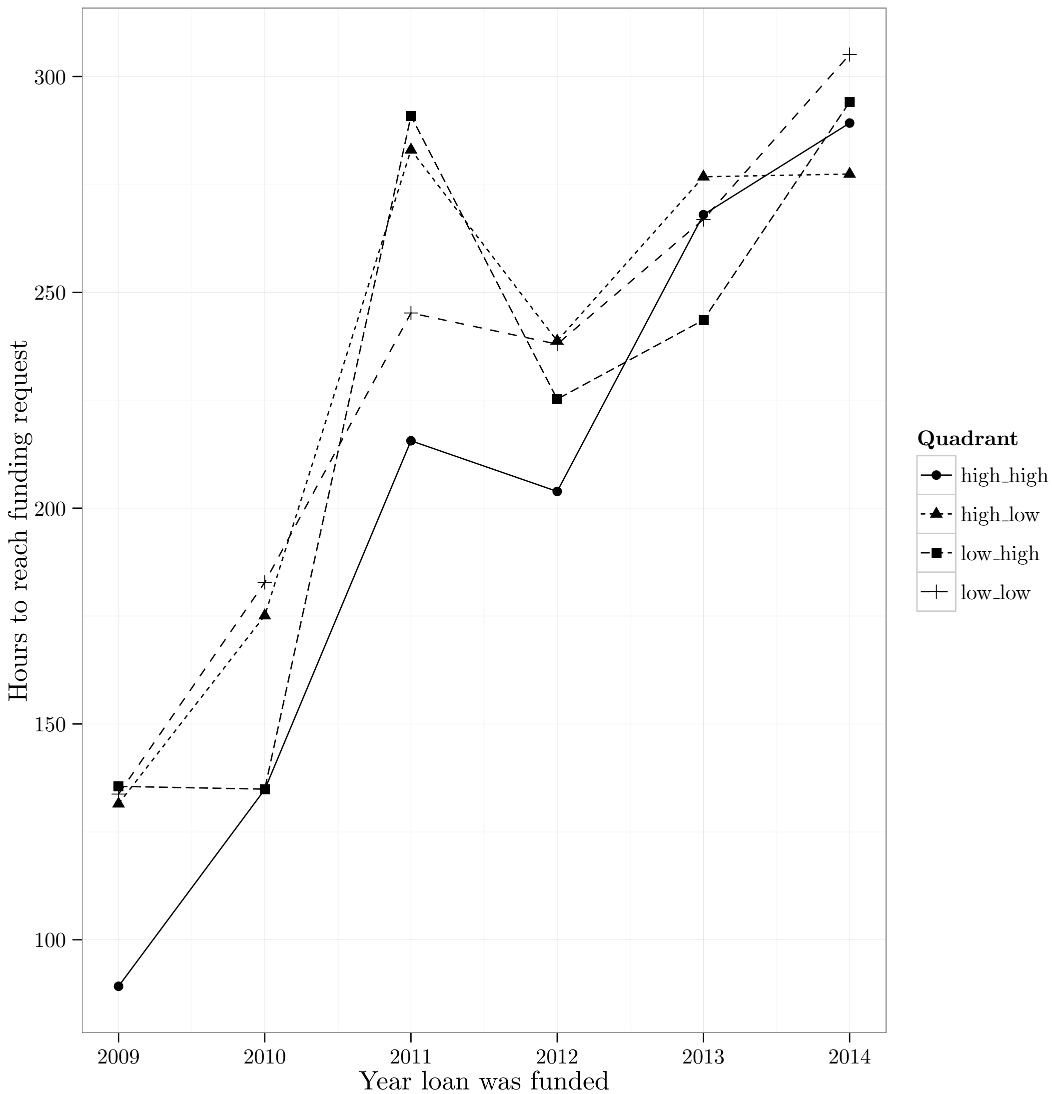


Figure 2.12: Aggregated changes over time in loan category performance for loans in survey respondents' portfolios. Aggregated to year level for clarity. Quadrant names represent: economic ability, personal need.

