12-2020

How do monetary incentives influence prosocial fundraising? An empirical investigation of matching subsidies on crowdfunding

Zhiyuan GAO

How Do Monetary Incentives Influence Prosocial Fundraising? An Empirical Investigation of Matching Subsidies on Crowdfunding

GAO ZHIYUAN

SINGAPORE MANAGEMENT UNIVERSITY
2020

How Do Monetary Incentives Influence Prosocial Fundraising? An Empirical Investigation of Matching Subsidies on Crowdfunding

GAO Zhiyuan

Submitted to School of Information Systems in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Information Systems

Dissertation Committee:

Zhiling Guo (Chair)

Associate Professor of Information Systems

Singapore Management University

Dan Ma

Associate Professor of Information Systems

Singapore Management University

Qian Tang

Assistant Professor of Information Systems

Singapore Management University

TAN Chuan Hoo

Associate Professor of Information Systems

National University of Singapore

Singapore Management University

2020

I hereby declare that this Ph.D. dissertation is my original work
and it has been written by me in its entirety.
I have duly acknowledged all the sources of information
which have been used in this dissertation.

This Ph.D. dissertation has also not been submitted for any degree
in any university previously.

GAO Zhiyuan
11 December 2020

How Do Monetary Incentives Influence Prosocial Fundraising? An Empirical Investigation of Matching Subsidies on Crowdfunding

GAO Zhiyuan

Abstract

Monetary incentives, such as matching subsidies, are widely used in traditional fundraising and crowdfunding platforms to boost funding activities and improve funding outcomes. However, its effectiveness on prosocial fundraising is still unclear from both theoretical (Bénabou and Tirole, 2006; Frey, 1997; Meier, 2007a) and empirical studies (Ariely et al., 2009; Karlan and List, 2007; Rondeau and List, 2008). This dissertation aims to examine the effectiveness of matching subsidies on prosocial fundraising in the crowdfunding context. Specifically, I study how the presence of matching subsidies affects overall funding outcomes and funding dynamics in the online prosocial crowdfunding environment.

The first essay utilizes a quasi-experiment on a prosocial crowdfunding platform to examine the effectiveness of matching subsidies, in which third-party institutions provide a dollar-for-dollar match of private contributions on selected campaigns, on funding outcomes, and lender behavior. Although matching subsidies offer matched loans competitive advantages over unmatched loans, we find that the total private contributions to both matched and unmatched loans increase compared to their pre-matching counterparts, suggesting a positive spillover effect on unmatched loans. However, matching subsidies lead to decreased private contributions on the platform after the matching event, showing an

intertemporal displacement effect on existing loans. Furthermore, we find matching subsidies effectively attract previously inactive lenders to contribute to matched loans, leading to a motivational crowding-out effect on active lenders to unmatched loans. These findings shed new light on the overall effectiveness of matching subsidies on the online crowdfunding platforms. These findings provide policy support to offer matching subsidies on prosocial crowdfunding websites to increase overall funding.

The second essay examines how matching subsidies affect the dynamics of prosocial crowdfunding, driven by herding behavior and payoff externalities. First, in contrast to the previous literature documenting that prior contributions may crowd out subsequent contributions in prosocial crowdfunding, we find that both herding behavior and positive payoff externalities exist, which suggests that higher cumulative contributions lead to an increase in the subsequent funding amount. Second, we identify the existence of the bystander effect, where the positive effect of prior contributions drops sharply when the campaign is close to success. Finally, we find a substitution effect between matching subsidies and prior cumulative contributions. Matching subsidies not only increase private contributions but also moderate the herding behavior and payoff externalities. Our findings shed new light on the effective strategies to boost fundraising on prosocial crowdfunding platforms.

Table of Contents

List of Figures

List of Tables

Acknowledgment

The research life at Singapore Management University is quite challenging and rewarding. I would like to express my sincere gratitude and respect to my advisor Guo Zhiling. It is fortunate for me to work with my advisor, who not only guides me in the research of Information Systems but also serves as my role model in my future career. I have learned a lot beyond research from my advisor. She is always supportive and patient in my research, providing suggestions and guidance when I need help.

I would like to thank Profs. Ma Dan, Tang Qian, and Tan Chuan Hoo for being on my committee and giving valuable advice on my work. I especially thank Prof. Tang Qian, who guides me to write interesting papers and publish them in conferences and journals. I appreciate the discussion and support from Prof. Robert J. Kauffman, Mei Lin, Youngsoo Kim, Wang Qiuhong, and my colleagues Dan Geng, Jing Ren, Jun Liu, Kustini Lim-Wave, Emmy Hoang, Deserina Sulaeman, Yuzhou hu, Yuecheng Yu, Shuohang Wang, Jianfei Yu, Bowen Xu, Yunshi Lan, Jiaqi Hong, and Jianhui Huang.

I would like to thank Prof. Fallaw Sowell and Mark Kalmet at Carnegie Mellon University, who guide me in time series research. Many thanks to the Living Analytics Research Centre at Singapore Management University and the Post-Graduate Research Program Office for funding my research and travel. I also thank Ms. Pei Huan Seow, Chew Hong Ong, Phoebe Yeo, Yong Fong Koh, Yar Ling Yeo, and Caroline Tan at SMU, and Barbara Decks at CMU for all the administrative help.

Finally, I would like to say thanks to my family members, including my parents, my wife, and my brother. I am forever grateful for their unconditional support and encouragement.

To my wife, Liu Man,

who have offered tremendous support in my life.

Chapter 1. Introduction

Prosocial fundraising, the process of gathering voluntary financial contributions from individuals, enables non-profit organizations to provide public goods and charity to individuals living in poverty. The development of information technology has dramatically transformed traditional prosocial fundraising. A new form of fundraising ─the prosocial crowdfunding on the Internet─ has received a great deal of attention in the Information Systems field (Gomber et al., 2018). As of 2017, fundraisers have received up to $410 billion in the United States, where $31 billion is collected from online fundraising (Non-profit Source 2018).

With the increasing popularity of prosocial fundraising, monetary incentives, a common strategy of offering financial rewards for prosocial behavior, have been widely used in both offline and online communities to facilitate prosocial fundraising. The effect of monetary incentives stems from the economic theory of prosocial behavior on the relative benefit and cost. The more expensive prosocial behavior is, the less it should be undertaken; the more benefit prosocial behavior brings, the more it will be undertaken (Meier 2007). Consequently, financial rewards can be provided to either reduce the relative cost or increase the benefit of prosocial behavior. In prosocial funding, there are mainly two mechanisms of monetary incentives- rebate and matching subsidy. The rebate mechanism is often implemented with a tax deduction to reduce the relative cost, while the matching subsidy mechanism is usually provided by third-party foundations to multiply the impact of private contributions. These monetary incentives increase the utility of making prosocial funding by reducing the cost of funding or increasing benefit, which affects both the funding behavior of lenders and the funding outcome of campaigns.

Nevertheless, the overall effectiveness of monetary incentives on prosocial funding is still unclear in both theoretical and empirical studies. From the theoretical perspective, *relative price theory* suggests that providing monetary incentives increases funding by reducing its cost, while the *crowding-out effect* demonstrates that monetary incentives dampen the fundraising by decreasing *intrinsic motivation* (Bénabou and Tirole 2006; Frey 1997; Meier 2007a). The empirical evidence of the effectiveness of monetary incentives on prosocial fundraising is also mixed (Ariely et a., 2009; Karlan and List, 2007; Rondeau and List, 2008).

To contribute to a clearer understanding of the effects, we use the setting of prosocial crowdfunding platforms to study how matching subsidies, as one of the most popular monetary incentives whereby third-party institutions provide a dollar-for-dollar match of the private contributions from individuals on selected campaigns, affect prosocial fundraising. We collect the transaction-level data from Kiva, one of the largest prosocial crowdfunding platforms in the world, to examine the overall and dynamic effectiveness of matching subsidies on funding behavior. Kiva enables crowds to lend to projects directly, providing alternative and supplement finance for small entrepreneurs who lack access to traditional finance. Although lenders in Kiva lend the money to fundraisers, they do not receive any interest from the loan, making Kiva a leading prosocial crowdfunding platform.

In recent years, the matching subsidy, because of its success in traditional fundraising to attract funders and boost funding, has been increasingly used by many online crowdfunding platforms, such as Kiva, Kickstarter, and Donorchoose.org. However, the ambiguity of monetary incentives' effectiveness on prosocial funding raises the concern of providing matching subsidies on selected campaigns. Prior literature in traditional fundraising has found mixed evidence of the effectiveness of matching subsidies on selected campaigns after excluding the matching grants (Karlan and List 2007; Karlan et al. 2011; Rondeau and List 2008). Additionally, matching subsidies may shift the contribution to other un-incentivized campaigns to incentive campaigns, leading to a negative spillover effect on campaigns that do not receive matching subsidies but solicit funds simultaneously (Deck and Murphy, 2019).

The literature that examines the effectiveness of matching subsidies on crowdfunding is still scarce. The crowdfunding market differs from the traditional funding market because of its easy access and great uncertainty. Without a financial intermediary, it is difficult for individual funders to determine a fundraiser's creditworthiness, reducing the funders' willingness to invest. In addition, thousands of campaigns in crowdfunding platforms solicit for funds simultaneously, making it necessary to consider the spillover effect of matching subsidies. The significant difference between crowdfunding and the traditional funding market calls for research on the overall effectiveness of matching subsidies on the new form of prosocial fundraising.

Essay 1 examines how the presence of matching subsidies affects funding activity in the prosocial crowdfunding context. In this essay, we first aggregated the transaction-level data into loan-daily panel data to analyze how matching subsidies affect loans' funding outcome. By analyzing the loan-daily panel data from Kiva, we find that matching subsidies increase the private contributions to matched projects by attracting a larger pool of funders and have positive spillover effects on unmatched projects (projects that don't receive matching subsidies) soliciting for funds simultaneously, leading to higher average contributions and the higher total private contributions from more contributors to unmatched projects. However, matching subsidies decrease the average contribution to matched campaigns and result in a negative effect when matching subsidies cease. Secondly, we use the transaction-level data to explore the underlying mechanism behind the effect of matching subsidies on funding outcomes in the transaction-level analysis. By analyzing the transaction-level data, we reveal that matching subsidies affect the funding outcomes of matched and unmatched projects by influencing funders' preferences and behavior.

Essay 1 provides evidence of the overall positive effect of matching subsidies on both incentivized campaigns and un-incentivized campaigns soliciting for funds simultaneously, which support the usage of matching subsidies on crowdfunding platforms. I am also interested in studying how the effect of matching subsidies on funding activities varies in the dynamic crowdfunding environment. On crowdfunding platforms, funders face significant risk and uncertainty due to the lack of intermediaries. Consequently, funders rely on other funders' funding behavior on the platform, such as accumulated prior contributions, the total number of prior contributors, and the percentage of goal attainment, to make funding decisions. Matching subsidies accelerate the funding activities by doubling funders' contributions, which affect the dynamics of crowdfunding.

Essay 2 examines how matching subsidies affect crowdfunding dynamics using the aggregated loan-daily level panel data. The essay focuses on herding behavior (Banerjee 1992) and payoff externalities (Ayres and Kneese, 1969; Katz and Shapiro, 1985). The herding behavior stems from the information asymmetry between funders and fundraisers, making individuals rely on *observational learning* - observing other funders' behavior to learn and make decisions. The reason is that individuals believe that other funders may have some private information on the quality of a project, which leads to herding behavior, where individuals refer to others' decisions and are more likely to fund campaigns with more other supporters. The payoff externalities in crowdfunding occur if the payoff of a funder's contribution to a campaign depends on other funders' funding behavior. Most crowdfunding platforms employ the *all-or-nothing* model, where the fundraisers receive nothing until the targeted amount is achieved. Consequently, funders can only receive the payoff from their contribution if the campaign's total funding amount contributed from other funders reach the target.

Essay 2 identifies that higher cumulative contributions and percentage of goal attainment lead to an increase in the subsequent funding amount in crowdfunding, which provides evidence of herding behavior and payoff externalities. However, the positive effect of prior contributions drops sharply when the campaign is close to success. We further find a substitution effect between matching subsidies and prior accumulative contributions. We find that matching subsidies moderate herding behavior and payoff externalities. The results in essay 2 suggest that matching subsidies are most effective in the early stage of funding, which is useful for crowdfunding platforms to design an effective promotion strategy of matching subsidies.

This dissertation provides both theoretical and managerial contributions. The dissertation contributes to the crowdfunding literature (Burtch et al., 2014; Liu et al., 2012; Sinanan, 2009) by demonstrating the positive effects of monetary incentives on prosocial lending. This dissertation extends the crowdfunding literature by showing that the monetary incentive is an effective tool to increase funding to a campaign. Previous literature focuses on studying how non-pecuniary factors such as the race of fundraisers, friendship, and social media help increase funding. This dissertation demonstrates that monetary incentives can have an overall positive effect on both incentivized campaigns and un-incentivized campaigns soliciting.

This dissertation contributes more broadly to the economics literature about monetary incentives' overall effectiveness on prosocial behavior. Extensive literature using laboratory or field experiments demonstrates that monetary incentives may crowd out prosocial behavior or lead to strong competition effect – reducing contributions to un-incentivized campaigns (Karlan and List, 2007; Karlan et al., 2011; Rondeau and List, 2008; Deck and Murphy 2019). This dissertation provides empirical evidence that monetary incentives positively affect both incentivized campaigns and their competitors in prosocial lending, suggesting the overall positive effect of monetary incentives. Additionally, compared with most prior studies that focus on campaign level analysis, the transaction level analysis in this dissertation reveals the underlying mechanism that drives the prosocial funding outcomes.

Finally, in addition to the overall effectiveness of monetary incentives on prosocial funding, this dissertation demonstrates that the effect of monetary incentives decays with the increasing percentage of goal attainment and accumulative contribution. Better understanding the crowd-funding dynamics provides new managerial insights about the most effective strategies of monetary incentives provision

Chapter 2. An Examination of the Effectiveness of Matching Subsidies on Prosocial Crowdfunding

2.1 Introduction

Online crowdfunding and microfinance have become an increasingly important tool to help small entrepreneurs get alternative access to capital, alleviate poverty, and improve social welfare in recent years (Gomper 2018). The global transaction value of crowdfunding has reached nearly $305 billion in 2019 (Cambridge Centre for Alternative Finance2020). Despite the popularity of crowdfunding platforms, many campaigns still have difficulty in getting sufficient funding (Zhao et al., 2017). To address this issue, many platforms such as Kiva, Kickstarter, and Donorchoose.org provide monetary incentives to attract funders and increase their contributions. The most popular monetary incentive is the matching subsidies, whereby third-party institutions provide a dollar-for-dollar match of the private contributions from individual funders on selected campaigns. Based on a recent survey of more than 300 of the world's largest companies, at least 92% of companies had offered at least one matching subsidy, and about 285.6 million funds were contributed through matching subsidies, accounting for 12% of total corporate cash contributions to nonprofits (CECP Coalition 2018).

Existing literature has provided competing theories on the effectiveness of matching subsidies on matched projects. On the one hand, matching subsidies make private contributions (contributions of funders excluding the matching grants) highly rewarding. Compared with campaigns without matching subsidies, individual lenders can double their impact on fundraising of matched campaigns with the same amount of contribution or achieve the same impact by half price. This is also known as the *relative price effect,* where the volume and intensity of activity increase when it is essentially cheaper to pursue (Andreoni 2006). Additionally, providing matching subsidies to a campaign may signal high quality to funders, increasing the contributions to the campaign. On the other hand, matching subsidies have a *crowding-out effect* on private contributions by reducing donors' intrinsic motivation (Andreoni, 1990; Frey and Oberholzer-Gee, 1997). Given the opposing theoretical perspectives, Karlan and List (2007) and Rondeau and List (2008) found that matching subsidies increase the private contribution, while Karlan et al. (2011) found no significant effect.

Additionally, matching subsidies may affect the funding of unmatched projects both during the matching subsidy event and after the event is over. There are two competing theories to predict the effect of matching subsidies on unmatched competing projects. The first theory states that private contributions may shift from unmatched campaigns to matched ones during the matching program, resulting in a spatial displacement effect. In contrast, an alternative theory argues for a positive effect of matching subsidies on unmatched loans (Charness and Holder, 2018; Deck and Murphy, 2019; Eckel and Grossman, 2017; Karlan and List, 2007; Huck et al., 2015; Meier, 2007b; Scharf et al., 2017). The rationale is that matching subsidies bring positive spillover effects for unmatched loans soliciting for funds simultaneously, resulting in an increased number of contributing lenders and total private contributions to unmatched loans during the event compared to the pre-event levels. When matching subsidies cease, the in-creased private contributions during the matching event may reduce funding after the event, leading to an intertemporal displacement effect (Meier 2007b; Scharf et al. 2017).

These competing theories in the literature reveal several research gaps. First, the crowding-out effect and displacement effect have raised concerns about the overall effectiveness of the matching subsidies on fundraising. Second, the matching subsidy, an effective monetary incentive to improve funding outcomes, has not received much attention in the crowdfunding literature. Most of the existing literature focuses on traditional prosocial funding, such as donations and charitable giving. The online crowdfunding platforms differ from traditional fundraising in several ways: the scale of the matching subsidies is much larger than traditional fundraising; the duration of the program is significantly shortened from the traditional several weeks to several days; information is more transparent online than in traditional channels. The large-scale and high-intensity nature of the subsidies may lead to different impacts on funding outcomes and lending behavior on the crowdfunding platforms. The available information online also makes it possible to trace the lenders' lending history and lending patterns. This provides us with both rich data and a unique opportunity to uncover the underlying driving forces that explain the observed outcomes, enhancing our understanding of the overall effectiveness of matching subsidies on the crowdfunding platforms.

In this essay, we utilize a quasi-experiment of an exogenous event on a prosocial crowdfunding platform to examine the effects of matching subsidies on funding outcomes and lender behavior. During the event, some loans are selected to receive matching subsidies based on loan characteristics. The matched loans are selected according to certain characteristics, instead of random assignment, which makes the event become a quasi-experiment (Cook and Campbell 1979). Specifically, we address the following research questions: How do matching subsidies affect private contributions of matched and unmatched loans during the event, respectively? How do matching subsidies affect private contributions on the platform after the event? What are the effects of matching subsidies on lenders' behavior at the individual level?

To answer these research questions, we leverage the "flash match" event (Kiva 2018) launched by Kiva, one of the largest prosocial crowdfunding platforms across the world, on September 12, 2018. During the "flash match" event, Kiva partnered with some generous anonymous lenders or third party foundation, such as Google, Women and Girls Empowered Foundation, and Bank of America to provide one-for-one matching funds to thousands of selected loans on Kiva. Additionally, Kiva and volunteer funders share the information of these matched loans in social media and online communities, such as Twitter, Facebook, YouTube, and Kiva Forum, to attract potential lenders[1]. We collected two weeks of transaction-level data from September 3, 2018, to September 16, 2018, that covers the "flash match" event, as well as information on all loans and lenders. Using the comprehensive data set and the quasi-experiment, we explore the effectiveness of matching subsidies on both funding outcomes of loans and lenders' funding behavior.

At the loan level, we find that matching subsidies have a positive effect on matched loans. Both the number of contributing lenders and total private contribution to matched loans increase, consistent with previous findings (Karlan and List, 2007; Huck et al., 2015; Eckel and Grossman, 2017; Charness and Holder, 2018). We further find matching subsidies bring *positive spillover* effects for unmatched loans soliciting for funds simultaneously, resulting in an increased number of contributing lenders and total private contribution to unmatched loans during the event compared to the pre-event levels. This contrasts

[1] The "flash match" is mainly a selected campaign marketing effort by volunteer funders to market matched loans.

with the spatial displacement effect (Scharf et al., 2017). In addition, for active loans on the platform after the event, we find evidence of *intertemporal displacement*. When the "flash match" event is over, open loans on the platform are, on average, less likely to receive any funding.

Given the ubiquitous presence of matching subsidies in crowdfunding, it is important to understand how the lenders' behavior drives the funding outcomes of loans. At the individual lender level, we find that matching subsidies make lenders more likely to lend, leading to a higher number of lenders contributing to loans. In particular, matched loans attract more previously inactive lenders. However, the average contribution per lender of matched loans decreases compared with their pre-matching counterparts, supporting the *crowding-out effect* of matching subsidies on individual lenders' average contribution per matched loan. At the same time, unmatched loans attract more active lenders with a higher average contribution per lender. In contrast to inactive lenders who are mainly attracted to matched loans due to one-for-one matching, active lenders are less influenced by the matching subsidies, showing different patterns of behavior change by the matching subsidies. All these findings provide new insights into the effectiveness of matching subsidies on the online prosocial crowdfunding platforms.

The rest of this chapter is organized as follows. Section 2.2 provides a brief review of related literature. Section 2.3 describes the study context and data. Section 2.4 provides a loan-level analysis of our empirical model. Section 2.5 presents the transaction-level analysis and results. Finally, Section 2.6 concludes the essay.

2.2. Literature Review

2.2.1 Crowdfunding and Online Microfinance

With the rapid development of information technology, many online crowdfunding platforms emerge as alternative finance channels (Galak 2011). Crowdfunding platforms enable small entrepreneurs who lack access to traditional financing tools to get funding from a large pool of individual investors. Agrawal et al. (2014) classify crowdfunding platforms as four types: equity-based, reward-based, loan-based, and donation-based. Our research setting is based on an online *microfinance* (Morduch 1999) platform, which is the combination of loan-based crowdfunding and donation-based crowdfunding, where lenders lend money to small entrepreneurs without interest. Contributors on the microfinance platforms may get their principals back within certain periods but earn zero interest from lending, making their contributions prosocial lending.

Crowdfunding and online microfinance platforms have become increasingly popular, but many campaigns on these platforms still suffer from a lack of support from funders (Massolution, 2015). The reason is that funders and fundraisers have asymmetric information on the quality of a campaign, which hinders funders from supporting the campaign.