Table 2.1: Organizational implications of the potential forms of duality at the levels of organizational units and external stakeholders.

	Organizational units	
External stakeholders	Ideographic	Holographic
Holographic	Potential for internal tension because stakeholder changes may favor the identity of one organizational unit over the other.	No tension, very stable. Easy to sync organizational identity to changes in stakeholder preferences.
Ideographic	High tension and organizational instability. The natural tendency is for the organization to split and individually serve each stakeholder group.	Organization at risk from stakeholder tension. Organization may have difficulty serving multiple stakeholders simultaneously.

Table 2.2: Depiction of the four proposed organization-stakeholder configurations. Top rows: organizational units. Bottom rows: external stakeholders.

Holographic-ideographic configuration:

<table>
<tr><td colspan="2">Hybrid org</td></tr>
<tr><td>Stakeholder A</td><td>Stakeholder B</td></tr>
</table>

Holographic-holographic configuration:

<table>
<tr><td>Hybrid org</td></tr>
<tr><td>Hybrid stakeholders</td></tr>
</table>

Ideographic-holographic configuration:

<table>
<tr><td>Unit A</td><td>Unit B</td></tr>
<tr><td colspan="2">Hybrid stakeholders</td></tr>
</table>

Ideographic-ideographic configuration:

<table>
<tr><td>Unit A</td><td>Unit B</td></tr>
<tr><td>Stakeholder A</td><td>Stakeholder B</td></tr>
</table>

Table 2.3: Hypothesized time required to meet funding request given a loan's levels of perceived personal need and economic ability.

		"Ability" Low	"Ability" High
"Need"	High	Medium	Fastest
"Need"	Low	Slowest	Medium

Table 2.4: Additional borrower descriptive statistics for the full population of loans

	mean
Avg. loan request	841.00
Avg. repayment term (months)	12.82
% women	74.37
% group loans	13.88
Avg. number of borrowers in group loans	7.97
Avg fund time (hours)	143.45

Table 2.5: Distribution of all 15 loan sector categories along with the number of sub-activities per sector. Data represents every loan request on Kiva.

	Sector	Count	Sub-categories	Most popular activity	Second most popular activity
1	Food	205616	20	Food Production/Sales	Grocery Store
2	Agriculture	187455	12	Farming	Agriculture
3	Retail	182893	33	General Store	Retail
4	Services	62526	31	Services	Sewing
5	Clothing	53817	4	Clothing Sales	Used Clothing
6	Housing	33200	2	Personal Housing Expenses	Property
7	Transportation	26127	4	Motorcycle Transport	Taxi
8	Education	18609	3	Higher education costs	Primary/secondary school costs
9	Arts	16130	9	Crafts	Weaving
10	Personal Use	14004	7	Personal Purchases	Home Appliances
11	Construction	13822	8	Construction	Construction Supplies
12	Manufacturing	10894	5	Manufacturing	Furniture Making
13	Health	7265	6	Pharmacy	Health
14	Wholesale	1603	2	Goods Distribution	Wholesale
15	Entertainment	1369	3	Entertainment	Games

Table 2.6: The 25 most prevalent of the 149 loan activity categories. Data represents every loan request on Kiva.

	Activity	Sector	Count	Avg fund time (h)
1	General Store	Retail	68373	162.5
2	Farming	Agriculture	67568	129.1
3	Retail	Retail	51521	181.2
4	Clothing Sales	Clothing	40478	182.3
5	Food Production/Sales	Food	40376	109.0
6	Agriculture	Agriculture	37569	154.6
7	Personal Housing Expenses	Housing	31101	274.9
8	Grocery Store	Food	28214	161.9
9	Fruits & Vegetables	Food	22820	108.6
10	Food Market	Food	21555	100.9
11	Pigs	Agriculture	19579	81.4
12	Fish Selling	Food	15596	95.9
13	Animal Sales	Agriculture	14287	160.3
14	Food Stall	Food	13249	129.7
15	Livestock	Agriculture	12943	178.0
16	Higher education costs	Education	12725	89.1
17	Services	Services	12267	191.7
18	Sewing	Services	11293	97.3
19	Food	Food	11069	132.1
20	Motorcycle Transport	Transportation	10565	142.9
21	Cattle	Agriculture	10180	192.5
22	Tailoring	Services	10033	74.9
23	Beauty Salon	Services	9694	140.8
24	Poultry	Agriculture	9554	89.1
25	Dairy	Agriculture	9193	106.7

Table 2.7: The 25 most prevalent of the 91 countries from where loans are requested. Data represents every loan request on Kiva.