To address the challenge, previous studies have investigated a number of campaign factors that influence the funding outcomes, including personal narrative and social entrepreneurship of borrowers (Sinanan 2009), provision points (Burtch et al. 2018), crisis shocks (Yang et al. 2016), race of borrowers (Younkin and Kuppuswamy 2017), and friendship networks of borrowers (Lin et al. 2013). Furthermore, from the lenders' perspective, herding behavior (Zhang and Liu 2012), cultural difference and geographic difference (Burtch 2014), the home bias between funders and fundraisers (Lin and Viswanathan 2016), the social network structure of advocating individuals (Hong et al. 2018), design of team communities (Chen et al. 2017), as well as characteristics of lenders (Liu et al. 2012) would influence their campaign preferences.

Although these prior findings provide important insights into the platform design to improve funding outcomes, the literature about how matching subsidies affect crowdfunding and online microfinance is relatively scarce. The following subsection will introduce the relevant work on the effect of matching subsidies on traditional donation and crowdfunding.

2.2.2 Matching Subsidies

Matching subsidies have been widely provided in traditional fundraising and prosocial crowdfunding, but the effectiveness of matching subsidies is still unclear. From the theory of relative price, making a one-for-one matching is equivalent to reducing the price of donation by half, which can significantly increase the response rate for donation solicitation (Chen et al. 2006; Frey 2017; Meier 2007a; Meier 2007b; Karlan and List 2007). Except for the price effect, donors will view matching subsidy as a signal of quality, which will also increase the response rate and donation amount (Heutel 2014). On the other hand, matching subsidies may impose a negative effect of crowding out the donation of private donors after excluding the matching grants (Andreoni 1990). From the *motivational crowding-out* theory, monetary incentives, including matching subsidies, have detrimental effects on intrinsic motivation, which may decrease the individual contribution (Bénabou and Tirole 2006; Frey 1997; Meier 2007a).

There is mixed empirical evidence about the effects of matching subsidies on private contributions to matched loans. Using field experiments, most of the previous studies found matching subsidies increase the private contribution of individual funders (Eckel and Grossman 2003; Eckel and Grossman 2008; Eckel and Crossman 2017; Gneezy et al. 2014; Huck et al. 2015; Karlan and List 2007), although Karlan et al. (2011) found that matching subsidies have no significant effect on the private contribution. Rondeau and List (2008) found matching subsidies significantly decrease private contributions.

The effects of matching subsidies on unmatched loans are also unclear. Scharf et al. (2017) and Deck and Murphy (2019) identified *spatial displacement* between matched campaigns and unmatched campaigns soliciting for funds simultaneously. They found that matching subsidies would exacerbate competition, leading to a shift of donation from unmatched projects to matched campaigns, increasing the contribution to matched campaigns, and decreasing the contribution amount of unmatched campaigns. Using lab experiments, Krieg and Samek (2017) found slightly positive spillover effects of matching subsidies on unmatched campaigns. Based on the daily aggregated data from an online microfinance platform Donorchoose.org, Meer (2017) found empirical evidence that matching subsidies increased giving to eligible requests without crowding out giving to similar others, either contemporaneously or overtime. However, Meier (2007b) found *intertemporal displacement* – matching subsidies increase the contribution amount in the short run, but the contribution amount decreases after the program.

To understand how funders' behavior is affected by the matching subsidies program, Eckel and Grossman (2008) found that continuing funders (i.e., funders who make regular contributions) decrease their contribution to matched campaigns, while lapsed (i.e., funders who contribute occasionally) and prospect funders (i.e., funders who have not contributed) not responsive to the matching subsidies. Meer (2017) also found that matching subsidies induce funders to consider other similar campaigns, generating new giving to unmatched loans. Different from these prior studies, we find that matching subsidies attract previously inactive lenders to contribute to matched loans, and active lenders tend to shift their contribution to unmatched loans. These findings provide new insights into the overall effectiveness of matching subsidies on crowdfunding platforms.

2.3. Research Context and Data Description

2.3.1 Research Context

Our research context is Kiva.org, the world's largest online peer-to-peer lending platform. It has raised $1.37 billion in funds for more than 3.4 million borrowers from 1.8 million lenders since its inception in October 2005. It is an online microfinance (Morduch 1999) platform for the poor, unbanked, and underserved. Most loans on Kiva are donation-based with a 0% interest rate for the borrowers who, by and large, are located in developing countries. Kiva collaborates with local microfinance institutions (MFI) to screen potential borrowers and select eligible ones. Local MFI then assists eligible borrowers in creating their profiles, including the borrower's biography, loan amount, repayment schedule, and loan purpose (Burtch et al. 2014). After the profiles are posted on Kiva, potential lenders around the world can provide funds in $25 increments. The fundraising for these loans follows the "all or nothing" model, where the borrowers receive nothing until the targeted loan amount is achieved. That is, the full loan amount must be raised within the fundraising period in order for funds to be sent to the borrowers; otherwise, the loan will expire, and any funds raised will be returned to the lenders.

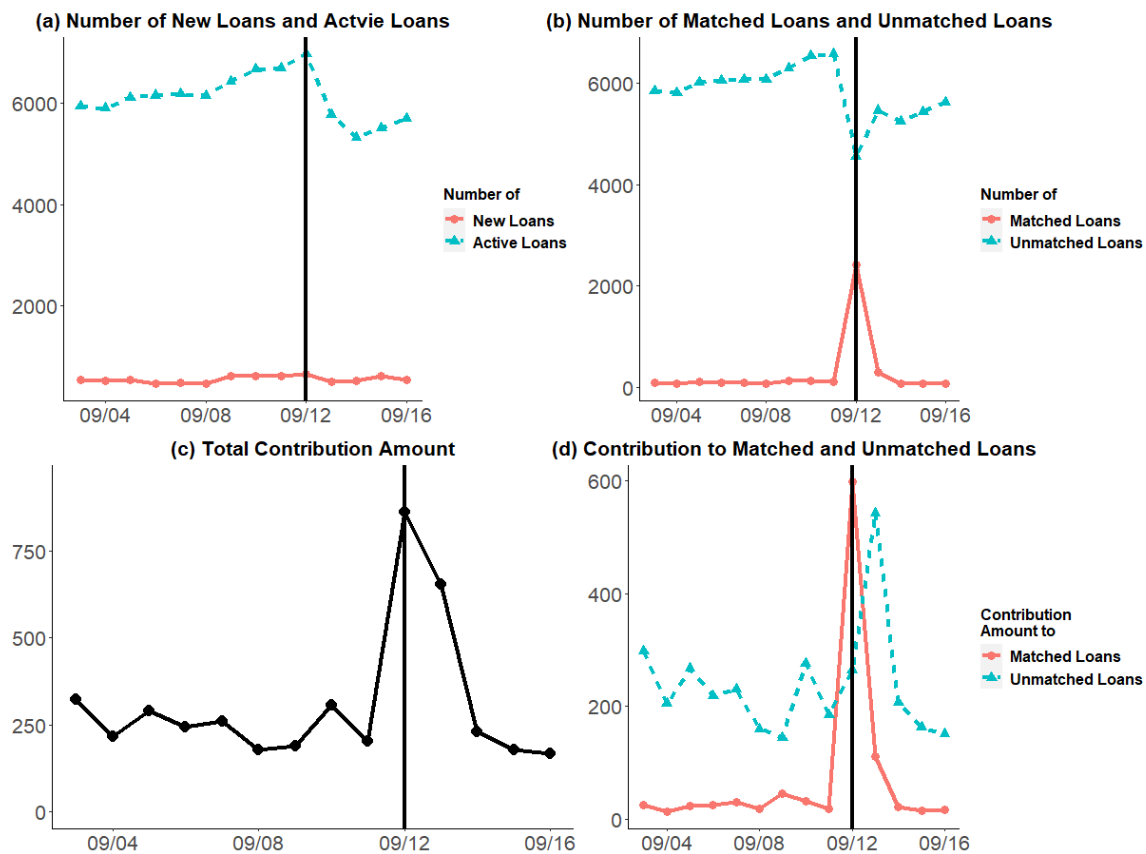
To help more small enterprises to achieve their funding goals, Kiva partners with some anonymous supporter or third-party foundations, such as Google, Women, and Girls Empowered Foundation, and Bank of America, to provide matching subsidies for selected loans. Under this program, the matching partner defines the criteria about which loans should be matched, and the qualified loans will then be displayed with an x2 badge and the partner's name. If any lender makes contributions to matched loans, the matching partners will lend the same amount to these loans. With these programs, approximately 94.7% of loans get fully funded on Kiva. This success rate is much higher than that of other prosocial crowdfunding platforms such as Donorchoose.org (68.3%), Kickstarter (43%), and Indiegogo (less than 10%) (Massolution 2015; Meer 2017). From time to time, Kiva organizes *Match Day* events, whereby a large number of loans are matched on one day, to attract more lenders and contribution.

2.3.2 Quasi-Experiment Setting and Data Collection

Our study utilizes one of the "flash match" events on Kiva as a quasi-experiment to examine the impacts of such programs on funding outcomes of both matched and unmatched loans. On 12 September 2018, Kiva launched the "flash match" event. Through this event, one million dollars matching grants were provided for approximately two-thousand loans. Figure 2.1 presents how daily aggregated lending activities change before and after the event.

As shown in Figure 2.1a, the number of new loans does not change on the match day compared to the days before the event, whereas the number of active loans decreases significantly after the match day, suggesting that more loans are fully funded because of the event. According to Figure 2.1b, the number of matched loans on the match day is more than 2,000 and dropped to almost zero on the following day. Many matched loans are funded fully on the matched day, and the rest are no longer matched after the event day. More than 4000 active loans on the event day are unmatched. The total daily contribution amount from lenders increases considerably on the match day and the day after, as shown in Figure 2.1c. Figure 2.1d shows a jump in total contribution to matched loans on the event day and an increase in contribution to unmatched loans on the day after the event.

Figure 2.1. Daily Aggregated Loan and Lender Level Data



Note : (a) Total number of new loans and active loans; (b) Total number of active matched and unmatched loans; figure (c) Total contribution amount to all active loans; (d) Total contribution amount to all active matched and unmatched loans. The x-axis represents the dates. The black vertical line indicates the match day (September 12, 2018)

To examine the influence of the "flash match" event on September 12, I collect granular transaction-level data on funding activities on Kiva from September 3 to 16, 2018[2].

[2] We only select data from 3 September 2018 to 16 September 2018. The matching subsidy is one of the most popular monetary incentives on Kiva because the third-party institutions who provide the match fund

The data contains detailed information for each lending activity, such as the lender, the borrower, the lending amount, and the timestamp. Our final dataset consists of 49,031 lending actions from September 3-16, 2018, taken by 24,404 lenders on 6,246 loans. Among the 6,246 loans, 1994 are matched loans. These 1994 loans are matched by 15 third-party institutions or lenders, who have different specific matching preferences. The preference of different matching funds providers is presented in Table A1.

At the loan level, we also have data on the funding outcomes of these sample loans, such as total funds raised, time taken to be fully funded, number of lenders, average contribution amount per lender, etc. At the lender level, each observation includes the lender's contribution amount and the number of loans funded. This unique dataset allows us to analyze the impacts of the event from the perspectives of both loan outcome and lender activities.

2.3.3 Key Variables and Summary Statistics

Key variables are defined in Table 2.1, and summary statistics are shown in Table 2.2. Now_t, $Post1_t$, and $Post2_t$ are time dummies for September 12 (the event day), September 13, and September 14 to 16[3]. There are 1,994 matched loans in the *Now* period, 204 of which remain matched in the *Post1* period. In the *Post2* period, all loans are unmatched. Using the three time dummies, we split the quasi-experiment period into four phases: before the event, during the event, one day after the event, and two days after the event. This

---

can receive tax deductions from the matching behavior. Consequently, Kiva also launches a matching event on 17 September 2018. Hence, we select the transactions before 17 September 2018 to eliminate the influence of other matching events.

[3] In this research, we explore the effect of matching subsidies on matched loans and unmatched loans. Consequently, we split the time window into four time periods according to the number of active matched loans each day. Before the event, there are almost no matched loans. After the event day, the number of active matched loans on September 12 and September 13 is significantly higher than that on subsequent days. Therefore, we decide to split the time window after the event day into three time periods: September 12 (the event day), September 13, and September 14 to 16.

allows us to study the temporary treatment effects of the matching subsidies over time. As some matched loans became unmatched after the event day, we can use this reversal to study the effect of treatment removal, in addition to the treatment effect.

Table 2.1: Definition of Key Variables

TYPE	VARIABLES	DEFINITION
Time Dummies	*Now*	Binary indicator for the event day, September 12, 2018
	Post1	Binary indicator for the day after the event, September 13, 2018
	Post2	Binary indicator for the period of September 14-16, 2018
Loan-Daily Level	$LendArrRate_{jt}$	Number of lenders who lent to loan j on day t
	$AvgContr_{jt}$	Average contribution amount per lender for loan j on day t.
	$FundAmount_{jt}$	Funding amount loan j received on day t
	$Match_{jt}$	1 if loan j is matched on day t, and 0 otherwise
	$Competition_{jt}$	Number of other active loans for loan j on day t
	$AcuumAmount_{jt}$	Funding amount that loan j had raised at the beginning of day t
Transaction Level	$Lend_{ij}$	1 if lender i lend to loan j, and 0 otherwise
	$LendAmount_{ij}$	Lending amount from lender i to loan j
	$Match_{ij}$	1 if loan j is matched when lender i lend to it
	$Active_{i}$	1 for active lender i, and 0 otherwise
	$AccuAmount_{ij}$	Funding amount that loan j had raised before lender i lend to loan j
	$Competition_{ij}$	Number of other active loans when lender i lend to loan j

To examine how the loan level funding outcomes are affected by matching subsidies, we first construct a loan-daily level panel data. The loans posted after the event or fully funded before the event were dropped to avoid the systematic difference between these loans and the loans active both before and after the event (Geva et al. 2019). Three variables measuring the funding outcomes are our dependent variables. First, $LendArrRate_{jt}$ is used to examine whether matching subsidies attract more lenders for a loan. Second, we are interested in how matching subsidies affect $AveContr_{jt}$, the average contribution per lender, which is also referred to as the *intensive margin* (Epperson and Reif 2017). Finally, $FundAmount_{jt}$, the product of $LendArrRate_{jt}$ and $AveContr_{jt}$, is used to measure the overall effect on the total funding amount. The main independent variable is $Match_{jt}$, the treatment indicator for matched loans. $Competition_{jt}$ and $AccumAmount_{jt}$ are used to control the impacts of competing loans (Ly and Mason 2012) and lenders' herding behavior (Zhang and

Liu 2012; Burtch et al. 2013).

We are also interested in exploring how matching affects lenders' choice of loans at the transaction level. To model the lender's choice of loans, we use the dummy variable $Lend_{ij}$ to indicate lender *i*'s decision of lending to loan *j*. The lenders' lending decisions where $Lend_{ij}$ equals 1 were directly observed. However, the lenders' not lending decisions where $Lend_{ij}$ equals 0 are not observed directly but rather assumed on all the other active loans, under the "potential dyads" approach (Liu et al. 2015; Lin and Viswanathan 2016). It is impossible to include all the potential lender-loan dyads given the number of sample lenders and loans. It is unrealistic to assume a lender would evaluate all active loans before taking any lending action either. Therefore, we randomly sample two active loans without lending actions for each lender out of all the potential dyads, with active defined as still receiving lending when the lender makes a lending action. As a result, for each lender *i* who took any lending action at time *t*, three dyads are constructed, one for the lent loan and two for the not-lend loans. For two dyads for not-lend loans, both $Lend_{ij}$ and $LendAmount_{ij}$ are 0. Overall, the dyadic data contains 309092 observations from 43175 lenders to 12333 loans.

Moreover, we examine the heterogeneity of lenders. Eckel and Grossman (2008), showing that active contributors are less responsive to the incentive programs such as matching subsidies. According to the number of loans they have lent before the event day ($PreLend_i$), we define active lenders ($Active_i$=1) as those with higher than median $PreLend_i$ (i.e., $PreLend_i$ >14), and the rest as inactive lenders ($Active_i$=0). Similar to the loan level analysis, $AccumAmount_{ij}$ *and* $TotalComp_{ij}$ are used to control for the herding effect (Zhang and Liu 2012) and the competition effect (Ly and Mason 2012).

Table 2.2. Descriptive Statistics

VARIABLES	OBS	MIN	MAX	MEAN	SD
$LendArrRate_{jt}$	67227	0	757	0.79	4.84
$AveContr_{jt}$	67227	0	2825	7.02	28.59
$FundAmount_{jt}$	67227	0	29075	27.91	187.69
$Match_{jt}$	67227	0	1	0.03	0.17
$Competition_{jt}$	67227	1	519	109.5	119.77
$AcuumAmount_{jt}$	67227	0	77600	109.5	741.1
$Lend_{ij}$	309092	0	1	0.33	0.47
$LendAmount_{ij}$	309092	25	5750	33.98	73.95
$Match_{ij}$	309092	0	1	0.09	0.28
$Active_{i}$	309092	0	1	0.39	0.49
$AccumAmount_{ij}$	309092	0	81275	708.3	3843.74
$TotalComp_{ij}$	309092	1	488	85.77	108.18

2.4. Loan-Level Analysis

2.4.1 Empirical Model

At the loan level, we use the generalized difference-in-differences (DID) estimation combined with propensity score matching (PSM) and zero-inflated models to estimate the impacts of matching subsidies on loan outcomes. The DID estimation identifies the treatment effect by comparing the difference of the treated group before and after the treatment with that of the control group (Card and Krueger 2000). The conventional DID model considers only two periods, before and after the treatment. This method is suitable for the context where the treated group remains treated once the treatment starts. However, in our research setting, some matched loans reverted to be unmatched after the event day. So instead of the two-period DID model, we use the generalized DID model where the treatment status can change more flexibly over time (Bertrand et al. 2004; Hansen 2007; Imbens and Wooldridge 2009). Thus, we use the following specification:

$$Outcome_{jt} = \beta_0 + \beta_1 Match_{jt} + \emptyset \boldsymbol{X_{jt}} + \mu_j + w_t + \varepsilon_{jt} \quad (2.1)$$

In Equation 2.1, $Outcome_{jt}$ is the funding outcome of loan j on day t, including

LendArrRate, *AveContr*, and *FundAmount*. $Match_{jt}$ is the treatment indicator. μ_j and w_t are loan and time-specific effects, respectively. For time-specific effects, in particular, we use three time period dummies of Now_t, $Post1_t$, and $Post2_t$ instead of daily dummies. $\boldsymbol{X_{jt}}$ is the control variables, including *Competition* and *AccumAmount*.

However, the DID model is valid only when the treatment and control groups follow parallel time trends. This assumption may not be reasonable if the matched and unmatched loans are fundamentally different because of the non-random selection of matched loans. To address this issue, we use PSM to construct a control group of unmatched loans that resemble the matched loans in all observables except for the treatment condition (Dehejia and Wahba 2002). As presented in Table A1, the third-party institutions select the matched loans based on the following loan characteristics: *LoanAmount*, which measures the target amount of the loan; *RepayTerm* represents the number of months over which the borrower will repay the loan; *IsGroup* is a binary variable, which equals to 1 if the loan has more than one borrower; *IsFemale* is a binary variable, which equal to 1 if the borrower of the loan is female; *Country*[4] is the country of that loan; *Sector*[5] represents the sector of that loan.

Using these loan characteristics, we estimate a logit model for a loan to be selected for matching subsidies and calculate the propensity scores. Then for each matched loan, an unmatched loan is identified using the PSM algorithm of the nearest neighbor and without replacement. The propensity scores matching procedure generate a sample consist of 1,425 control loans for the 1,425 matched loans. The balanced check of propensity matching is

[4] There are borrowers from 74 countries that publish their projects and raise funding. Most of these countries are developing countries in Africa, Asia, and South America.
[5] There are 15 sectors of projects in Kiva: Construction, Clothing, Education, Agriculture, Food, Services, Retail, Health, Entertainment, Arts, Transportation, Personal Use, Wholesale, Housing, Manufacturing

presented in Table 2.3.

As a rule of thumb, the standardized mean deviation (SMD) of variables between matched and unmatched loans should be no larger than 0.2, and preferably 0.1 if the matched data is balanced (Austin 2009; Rosenbaum 2010). From the result of after matching balance check, most of the SMD is smaller than 0.1, and only the SMD of *Country* is 0.17. The result indicates that loans in the treated group and the control group are balanced. The distribution of propensity scores presented in Figure A1 also shows that the matching procedure produces balanced samples. Finally, we create a sample containing 29381 loan-daily observations involving these selected 2850 loans for further analysis.

Table 2.3. Propensity Score Matching Results

VARIABLE	BEFORE MATCHING			AFTER MATCHING		
	CTRL	TREAT	SMD	CTRL	TREAT	SMD
Count	4252	1994		1425	1425	
LoanAmount (Log)	6.52	6.58	0.08	6.55	6.61	0.07
RepayTerm	15.81	16.07	0.05	16.00	16.07	0.01
IsGroup	0.1	0.12	0.05	0.11	0.12	0.02
IsFemale	0.59	0.76	0.37	0.66	0.68	0.06
Country	NA	NA	0.96	NA	NA	0.17
Sector	NA	NA	0.36	NA	NA	0.1

Note: The Treat column presents the mean of variables for loans receiving matching subsidies. The Ctrl column presents the mean of variables for loans without receiving matching subsidies. The standardized mean deviation (SMD) is widely used in literature to measure the balance of variables between treated groups and control groups.

For the matched and unmatched loans selected by PSM, we use zero-inflated models to estimate the effect of the matching subsidies for two reasons. First, our dependent variables of funding outcomes such as funding amount and number of lenders are all non-negative variables. Second, according to Table 2, they are also over-dispersed with many zero observations. In fact, only 20% of observations have non-zero funding outcomes. The zero-inflated model is suitable for non-negative data that exhibit overdispersion and excess zeros. It assumes that the positive values are generated according to a non-negative distribution, and the excess zeros are generated by a separate inflation process of a binary distribution. The separate data generation process for excess zeros is appropriate in our context, as the zero funding or lenders for many loans can be due to either lenders' no-lending decisions after consideration or not being considered by lenders at all. A zero-inflated model can be specified as:

$$\mathbf{P}\mathrm{r}(Y_i = y_i) = \begin{cases} \emptyset + (1-\emptyset) f(y_i = 0|\theta) & y_i = 0 \\ (1-\emptyset)\, f(y_i|\theta) & y_i > 0 \end{cases} \tag{2.2}$$

In Equation 2.2, Y_i is the outcome variable. ϕ is the probability of the zero value in the logit distribution. *f* is the distribution function for the positive values, and θ is the vector of parameters of the distribution function *f*. Because *LendArrRate* and *FundAmount* are count data, we use the negative binomial distribution function for *f* and thus the zero-inflated negative binomial (ZINB) models. As *AveContr* is continuous, we use the truncated Gaussian distribution function for *f* and thus the zero-inflated Gaussian model.

2.4.2 Estimation Results

The estimation results are presented in Table 2.4. Since all three dependent variables have the same occurrence pattern of zeros, the estimation results of their inflation process are the same, shown in column (1) and estimated using a logit model with the dependent variable being one for zero observations. For ease of interpretation, we present all coefficients in column (1) in log odds ratios (Bland and Altman 2000), the relative probability of receiving zero funding. According to column (1), the odds ratio of zero funding for matched loans versus unmatched loans is 2.1% (=exp (-3.88)). That is, compared to unmatched loans, matched loans are extremely unlikely to receive zero funding, suggesting that matched loans are more likely to be considered by potential lenders.

Table 2.4. Loan Daily Level Estimation of Zero Inflated Models

VARIABLE	(1) LOGIT	(2) LENDARRRATE	(3) NEG BINOMIAL AVECONTR	(4) FUNDAMOUNT
Match	-3.88***(0.17)	1.35***(0.08)	-0.05**(0.02)	0.84***(0.05)
Now	0.01(0.09)	0.57***(0.08)	0.09***(0.02)	0.35***(0.05)
Post1	-0.68***(0.07)	1.54***(0.06)	0.01(0.01)	0.93***(0.04)
Post2	0.88***(0.05)	0.51***(0.07)	-0.01(0.01)	0.3***(0.04)
AccuAmount	-0.92***(0.02)	0.11***(0.02)	0.06***(0)	0.14***(0.01)
#Competition	0.09***(0.02)	-0.08***(0.02)	0.02***(0)	-0.03***(0.01)
Loan Fixed Effect	Y	Y	Y	Y
#Observation	29,381	29,381	29,381	29,381
Note: Standard Errors are provided in parentheses[6]. ***p<0.01;**p<0.05;*p<0.10				

The coefficients of the three time dummies show how matching subsidies affect all loans after controlling the match indicator for the three periods compared to the period before the event. From column (1), The coefficient of *Now* is insignificant, indicating that matching subsidies have no significant influence on the probability of being considered by potential lenders for unmatched loans on the match day. However, on the next day after the event, unmatched loans are more likely to be considered by potential lenders, showing from the positive and significant coefficient of *Post1*. Finally, the positive and significant sign of *Post2* demonstrates that active loans are less likely to be considered by potential lenders when the matching subsidies ceased, providing evidence of *intertemporal displacement* – loans are less likely to receive funding when the matching subsidy is over. The existence of intertemporal displacement may be explained by the shift of timing of lending. Potential lenders who plan to make contributions to unmatched loans after the event may decide to contribute to matched loans during the event, which makes these unmatched loans less likely to receive funding after the event.

[6] The zero-inflated model with the fixed effect is estimated with maximum likelihood estimation, instead of least squared estimation. The maximum likelihood estimation does not provide clustered standard errors. Consequently, we use standard errors, instead of clustered standard errors here.

Column (2)-(4) presents the estimation results for the non-zero outcomes of the three dependent variables. The coefficient estimates of *Match* show that conditional on being considered by lenders, matched loans receive total funding from more lenders than unmatched loans. This finding is consistent with the intuition that receiving matching subsidies makes the matched loans more attractive for lenders. However, as shown in column (3), an average lender would contribute 5% less to a matched loan compared to his contribution amount to an unmatched loan. This finding supports the crowding-out effect of matching subsidies that the average private contribution decreases while contributions from other sources increases (Adena and Huck 2017; Bekkers 2015; Rondeau and List 2008).

Our result demonstrates that the *relative price effect* dominates the *crowd out effect* in the crowdfunding context, which leads to a higher total contribution amount per day to matched loans. The total contribution amount of a loan is the multiplication of the number of lenders and the average contribution per lender. The *relative price effect* suggests that the reduced price of contribution increases the total contribution by attracting more lenders, while the *crowd out effect* suggests that matching subsidies reduce the total contribution by decreasing the average contribution. In the previous literature that uses laboratory experiments to study the effect of matching subsidies, the number of contributors usually does not increase too much due to the limited potential contributors. However, on the crowdfunding platforms, millions of potential lenders have easy access to information about matching subsidies. The existence of social media and discussion forums also help spread the information to more potential lenders. Consequently, matching subsidies on the crowdfunding platforms may attract a much larger pool of lenders. In our estimation result, matching subsidies not only significantly increase the probability of receiving funding from any lender but also increase the number of contributing lenders by 285%. While *crowd out effect* only reduces 5% average contribution per lender.

The coefficients of *Now* are significant and positive in columns (2)-(4), suggesting that unmatched loans receive funding from more lenders, higher funding amount per lender, and higher total contribution. In total, the contribution amount to unmatched loans increases by 46% on the match day. In general, although matching subsidies are provided for matched loans only, such subsidies also benefit unmatched loans. Our results support positive spillover effects instead of *spatial displacement* effect (Scharf et al. 2017) of the match day event for unmatched loans.

Our estimation results support the existence of the temporary positive spillover effect instead of the spatial displacement effect in the crowdfunding context. The reason may be that most of the crowdfunding platforms, including Kiva, follow the "all or nothing" model, also known as the provision point mechanism (Burtch et al., 2018). Under this model, a fundraiser can only receive funds pledged to the campaign if it reaches the predetermined target before the deadline. Otherwise, the funds will be returned to contributors, incurring opportunity costs. Consequently, the potential contributors cannot always lend to matched loans. As matched loans receive full funding speedily and get closed, potential lenders can only lend to unmatched loans, leading to higher contributing lenders to unmatched loans (positive spillover effect).

The coefficients of *Post1 and Post2* are significant and positive for the number of lenders and the total funding amount, suggesting that the positive spillover effect of attracting more lenders for unmatched loans is also relatively persistent. The insignificant coefficients of *Post1 and Post2* for average contribution per lender suggest that the effect on motivating more contribution from a lender is only temporary. Therefore, our results indicate that the event had a persistent effect on promoting the platform and attracting more lenders to the platform, but only a temporary effect on changing lender behavior.

The coefficients of the control variables are mostly as expected. *AccuAmount* has a significant and positive coefficient in column (2)-(4), consistent with the herding effect that loans with higher accumulated funding receive more contributions from more lenders (Zhang and Liu 2012). The coefficient of *Competition* is negative and significant in columns (2) and (4), indicating that competition across loans reduces lenders and total funding for each loan.

2.4.3. Robustness Check

Our choice of zero-inflated model is appropriate for the data set. The calculated overdispersion ratio from the negative binomial model with the dependent variables *LendArrRate* and *FundAmount* are 1.75 and 9.25, respectively, which suggests overdispersion of the count dependent variables. Besides, we use the Vuong closeness test (Vuong 1989) to check whether the zero-inflated model is preferred by the negative binomial model. According to the Vuong test statistics calculated, 24.81($p<0.01$) for *LendArrRate* as the dependent variable and 60 ($p<0.01$) for *FundAmount* as the dependent variable, we reject the null hypothesis that the two models are equally close respectively. Consequently, the zero-inflated model is preferred.

We also conduct robustness checks using the negative binomial model with the dependent variables *LendArrRate* and *FundAmount*, as well as the OLS model conditional on positive contribution with the dependent variable *AveContr*. The estimation results are presented in Table 2.5. We find that the matching subsidies increase the number of contributing lenders and total contribution amount to matched loans, as well as decrease the average contribution to matched loans. Besides, the matching gift programs have positive spillover effects for unmatched loans, and the positive effect disappears when the matching grants ceased. These results are consistent with those from zero-inflated model estimation.

Table 2.5. Robustness Check with Negative Binomial Model

	(1) ARRRATE NEGBIN	(2) AVECONTR OLS	(3) AMOUNT NEGBIN
Match	1.00***(0.04)	-0.05**(0.02)	1.23***(0.04)
Now	0.46***(0.04)	0.07***(0.02)	0.28***(0.04)
Post1	0.92***(0.03)	0.03(0.02)	0.55***(0.03)
Post2	-0.11***(0.03)	0.02(0.02)	-0.51***(0.03)
AccuAmount	0.53***(0.01)	0.06***(0.01)	0.66***(0.01)
#Competition	-0.1***(0.02)	0.09***(0.03)	-0.11***(0.01)
Fixed-Effect	Y	Y	Y
#Observation	34,000	10,027	34,000
Adjusted R^2		0.01	

Note: Standard Errors are provided in parentheses. In column (1), the dependent variable is the lender arrival rate. Since the variable is count variable and overdispersion, we use the negative binomial model to make the estimation. In column (2), the dependent variable is the average contribution per lender conditional on positive contribution. Since the variable is a continuous variable and highly skewed, we use the log-transformed OLS model to make the estimation. In column (3), the dependent variable is the total contribution amount. Since the variable is count variable and overdispersion, we use the negative binomial model to make the estimation.
***p<0.01;**p<0.05;*p<0.10

As presented in Table A1, the matching grant during the event is provided by different third-party lenders or institutions. There is a concern that the specific institution may have a brand-ing effect (Chapleo 2015) – the brand of an institution may express a quality signal and affect the funding outcomes. From Table A1, we see that the anonymous supporters provide matching subsidies to 1112 loans among the 1994 matched loans. Consequently, we believe that the branding effect is not strong since more than half of the loans are matched by anonymous funders without the branding effect. To further address the issue, we split the main independent variable Match into multiple dummy variables based on the matching grant's provider of a campaign: Anonym (Anonymous Supporters), WAGE (Women and Girls Empowered Foundation), BOA (Bank of America), MillerFam (Miller Family Foundation), and WoodsFam (Woods Family Foundation). Using the new dummy variables, we test whether the branding effect ex-ists by replicating estimation in Table 2.5. The estimation results of the branding effects are presented in Table 2.6.

Table 2.6. Robustness Check with Branding Effect

	(1) ARRRATE NEGBIN	(2) AVECONTR OLS	(3) AMOUNT NEGBIN
BOA	0.9***(0.11)	-0.05(0.05)	1.37***(0.12)
MillerFam	0.77***(0.13)	-0.12**(0.05)	1.2***(0.15)
WoodsFam	1***(0.11)	-0.11**(0.05)	1.05***(0.12)
WAGE	1.43***(0.13)	0.04(0.05)	1.42***(0.11)
Anonym	1.07***(0.06)	-0.06**(0.03)	1.37***(0.06)
Now	0.31***(0.05)	0.06**(0.03)	0.18***(0.05)
Post1	0.83***(0.04)	0.001(0.02)	0.61***(0.04)
Post2	-0.2***(0.04)	-0.003(0.02)	-0.5***(0.04)
AccuAmount	0.59***(0.01)	0.06***(0.01)	0.7***(0.01)
#Competition	-0.11***(0.02)	0.06*(0.03)	-0.1***(0.01)
Fixed-Effect	Yes	Yes	Yes
#Observation	23,686	6,948	23,686
Adjusted R^2		0.01	

Note: Standard Errors are provided in parentheses. In column (1), the dependent variable is the lender arrival rate. Since the variable is count variable and overdispersion, we use the negative binomial model to make the estimation. In column (2), the dependent variable is the average contribution per lender conditional on positive contribution. Since the variable is a continuous variable and highly skewed, we use the log-transformed OLS model to make the estimation. In column (3), the dependent variable is the total contribution amount. Since the variable is count variable and overdispersion, we use the negative binomial model to make the estimation.
***p<0.01;**p<0.05;*p<0.10

The main results in Table 2.6 are consistent with those in Table 2.5. From the results in column (1) and (3), the five dummy variables of matching providers all have a positive and significant sign, which shows that matching subsidies with different matching provid-ers all increase the number of funders and total contributions. The test of coefficients shows that the coefficients of BOA, MillerFam, WoodsFam, and Anonym are not significantly different in columns (1)-(3). However, the coefficient of WAGE is significantly larger than other dummy variables of matching grants' providers, which indicates that campaigns matched by Women and Girls Empowered Foundation attract more potential lenders with higher total private contributions. The results indicate the branding may strengthen the effect of matching subsidies. However, we don't find a strong branding effect since most of the matching providers bring a similar effect on funding outcomes.

2.5 Lender-Level Analysis

The impacts of matching subsidies on the funding outcomes of loans provide an understanding of lender behavior change at the aggregate level without considering lender heterogeneity (Andreoni and Miller 2002). Previous research has found that matching subsidies have different effects on different types of lenders (Beckkers 2015; Eckel and Grossman 2008; Karlan and List 2007; Meier 2007a). As matching subsidies serve as additional incentives for lenders, they are likely to be more effective for the lenders who have lower incentives to contribute without the program. That is, more prosocial lenders who have sufficient self-motivation may be less likely to change their lending behavior because of the matching subsidies. In this section, we further explore how the lenders are affected by the program differently. We differentiate two types of lenders according to the activity level of the lender prior to the event ($PreLend_i$). We define active lenders as those whose $PreLend_i$ is greater than the sample median, and the rest as inactive lenders. Among our sample lenders, besides more frequent contributions, active lenders also have a higher average contribution amount than that of inactive lenders ($35.5 vs. $30.9).

2.5.1. Empirical Model

We use a logit model specification with fixed effects for lender *i*'s funding decision of loan *j*. The probability of lender *i* funding to loan *j* is modeled as follows:

$$Prob[Lend_{ij}] = \beta_0 + \beta_1 Match_{ij} + \beta_2 Active_{ij} + \beta_3 Active_{ij} * Match_{ij} + \boldsymbol{\delta Time_t} + \boldsymbol{\theta Time_t} * Active_{ij} + \emptyset \boldsymbol{X_{ij}} + \mu_j + \varepsilon_{ij} \qquad (2.3)$$

In Equation 2.3, $Match_{ij}$ is used to capture the effect of matching subsidies on lending decisions, $Active_{ij}$ is the binary indicator for active lenders, $Active_{ij}*Match_{ij}$ captures the differential impact of matching subsidies on active lenders. $\boldsymbol{Time_t}$ is the vector including the three time dummy variables Now_t, $Post1_t$, and $Post2_t$, where *t* refers to the day when $Lend_{ij}$ is decided. $\boldsymbol{Time_t}$ *Active_{ij} is used to examine how the three time periods affect active lenders' lending decisions for both matched and unmatched loans, compared to in-active lenders. $\boldsymbol{X_{ij}}$ contains control variables including competition and accumulated funding amount. μ_j is the loan fixed effects, capturing the impacts of time-invariant loan characteristics. Finally, ε_{ij} is the error term. Similarly, the (log-transformed) funding amount from lender *i* to loan *j* can be modeled as:

$$LendAmount_{ij} = \beta_0 + \beta_1 Match_{ij} + \beta_2 Active_{ij} + \beta_3 Active_{ij} * Match_{ij} + \boldsymbol{\delta Time_t} + \boldsymbol{\theta Time_t} * Active_{ij} + \emptyset \boldsymbol{X_{ij}} + \mu_j + \varepsilon_{ij} \qquad (2.4)$$

2.5.2. Estimation Results

The estimation results of the lender-level models are presented in Table 2.7. Column (1) shows the results of the logit estimation for the binary lending decision, while column (2) shows the results of the linear estimation for funding amount. According to the coefficient estimates of *Match*, lenders are more likely to contribute to but contribute less to matched loans than unmatched loans, consistent with our results from the loan-level analysis. The positive and significant coefficients of *Active* in both columns confirm that active lenders are not only more likely to contribute but also make higher contributions on average. The coefficients of *Now* and *Post1* are positive and significant in column (1) but negative in column (2), indicating that inactive lenders are more likely to contribute but contribute less during the event, although such changes are temporary, according to the insignificant coefficients of *Post2*. The coefficients of control variables are consistent with those from the loan-level estimation.

Table 2.7: Estimation of Lenders' Individual Choices

Variables	**(1)** **LEND** **LPM**	**(2)** **LENDAMOUNT** **LINEAR**
Match	0.47***(0.01)	-0.05***(0.01)
Active	0.01***(0.004)	0.02**(0.01)
*Match*Active*	-0.04***(0.01)	-0.05***(0.01)
Now	0.09***(0.01)	-0.01(0.01)
Post1	0.21***(0.01)	-0.06***(0.01)
Post2	-0.002(0.01)	0.02(0.02)
*Now*Active*	0.06***(0.01)	0.03***(0.01)
*Post1*Active*	0.02**(0.01)	0.01(0.01)
*Post2*Active*	0.05***(0.01)	-0.05**(0.02)
AccuAmount	0.07***(0.005)	0.05***(0.004)
#Competition	-0.11***(0.01)	0.06***(0.02)
Loan Fixed Effects	Yes	Yes
R2	0.349	0.005
#Observation	102,079	49,013
Note: Model (1) is estimated with the linear probability model with fixed effect. Model (2) is estimated with a fixed model with the log form dependent variable. Robust Standard errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10		

We are most interested in the coefficients of the interaction terms. The negative and significant coefficients of *Match*Active* in both columns suggest that, compared to inactive lenders, active lenders are less likely to fund matched loans, and they contribute to matched loans with a lower amount. The positive and significant coefficients of *Now*Active* and *Post1*Active* suggest that, compared to inactive lenders, active lenders are more likely to fund unmatched loans, and they contribute to unmatched loans with a higher amount on the event day and the day after the event. These results imply that active lenders are indeed less affected by the event. Compared to inactive lenders who are motivated to fund matched loans, active lenders fund more unmatched loans with higher contributions but decrease their contributions to matched loans. Our finding supports the *motivational crowding-out* theory by confirming that extrinsic monetary incentives reduce intrinsic motivation, especially for more prosocial individuals. According to the coefficients of *Post2*Active*, the active lenders' inclination of selecting unmatched loans is persistent throughout the post-event period, whereas their contribution amount to unmatched loans lowers to less than that of inactive lenders shortly after the event.

2.6. Conclusion

Matching subsidies have been widely used by online crowdfunding platforms to boost funding. Using a quasi-experiment on a prosocial crowdfunding platform Kiva, we examine the effectiveness of matching subsidies on the funding outcomes and lender behavior. We find that matching subsidies have an overall positive effect on all campaigns on the crowdfunding platform. This is consistent with previous research that monetary incentives can increase the total prosocial contributions to campaigns (Lacetera et al., 2014). However, in contrast to most previous studies that documented a positive effect on matched campaigns but a negative effect on unmatched ones, we find that matching subsidies positively affect both matched and unmatched loans. Although matched loans are more likely to receive private contributions than unmatched loans, the competition effect is dominated by the positive spillover effect. As a result, unmatched loans benefit as well.

In addition, we find that matching subsidies negatively affect fundraising after the event, suggesting an intertemporal displacement effect – loans are less likely to receive any funding when the matching event is over. Large scale, short duration, and high intensity of the online matching subsidies distinguish them from traditional ones. We find the effect of matching subsidies is strong on the event day, but the effect is only temporary – lenders tend to shift their contributions to the event day, leading to decreased funding activities after the event. Similar to traditional matching subsidies, this finding suggests a short-term, time-shifting effect of matching subsidies on online fundraising.

We find that the matching subsidies attract a large number of contributing lenders, most of them are previously inactive lenders. These lenders are mostly interested in contributing to matched loans, crowding out some active lenders who then shift their contributions to unmatched loans. In addition, we find that the average contribution per lender per matched loan decreases compared with their pre-matching counterparts, suggesting a detrimental effect of matching subsidies on lenders' intrinsic motivation of contribution. At the same time, unmatched loans receive a higher average contribution per lender per loan than their pre-matching counterparts. This is mainly due to active lenders who have higher remaining funding after contributing to matched loans shifting their contributions to unmatched loans. Compared with inactive lenders who are mainly attracted to matched projects due to one-for-one matching, active lenders are less influenced by matching subsidies, showing different patterns of behavior change induced by the monetary incentives.

Overall, our research provides several practical implications on the use of matching subsidies on crowdfunding platforms. First, different from traditional matching subsidies that mostly benefit matched loans but hurt unmatched loans, we find matching subsidies on crowdfunding platforms have positive effects on both matched and unmatched loans. This alleviates the concerns about the negative effect of matching subsidies on unmatched loans and thus supports the use of monetary incentives to boost fundraising. Second, our analysis of lender behavior reveals different contribution preferences. We find the matching subsidies effectively induce previously inactive lenders to become active and be willing to contribute. These findings suggest that the online crowdfunding platform could frequently offer matching subsidies as an effective mechanism to awaken inactive lenders to become active on the platform. Finally, due to the data limitation, we are unable to discover the long-term effect of matching subsidies. How to maintain a high-level private contribution, in the long run, is of particular importance to increase the overall effectiveness and sustainability of the matching subsidies on the online crowdfunding platforms. This would be an interesting topic for future research.