	Country	Count	% total	Avg fund time (h)
1	Philippines	140840	16.9	94.0
2	Kenya	72240	8.6	129.0
3	Peru	69903	8.4	106.5
4	Cambodia	46774	5.6	96.9
5	Nicaragua	35096	4.2	214.6
6	El Salvador	33851	4.1	301.5
7	Uganda	31095	3.7	153.2
8	Tajikistan	26017	3.1	253.1
9	Ecuador	20989	2.5	157.6
10	Pakistan	19784	2.4	149.8
11	Bolivia	18432	2.2	229.3
12	Ghana	18091	2.2	52.0
13	Mexico	14711	1.8	81.2
14	Colombia	14655	1.8	313.8
15	Paraguay	13887	1.7	108.0
16	Vietnam	12309	1.5	96.0
17	Nigeria	11997	1.4	75.4
18	Sierra Leone	11669	1.4	124.7
19	Tanzania	11600	1.4	74.9
20	Rwanda	11237	1.3	104.0
21	Togo	11117	1.3	124.2
22	Honduras	10746	1.3	205.7
23	Lebanon	10458	1.3	294.5
24	Samoa	10032	1.2	120.7
25	Senegal	9902	1.2	157.9

Table 2.8: The 5 most prevalent of the 51 home countries of the total 1509 survey respondents. The “matched” column is the number of respondents that could be matched to loans.

	Survey respondent location	N	Matched
1	United States of America	909	544
2	Canada	173	98
3	Australia	127	78
4	United Kingdom of Great Britain and Northern Ireland	67	44
5	Germany	39	27

Table 2.9: Descriptive statistics for respondent demographic questions, by category. The only significant differences are between the percentage of women in the "ability" and "need" categories and the "ability" and "mixed" categories.

category	N	% female	% USA
ability	534	53.0	60.9
need	635	62.8	58.4
mixed	340	61.4	64.1

Table 2.10: Respondent demographic statistics for each of the low-high ability/need quadrants. For gender, high ability/low need has statistically fewer women than every other category. For country, low/high has statistically fewer respondents in the USA than both of the high ability quadrants, and low/low has statistically fewer than high/high.

Comparative pref for ability, need	N	% female	% USA
High, low	379	47.7	62.1
High, high	530	63.0	66.7
Low, low	298	60.2	56.6
Low, high	302	65.0	51.8

Table 2.11: Descriptive statistics for respondent demographic questions by category, for respondents matched with loan data. Need and ability are significantly different in the number of female borrowers. The other values are not statistically different.

category	N	% female	% USA	# loans made	Mean join date
ability	312	51.8	60.2	50.1	2010-10-23
need	392	62.1	57.8	42.6	2010-10-23
mixed	205	58.0	64.7	50.5	2011-01-10

Table 2.12: Summary statistics for loans in each of the three categories based on survey responses from Figure 2.6. “Mixed” indicates no consistent preference or conflicting preferences if two respondents lent to the same loan but disagreed. Comparisons of the differences between each mean fund time are significant at a 95% confidence level. Mixed also have significantly larger loan requests. The differences in gender and group loans percentages are also significant.

	need	ability	mixed
N	13624	12800	9839
Avg fund time (hours)	238	225	248
Loan request amount	1523	1566	1989
% borrower female	73	71	69
% group loan	22	24	27

Table 2.13: Average funding times for loans in each of the four quadrants. Pairwise comparisons of each mean value are significant at a 95% confidence level with the exception of the difference between "high ability, low need" and each of the low ability quadrants.