Chapter 3. An Economic Analysis of Matching Subsidies on the Dynamics of Crowdfunding

3.1 Introduction

The development of information technology enables numerous individual funders to support small entrepreneurs without access to traditional financial channels through crowdfunding. However, fundraising in the crowdfunding context differs from traditional fundraising in several distinct ways. First, it is difficult for individual funders to determine a fundraiser' creditworthiness or a campaign's quality due to the lack of intermediaries. Second, fundraising on crowdfunding platforms typically follows the "all or nothing" model, where the fundraisers only receive funding if the target funding goal is reached within a limited fundraising period (e.g., one month), which introduces huge uncertainty about the success of a campaign.

Facing uncertainty about the campaign quality and campaign success, funders mainly rely on various dynamic information revealed on the crowdfunding platform， such as the number of prior funders, the contribution amount from prior funders, etc., to determine which campaign to support. Crowdfunding dynamics significantly affect the success of a campaign. It has been found that early funding plays an important role in attracting potential funders and increasing the probability of funding success (NESTA, 2014; Vismara, 2018). Since the dynamics of crowdfunding plays a pivotal role in determining the success of campaigns, it is necessary for funders, fundraisers, and platforms to understand the underlying mechanisms that drive the crowdfunding dynamics.

A large body of literature has studied the mechanisms behind crowdfunding dynamics. They find that the effect of dynamic information revelation and sharing is mainly driven by herding behavior and payoff externalities (Burtch 2013; Kim et al. 2020; Kuppuswamy and Bayus 2018; Li et al. 2020; Zhang and Liu 2012). Herding behavior in crowdfunding, referring to the activity that individuals refer to others' decisions and are more likely to fund campaigns with more other supporters, stems from the peer influence theory that an individual follows the behavior of others (Banerjee 1992; Zhang and Liu 2012). In the crowdfunding context, potential funders face the uncertainty of campaign quality and risk of loss, which makes them rely on the observation of other funders' behavior in making funding choices. Burtch et al. (2013) and Zhang and Liu (2012) find that the accumulated funding amount of a campaign reflects previous funders' collective evaluations of the campaign as manifested in their funding allocation decisions. Consequently, potential funders follow the previous funders' allocation decisions and contribute to campaigns with higher accumulated funding, leading to herding behavior. The payoff externalities stem from the "all or nothing" model in crowdfunding platforms. With this funding model, an individual funder gets the payoff from the contribution only if the contributed campaign receives full funding. As the number of funders funding a given campaign increases, or the total funding amount increases, it becomes more likely that the campaign reaches its funding goal by the deadline. Such payoff externalities also affect the dynamics of crowdfunding.

In recent years, there have been several studies on promotion strategies, such as investment matching, to change crowdfunding dynamics and boost funding activities (Kim et al. 2020; Li et al. 2020). These studies employ the simulation method and find that the promotion strategy can significantly increase the contribution demand. However, there is limited research to examine the effect of monetary promotion strategies on funding activity using observational data. To bridge the research gap, this essay uses the transaction data from a crowdfunding platform to study how matching subsidies, as one of the most popular promotion strategies on crowdfunding platforms, affect crowdfunding dynamics.

Matching subsidies refer to the promotion strategy that some third-party institutions provide a dollar-for-dollar match of the private contributions from individuals on selected campaigns. Matching subsidies have been very effective in increasing the success rates of campaigns and have been adopted by many prestigious crowdfunding platforms, such as Kiva, Kickstarter, and Donorchoose.org. Matching subsidies provide supplemental funding for campaigns and accelerate the campaign progress, which directly changes the dynamic patterns of the crowd fundraising. Besides, matching subsidies may affect the dynamics of crowdfunding by influencing herding behavior and payoff externalities. First of all, third-party institutions contribute to a campaign by providing matching funds, which make individual funders follow their contributions, leading to herding behavior (Herzenstein et al., 2011). Secondly, providing matching subsidies to a campaign makes the campaign become more likely to receive full funding, which affects the payoff externality. In this essay, we study the effects of matching subsidies on the dynamics of crowdfunding through herding behavior and payoff externalities. We aim to address the following research questions: (1) How do matching subsidies affect funders' herding behavior? (2) How do matching subsidies affect funders' payoff externalities? (3) What are the managerial implications of implementing matching subsidies on the crowdfunding platform?

To answer the research questions, we leverage the comprehensive data set ranging from September 21, 2018, to November 21, 2018, to examine the effects of matching subsidies on crowdfunding dynamics. The data is crawled from Kiva, one of the largest prosocial crowdfunding platforms, where funders lend to campaigns without interest. The data contains all information about campaigns, funders, and transactions.

This study finds strong evidence of both herding behavior and positive payoff externalities on the crowdfunding platform. In contrast to the previous literature in traditional prosocial fundraising that prior contributions may crowd out subsequent funding (Burtch et al., 2013), we find that prior contributions of a campaign are associated with higher subsequent funding in prosocial crowdfunding. However, matching subsidies will moderate the effect of herding and payoff externalities. The reason is that matching subsidies provide signals of the quality of a campaign, which moderates the herding momentum. The finding supports the rational herding theory that lenders follow the funding activity of other funders by observation learning – inferring the quality of a campaign from other funders' behavior (Zhang and Liu). Besides, matching subsidies reduce the uncertainty of the success of a campaign, which further moderates the payoff externalities.

Interestingly, we find the existence of a "bystander effect," where funders are less likely to provide support, instead of a "completion effect," where funders race to goal when a campaign is close to success. Contrary to the U-shaped funding patterns on reward-based crowdfunding platforms, we find that most of the campaigns on Kiva receive relatively less funding in the early stage of fundraising compared with the funding in the later stage. We also find that matching subsidies are most effective in the early stages of fundraising. As the fundraising progresses, the positive effect of matching subsidies disappears near the end of funding.

The rest of the chapter is organized as follows. Section 3.2 develops our hypotheses. Section 3.3 describes our data and summary statistics. Section 3.4 presents our empirical model and estimation results. Section 3.5 provides several robustness checks. Section 3.6

discusses managerial implications and Section 3.7 concludes the paper with future research directions.

3.2. Hypothesis Development

Crowdfunding dynamics have been found to significantly affect campaign funding outcomes in the crowdfunding literature. Previous studies identified three phases of fund-raising on the crowdfunding platforms (Agrawal et al. 2014; Fisk et al. 2011; Kim et al. 2020): a “friend funding” phase when funding mainly comes from the friends of fundraisers; a “getting crowded” phase when information cascading and externalities stimulate funding; a “race to goal” phase when funding activities accelerate before the goal is reached. It has been found that most of the unsuccessful campaigns fail in the “friend funding” phase due to the lack of early support. Since the dynamics of crowdfunding play a pivotal role in determining the success of campaigns, it is necessary for funders, fundraisers, and platforms to understand the underlying mechanisms that drive the crowdfunding dynamics.

3.2.1 Herding Behavior

Herding behavior refers to the phenomenon that individuals follow the behavior of others and invest in well-funded projects (Devenow and Welch 1996). There are mainly two streams of literature that explain the mechanisms behind herding behavior – the irrational herding theory and the rational herding theory. The irrational herding theory, also called information cascade, stems from social influence, where an individual funder refers to others’ decisions as a descriptive social norm (Aderson and Holt 1997; Croson and Shang 2008; Simonsohn and Ariely 2008; Vismara 2018). Consequently, an individual funder just mimics the behavior of other funders. Rational herding behavior is rooted in information asymmetry between two parties involved in transactions, where one party has more or better information than the other (Akerlof 1970). In business, the company owners and sellers have more information than investors and buyers. Consequently, investors and buyers tend to rely on observational learning – inferring the behavior of other investors and buyers to get information and follow their behavior, leading to herding behavior (Banerjee 1992; Bikhchandani; Zhang and Liu 2012).

Herding behavior has been identified and studied in economics and business literature in recent several decades. In finance, herding behavior has been identified among institutional investors, who tend to follow each other in buying and selling the same securities in both the US stock market and non-US stock markets (Lakonishok et al. 1992; Sias 2004; Walter and Webber 2006; Change 2010). Additionally, individual investors tend to be more likely to herd compared with institutional investors (Kim and Wei, 2002; Tan et al., 2008). Herding behavior also occurs in aggregate market activity. For example, Hwang and Salmon (2004) found significant herding in the US and Korean stock markets, which does not depend on market conditions and fundamental macroeconomic variables.

Enormous literature in Marketing and Information Systems has also explored herding behavior. In marketing, consumers tend to choose products with more prior consumption, leading to herding behavior (Salganik et al., 2006; Cai et al., 2009; Zhang, 2010; Tucker and Zhang, 2011). In Information Systems, herding behavior has been examined in a variety of contexts, including the adoption of Information Technology (Kauffman and Li 2003; Sun 2013), online auctions (Simonsohn and Ariely 2008), online retailing (Li and Wu 2018), and open source community (Oh and Jeon 2007).

In particular, herding behavior has been widely discussed in the crowdfunding and microfinance literature (Burtch et al. 2018; Greenwood and Gopal 2016; Herzenstein et al. 2011; Kim et al. 2020; Li et al. 2020; Liu et al. 2015; Zhang and Liu 2012). These studies use the theory of observational learning (Banerjee et al. 1992) to explain herding - potential contributors view higher accumulated capital of campaigns as signals of higher quality, resulting in higher subsequent contribution amount to these campaigns. Although Burth et al.(2013) find that prior contribution may crowd out the subsequent funding on a donation-based crowdfunding platform that provides public goods, we still expect that herding behavior exists in prosocial lending. The reason is that funders in donation-based crowdfunding do not expect repayment. In prosocial lending, funders face the risk of losing their repayment, which makes them more likely to fund campaigns with higher quality. We expect individual funders to rely on the quality signal of accumulated capital to make the inference, leading to herding behavior. Therefore, we expect:

Hypothesis 1a (Herding Behavior): *As cumulative prior contributions increase, the subsequent funding amount of a campaign increases.*

3.2.2 Payoff Externality

Payoff externalities occur if the payoff of a funder's contribution to a campaign depends on other funders' funding behavior (Ayres and Kneese 1969; Katz and Shapiro 1985). For example, the utility of a user of an ATM depends on the total number of ATM users. Externalities have been widely studied in Information System literature, including IT adoption (Kauffman et al. 2000), software market (Gallaugher and Wang 2002), and user-generated content (Zhang and Zhu 2011; Goes et al. 2014).

Payoff Externalities also exist in the crowdfunding context since most crowdfunding platforms follow the “all or nothing” model, also known as the provision point mechanism, assurance contract, and threshold public goods (Rondeau et al. 1999). Under this model, a fundraiser can only receive funds pledged to the campaign if it reaches the predetermined target before the deadline. Otherwise, the funds will be returned to funders, incurring opportunity costs. Consequently, funders may face the uncertainty that their contributed campaigns may not receive full funding, and they receive zero utility. Due to the high uncertainty of campaigns, funders are more likely to contribute to a campaign that has already reached a high percentage of funding goals because of its greater likelihood of success.

However, the higher percentage of funding goals may also lead to negative payoff externalities through the bystander effect in prosocial crowdfunding. The bystander effect stems from the theory that “impact philanthropists” want their contributions to make a difference (Duncan 2004). Consequently, if contributions from other funders are sufficient to reach the target goal, then an individual’s own contribution is no longer pivotal and can decrease without much loss in utility. Alternately, if others are not giving, the value from an individual’s contribution is higher (Andreoni 1998; Shang and Croson 2009).

In summary, the effect of the higher percentage of the funding goal is not clear due to the competing theories of the payoff externalities and bystander effect. Nevertheless, most of the prior empirical studies have documented positive externalities on crowd-funding platforms (Burtch et al., 2018; Herzenstein et al., 2011; Kim et al., 2020; Li et al., 2020; Zhang and Liu 2012). Although some prior studies find the existence of bystander effect (Agrawal et al. 2014; Kim et al. 2020; Herzenstein et al. 2011; Kuppuswamy and Bayus 2018), they also demonstrate that payoff externalities dominate the bystander effect. All of these studies have shown that higher goal attainment is associated with higher subsequent funding, while the bystander effect will reduce the effect of positive payoff externalities with increasing goal attainment level. Consequently, we expect that the same insight can be carried over to prosocial crowdfunding. Thus, define the percentage of goal attainment of a loan at any time as the ratio of total funds received at that time to its target fundraising amount. We have the following hypothesis:

Hypothesis 1b (Payoff Externalities): *As the percentage of goal attainment increases, the subsequent funding amount of a campaign increases.*

3.2.3 The Role of Matching Subsidies in Herding Behavior and Payoff Externalities

Recent studies also explore the mechanisms underlying the herding behavior. There are two competing theories to explain the herding behavior - *irrational herding* and *rational herding*. The irrational herding theory, also called the *information cascade* (Vismara 2018), assumes that lenders passively mimic others' choices, refer to others' decisions as a descriptive social norm, or follow well-funded and hence salient listings. In contrast, rational herding assumes that funders believe that other funders have private information on the campaign's quality (Zhang and Liu 2012). Most of the previous empirical research supports the rational herding theory in crowdfunding and finds that quality information of campaigns, such as risk assessment and friends' endorsement, moderate the herding behavior (Burtch et al., 2018; Zhang and Liu, 2012). These studies suggest that individuals rely more on other available quality information, instead of only prior contributions, to make more informed decisions.

Although previous studies find that quality information of campaigns can affect herding behavior, the role of matching subsidies in crowdfunding dynamics is unknown.

Matching subsidies is one of the most popular promotional strategies used on crowdfunding platforms, such as Kiva, Kickstarter, and Donorchoose.org, in recent years. Matching subsidies are usually provided by third-part institutions on selected projects (i.e., campaigns) during a short time period. The most popular and most commonly used matching method is the dollar-for-dollar match. If a funder contributes to matched campaigns, the third-party institution will match the funder's contribution amount for the campaign. The matching subsidies not only double the contribution amount of a funder but accelerate funding activities on matched campaigns.

In the traditional fundraising environment, matching subsidies provide a signal of quality for a matched campaign (Karlan and List 2007). The reason is that the third-party funders providing matching subsidies will serve as a lead contributor that promise to contribute half of the funding target of a campaign. Consequently, individual funders may expect that the lead contributor who promises to provide matching grants may have private quality information of campaigns, increasing these campaigns' creditworthiness (Andreoni 2006b; Glazer and Konrad 1996; Potters et al. 2007; Vesterlund 2003). Similar to traditional fundraising, matching subsidies on the online crowdfunding platforms also provide creditable quality signals for matched campaigns. The signal of matching subsidies may have different effects on herding behavior according to different mechanisms behind herding. If irrational herding theory holds, an individual funder may just mimic the funding activity of other funders, ignoring the signal of information of matching. Consequently, matching subsidies may have no significant effect on herding behavior. Nevertheless, if rational herding theory holds, the quality information of matching subsidies may moderate the herding behavior. The explanation is that rational individuals care not only about the presence of herding but also the reasons behind the herding. For a campaign without the quality information of matching subsidies, a rational individual funder can only rely on the herding information to make inferences on the quality of the campaign. For a campaign with high-quality information from matching subsidies, a rational individual has already learned the quality information, which makes them ignore the quality information of herding.

To understand the interaction between the signal of herding momentum and matching subsidies, we consider the following scenario. There are two well-funded loans with identical high accumulative funding except that loan one is provided with matching subsidies, and loan two do not receive matching subsidies. For a potential rational lender, he may partially attribute the herding momentum of loan 1 to the quality information of matching subsidies. However, the lender may reason that loan two is well funded because the loan has a very high quality so that other lenders are willing to lend to this loan even without being matched. Consequently, the positive effect of herding momentum for loan two should be stronger than that of loan 1. A lot of empirical studies also show that the quality information of other factors, such as friend endorsement (Zhang and Liu 2012) and provision point mechanism (Burtch et al. 2018), has a substitution effect with herding momentum.

As stated above, most of the empirical evidence suggests that rational herding theory holds in crowdfunding, especially in prosocial lending. In the prosocial lending context, funders lend money to fundraisers instead of donating money to them. Most of the lenders expect to get repayment, which makes the rational decision-makers to choose campaigns with higher quality aiming to make a bigger impact with their limited budget (Burtch et al.

2014; Vesterlund 2003). Accordingly, we conjecture that matching subsidies provide credible quality signals of campaigns, which may substitute prior cumulative contributions to serve as signals of quality, attenuating the effect of prior cumulative contribution on subsequent fundraising for matched campaigns. Therefore, we hypothesize that:

H2a: (Effect of Matching Subsidies on Herding Behavior) *Matching subsidies moderate (attenuate) the herding behavior such that the effect of prior cumulative contributions on subsequent funding amount of a campaign is weaker for campaigns with matching subsidy than without it.*

The matching subsidy reduces the uncertainty of campaign success since it provides half the amount of the total funding required. However, the less uncertainty of success may lead to a “bystander effect,” where funders may be less likely to contribute to a campaign with a higher probability of reaching the target amount. The reason is that individual funders may think their contributions do not play a pivotal role in determining the success of the campaign since the campaign will reach the target regardless (Kim et al. 2020). Prior field experiment has provided evidence that matching subsidies lead to strong bystander effect and reduce the subsequent contributions in prosocial funding (Shang and Croson 2009).

In our research context, campaigns receiving matching subsidies are expected to be more likely to reach the target goal since third party institutions will fulfill half of the target funding amount. The potential funders may believe matched campaigns will be fully funded even without their contributions, which leads to a strong bystander effect on matched loans. Consequently, we expect that matching subsidies moderate the effect of payoff externalities measured by the percentage of goal attainment.

H2b: (Effect of Matching Subsidies on Payoff Externalities) *Matching subsidies moderate (attenuate) the payoff externalities such that the effect of goal attainment on subsequent funding amount of a campaign is weaker for campaigns with matching subsidy than without it.*

3.3. Data Description

This study utilizes a comprehensive transaction-level data set collected from Kiva.org, which is the world's largest online peer-to-peer lending platform. It has raised $1.37 billion in funds for more than 3.4 million borrowers from 1.8 million lenders since its inception in October 2005. It is an online microfinance platform for the poor, unbanked, and under-served.

Most loans on Kiva are donation-based with a 0% interest rate for the borrowers who, by and large, are located in developing countries. However, borrowers in Kiva are still expected to repay the principal to lenders within the repayment term. Kiva will partner with local field partners to collect the repayment, which guarantees that 95.9% of loans make the repayment (Kiva 2020). Although loans in Kiva have relatively high repayment rates, lenders still face the risk of losing their money if a loan defaults. Consequently, the lending decision in Kiva is driven by both financial and prosocial motives. Liu et al. (2012) provide evidence that lenders in Kiva make lending decisions with both extrinsic and intrinsic motivations. Galak et al. 2011 also demonstrate that both financial and psychological factors affect the funding outcomes in Kiva.

To help funders select high-quality loans with lower risk, Kiva makes a great effort to disclose information about loans. For example, Kiva provides loan-level information, including the field partner's credit rating, the business plan of the loan, and the borrower's description. The platform also shares the dynamic updates of a loan on the loan page. Kiva provides real-time information about accumulative funding amount, the percentage of goal attainment level, and the number of accumulative lenders. The transparent information disclosure helps reduce in-formation asymmetry and ease fundraising. However, there are still many failed loans due to the lack of funding.

To help more small enterprises to achieve their funding goals, Kiva partners with some anonymous lenders and third party foundations, such as Google and WAGE(Women and Girls Empowered Foundation), to provide matching subsidies for selected loans[7]. Under this program, the matching partner defines the criteria about which loans should be matched, and the qualified loans will then be displayed with an “x2” badge with the partner’s name on the platform. If any lender makes contributions to matched loans, the matching partners will lend the same amount to those loans. Accordingly, lenders can double the impact of their contributions when they lend to matched loans. Matching subsidies promote campaigns and accelerate funding activities, which may affect the dynamics of crowdfunding. Therefore, we utilize the observations on Kiva to study the influence of matching subsidies on crowdfunding dynamics.

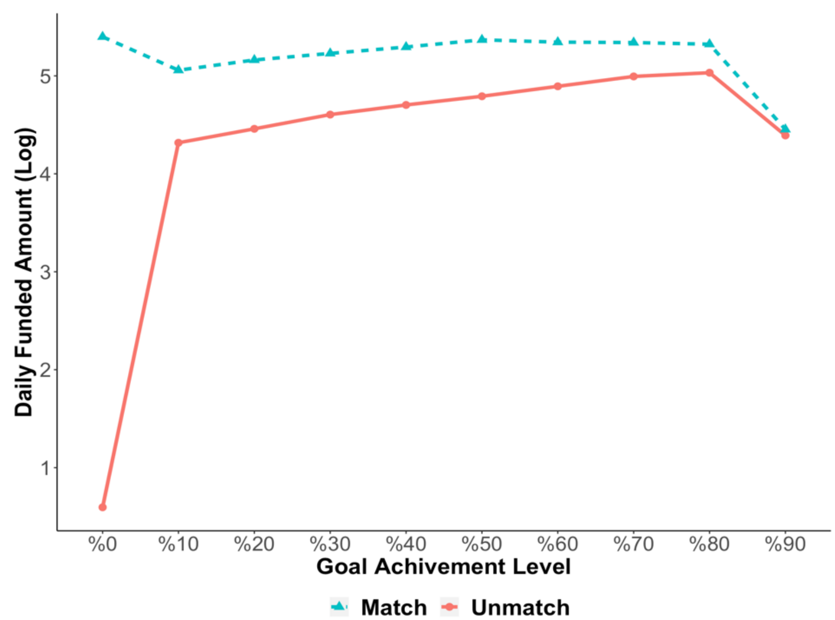
We retrieve granular transaction-level observations occurring from August 21, 2018, to September 21, 2018, using Kiva public API. The data contains detailed information for

[7] As shown in Essay 1, more than half of the loans are matched by anonymous supporters in the matching event. The data in essay 2 have a longer period, which contains both matching events and regular matching subsidies. The data in Essay 2 shows that 9003 loans are matched by anon-ymous supporters among the 14964 matched loans. Consequently, Consequently, we also believe that the branding effect is not strong in Essay 2. I also provide a robustness check in Table B2 to further address the issue.

each lending activity, such as the lender, the borrower, the lending amount, and the timestamp. The data set contains 1,138,070 lending actions taken by 202,879 lenders. Aggregating the transaction-level data, we construct a loan-daily level panel data, consisting of 63897 loans in the three-month period.

Figure 3.1 presents how the average daily funded amounts of matched and unmatched loans at different goal attainment levels. Since there is a lot of extremely large values of the daily funded amount, we use the log form of the funded amount in the figure. Unmatched loans receive, on average, relatively little support ($34.3 per day) at the beginning stages of the funding.

Figure 3.1. Dynamic patterns based on goal attainment level



The pattern in Figure 3.1 is consistent with the previous findings that most of the crowdfunding campaigns suffer from a lack of early support, which reduces the probability of reaching the target goals (Kim et al., 2020; Li et al., 2020). Once the funded amount reaches 10% of the target goal, the daily funding amount continuously increases. However, when the funded amount reaches 90% of the target amount, the average funding amount drops sharply. The pattern is different from previous findings that campaign close to successfully receive more support.

Matching subsidies significantly promote campaigns in the early stage of funding. For matched loans with less than 10% of target goals, matching subsidies increase their average daily funded amount significantly, and the daily funded amount continuously increases once the matched loan reaches 10% of target goals, similar to the pattern of unmatched loans. The daily funded amount to matched loans also drops to the same level as unmatched loans when it is close to success.

The dependent variable for the empirical model is $FundAmount_{it}$, the amount of donations (in US Dollars) received by campaign i on day t, after excluding matched contributions. The first independent variable of interest is $AccumAmount_{it}$, referring to the accumulated funding amount of campaign i before day t. The accumulated funding amount is often used to measure herding activity in previous studies (Burtch et al., 2013; Kuppuswamy and Bayus, 2018). Our second variable of interest is $Percent_{it}$, accounting for the percentage of goal attainment of a campaign i before day t. The variable is used to measure payoff externalities. The binary variable $Match_{it}$ equals 1 if the campaign i is matched on day t.

We use two sets of control variables to address the concern of endogeneity. First, the time-varying control variables are included to mitigate the potential omitted variables concern. The variable $Competition_{it}$, referring to the number of other active and similar loans competing with loan i on day t, is included to control for competition (Ly and Mason 2012). Similar loans are defined as loans with the same country and sector. We also use the variable $DaysLapsed_{it}$, referring to the number of days between the current day t and the posted day of loan i, to control for the timing of lending. Additionally, we include the variable

GTrends$_{it}$, referring to the Google Trends Index of loan *i* at day *t*, to control for the time-variant popularity of a loan caused by exogenous shocks. The Google Trends Index is retrieved from Google Analytics by employing two keywords of country and sector associated with each loan on each day. The variable represents the relative search volume of keywords, which is widely used in the IS literature to serve as a proxy for the popularity of campaigns (Burtch et al., 2013).

Second, we use the time-invariant and day dummies to control the individual heterogeneity of loans and time effects. The funding activities of a campaign may be driven by the individual characteristics of loans. Especially on the crowdfunding platforms, the "soft information," such as pictures of fundraisers, narratives of projects' descriptions, plays a pivotal role in influencing the funding amounts of loans. We thus include loan fixed effects to control the heterogeneity. Besides, the funding activities of a campaign may also be affected by some exogenous shocks, which are difficult to measure. Consequently, we use the day dummies to control for the exogenous shocks. Descriptive statistics of the main variables are presented in Table 3.1.

Table 3.1. Descriptive statistics

N=612,088	MIN	MAX	MEAN	SD
FundAmount	0	46275	59.19	260.67
AccumAmount	0	99925	130.1	663.7
Percent	0	0.99	0.1	0.17
Match	0	1	0.02	0.2
Competition	1	603	116.7	135.01
DayLapsed	0	80	11.44	8.92
GTrends	10	100	73.36	19.56

Since both *AccumAmount*$_{it}$ and *Percent*$_{it}$ change with prior contributions, we provide the correlation matrix in Table 3.2 to check multicollinearity. As shown in Table 3.2, all of the correlation coefficients are within the acceptable range. The highest correlation is between the variables $AccumAmount_{it}$ and $Percent_{it}$ 0.38, which is still lower than the rule of thumb cut-off value 0.7 (Dormann et al. 2013). This low correlation is understandable because the percentage of goal attainment is determined by both the accumulated funded amounts and the target goals of campaigns. We also conduct the variance inflation (VIF) test to check multicollinearity. As shown in the Table B1 of VIF test results, the largest VIF values are 2.69 and 2.37 for variables $AccumAmount_{it}$ and $Percent_{it}$ respectively, below the rule of thumb cut-off value 10 (Dormann et al. 2013).

Table 3.2. Variables correlation

VARIABLE	1	2	3	4	5	6	7
FundAmount	1						
AccumAmount	0.28	1					
Percent	0.15	0.38	1				
Match	0.13	0.1	0.15	1			
Competition	-0.1	-0.1	-0.17	-0.07	1		
DayLapsed	-0.06	0.09	0.2	-0.07	0.08	1	
GTrends	0	0	0	0.01	0.18	-0.01	1

3.4. Model and Estimation

We now introduce the econometric model used to test the hypotheses. Our dependent variable of the funded amount is non-negative and integer, which is a count variable because potential lenders can only provide funds in $25 increments instead of any value on Kiva. Simple OLS regression will lead to biased and inconsistent estimation for count dependent variables. Besides, our count dependent variables exhibit overdispersion, which is evident from Table 3.1 that the variance of the dependent variables is significantly larger than their mean values. The overdispersion of dependent variables makes the negative binomial model (Hausman et al. 1984) preferred over the Poisson model in our research. The empirical model testing the Hypotheses is presented in Equation 3.1.

$$FundAmount_{it} = \; f(\alpha_1 AccumAmount_{it} \; + \alpha_2 Percent_{it} + \alpha_3 Match_{i,t} +$$

$$\beta_1 Match_{it} * AccumAmount_{it} + \beta_2 Match_{,t} * \quad Percent_{it} + \boldsymbol{\gamma X_{it}} + \mu_t + \lambda_i + \varepsilon_{i,t} \;)$$

(3.1)

In Equation 3.1, we use a count model to estimate the relationship between *FundAmount*$_{it}$ and other independent variables. The function *f* represents the negative binomial regression model. The coefficients of interest are *AccumAmount*$_{it}$ and *Percent*$_{it}$, measuring the herding momentum and the percentage of goal attainment, respectively. We use the dummy variable *Match*$_{it}$ to indicate whether a campaign receives matching subsidies on a specific day. We include the interaction terms *Match*$_{it}$* *AccumAmount*$_{it}$ and *Match*$_{it}$**Percent*$_{it}$, to study the effects of matching subsidies on herding behavior and payoff externalities, respectively. A vector of time-varying control variables *X*, containing *Competition*$_{it}$, *DayLapsed*$_{it,}$ and *GTrends*$_{it}$, is included to control the competition effect and time effect. The variable μ_t is the day fixed effect; λ_i is the loan fixed effect, controlling for the time-invariant loan-specific preference; ε_{it} is the loan-day idiosyncratic error term.

The variable *AccumAmount*$_{it}$ and *Percent*$_{it}$ are both included in the main model since both herding behavior, and payoff externalities are important drivers of crowdfunding dynamics. Consider the following scenario: there are two otherwise identical loans with different accumulated contributions. The loan with a higher accumulated contribution is more desirable than the other since it is more likely to be fully funded. This can be due to both herding (reflected by accumulated contribution) and payoff externality (reflected by the higher percentage of goal attainment). Missing of payoff externalities may lead to overestimation of the herding effect and vise versa.

To better understand the difference between the effect of accumulative funding amount and percentage of goal attainment, consider the scenarios presented in Table 3.3. There are two loans with different target amount: loan A expects to borrow $1000, while loan B expects to borrow $10000. In scenario 1, the two loans have the same accumulative funding amount. Without considering payoff externalities, the two loans should have the same subsequent fund-ing due to the same accumulative funding amount. However, loan A is close to success, while loan B still needs to raise the remaining 92% funding. Consequently, the existence of payoff externalities will make loan A attract higher subsequent funding than that of loan B even with the same herding momentum. Without the consideration of payoff externalities in scenario one will lead to biased estimation.

Table 3.3. Thought Experiment to Distinguish Herding and Payoff Externalities

		A	B
	Target	$1000	$10000
Scenario 1	*AccumAmount*	$800	$800
	Percent	80%	8%
Scenario 2	*AccumAmount*	$800	$8000
	Percent	80%	80%

Note: This table presents two scenarios to distinguish the herding behavior measured by the accumulative funding amount(AccumAmount) and payoff externalities measured by the percentage of goal attainment (Percent).

In scenario one, the two loans have the same 80% percentage of goal attainment level. Both loans have high probabilities of receiving full funding. Without considering herding behavior, the two loans should have the same subsequent funding due to the same payoff externalities of the goal attainment level. However, the fact that loan B has received higher prior contributions from more funders makes potential funders perceive that loan B has a higher quality because prior funders collectively lend a larger amount to loan B. Consequently, the existence of herding momentum will make loan B attract more subsequent funding than that of loan A even with the same payoff externalities. Without the consideration of herding behavior in scenario two will also lead to biased estimation.

Additionally, the variable correlations in Table 3.2 and VIF test in Table B1 indicate no multi-collinearity issue when the two variables AccumAmountit and Percentit are included in the estimation model

Our hypotheses in Section 3.2 can be empirically tested by estimating the coefficients of variables in Equation 3.1. The Hypotheses 1a and 1b suggest that the funded amount is positively associated with higher prior accumulated contributions and percentage of goal attainment, respectively, i.e., the coefficients of $AccumAmount_{it}$ and $Percent_{it}$ are expected to be positive. Hypotheses H2a and H2b suggest that matching subsidies moderate the herding behavior and payoff externalities, which indicates that the coefficients of interaction terms $Match_{it}$* $AccumAmount_{it}$ and $Match_{it}$ *$Percent_{it}$, should be negative.

The estimation results of Equation 3.1 are presented in Table 3.4. Column (1) and (2) shows the estimation with and without interaction terms, respectively. We include control variables in columns (3) and (4) to control the time-variant factor. The independent variables *AccumAmount*, *Competition,* and *DayLapsed* are transformed into log form since the variables are highly skewed. The variable *GTrends* is divided by 100 to scale it between 0 and 1. From the estimation results, the coefficients of *AccumAmount* are positive and significant in all of the columns, which supports the hypothesis of herding behavior (H1a). Additionally, the positive and significant coefficients of *Percent* in four columns suggest that a campaign with a higher percentage of goal attainment receives a larger amount of funds, which supports the hypothesis of payoff externalities (H1b). The results are consistent with prior literature that underscores the importance of herding behavior and payoff externalities in crowdfunding dynamics. Besides, the coefficient of *Match* is also positive and significant, implying that matching subsidies increase private contributions.

The magnitude of the coefficients is also significant. The estimated coefficient of *AccumAmount* in column (4) is 0.36, which implies that a one percent increase of accumulated contributions corresponds to 0.36% higher daily contributions. Likewise, one additional percent increase in the percentage of goal attainment is associated with 1.64% higher total daily contributions. The results provide evidence that matching subsidies are very effective in boosting funding, supporting the usage of matching subsidies on crowdfunding platforms.

Table 3.4. The Effects of Matching Subsidies on Crowdfunding Dynamics

	NEGATIVE BINOMIAL FIXED-EFFECTS			
	(1)	**(2)**	**(3)**	**(4)**
AccumAmount	0.32***(0)	0.31***(0)	0.37***(0)	0.36***(0)
Percent	1.56***(0.02)	1.91***(0.02)	1.32***(0.02)	1.64***(0.02)
Match	1.33***(0.01)	2.62***(0.02)	1.18***(0.01)	2.33***(0.02)
Match AccumAmount*		-0.24***(0.01)		-0.22***(0.01)
*Match*Percent*		-1.62***(0.05)		-1.35***(0.05)
Competition			-0.19***(0)	-0.19***(0)
DayLapsed			-0.42***(0)	-0.42***(0)
GTrends			0.17***(0.01)	0.14***(0.01)
Observations	561,086	561,086		561,086

Note: Standard Errors are provided in parentheses. ***p<0.01; **p<0.05;*p<0.10. The standard errors are 0 because they are less than 0.01. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects. The estimation drops all of the loans with all zero outcomes and only one observation per loan.

The interaction terms of *Match*AccumAmount* and *Match*Percent* in columns (2) and (4) are all negative and significant, implying that matching subsidies moderate the herding behavior and payoff externalities, respectively. The results support H2a and H2b. For matched loans, the herding momentum and the percentage of goal attainment of a campaign are still positively associated with higher daily contributions since the sum of *Match* and *Match*AccumAmount*, as well as the sum of *Match* and *Match*Percent* are still positive. However, the magnitude of the herding effect and payoff externalities of matched loans are smaller than that of unmatched loans.

The coefficients of control variables also make sense. The coefficients of *Competition* in columns (3) and (4) are all negative and significant, suggesting that competition between similar loans reduces the funding amounts to these loans (Ly and Mason 2012). The negative and significant sign of *DayLapsed* indicates that the funding speed reduces as time lapses, consistent with the prior literature (Kim et al. 2020). The positive and significant sign of *GTrends* demonstrates that more popular loans receive higher funding amounts, which all make intuitive sense.

3.5. Robustness Checks

3.5.1 Endogeneity of Matching Subsidies

On Kiva, whether a loan receives matching subsidies is not a random decision. Instead, the matched loans are selected by certain criteria based on loan characteristics (Kiva 2020). Without a random assignment, bias may arise because of the systemic differences between matched and unmatched loans, which the fixed effects regression may be unable to capture. Consequently, we use propensity score matching (PSM) to address this issue, which involves the pairing of control and treated observations with similar characteristics (Dehejia and Wahba 2002).

In our study, different loans are provided with matching subsidies at different dates. However, the decision of providing matching subsidies to a loan is only determined by time-invariant loan characteristics. Consequently, we match the loans receiving matching subsides with active loans that do not receive matching funds on the same day.

In the matching procedure, an indicator of matched loan is modeled as a function of loan-level characteristics: *LoanAmount*, which measures the target amount of the loan; *RepayTerm* represents the number of months over which the borrower will repay the loan; *IsGroup* is a binary variable, which equals to 1 if the loan has more than one borrower; *IsFemale* is a binary variable, which equal to 1 if the borrower of the loan is female; *Country* is the country where the loan is located; *Sector* represents the sector of the loan. These characteristics are all important criteria to determine whether the loan will be matched.

Using these loan characteristics, we estimate a logit model to predict whether a loan should be matched. Based on the predicted propensity scores from the logit model, one treated loan is matched with one untreated loan with replacement using the nearest neighbor algorithm. The balanced check of propensity score matching is presented in Table 3.5.

Table 3.5. Propensity Score Matching Results

VARIABLE	BEFORE MATCHING			AFTER MATCHING		
	CTRL	TREAT	SMD	CTRL	TREAT	SMD
Count	52345	10864		3577	4177	
LoanAmount	729.25	1079.11	0.22	834.88	951.96	0.08
RepayTerm	14.09	11.44	0.42	12.18	12.34	0.03
IsGroup	0.1	0.2	0.3	0.13	0.14	0.02
IsFemale	0.75	0.78	0.06	0.77	0.74	0.06
Country	NA	NA	0.69	NA	NA	0.2
Sector	NA	NA	0.34	NA	NA	0.07

Note: The Treat column presents the mean of variables for loans receiving matching subsidies. The Ctrl column presents the mean of variables for loans without receiving matching subsidies. The standardized mean deviation (SMD) is widely used in the literature to measure the balance of variables between treated groups and control groups.

As a rule of thumb, the standardized mean deviation (SMD) of variables between matched and unmatched loans should be no larger than 0.2, and preferably 0.1 if the matched data is balanced (Rosenbaum 2010). From the result of the after-matching balance check in Table 3.5, most of the SMD is smaller than 0.1, and only the SMD of *Country* is 0.2. The results indicate that loans in the treated group and the control group are balanced. Finally, we create a sample consisting of 7694 loans for further analysis.

The data set sampled from propensity score matching contains 77231 loan-daily observations involving 7694 loans. We re-estimate the main specification, utilizing the matched data set. The estimation results are presented in Table 3.6. The estimated coefficients are consistent with those in the main regression.

Table 3.6. Robustness Check with Propensity Score Matching

	NEGATIVE BINOMIAL FIXED-EFFECTS
AccumAmount	0.31***(0.01)
Percent	2.12***(0.04)
Match	2.49***(0.04)
Match AccumAmount*	-0.2***(0.02)
*Match*Percent*	-1.79***(0.1)
Competition	-0.17***(0.01)
DayLapsed	-0.2***(0.01)
GTrends	0.38***(0.04)
Observations	74,091

Note: Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10. The standard errors are 0 because they are less than 0.01. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects. The estimation drops all of the loans with all zero outcomes and only one observation per loan.

3.5.2. Fixed Effects vs. Negative Binomial Fixed Effects

Considering that the dependent variable is a count variable, we have employed the negative binomial fixed effects model in our main model analysis. The negative binomial fixed effects model, proposed by Hausman, Hall, and Griliches (1984), assumes that the joint probability of the counts for each group depends on the sum of the counts for the group. Consequently, the model is not a fully true fixed-effects model since it does not, in fact, control for all stable covariates (Allison and Waterman 2002). To address the issue, we use the fixed effects model (Woodridge 2010) to check for robustness. The estimation results of the fixed effects model are presented in Table 3.7. using the full sample and sampled data selected from the propensity score matching procedure. From the estimation results, all of the hypotheses are still supported, indicating that our results are robust against the estimation method.

Table 3.7. Robustness Checks with Fixed Effects Model

	FIXED EFFECTS FULL SAMPLE	FIXED EFFECTS PSM SAMPLE
AccumAmount	0.24***(0)	0.18***(0.01)
Percent	2.69***(0.04)	3.83***(0.1)
Match	3.33***(0.03)	3.32***(0.05)
Match AccumAmount*	-0.12***(0.02)	-0.07**(0.03)
*Match*Percent*	-2.88***(0.1)	-3.89***(0.18)
Competition	-0.36***(0.01)	-0.27***(0.04)
DayLapsed	-0.03***(0)	-0.02**(0.01)
GTrends	0.06**(0.02)	0.48***(0.06)
Observations	612,088	77,231
Adjusted R-Square	0.28	0.354

The estimation is implemented with the fixed effects model controlling the loan fixed effects. The first column presents the estimation of the fixed effects model using the full sample data. The second column presents the estimation of the fixed effects model using the sampled data selected from the propensity score matching procedure.
Note: Robust Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10. The standard errors are 0 because they are less than 0.01.

3.5.3 Alternative Measure of Herding Momentum

Although a loan's accumulated funding amount is a good measure of herding momentum, prior empirical studies have proposed multiple alternative constructs to measure the strength of the herd. For example, Burtch et al. (2013) measure the herding momentum by *contribution frequency*, calculated as the cumulative funding amount contributed to a given campaign, divided by the days lapsed (the number of days between the posted day and current time) of a campaign on the crowdfunding platform. They find that higher prior contribution frequency partially crowds out the future funding in prosocial crowdfunding.

To test whether the alternative measure of herding momentum may affect the estimation result, we re-estimate the model of Equation 3.1 by replacing $AccuAmount_{it}$ with $AccumLender_{it}$ (cumulative number of prior lenders who have lent to campaign *i* before day *t*) and $ContrFreq_{it}$ (the contribution frequency of campaign *i* before day *t*) respectively. We also transform the alternative measures of herding momentum into the log form.

Table 3.8. Robustness Checks with Alternative Measures of Herding Momentum

	ACCUMLEND AS ALTERNATIVE	CONTRFREQ AS ALTERNATIVE
AccumLender	0.77***(0)	
ContrFreq		0.41***(0)
Percent	1.01***(0.02)	1.84***(0.02)
Match	2.34***(0.02)	2.67***(0.02)
Match AccumLender*	-0.45***(0.01)	
Match ContrFreq*		-0.44***(0.01)
*Match*Percent*	-1.08***(0.05)	-1.05***(0.05)
Competition	-0.15***(0)	-0.21***(0)
DayLapsed	-0.4***(0)	-0.13***(0)
GTrends	0.1***(0.01)	0.09***(0.01)
Observations	561,086	561,086

Note: The table reports the estimation results of robustness checks using *AccumLender* and *ContrFreq* as alternative measures of herding momentum. Standard Errors are provided in parentheses.***p<0.01;**p<0.05;*p<0.10. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects. The estimation drops all of the groups (loans) with all zero outcomes and only one observation per group.

Table 3.8 provides the estimation results for robustness checks. The hypotheses H1a and H1b are still supported by alternative measures of herding momentum. Besides, the herding effect and payoff externalities are also moderated by matching subsidies, supporting Hypotheses H2a and H2b. It indicates that our results about herding behavior are robust against other measures of herding momentum. Because Kiva is a lending-based prosocial crowdfunding platform, lenders care very much whether they can receive repayment in the future. Consequently, lenders on Kiva respond positively to the herding momentum, which often contains credible quality information about the campaigns.

3.5.4 Alternative Data Sampling

Another concern of the estimation results is rooted in the data. First, most of the loans on Kiva have a relatively small target amount. Since Kiva only allows lenders to make contributions with $25 increments, loans with a small target amount can be easily influenced by a single lender. For example, a loan with a $100 target amount will easily reach 50% of the funding goal by a funder who contributes $50. Consequently, the estimation results may be affected by loans with a small target amount. To address this issue, we sample loans with more than $500 (median of all loans) target amount for robustness check. Second, some loans in our data set are posted before August 21, 2018, or closed after November 21, 2018. Therefore, our data set cannot contain all time periods of these loans. We thus drop these loans for which we do not have full observations. Table 3.9 presents the estimation results for the sampled data. The results still support all of the hypotheses.