		"Ability": Low	"Ability": High
"Need"	High	234	221
	Low	250	242

Chapter 3: Social and Financial Motives in Peer-to-peer Lending: an Online Experiment

3.1 Introduction

Online crowdfunding platforms represent a promising context for controlled field experiments. This is because the interaction between those seeking funds and those providing funds is mediated by third-parties: the crowdfunding platforms. Various permutations of this technology can be randomly tested against each other at a relatively low cost. To my knowledge, however, few academic studies have employed the method. One exception is Burtch et al. (2015), which collaborated with a reward-based platform to experimentally manipulate the presentation of privacy options and measure changes in the propensity and size of funding decisions.

This study presents another such experiment. The general framework presented in the introduction to this dissertation highlights the multitude of potential motives that funders can have for participating in crowdfunding. Motives are important because they determine the conditions under which a funder—in this case a lender—is willing to provide money. For example, a lender with high *external* motives might lend even if there is no expectation of financial returns. In this experiment, the *structure* of the platform remains fixed, but the platform's *identity* is experimentally manipulated. The ratio of proposed *internal* and *external* returns is varied between the treatment and control groups. I measure whether this treatment influences the propensity of subjects to create an account on the platform. While the scope of this particular experiment is limited, the potential for randomized experimentation in crowdfunding contexts is significant.

The setting is a small for-profit Chinese peer-to-peer lending website in mid-2013. At the time, the industry in China was fairly new and there were many small startups (Li, 2013). Given this newness, it was unclear whether lenders treated the service as a pure substitute for other forms of investment or if they would be responsive to the potential social benefits of the activity. The first chapter of this dissertation provides additional context on the industry.

Like all crowdfunding platforms, new user registration was an important step in increasing the amount of funds lent through the platform. Lender registration involved filling out an online form including name, email address, and phone number, and creating a user name and password. Registration represented a necessary first step in making actual loans. After each registration, a company representative would call the new registrant to provide additional information and answer questions.

Two channels existed for new user registration: a form linked from the homepage (a "natural" registration) and special registration-only pages designed for incoming web traffic from online advertisements. These advertisements were placed on a range of other websites using Internet advertising networks and were specifically targeted to lenders (conversely, potential borrowers could register through other means). When a user clicked on an ad they were directed to a special "landing page" on the company's website, where they were presented with information on the platform's features and benefits and the ability to register as a user. A subset of these landing-page visitors actually successfully completed registration with the company. The difference between the total number of people that viewed the page and the number that successfully registered—typically called the "conversion rate"—represents an important metric that was tracked by the marketing manager and followed by the CEO. Similar metrics are used in many online services and strategies to optimize them are widely discussed by practitioners (e.g., Harwood and Harwood, 2009).

3.2 Treatment design

The experimental treatment takes the form of a manipulation to the landing page. Two separate web pages were designed for the test. Care was taken to limit the differences between each of the web pages to only the elements important to the treatment, while at the same time ensuring that each page looked natural. In practice, this involved manipulating one line of text. When a user arrived at the website they were randomly presented with one of the two page designs, and their subsequent decision of whether to complete the registration process was logged. A third-party tool was used to assist page design, randomization, and tracking of user decisions.[26]

To test this, a single sentence of the standard landing page material was al-

[26] Visual Website Optimizer: `visualwebsiteoptimizer.com`

tered to highlight the social benefit to borrowers. Figure 3.1 shows each version of page and highlights the differences. In the default "financial" version (Figure 3.1a), the sentence of interest read: "Use [the platform] to invest your spare funds and increase your personal wealth." In the "social" version (Figure 3.1b) it read: "Use [the platform] to invest your spare funds and help others realize their dreams." Everything else on the two pages was identical.[27] Because the financial elements were already highlighted, emphasizing the social element was hypothesized to increase the total expected utility of using the platform. If users do derive non-financial benefit in addition to financial, then highlighting the social element of peer-to-peer lending should increase registration compared to only highlighting the financial element.

If true, this could substantially alter the strategy of a platform. Implications can range from marketing strategy to the definition of industry competitors. For example, should focus be placed on the collection and display of borrower personal information, or can borrowers be anonymized and packaged into investment products? Understanding why funders derive benefit from their activity is therefore an important question.

3.3 Results

For internal auditing purposes at the company, each ad network already had its own landing-page URL, and the number of incoming visitors from each ad network fluctuated significantly given the amount of budget allocated to it during any

[27]It is worth noting that the financial benefit was highlighted on other portions of the page, therefore the "social" version does not represent the absence of content related to financial benefits. However, the opposite is true.

particular time period. Further, the registration rates between networks varied significantly. The cause of this variance was attributed to the type of consumers to which different ad networks had access. Experimental data from ad networks with very low volume or conversion rates of less than one percent are not reported (randomization occurred at the ad network level, so this does not impact validity).

Because the treatment is temporally and spatially discrete, issues related to self-selection into and out of the experimental groups are greatly minimized. Therefore, a simple comparison of means is sufficient to understand the causal effect of the treatment. The "social" condition was shown to 1,482 visitors and resulted in 341 registrations (23.0%). The "financial" condition was shown to 1,539 visitors and resulted in 349 registrations (22.7%). The difference in registration rates was therefore not significant between the treatment and control (z score of 0.22). Potential lenders did not appear to respond to the potential social benefits.

The lack of results can be interpreted in a number of ways. The simplest and most straightforward explanation is that the difference between the treatment and control stimuli was too marginal to register with subjects. The design of this type of experiment faces a trade off: if the difference between the treatment and control version is too great, it can be difficult to isolate the theoretical mechanism that causes the response. If it is too small, however, it may have no impact. The later is possible in this case. Second, it is possible that the landing page itself was less salient to potential lenders than a previous exposure to the company. Participants may have had prior knowledge of the industry, for example, and all participants reached the landing page via the advertising networks discussed above. It is possible that participants responded strongly to these advertisements and less strongly to the content of the landing page. If participants already knew how they wanted to behave before the treatment, then this experiment may have had little opportunity to impact their behavior.[28]

It is also possible that lenders simply did not care about non-financial benefits and other sections of the page were sufficient to convince them of the financial benefits. This appears consistent with the ex-ante behavior of the firm, which had not previously highlighted social elements. If there were a significant social element then one might expect a manager to have already incorporated this into their promotion of the platform. Finally, it is even possible that lenders who derive social benefit do so at the exclusion of financial benefits, meaning the extra financial information canceled out the social benefits.

3.4 Conclusion

I presented a simple experiment conducted on an online peer-to-peer lending website. Additional social benefits of lending were proposed to prospective lenders in the treatment condition. There was no difference between the treatment and control groups in the propensity of participants to register for the platform. This null result can be interpreted in a number of ways, ranging from issues of treatment design

[28]The content of the advertisements took the form of brief “banner ads” and focused on the financial investment aspect of the platform. These ads were not experimentally manipulated, so all participants would have seen the same content before being assigned to the treatment or control group. The null result is consistent with a scenario where participants decided their level of interest based on these ads and not the landing page content. However, if this were the case it is unclear why a higher conversion rate is not observed for both treatment and control groups, as those that did not wish to register would not have clicked on the ad and would not have been part of the sample.

to more substantial theoretical interpretations. Hopefully this simple example will lead to more work in this area, as crowdfunding is a phenomena that is particularly suited to field experimentation.

(a) Financial

(b) Social

Figure 3.1: The treatment and control versions of the lender registration page. The only difference between the two is the sentence circled in red in the center of the page. Financial: "Use [the platform] to invest your spare funds and increase your personal wealth." Social: "Use [the platform] to invest your spare funds and help others realize their dreams."
Other sections of both pages highlight the financial benefit, including just below and to the right of the treatment text: "High annual interest rates of 12–15%, 100% principle and interest guarantee, fund security."

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