Table 3.9. Robustness Checks with Sampled Data

	LARGE AMOUNT LOANS	LOANS WITH FULL-TIME PERIODS
AccumAmount	0.38***(0)	0.35***(0)
Percent	1.49***(0.02)	1.6***(0.02)
Match	2.2***(0.03)	2.25***(0.02)
Match AccumAmount*	-0.18***(0.01)	-0.21***(0.01)
*Match*Percent*	-1.49***(0.06)	-1.31***(0.06)
Competition	-0.19***(0)	-0.2***(0)
DayLapsed	-0.44***(0)	-0.42***(0)
GTrends	0.1***(0.02)	0.07***(0.02)
Observations	411,052	421,454

Note: The table reports the estimation results of robustness checks using groups (loans) with more than $500 funded amount and loans with complete funding history. Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects. The estimation drops all of the groups with all zero outcomes and only one observation per group.

3.5.5. Branding Effect

Since matching subsidies are provided by different third-party lenders or institutions, the concern of the branding effect of matching providers also exists in Essay 2. The data set in Essay 2 contains both matching events and regular matching subsidies. Among the 14964 matched loans, 9003 loans are matched by anonymous supporters. Consequently, we believe that the branding effect is not a concern in Essay 2.

To future address the issue of branding effect, I also conduct a robustness check similar to Table 3.10. I split the main independent variable Match into multiple dummy variables based on the matching grant's provider of a campaign. Due to the space limitation, I only include the anonymous supporters and the other top 5 matching providers that match the most number of loans: Anonym (Anonymous Supporters matches 9003 loans), Google (matching 597 loans), WAGE(Women and Girls Empowered Foundation matches 586 loans), UNHCR (United Nations High Commissioner for Refugees matches 550 loans), BobFund (Bobbi Brown Cosmetics matches 481 loans), and RichardFund(the Richard Brindle Foundation matches 324 loans). Using the new dummy variables, I test whether the branding effect exists in Table 3. 10.

The main results in Table 3.10 are consistent with those in Table 3.4. From the results in column (1) and (2), the six dummy variables of matching providers all have a positive and significant sign, which shows that matching subsidies with different matching providers all increase the number of funders and total contributions. Additionally, almost all of the interaction terms in column (2) are consistent with those in Table 3.4. The only difference is that the interaction term of Wage*AccuAmount is positive and significant. However, we don't find a strong branding effect since most of the matching providers bring a similar effect on funding outcomes.

Table 3.10. Robustness Check with Branding Effect

	NEGATIVE BINOMIAL FIXED-EFFECTS (1)	(2)
AccumAmount	0.35***(0.01)	0.33***(0.01)
Percent	1.5***(0.05)	2.16***(0.05)
Anonym	1.43***(0.03)	2.54***(0.06)
BobFund	1.25***(0.18)	2.68***(0.34)
Google	1.1***(0.1)	2.67***(0.25)
RichardFund	1.2***(0.09)	2.24***(0.19)
WAGE	1.87***(0.09)	1.41***(0.29)
UNHCR	1.69***(0.1)	2.39***(0.24)
*Anonym*AccumAmount*		-0.24***(0.03)
*BobFund*AccumAmount*		-0.14(0.16)
*Google*AccumAmount*		-0.25***(0.06)
*RichardFund*AccumAmount*		-0.34***(0.09)
*WAGE*AccumAmount*		0.99***(0.15)
*UNHCR*AccumAmount*		-0.08(0.11)
*Anonym*Percent*		-1.86***(0.16)
*BobFund*Percent*		-3.08***(0.97)
*Google*Percent*		-1.27***(0.36)
*RichardFund*Percent*		-0.64(0.62)
*WAGE*Percent*		-7.25***(0.63)
*UNHCR*Percent*		-2.12***(0.66)
Competition	-0.19***(0.01)	-0.18***(0.01)
DayLapsed	-0.18***(0.01)	-0.19***(0.01)
GTrends	0.4***(0.04)	0.36***(0.04)
Observations	64,602	64,602
Note: Standard Errors are provided in parentheses. ***p<0.01; **p<0.05;*p<0.10. The standard errors are 0 because they are less than 0.01. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects. The estimation drops all of the loans with full zero outcomes and only one observation per loan.		

3.5.6. Alternative Data Set

Our data set only has a three-month time period from 21 August 2018 to 21 November 2018. There may be a seasonal trend in funding activities on Kiva, which may affect the estimation results. To address the issue, we collect two alternative data sets in different time periods for robustness checks. These data sets are all loan-daily level panel data set, which contains the same information with the data set used in the main model estimation.

The first data set is from January 5, 2019, to March 4, 2019, consisting of 445,368 observations involving 42,229 loans. The second data set is from June 4, 2019, to August 232019, consisting of 556,858 observations involving 52,875 loans. These alternative data sets cover different time range and seasons compared with the data set used in the main model estimation. The estimation results of the negative binomial fixed effects model using the two alternative data sets are presented in Table 3.11.

The estimation results in Table 3.11 still support all of the hypotheses. Additionally, we also provide the variable statistics, correlation matrix, multicollinearity check, and other robustness estimation using the first and second alternative data sets in Appendix C and D, respectively.

Table 3.11. Robustness Check with Alternative Data Sets

	JANUARY 5, 2019 TO MARCH 4, 2019	JUNE 4, 2019 TO AUGUST 23, 2019
AccumAmount	0.39***(0)	0.33***(0)
Percent	1.58***(0.02)	1.86***(0.02)
Match	2.21***(0.04)	2.17***(0.02)
Match AccumAmount*	-0.25***(0.01)	-0.18***(0.01)
*Match*Percent*	-0.73***(0.09)	-1.27***(0.05)
Competition	-0.14***(0)	-0.18***(0)
DayLapsed	-0.49***(0)	-0.47***(0)
GTrends	0.38***(0.02)	0.002(0.01)
Observations	397,209	517,024

Note: The table reports the estimation results of robustness checks using two alternative data sets in different periods. The first column presents the estimation results using the data set that starts from January 5, 2019, to March 4, 2019. The second column presents the estimation results using the data set that starts from June 4, 2019, to August 23, 2019. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects. The estimation drops all of the groups with all zero outcomes and only one observation per group. Standard Errors are provided in parentheses.
***p<0.01;**p<0.05;*p<0.10.

3.6. Managerial Implications

Our empirical analyses show that matching subsidies moderate the herding effect and payoff externalities. A natural question is how to design an optimal promotional strategy of matching subsidies. Our main model analysis suggests that it is more effective to provide matching subsidies in the early stages since the effect of promotion diminishes in the later stages. However, the moderating effect of matching subsidies may not be linear. Based on the percentage of goal attainment, we are interested in examining the effectiveness of matching subsidies in different fundraising stages. We replace the continuous independent variable *Percent* with a vector of dummy variables that reflect increments of 10 percent toward the fundraising target, up to 90 percent, omitting the dummy for capital accumulation between 0 and 9.99 percent of the target, in Equation 3.1. Additionally, we drop the interaction term of *Match*AccumAmount*. The estimation results are showed in Table 3.12.

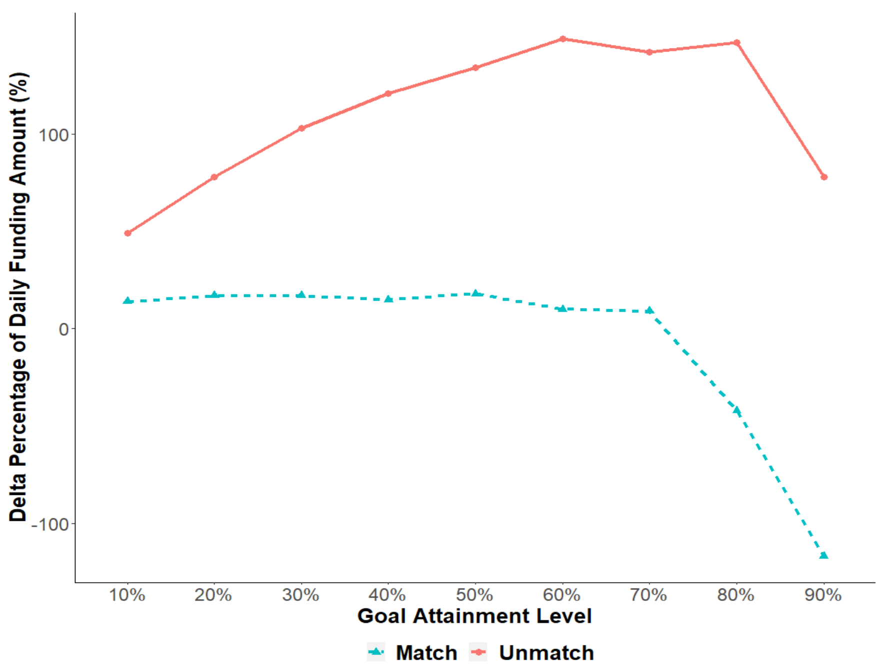
Table 3.12. The Effects of Matching Subsidies on Different Stages of Funding

	NEGATIVE BINOMIAL FIXED-EFFECTS
AccumAmount	0.31***(0)
Match	2.06***(0.02)
10 Percent	0.49***(0.01)
20 Percent	0.78***(0.01)
30 Percent	1.03***(0.01)
40 Percent	1.21***(0.01)
50 Percent	1.34***(0.01)
60 Percent	1.49***(0.02)
70 Percent	1.42***(0.02)
80 Percent	1.47***(0.02)
90 Percent	0.78***(0.03)
*Match*10 Percent*	-0.35***(0.03)
*Match*20 Percent*	-0.61***(0.03)
*Match*30 Percent*	-0.86***(0.03)
*Match*40 Percent*	-1.06***(0.04)
*Match*50 Percent*	-1.16***(0.04)
*Match*60 Percent*	-1.39***(0.04)
*Match*70 Percent*	-1.33***(0.05)
*Match*80 Percent*	-1.89***(0.06)
*Match*90 Percent*	-1.95***(0.08)
Competition	-0.19***(0)
DayLapsed	-0.45***(0)
GTrends	0.16***(0.01)
Observations	561,086
Note: Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects. The estimation drops all of the loans with all zero outcomes and only one observation per loan.	

According to Table 3.11, the effect of payoff externalities of matched loans is always weaker than that of unmatched loans because interaction terms between *Match* and percent dummy variables are all negative and significant. The result is consistent with the findings in the main model estimation.

Figure 3.2 presents the marginal effect of the percentage dummies. As shown in Figure 3.2, an additional 10% increase in goal attainment leads to a higher level of increment of unmatched loans than that of matched loans. Besides, we find a first increasing then decreasing pattern of the effect on goal attainment level for unmatched loans. That is, the positive effect of goal attainment increases in the early stages (0-60% of the target goal), stays stable in the middle stages (61%-90% of the target goal), and drops significantly in the final stage of funding.

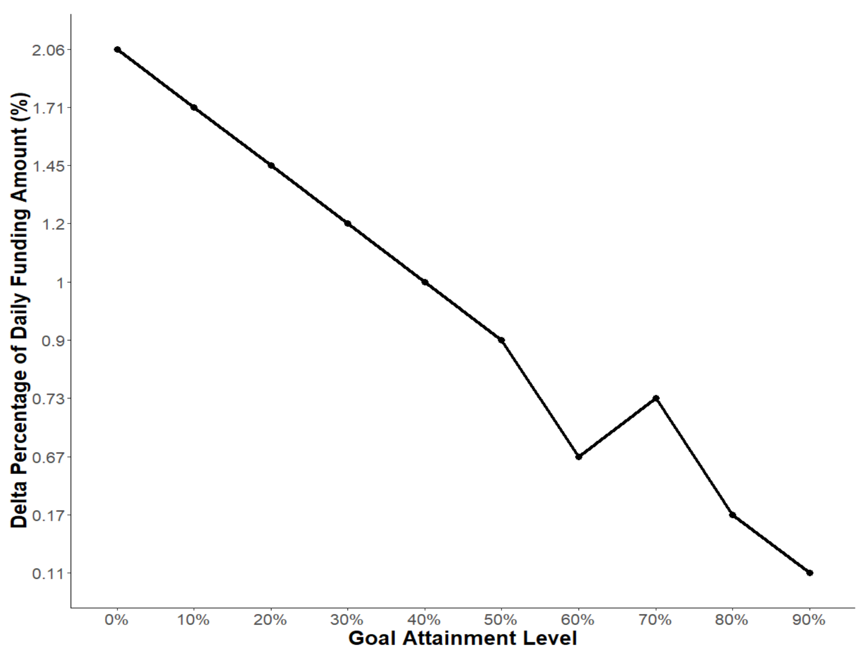
Figure 3.2. The Effects of Goal Attainment Level on Matched and Unmatched Loans



For matched loans, the effect stays stable when the loan reaches 0-70% of the target, but becomes negative after the funding amount reaches 80% of the target. Our results indicate the extremely strong "bystander effect" when the funding amount is close to reaching the target for both matched and unmatched loans. The result is different from the previous finding of the "completion effect," where funders contribute more as a campaign's cumulative funding gets closer to its target goal (Argo et al. 2020; Kuppuswamy and Bayus 2017; Wash 2013).

Figure 3.3 visualizes the marginal effects of matching subsidies in different stages of goal attainment. The vertical axis shows the percentage change of the daily funding amount compared with the daily funding amount in the stage with less than 10% goal attainment. We see that matching subsidies are most effective in the early stages of funding. The effect of matching subsidies decreases as the goal attainment level increases. Once a loan reaches 90% of the target goal, the matching subsidies no longer have a significant and positive effect.

Figure 3.3. The Effects of Matching Subsidies in Different Stages of Funding



3.7. Conclusion

This study identifies both herding behavior and positive payoff externalities on a prosocial crowdfunding platform. We find that higher prior contributions serve as a signal of high quality, leading to more subsequent funding. Additionally, the higher percentage of goal attainment increases the possibility of success for a campaign, inducing higher subsequent contributions.

However, we find that promotional strategies, such as matching subsidies, may moderate the herding behavior and positive payoff externalities. In other words, as cumulative contributions and percentage of goal attainment increase, the subsequent funding amount of a campaign matched by a prestigious institution increases less than that of an unmatched campaign.

We also examine the crowdfunding dynamics by studying the effects of cumulative contributions in different stages of funding for both matched and unmatched loans. Overall, we find that the positive effect of cumulative contributions on subsequent funding of a campaign increases until it reaches 60% of the target goal. We do not find evidence of the "completion effect," where a campaign close to completion receives higher funding than any other stage. Instead, we find that the positive effect of cumulative prior contributions drops sharply once it reaches 90% of the target goal, suggesting a "bystander effect," where funders are less likely to contribute to a campaign with a higher probability of reaching the target amount because individual funders may think their contributions do not play a pivotal role in determining the success of the campaign on the prosocial crowdfunding platform.

Our study also helps quantify the effectiveness of matching subsidies as a promotional strategy. We find that it is most effective to provide matching subsidies to a campaign at the early stages of funding (e.g., before it reaches 10% of the target goal). Besides, matching subsidies do not significantly increase private contributions at the final stages of funding.

Essay 2 makes both theoretical and practical contributions in multiple streams of literature. First, the essay contributes to the literature on crowdfunding by providing strong evidence of herding behavior and positive payoff externalities on prosocial crowdfunding platforms. Essay 2 also provides additional empirical evidence to the literature studying the relationship be-tween herding momentum and quality information (Burtch et al., 2018; Zhang and Liu 2012). The findings are consistent with previous literature that the presence of matching subsidies signals the quality of a campaign, which may have a substitution effect with the quality information of herding momentum.

Second, essay 2 contributes to the literature on crowdfunding dynamics. Previous literature has used the structural choice model and counterfactual simulation to explore how the effect of promotion strategy varies with crowdfunding dynamics and find that promotion strategy is most effective in the early stage of funding (Kim et al. 2020; Li et al. 2020). Using the loan dai-ly-level panel data, Essay 2 provides consistent empirical evidence that the promotion strategy of matching subsidies has a stronger effect in the early stage of funding. The finding provides managerial insights that the third part institutions can most effectively provide matching subsidies in the early stages of fundraising.

Finally, essay 2 contributes to the literature on matching subsidies in economics. Previous economics literature focuses on the overall effectiveness of matching subsidies on funding out-comes (Karla and List 2007; Kalan et al. 2011; Rondeau and List 2008; Deck and Murphy 2019). This essay enriches the literature by demonstrating that the effect of matching subsidies depends on the levels of goal attainment and accumulated funding. Our findings offer new insights into the design of effective promotional strategies on prosocial crowdfunding platforms

Chapter 4. Challenges and Skills Set in Empirical Research

All the essays in my thesis are the results of five years of largely independent idea generation, data collection, and research development in the context of crowdfunding. This chapter shares the experience of research development in topic generation, data collection, technical skills, methodology, and experiment, as well as writing and communication.

4.1. Topic Generation

The first challenge of empirical research is how to generate interesting research ideas. In the crowdfunding context, there are numerous interesting, and novel topics remain un-explored. However, it is difficult to find a novel research topic due to the lack of theoretical foundations or data sources. As a business researcher, we aim to make theoretical contributions instead of only conducting data analytics. Additionally, our research should be innovative, which requires us to be knowledgeable about the current literature and the research gaps.

The comprehensive literature review and a wide range of reading help me overcome the challenge. The literature review helps me identify research gaps and theoretical foundations, while the reading of online news and website helps me find interesting topics and available data sources. Consequently, my essays aim to make theoretical contributions to the existing literature of Information Systems and Economics. Essay 1 extends the theory of philanthropic behavior by examining the effectiveness of matching subsidies on crowdfunding activities. Essay 2 makes theoretical contributions to better understand herding behavior and payoff externalities in the new crowdfunding context.

4.2. Data Collection and Technical Skills

Interesting research topics may not be feasible to study due to the lack of data sources. Nevertheless, the rich and available transaction data from crowdfunding platforms enables us to overcome the challenge. The transaction data sets in essay 1 and essay 2 are crawled from the API of Kiva. In fact, Kiva API does not provide comprehensive transaction-level data. Instead, it only provides the most recent 100 transactions updated every few seconds. We overcome the challenge by designing a web crawler to collect the most recent 100 transactions every 30 seconds, which help us get almost all of the transactions that occurred on the Kiva platform. The web crawler was initiated on 20 August 2018 and ran till 25 December 2019, which help us collect more than 99.9% transaction data and enable us to conduct the research in prosocial crowdfunding.

The collected data is a large size and unstructured data set. The characteristics of un-structured big data require us to use sophisticated technical skills to construct the data set before estimation. The bid data framework, such as Rspark, is used to reorganize the data. Python and C++ codes are used to boost computation and generate appropriate variables to make estimations. These technical skills enable us to conduct research in prosocial crowdfunding.

The well-organized data set is still not ideal due to the missing data problem. In Essay 1, there is no dyadic data to explore the driving force of funders' funding decisions. We use the potential dyadic method to generate the available dyadic data to perform the model estimation. There are no ideal data set in real empirical studies, which require us to use technical skills to handle the limitation of the data set.

4.3. Empirical Methodology

Another challenge in empirical research is the model specification, referring to the choice of appropriate function form of the model and variables. The misspecification of statistical models may cause biased coefficients and error terms, leading to biased parameter estimations. The model specification depends on the nature of the data and theoretical foundations. The comprehensive knowledge in statistics and economic theory, as well as the practical experience, help us overcome the challenge of model specification.

In my first two years of Ph.D. course work, the courses of Econometrics and Time Series help me build deep and solid methodology foundations in business empirical research. The continuous self-learning of statistical models and estimation methods, including count regression models and panel regression models, enables me to find the most appropriate models and estimation methods for different data sets.

In Essay 1 and Essay 2, the endogeneity of the estimation model is also challenging. The selection of loans receiving matching subsidies is not a random choice, which may lead to the endogeneity of selection bias. To address the endogeneity, we use the propensity score matching method to generate the balanced sampled data. In the empirical analysis, we need to find the most suitable model specification for different data sets.

4.4. Writing and Communication

Writing and communication skills are the essential tools to help Ph.D. students make academic progress, publish papers in conferences and journals, and make academic contributions. As a business scientist, we need not only to identify the most interesting and solid academic findings but also present the findings with readable and precise writing. With the help of my advisor Zhiling Guo and Professor Robert J. Kauffman, my writing skills have improved significantly in recent years. The improvement of writing skills enables me to share my academic progress and findings with my advisor more efficiently, which helps me receive more suggestions to improve my research.

Presentation in the conference is always the most efficient way to share the research with colleagues and receive feedback to improve the paper and help it publish in journals. Essay 1 has been presented in the 2019 Statistical Conference in E-Commerce Research (SCECR) and the 2019 Pacific Asia Conference on Information Systems (PACIS). Many of the feedback and comments received from SCECR reviewers, attendees, and many other academic researchers will be incorporated into the study for journal submission.

Finally, communication and relationship management are always the cornerstones of a successful business researcher. My research experience has given me a better understanding of communication and relationship management. Firstly, I learn that keeping close contact with my advisor enable me to progress the research efficiently. Discussing the academic findings with my advisor helps me learn more about the theoretical foundation of my research. Secondly, communicating with other Ph.D. students, especially other senior Ph.D. students and computer science students, helps me address the technical and methodology challenges.

4.5. Challenges of Working with Data Sponsors

It would be desirable if researchers can collaborate with industry data sponsors, conduct field experiments, and provide managerial insights. However, working with companies is challenging. During my Ph.D. study, I have participated in a research project using the data sponsored by a financial telecommunication institution. The institution provided us with monthly bilateral payment-related messaging data for non-financial market payments for 200 countries from 2004 to 2015, representing 20,000 country-pairs. I have used the data to identify anomalies in bilateral cross-border payment flows and built an explanatory econometric model to interpret the occurrence and magnitude of anomalies.

The study finds that countries with more stable and resilient forms of governance are less likely to exhibit payment anomalies when there are various kinds of shocks, while countries with more trade openness are more likely to exhibit anomalies. These findings are consistent with economic resilience and vulnerability theory, providing policy insight that trade openness and governance level of government play a pivotal role in determining the economic and payment stability. Furthermore, the essay suggests building the Early Warning Systems for international trade and economic activity using the anomaly detection methods in payment flows.

We have presented the work at the Statistical Conference in E-Commerce Research (SCECR), and the outcome of the project was an industry research report in the year 2018. However, due to the non-disclosure agreement, details of the research findings were not permitted to be included in the dissertation. Although the research has significant academic value, unfortunately, it cannot be finally published in academic journals. I learned the difficulty and challenge when working with industry data sponsors.

Chapter 5. Conclusion

The development of information technology transforms prosocial fundraising through crowdfunding platforms, which enables individual funders to contribute to campaigns that raise funds for small entrepreneurs, by and large, from developing countries. To facilitate fundraising activities, matching subsidies are widely provided on crowdfunding platforms. However, the effects of matching subsidies on prosocial fundraising in the crowdfunding context are still ambiguous.

Motivated by this research gap, I examine the effectiveness of matching subsidies on the crowdfunding platforms and identify positive effects of matching subsidies on both matched loans and unmatched loans, which alleviate the concern of the uncertain effects of matching subsidies on unmatched campaigns in traditional offline donations. Additionally, I examine how the effects of matching subsidies on boosting fundraising vary in different stages of a campaign, which depend on the cumulative prior contribution and completed percentage of the funding goal. These findings help Kiva identify the most effective promotion strategy of matching subsidies on its platform.

The first essay contributes to our overall understanding of the effect of matching subsidies on philanthropic behavior in the crowdfunding context. There are competing theories about the effect of matching subsidies on private contributions in the traditional donation environment. The relative price theory suggests that matching subsidies increase the private contribution by reducing the cost of contribution, while the motivational crowding out theory suggests that matching subsidies have a detrimental effect on the intrinsic motivation of prosocial behavior, leading to decreased levels of the private contribution. We find that matching subsidies increase the total private contribution to matched loans by attracting a larger pool of lenders, which provides evidence to support the theory of relative price in the crowdfunding context. Additionally, we find that matching subsidies have positive spillover effects on unmatched loans temporarily. Our work provides management insight for running one-for-one matching campaigns on the crowdfunding platforms. Our findings support the wide usage of matching subsidies on crowdfunding platforms and demonstrate its effectiveness in increasing the private contributions to both matched and unmatched loans.

The second essay contributes to the theory of herding behavior and payoff externalities by investigating how matching subsidies affect the dynamics of crowdfunding. First, we find that the higher accumulative prior contributions and completed percentage of the funding goal are both associated with higher subsequent funding, which supports the theories of herding behavior and payoff externalities in the prosocial crowdfunding context. We also find that matching subsidies moderate the herding behavior and payoff externalities by providing signals of quality and reducing the uncertainty of loans. Our work also provides policy insights about how to use matching subsidies to boost funding activity more efficiently. The analysis of the effect of matching subsidies in different stages of funding suggests that matching subsidies are most efficient in the early stages of funding. However, the matching subsidies have no influence on total private contribution when the loan is close to reaching the target goal. Consequently, we recommend providing matching subsidies only in the first stage of funding, which helps use the matching grants more efficiently. For example, prosocial crowdfunding platforms can cooperate with third-party institutions to provide matching subsidies when the goal attainment level has not reached 10%. Crowdfunding platforms can also provide *seed money* (List and Lucking-Reiley,

2002) to help the funding amount reach a certain goal attainment level quickly.

There are some limitations and future research directions. In the first essay, the data limitation prevents us from assessing the long term effect of matching subsidies since our data set only has 14 days and 5 days after the match day. In the second essay, there could be alternative ways to model dynamics. For example, Kim et al. (2020) model the crowdfunding dynamics with the variation of time lapse. My future research will extend the two essays. I will expand my research on the long term effect of matching subsidies in crowdfunding platforms by collecting more transaction data with a longer time horizon. In addition, I am planning to explore how social media, google search trends, and team endorsement in the crowdfunding context help spread the information of matching subsidies to attract potential lenders and affect funding dynamics.

Reference

Adena, M., & Huck, S. 2017. Matching donations without crowding out? Some theoretical considerations, a field, and a lab experiment. Journal of Public Economics, 148, 32-42.

Anderson, L.R. and Holt, C.A., 1997. Information cascades in the laboratory. The American Economic Review, pp.847-862.

Agrawal, A., Catalini, C. and Goldfarb, A. 2014. Some simple economics of crowdfunding, innovation policy and the economy, 14(1), 63-97.

Akerlof, G.A., 1978. The market for “lemons”: Quality uncertainty and the market mechanism. In Uncertainty in economics (pp. 235-251). Academic Press.

Allison, P.D. and Waterman, R.P., 2002. Fixed–effects negative binomial regression models. Sociological Methodology, 32(1), pp.247-265.

Andreoni, J. 1990. Impure Altruism and donations to public goods: A theory of warm-glow giving. The Economic Journal, 100(401), 464-477.

Andreoni, J., 1998. Toward a theory of charitable fund-raising. Journal of Political Economy, 106(6), pp.1186-1213.

Andreoni, J., 2006a. Leadership giving in charitable fundraising. Journal of Public Economic Theory, 8(1), pp.1-22.

Andreoni, J., 2006b. Philanthropy. Handbook of the economics of giving, altruism and reciprocity, 2, 1201-1269.

Andreoni, J. and Miller, J., 2002. Giving according to GARP: An experimental test of the consistency of preferences for altruism. Econometrica, 70(2), 737-753.

Argo, N., Klinowski, D., Krishnamurti, T. and Smith, S., 2020. The completion effect in charitable crowdfunding. Journal of Economic Behavior & Organization, 172, pp.17-32.

Astebro, T.B., Fernández Sierra, M., Lovo, S. and Vulkan, N., 2019, June. Herding in equity crowdfunding. In Paris December 2018 Finance Meeting EUROFIDAI-AFFI.

Austin, P.C., 2009. Balance diagnostics for comparing the distribution of baseline covariates between treatment groups in propensity score matched samples. Statistics in Medicine, 28(25), 3083-3107.

Ayres, R.U. and Kneese, A.V., 1969. Production, consumption, and externalities. The American Economic Review, 59(3), pp.282-297.

Cambridge Center for Alternative Finance. 2020. The global alternative finance market benchmarking report. Cambridge, United Kingdom.

Charness, G., & Holder, P. 2018. Charity in the laboratory: Matching, competition, and group identity. Management Science, 65(3), 1398-1407.

Banerjee, A.V., A simple model of herd behavior. The Quarterly Journal of Economics, 107(3), 1992, pp.797-817.

Bekkers, R. 2015. When and Why Matches are More Effective Subsidies than Rebates. Replication in Experimental Economics, 183-211.

Bertrand, M., Duflo, E. & Mullainathan, S. 2004. How much should we trust differences-in-differences estimates? The Quarterly Journal of Economics, 119(1), 249–275.

Bikhchandani, S., Hirshleifer, D. and Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy, 100(5), pp.992-1026.

Burtch, G., Ghose, A. and Wattal, S. 2013. An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets. Information Systems Research, 24(3), 499-519.

Burtch, G., Ghose, A. and Wattal, S. 2014. Cultural differences and geography as determinants of online prosocial lending, Management Information Systems Quarterly, 38(3), 773-794.

Burtch, G., Hong, Y. and Liu, D., 2018. The role of provision points in online crowdfunding. Journal of Management Information Systems, 35(1), 117-144.

Cai, H., Y. Chen, H. Fang. 2009. Observational learning: Evidence from a randomized natural field experiment. The American Economic Review 99(3) 864–882.
Cambridge Center for Alternative Finance. 2020. The global alternative finance market benchmarking report. Cambridge, United Kingdom.
Card, D. and Krueger, A.B., 2000. Minimum wages and employment: a case study of the fast-food industry in New Jersey and Pennsylvania: reply. The American Economic Review, 90(5), 1397-1420.

CECP Coalition. 2018. Giving in numbers, New York, NY.

Chang, C., 2010. Herding and the role of foreign institutions in emerging equity markets. Pacific-Basin Finance Journal, 18(2), pp.175-185.

Chen, Y., Li, X. and MacKie-Mason, J.K. 2006. Online fund-raising mechanisms: A field experiment. The BE Journal of Economic Analysis & Policy, 5(2).

Cook, T.D., Campbell, D.T. and Day, A., 1979. Quasi-experimentation: Design & analysis issues for field settings (Vol. 351). Boston: Houghton Mifflin.

Croson, R. and Shang, J.Y., 2008. The impact of downward social information on contribution decisions. Experimental Economics, 11(3), pp.221-233.

Deck, C. and Murphy, J.J. 2019. Donors change both their level and pattern of giving in response to contests among charities. European Economic Review, 112, 91-106.

Dehejia, R. H., & Wahba, S., Propensity score matching methods for nonexperimental causal studies. Review of Economics and Statistics, 84(1), 2002, pp.151-161.

Devenow, A. and Welch, I., "Rational herding in financial economics," European Economic Review, 40(3-5), 1996, pp.603-615.

Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B., Leitão, P.J. and Münkemüller, T., Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, 36(1), 2013, pp.27-46.

Duncan, B., 2004. A theory of impact philanthropy. Journal of public Economics, 88(9-10), pp.2159-2180.

Eckel, C.C. and Grossman, P.J., 2008. Subsidizing charitable contributions: a natural field experiment comparing matching and rebate subsidies. Experimental Economics, 11(3), 234-252.

Eckel, C., & Grossman, P. J. 2017. Comparing rebate and matching subsidies controlling for donors' awareness: Evidence from the field. Journal of Behavioral and Experimental Economics, 66, 88-95.

Epperson, R., & Reif, C. 2017. Matching schemes and public goods: A review. ZEW-Centre for European Economic Research Discussion Paper, 17-070.

Fisk, R.P., Patricio, L., Ordanini, A., Miceli, L., Pizzetti, M. and Parasuraman, A. Crowdfunding: Transforming customers into investors through innovative service platforms," Journal of Service Management, 22(4), 2011, pp. 443-470

Frey, B.S. and Oberholzer-Gee, F., 1997. The cost of price incentives: An empirical analysis of motivation crowding-out. The American Economic Review, 87(4), 746-755.

Frey, B. S. 2017. The Relative price effect explains behavior. In Economic Ideas You Should Forget (59-60). Springer, Cham.

Galak, J., Small, D. and Stephen, A.T. 2011. Microfinance decision making: a field study of prosocial lending, Journal of Marketing Research, 48, S130-S137.

Gallaugher, J.M. and Wang, Y.M., 2002. Understanding network effects in software markets: evidence from web server pricing. Management Information Systems Quarterly, pp.303-327.

Geva, H., Barzilay, O. and Oestreicher-Singe, G., 2019. A potato salad with a lemon twist: using a supply-side shock to study the impact of opportunistic behavior on crowdfunding platforms. Management Information Systems Quarterly., 43(4), 1227-1248.

Glazer, A., and Konrad, K., 1996. A Signaling Explanation for Charity. The American Economic Review, 86(4), 1019-1028.

Gneezy, U., Keenan, E.A. and Gneezy, A., 2014. Avoiding overhead aversion in charity. Science, 346(6209), 632-635.

Goes, P.B., Lin, M. and Au Yeung, C.M., 2014. "Popularity effect" in user-generated content: Evidence from online product reviews. Information Systems Research, 25(2), pp.222-238.

Gomber, P., Kauffman, R.J., Parker, C. and Weber, B.W., 2018. On the fintech revolution: interpreting the forces of innovation, disruption, and transformation in financial services. Journal of Management Information Systems, 35(1), pp.220-265.

Greenwood, B.N. and Gopal, A., 2016. Ending the mending wall: herding, media coverage, and co-location in it entrepreneurship. Media Coverage, and Co-Location in IT Entrepreneurship (October 15, 2016).

Hamilton, J. D., 1994. Time series analysis. Vol. 2, Princeton University Press, Princeton, NJ.

Hansen, C.B., 2007. Generalized least squares inference in panel and multilevel models with serial correlation and fixed effects. Journal of Econometrics, 140(2), 670-694.

Hausman, J., Hall, B.H. and Griliches, Z., 1984. Econometric models for count data with an application to the patents-R&D relationship. Econometrica, 52(4), pp.909-938.

Herzenstein, M., Dholakia, U.M. and Andrews, R.L., Strategic herding behavior in peer-to-peer loan auctions. Journal of Interactive Marketing, 25(1), 2011, pp.27-36.

Heutel, G., 2014. Crowding out and crowding in of private donations and government grants. Public Finance Review, 42(2), 143-175.

Hong, Y., Hu, Y. and Burtch, G., 2018. Embeddedness, pro-sociality, and social influence: Evidence from online crowdfunding. Management Information Systems Quarterly, 42(4), 1211-1224.

Hornuf, L. and Schwienbacher, A., 2018. Market mechanisms and funding dynamics in equity crowdfunding. Journal of Corporate Finance, 50, pp.556-574.

Huck, S., Rasul, I., & Shephard, A. (2015). Comparing charitable fundraising schemes: Evidence from a natural field experiment and a structural model. American Economic Journal: Economic Policy, 7(2), 326-69.

Hwang, S. and Salmon, M. (2004), Market stress and herding. Journal of Empirical Finance, Vol. 11 No. 4, pp. 585-616.

Imbens, G.W. and Wooldridge, J.M., 2009. Recent developments in the econometrics of program evaluation. Journal of Economic Literature, 47(1), 5-86.

Karlan, D. and List, J.A. 2007. Does price matter in charitable giving? evidence from a large-scale field experiment. American Economic Review, 97(5), 1774-1793.

Karlan, D., List, J.A. and Shafir, E., 2011. Small matches and charitable giving: Evidence from a natural field experiment. Journal of Public Economics, 95(5-6), 344-350.

Katz, M. L. and Shapiro, C., 1985. Network externalities, competition, and compatibility. American Economic Review. 75(3), 424–440.

Kauffman, R.J. and Li, X., 2003. Payoff externalities, informational cascades and managerial incentives: a theoretical framework for IT adoption herding. In Proceedings of the 2003 INFORMS Conference on IS and Technology, Atlanta, GA (Vol. 2003).

Kauffman, R.J., McAndrews, J. and Wang, Y.M., 2000. Opening the "black box" of network externalities in network adoption. Information Systems Research, 11(1), pp.61-82.

Karlan, D. and List, J.A. 2007. Does price matter in charitable giving? Evidence from a large-scale natural field experiment. American Economic Review (97:5), pp.1774-1793.

Kim, C., Kannan, P.K., Trusov, M. and Ordanini, A, 2020. Modeling dynamics in crowdfunding," Marketing Science, 39(2) , pp.339-365.

Kiva, 2020a. Loan matching. [online] Available at: https://www.kiva.org/partner-with-us/loan-matching [Accessed 1 May 2020]

Kiva, 2020b. The risks of lending. [online] Available at: https://www.kiva.org/about/due-diligence/risk [Accessed 10 December 2020]

Krieg, J. and Samek, A. 2017. When charities compete: a laboratory experiment with simultaneous public goods. Journal of Behavioral and Experimental Economics, 66, 40-57. \

Kuppuswamy, V. and Bayus, B.L., 2017. Does my contribution to your crowdfunding project matter?. Journal of Business Venturing, 32(1), pp.72-89.

Kuppuswamy, V. and Bayus, B.L., "Crowdfunding creative ideas: The dynamics of project backers. In the Economics of Crowdfunding (pp. 151-182). Palgrave Macmillan, 2018, Cham.

Lacetera, N., Macis, M., & Slonim, R. 2014. Rewarding volunteers: A field experiment. Management Science, 60(5), 1107-1129.

Lakonishok, J., Shleifer, A. and Vishny, R.W., 1992. The impact of institutional trading on stock prices. Journal of Financial Economics, 32(1), pp.23-43.\

Li, Z., Duan, J.A. and Ransbotham, S., 2020 Coordination and dynamic promotion strategies in crowdfunding with network externalities. Production and Operations Management, 29(4), pp.1032-1049.

Li, X. and Wu, L., 2018. Herding and social media word-of-mouth: evidence from groupon. Management Information Systems Quarterly, 42(4), pp.1331-1351.

Lin, M., Prabhala, N.R. and Viswanathan, S. 2013. Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending, Management Science, 59(1), 17-35.

Lin, M. and Viswanathan, S., 2016. Home bias in online investments: An empirical study of an online crowdfunding market. Management Science, 62(5), pp.1393-1414.

List, J.A. and Lucking-Reiley, D., 2002. The effects of seed money and refunds on charitable giving: Experimental evidence from a university capital campaign. Journal of political Economy, 110(1), pp.215-233.

Liu, D., Brass, D.J., Lntu, Y. and Chen, D. 2015. Friendships in online peer-to-peer lending: pipes, prisms, and relational herding, Management Information Systems Quarterly., 39(3), 729-742.

Liu, Y., Chen, R., Chen, Y., Mei, Q. and Salib, S. 2012. I loan because...: Understanding motivations for pro-social lending, In Proceedings of the 5th ACM International Conference on Web Search and Data Mining, New York: ACM Press, pp. 503-512

López-de-Lacalle, J., 2017. Detection of outliers in time series. Package 'tsoutliers,' v. 6.6, CRAN Repository, May 27.

Ly, P. and Mason, G. 2012. Competition between microfinance ngos: evidence from kiva, World Development. 40(3), 643-655.

Low, S. W., Tee, L. T., Kew, S. R., 2015. Does the quality of governance matter for equity market risk? Evidence from emerging and developed equity markets. Journal of Business Economics and Management, 16(3), 660-674.

Massolution, 2015. Global crowdfunding market to reach $ 34.4B in 2015 Available at: http://www.crowdsourcing.org/editorial/global-crowdfundingmarket-to-reach-344b-in-2015-predicts-massolutions-2015cf-industry-report/45376.

Meer, J. 2017. Does fundraising create new giving? Journal of Public Economics, 145, 82-93.

Meier, S. 2007a. A survey of economic theories and field evidence on pro-social behavior. In B. S. Frey & A. Stutzer (Eds.), CESifo seminar series. Economics and psychology: A promising new cross-disciplinary field (p. 51–87). MIT Press.

Meier, S., 2007b. Do subsidies increase charitable giving in the long run? Matching donations in a field experiment. Journal of the European Economic Association, 5(6), 1203-1222.

Morduch, J. 1999. The microfinance promise. Journal of Economic Literature, 37(4), 1569-1614.

NESTA (2014). Understanding alternative finance: The UK alternative finance industry report 2014. London, UK: Nesta.

Nonprofit Source, 2018. The ultimate list of charitable giving statistics for 2018. [online] Available at: https://nonprofitssource.com/online-giving-statistics/ [Accessed 19 September 2020]

Oh, W. and Jeon, S., 2007. Membership herding and network stability in the open source community: The Ising perspective. Management science, 53(7), pp.1086-1101.

Potters, J., Sefton, M. and Vesterlund, L., 2007. Leading-by-example and signaling in voluntary contribution games: an experimental study. Economic Theory, 33(1), pp.169-182.

Rondeau, D. and List, J.A. 2008. Matching and challenge gifts to charity: Evidence from laboratory and natural field experiments, Experimental Economics, 11(3), 253-267.

Rondeau, D., Schulze, W.D. and Poe, G.L., 1999. Voluntary revelation of the demand for public goods using a provision point mechanism. Journal of Public Economics, 72(3), pp.455-470.

Rosenbaum, P.R., Design of observational studies (Vol. 10). Springer, 2010, New York.

Salganik, M.J., Dodds, P.S. and Watts, D.J., 2006. Experimental study of inequality and unpredictability in an artificial cultural market. Science, 311(5762), pp.854-856.

Scharf, K.A., Smith, S. and Wilhelm, M. 2017. Lift and shift: The effect of fundraising interventions in charity space and time, CEPR Discussion Paper No. DP12338.

Shang, J. and Croson, R., 2009. A field experiment in charitable contribution: The impact of social information on the voluntary provision of public goods. The Economic Journal, 119(540), pp.1422-1439.

Sias, R.W. 2004. Institutional herding. Review of Financial Studies, Vol. 17 No. 1, pp. 165-206.

Simonsohn, U. and Ariely, D., 2008. When rational sellers face nonrational buyers: evidence from herding on eBay. Management science, 54(9), pp.1624-1637.

Sinanan, J. 2009. Lenders, borrowers and fellows: Personal narrative and social entrepreneurship in online microfinance, In Proceedings of the 21st Annual Conference of the Australian Computer-Human Interaction Special Interest Group: Design: Open 24/7, New York: ACM Press, pp. 293-296).

Statista. 2020. Alternative financing report 2019, Retrieved from https://www.statista.com/study/47352/fintech-report-alternative-financing

Sun, H., 2013. A longitudinal study of herd behavior in the adoption and continued use of technology. Management Information Systems Quarterly, pp.1013-1041.

Tan, L., Chiang, T.C., Mason, J.R. and Nelling, E., 2008. Herding behavior in Chinese stock markets: An examination of A and B shares. Pacific-Basin Finance Journal, 16(1-2), pp.61-77.

Tucker, C. and Zhang, J., 2011. How does popularity information affect choices? A field experiment. Management Science, 57(5), pp.828-842.

Vesterlund, L., 2003. The informational value of sequential fundraising. Journal of public Economics, 87(3-4), pp.627-657.

Vismara, S., 2018. Information cascades among investors in equity crowdfunding. Entrepreneurship Theory and Practice, 42(3), pp.467-497.

Vuong, Q.H., 1989. Likelihood ratio tests for model selection and non-nested hypotheses. Econometrica, 307-333.

Walter, A and Weber, F.M. (2006), "Herding in the German mutual fund industry", European Financial Management, Vol. 12 No. 3, pp. 375-406.

Wash, R. (2013). The value of completing crowdfunding projects. Presented at ICWSM-13: The 7th InternationalAAAI Conference on Weblogs and Social Media, MIT Media Lab and Microsoft, Cambridge, MA.

Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data. MIT press.

Yang, L., Wang, Z., Ding, Y. and Hahn, J. 2016. The Role of Online Peer-to-Peer Lending in Crisis Response: Evidence from Kiva, in Proceedings of the 34th International Conference on Information Sciences, Dublin, Ireland.

Younkin, P., & Kuppuswamy, V. 2017. The colorblind crowd? Founder race and performance in crowdfunding. Management Science, 64(7), 3269-3287.

Zhang, J., 2010. The sound of silence: Observational learning in the US kidney market. Marketing Science, 29(2), pp.315-335.

Zhang, J. and Liu, P. 2012. Rational herding in microloan markets, Management Science, 58(5), 892-912.

Zhao, Q., Chen, C.D., Wang, J.L. and Chen, P.C. 2017. Determinants of backers' funding intention in crowdfunding: Social exchange theory and regulatory focus, Telematics and Informatics, 34(1), 370-384

Zhang, X.M. and Zhu, F., 2011. Group size and incentives to contribute: A natural experiment at Chinese Wikipedia. The American Economic Review, 101(4), pp.1601-15

APPENDIX A. An Examination of the Effectiveness of Matching Subsidies on Pro-social Crowdfunding

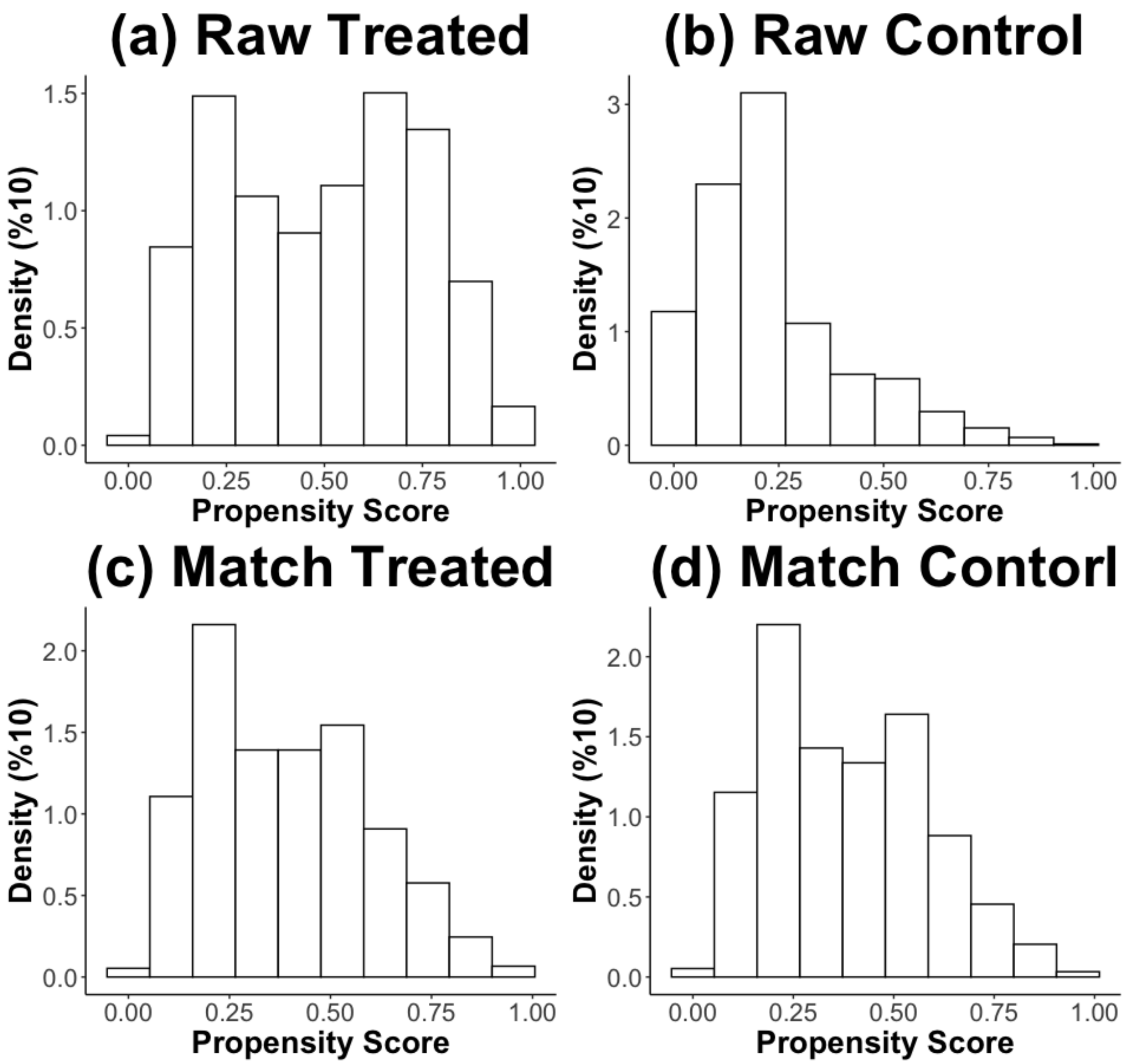
Table A1: The Matching Preference of Matching Funds Providers

Institutions	#Loans	Country	Sector	Group	Gender
Anonymous Supporter	1112	No	Agricultural, Food	No	No
Women and Girls Empowered	419	El Salvador, Honduras	No	Single	Female
Google	41	United States	No	Single	No
Woods Family Foundation	145	No	Agricultural, Food	No	No
Bank of America	257	No	Agricultural, Food	No	Female
Miller Family Foundation	194	Kenya, Tanzania	Personal Use	No	No
Anonymous Supporter	5	Cambodia	Personal Use	Group	No
Google	4	United States	No	Single	No
Diller-von Furstenberg Family Foundation	2	United States	Retail, Service	Single	No
Milwaukee 7 / MUSIC	1	United States	Retail	Single	Female
TRF	30	No	No	No	No
VMware	30	No	Health	No	No
VMware	15	Vietnam	Housing	No	No
Pepsi	21	No	Agriculture	No	No
Vmware	29	No	Food	No	No

Note: Some institutions have multiple accounts to provide matching funds for different loans.

Note: On 12 September 2018, 15 third-party institutions or funders are providing matching subsidies for 1994 loans. After discussing with staffs in Kiva, we learn that these third-party funders select matched loans based on several different criteria: the target amount of the loan, the number of months over which the borrower will repay the loan, whether the number of borrowers is larger than 1, whether the borrower of the loan is female, the country of that loan, the sector of that loan. These characteristics are all important criteria to determine whether the loan will be matched. In Table A1, we present the preference of different matching funds providers in multiple categorical criteria. We present the number of loans the institutions have provided matching subsidies (#Loans). An institution may select loans from multiple countries or sectors to provide matching subsidies. We list the preferred countries of an institution (Country) if the number of selected loans from the top two countries accounts for more than 50% of the total number of selected loans. We also list the preferred sectors of an institution (Sector) if the number of selected loans from the top two sectors accounts for more than 50% of the total number of selected loans. We also list the preference of single borrower or group borrowers for an institution (Group). The preference of a single borrower means that the institution only matches loans with a single borrower, while the preference of group borrowers means that the institution only match loans with more than one borrower. Finally, we list the preference of gender for an institution (Gender). The preference of female borrowers means that the institution only match loans with female borrowers.

Figure A1. The Distribution of Propensity Scores Before and After Matching Procedure



Note: The histogram of propensity scores is presented in Table B1. The horizontal axis represents the propensity score, while the vertical axis represents the density of propensity scores. From figure B1a and figure B1b, the propensity score of treated loans and control loans have different distributions before matching. Nevertheless, the propensity scores of treated loans and control loans have similar distributions after the propensity score matching procedure.

APPENDIX B. An Economic Analysis of Matching Subsidies on the Dynamics of Crowdfunding

Table B1. Multicollinearity Check of Variance Inflation Factor

	ESTIMATION RESULT	VIF
AccumAmount	0.2***(0)	2.72
Percent	3.62***(0.02)	2.38
Match	2.1***(0.02)	1.06
Competition	-0.18***(0)	1.17
DayLapsed	-0.6***(0)	1.21
GTrends	0.25***(0.01)	1.01
Observations	612,088	
Adjusted R-Square	0.343	

Note: The table reports the estimation results of the variance inflation factor. Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10.

Note: The table presents the multicollinearity check result of the variance inflation factor (VIF). The VIF test is the most popular method to conduct a multicollinearity check. To get the VIF value of an independent variable X_i, we at first regress the variable on all other independent variables and get the R-square R_i^2. The variance inflation factor value of variable X_i equals 1/(1-R_i^2). Following the process, we get the VIF value for every independent variable, shown in Table C1.

APPENDIX C. An Economic Analysis of Matching Subsidies on the Dynamics of Crowdfunding with Alternative Data Set from January 4, 2019, to March 5, 2019.

Table C3. Descriptive Statistics

N=612,088	MIN	MAX	MEAN	SD
FundAmount	0	27900	53.03	222.42
AccumAmount	0	40625	122.16	403.38
Percent	0	1	0.09	0.17
Match	0	1	0.01	0.09
Competition	1	1098	198.51	272.98
DayLapsed	1	46	12.63	9.02
GTrends	16	100	78.56	16
Note: The table presents the statistics of variables generated from the data set starting from January 4 2019 to March 5, 2019.				

Table C4. Variables Correlation

VARIABLE	1	2	3	4	5	6	7
FundAmount	1						
AccumAmount	0.3	1					
Percent	0.2	0.59	1				
Match	0.06	0.11	0.09	1			
Competition	-0.08	-0.14	-0.15	-0.04	1		
DayLapsed	-0.04	0.13	0.18	-0.03	0.01	1	
GTrends	0.03	0.06	0.04	-0.01	-0.22	-0.03	1
Note: The table presents the correlation of variables generated from the data set starting from January 4 2019 to March 5, 2019.							

Table C3. Multicollinearity Check of Variance Inflation Factor

	ESTIMATION RESULT	VIF
AccumAmount	0.23***(0)	2.86
Percent	3.77***(0.02)	2.52
Match	1.87***(0.03)	1.02
Competition	-0.12***(0)	1.16
DayLapsed	-0.58***(0)	1.13
GTrends	0.23***(0.02)	1.02
Observations	445,368	
Adjusted R-Square	0.341	
Note: The table reports the estimation results of the variance inflation factor using the data set from January 4 2019 to March 5, 2019. Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10.		

Table C4. Propensity Score Matching Results

VARIABLE	BEFORE MATCHING			AFTER MATCHING		
	CTRL	TREAT	SMD	CTRL	TREAT	SMD
Count	39239	2990		1415	1467	
LoanAmount	794.90	1169.46	0.26	1218.34	951.96	0.08
RepayTerm	13.35	14.86	0.23	13.10	13.33	0.03
IsGroup	0.12	0.25	0.06	0.21	0.19	0.06
IsFemale	0.75	0.83	0.20	0.80	0.79	0.02
Country	NA	NA	1.24	NA	NA	0.21
Sector	NA	NA	0.26	NA	NA	0.09

Note: The table presents the propensity score matching results using the data set starting from January 4 2019 to March 5, 2019. The Treat column presents the mean of variables for loans receiving matching subsidies. The Ctrl column presents the mean of variables for loans without receiving matching subsidies. The standardized mean deviation (SMD) is widely used in literature to measure the balance of variables between treated groups and control groups.

Table C5. Robustness Check with Propensity Score Matching

	NEGATIVE BINOMIAL FIXED-EFFECTS
AccumAmount	0.36***(0.01)
Percent	1.9***(0.05)
Match	2.26***(0.05)
Match AccumAmount*	-0.26***(0.02)
*Match*Percent*	-1.09***(0.15)
Competition	-0.13***(0.01)
DayLapsed	-0.39***(0.01)
GTrends	0.25***(0.07)
Observations	41,505

The table presents the estimation results using the data set starting from January 4 2019 to March 5, 2019. The data set is also sampled with the propensity score matching procedure.The standard errors are 0 because they are less than 0.01. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects. The estimation drops all of the loans with all zero outcomes and only one observation per loan.

Note: Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10.

Table C6. Robustness Check with Fixed Effects Model

	FIXED EFFECTS FULL SAMPLE	FIXED EFFECTS PSM SAMPLE
AccumAmount	0.23***(0)	0.19***(0.01)
Percent	2.98***(0.05)	3.7***(0.13)
Match	3.23***(0.05)	2.99***(0.07)
Match AccumAmount*	-0.17***(0.02)	-0.17***(0.03)
*Match*Percent*	-2.79***(0.16)	-3.5***(0.26)
Competition	-0.2***(0.02)	-0.4***(0.05)
DayLapsed	0.03***(0)	-0.08***(0.01)
GTrends	0.22***(0.03)	0.11(0.09)
Observations	445,368	43,708
Adjusted R-Square	0.27	0.354

The estimation is implemented with the fixed effects model controlling the loan fixed effects, using the data set starting from January 4 2019 to March 5, 2019. The first column presents the estimation of fixed effects model using the full sample data. The second column presents the estimation of fixed effects model using the sampled data selected from propensity score matching procedure.
Note: Robust Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10. The standard errors are 0 because they are less than 0.01.

Table C7. Robustness Check with Alternative Measures of Herding Momentum

	ACCUMLEND AS ALTERNATIVE	CONTRFREQ AS ALTERNATIVE
AccumFunder	0.85***(0)	
ContrFreq		0.45***(0)
Percent	0.93***(0.02)	1.74***(0.02)
Match	2.2***(0.03)	2.6***(0.03)
Match AccumFunder*	-0.5***(0.02)	
Match ContrFreq*		-0.5***(0.02)
*Match*Percent*	-0.57***(0.1)	-0.59***(0.08)
Competition	-0.11***(0)	-0.17***(0)
DayLapsed	-0.46***(0)	-0.18***(0)
GTrends	0.35***(0.02)	0.4***(0.02)
Observations	397,209	397,209

Note: The table reports the estimation results of robustness checks using *AccumFunder* and *ContrFreq* as alternative measures of herding momentum. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects, using the data set starting from January 4 2019 to March 5, 2019. The estimation drops all of the groups (loans) with all zero outcomes and only one observation per group.
Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10.

Table C8. Robustness Check with Sampled Data

	Large Amount Loans	Loans with Full-time periods
AccumAmount	0.41***(0)	0.4***(0)
Percent	1.37***(0.02)	1.27***(0.02)
Match	2.07***(0.05)	2.04***(0.04)
Match AccumAmount*	-0.23***(0.02)	-0.27***(0.02)
*Match*Percent*	-0.59***(0.11)	-0.46***(0.1)
Competition	-0.15***(0)	-0.15***(0)
DayLapsed	-0.51***(0)	-0.49***(0)
GTrends	0.33***(0.03)	0.29***(0.03)
Observations	283,854	270,521

Note: The table reports the estimation results of robustness checks using groups (loans) with more than $500 funded amount and loans with complete funding history. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects, using the data set starting from January 4 2019 to March 5, 2019. The estimation drops all of the groups with all zero outcomes and only one observation per group.
Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10.

APPENDIX D. An Economic Analysis of Matching Subsidies on the Dynamics of Crowdfunding with Alternative Data Set from June 4 2019 to August 23, 2019.

Table D5. Descriptive Statistics

N=612,088	MIN	MAX	MEAN	SD
FundAmount	0	42175	56.98814	260.0447
AccumAmount	0	92000	138.5644	718.2864
Percent	0	0.9995	0.1100552	0.1748891
Match	0	1	0.0269171	0.1618413
Competition	1	1362	184.4594	261.7525
DayLapsed	1	101	13.53027	10.65891
GTrends	6	100	68.84944	20.02522
Note: The table presents the statistics of variables generated from the data set starts from June 4 2019 to August 23, 2019.				

Table D6. Variables Correlation

VARIABLE	1	2	3	4	5	6	7
FundAmount	1						
AccumAmount	0.29	1					
Percent	0.15	0.35	1				
Match	0.11	0.06	0.12	1			
Competition	-0.07	-0.08	-0.12	-0.03	1		
DayLapsed	-0.05	0.06	0.15	-0.03	0.03	1	
GTrends	-0.02	-0.02	-0.04	0.01	0.03	0.05	1
Note: The table presents the correlation of variables generated from the data set starts from June 4 2019 to August 23, 2019.							

Table D3. Multicollinearity Check of Variance Inflation Factor

	ESTIMATION RESULT	VIF
AccumAmount	0.18***(0)	2.58
Percent	3.65***(0.02)	2.26
Match	2.2***(0.01)	1.03
Competition	-0.14***(0)	1.17
DayLapsed	-0.6***(0)	1.12
GTrends	-0.05***(0.01)	1.01
Observations	556,858	
Adjusted R-Square	0.329	
Note: The table reports the estimation results of the variance inflation factor. Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10.		

Table D4. Propensity Score Matching Results

VARIABLE	BEFORE MATCHING			AFTER MATCHING		
	CTRL	TREAT	SMD	CTRL	TREAT	SMD
Count	42567	10308		4647	5375	
LoanAmount	786.58	1074.91	0.19	969.88	981.28	0.01
RepayTerm	13.60	13.60	0.01	13.44	13.39	0.01
IsGroup	0.11	0.19	0.23	0.17	0.16	0.02
IsFemale	0.78	0.79	0.02	0.79	0.79	0.01
Country	NA	NA	0.96	NA	NA	0.21
Sector	NA	NA	0.41	NA	NA	0.06

Note: The table presents the propensity score matching results using the data set starting from June 4 2019 to August 23 2019. The Treat column presents the mean of variables for loans receiving matching subsidies. The Ctrl column presents the mean of variables for loans without receiving matching subsidies. The standardized mean deviation (SMD) is widely used in literature to measure the balance of variables between treated groups and control groups.

Table D5. Robustness Check with Propensity Score Matching

	NEGATIVE BINOMIAL FIXED-EFFECTS
AccumAmount	0.31***(0)
Percent	2.14***(0.03)
Match	2.13***(0.03)
Match AccumAmount*	-0.17***(0.01)
*Match*Percent*	-1.69***(0.08)
Competition	-0.17***(0)
DayLapsed	-0.32***(0.01)
GTrends	-0.08***(0.02)
Observations	130,495

The table presents the estimation results using the data set starting from June 4 2019 to August 23 2019. The data set is also sampled with the propensity score matching procedure. The standard errors are 0 because they are less than 0.01. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects. The estimation drops all of the loans with all zero outcomes and only one observation per loan.

Note: Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10.

Table D6. Robustness Check with Fixed Effects Model

	FIXED EFFECTS FULL SAMPLE	FIXED EFFECTS PSM SAMPLE
AccumAmount	0.2***(0)	0.16***(0.01)
Percent	3.03***(0.04)	3.87***(0.07)
Match	3.38***(0.03)	2.83***(0.04)
Match AccumAmount*	-0.12***(0.01)	-0.05***(0.02)
*Match*Percent*	-3.1***(0.1)	-3.72***(0.14)
Competition	-0.24***(0.01)	-0.37***(0.03)
DayLapsed	-0.01**(0)	-0.09***(0.01)
GTrends	0.34***(0.02)	0.23***(0.05)
Observations	556,858	135,318
Adjusted R-Square	0.26	0.332

The estimation is implemented with the fixed effects model controlling the loan fixed effects, using the data set starting from June 4 2019 to August 23, 2019. The first column presents the estimation of the fixed effects model using the full sample data. The second column presents the estimation of the fixed effects model using the sampled data selected from the propensity score matching procedure.
Note: Robust Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10. The standard errors are 0 because they are less than 0.01.

Table D7. Robustness Check with Alternative Measures of Herding Momentum

	ACCUMLEND AS ALTERNATIVE	CONTRFREQ AS ALTERNATIVE
AccumFunder	0.8***(0)	
ContrFreq		0.39***(0)
Percent	1.08***(0.02)	1.96***(0.02)
Match	2.21***(0.01)	2.62***(0.02)
Match AccumFunder*	-0.46***(0.01)	
Match ContrFreq*		-0.5***(0.01)
*Match*Percent*	-0.75***(0.05)	-0.64***(0.04)
Competition	-0.14***(0)	-0.19***(0)
DayLapsed	-0.47***(0)	-0.2***(0)
GTrends	0.06***(0.01)	-0.01(0.01)
Observations	517,024	517,024

Note: The table reports the estimation results of robustness checks using *AccumFunder* and *ContrFreq* as alternative measures of herding momentum. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects, using the data set starting from June 4 2019 to August 23, 2019. The estimation drops all of the groups (loans) with all zero outcomes and only one observation per group.
Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10.

Table D8. Robustness Check with Sampled Data

	Large Amount Loans	Loans with Full-time periods
AccumAmount	0.36***(0)	0.33***(0)
Percent	1.67***(0.02)	1.62***(0.02)
Match	2.17***(0.02)	1.89***(0.02)
Match AccumAmount*	-0.19***(0.01)	-0.15***(0.01)
*Match*Percent*	-1.14***(0.06)	-1.09***(0.06)
Competition	-0.19***(0)	-0.17***(0)
DayLapsed	-0.46***(0)	-0.45***(0)
GTrends	-0.01(0.01)	-0.07***(0.02)
Observations	395,486	364,125

Note: The table reports the estimation results of robustness checks using groups (loans) with more than $500 funded amount and loans with complete funding history. The estimation is implemented with the negative binomial model controlling the loan-specific fixed effects, using the data set starting from June 4 2019 to August 23, 2019. The estimation drops all of the groups with all zero outcomes and only one observation per group.
Standard Errors are provided in parentheses. ***p<0.01;**p<0.05;*p<0.10.