Do Monetary Incentives Increase Microfinance Lending? An Empirical Study of Matching Gift Programs on Kiva

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Zhiyuan Gao

Abstract

Although there are a variety of studies in IS field exploring funding behavior on crowdfunding and online microfinance platforms, the literature about how external monetary incentive will influence the crowdfunding behavior is very scarce. In this research, we utilize a "match day" event on Kiva to study how matching gift programs, as one of the most important tools of monetary incentives in crowdfunding, will affect the matched loans and unmatched loans. We find that matching gift programs benefit both matched and unmatched loans. Besides, we also find that the higher intensity of matching among competitor of the loan will induce lenders making higher contributions. The result indicates that matching gift programs have a positive spillover effect for unmatched loans, which support the use of matching gift programs on prosocial lending websites to increase overall funding.

Keywords: crowdfunding, microfinance, monetary incentive, matching gift

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. With the popularity of online crowdfunding and microfinance, there are a variety of studies in IS field trying to learn what mechanisms can affect the funding behavior on crowdfunding platforms. They have found that geographic and cultural difference (Burtch et al. 2014), team recognition (Chen et al. 2017), social distance (Galak et al. 2011) as well as the friendship relationship between lenders and borrowers (Liu et al. 2015) affected the funding behavior.

However, most of these studies only focus on non-pecuniary factors, and no one has tried to study how external monetary incentive influenced the funding behavior in crowdfunding. In fact, monetary incentive, because of its success in traditional fundraising to attract lenders and boost funding, has been increasingly used by many online crowdfunding platforms, such as Kiva, Kickstarter, and Donorchoose.org, in recent years. One of the most popular monetary incentive mechanism is *matching gift* programs whereby third-party institutions provide a dollar-for-dollar match of the private contributions from individuals on selected projects. In the context of traditional donations, *matching gift* programs can increase private contribution for matched projects (Karlan and List 2007; Rondeau and List 2008), but may reduce the contribution for unmatched projects, making them harder to get sufficient funding (Deck and Murphy 2019). The negative effect of *matching gift* on unmatched projects is a major concern of the third-party foundations for the overall efficacy of their matching funds.

In this research, we examine the effectiveness of the *matching gift* programs in the context of online microfinance and prosocial crowdfunding. Specifically, we address the following research questions: (1) How does the *matching gift* program affect matched projects? (2) How does the *matching gift* program affect unmatched projects? (3) How different intensity of matching among similar competing projects will influence the funding outcome? Our main interest is in understanding the different impacts of the *matching gift* program on the matched projects and unmatched projects.

To answer the research questions, we leverage the first "match day" program launched by Kiva on July 10, 2014, as an intervention, to make before and after analysis and study how matching gift programs affect prosocial behavior in crowdfunding. Under the "match day" program, Kiva partnered with Google, Grameen-Jameel and Richard Brindle foundation in providing matching funds to selected loans active on and after the "match day". We collected data for all loans posted between 1 April to 31 July. We further group these loans into three categories: (1) loans posted and closed before the event day and thus not influenced by the event (baseline loans), (2) loans posted after the event day and matched (matched loans), and (3) loans posted after the event day but not matched (unmatched loans). We compare the performance of the matched and unmatched loans with baseline loans respectively, to identify the effect of *matching gift* programs.

Our estimation result indicates that *matching gift* programs not only benefit the matched loans but also have indirect spillover benefit for unmatched loans. The matched loans and unmatched loans will both have higher lender arrival rate, shorter funding time and the higher possibility to get fully funded. But the matched loans will get a lower average contribution per lender, and unmatched loans will get a higher average contribution. Prior literature suggests that monetary incentives, including *matching gift* programs, would shift the contribution from unmatched projects to matched projects (Scharf et al. 2017). This raises the concern on the overall effectiveness of the campaign. However, we find that this applies to non-threshold projects only. For threshold fundraising projects with pre-determined target amount, *matching gift* programs bring a positive effect for both matched loans and unmatched loans. Our findings highlight the important difference in project types and support the use of *matching gift* programs on prosocial lending websites to increase overall funding. Besides, we also find that loans with higher intensity of matching among similar competitors will receive stronger benefit, which suggests that *matching gift* programs will induce lenders to make more contribution to other similar loans, consistent with the previous findings (Aldashev and Verdier 2010; Meer 2017; Sulaeman 2019).

Literature Review

Crowdfunding and Online Microfinance

At the end of twenty century, Morduch (1999) has stated the promise and the advantage of microfinance compared with the traditional donation. According to the paper, traditional donations will create dependency and disincentives that make matters worse, not better. And he believed that microfinance – lending capital to help people living in poverty and lack of access to traditional financial institutions to operate small-scale businesses, could help them feed themselves and get out of poverty. However, at that time, microfinance faced the problem of moral hazard and adverse selection problems caused by the information asymmetric between the lenders and borrowers.

With the development of information technology, the emergence of online crowdfunding platforms help solve the problems of information asymmetric and further develop the microfinance (Galak 2011). Crowdfunding platforms enable lenders to choose their interested projects to invest through the online platform, which helps small entrepreneurs lack access to traditional financial tools to get alternative funding. Usually, scholars classify these platforms as four types of crowdfunding: equity-based, reward-based, loan-based and donation-based (Agrawal et al. 2014). And online microfinance is the combination of loan-based crowdfunding and donation-based crowdfunding, where lenders lend money to small entrepreneurs without interest. Contributors in microfinance platforms can get their principal back within certain time periods. And they also don't earn interest from lending, making their contribution as prosocial lending.

In online microfinance platforms, such as Kiva, people living in poverty can post their loans on the website and attract millions of "crowds" from the whole world as a source of funding. With the project description and borrower's personal information posted on the website, asymmetric information problems can also be alleviated, which help online microfinance become increasingly more popular. And there is also a growing body of IS literature studying mechanism influencing the funding behavior on crowdfunding and online microfinance platforms. From supply side, scholars have found that herding behavior (Zhang and Liu 2012), cultural difference and geographic difference (Burtch 2014), team competition (Chen et al. 2017), as well as characteristics of lenders (Liu et al. 2012) would influence the behavior of lenders, and thus affect the funding outcomes. From the perspective of demand side, studies found that personal narrative and social entrepreneurship of borrowers (Sinanan 2009), crisis events shocks near the posted date of loans (Yang et al. 2016), and the friendship of borrowers (Lin et al. 2013) affected the funding outcome of projects in crowdfunding platforms.

Although there is already a bunch of literature studying how lenders and borrower's characteristics will influence the crowdfunding and microfinance behavior, the literature about how monetary incentives, such as *matching gift* programs will affect the crowdfunding and online microfinance is relatively scarce. The following subsection will introduce the relevant work about the effect of *matching gift* programs on traditional donation and crowdfunding.

Matching Gift

Matching gift programs, usually provided by large companies and prosocial foundations, have become increasingly popular in recent years. Based on the most recent survey of more than 300 of the world's largest companies, the Giving in Numbers (CECP Coalition 2018) reported that at least 92% companies had offered at least one *matching gift* programs. Besides, about 285.6 million funds were contributed through *matching gift* programs, accounting for 12% of total corporate cash contributions to nonprofits. *Matching gift* programs are so popular because they can actually increase the response rate and contribution amount in the traditional pro-social donation. From the theory of relative price, making a 1:1 matching equals to reducing the price of donation for 50%, which can significantly increase the response rate for donation solicitation (Chen et al. 2006; Meier 2007; Karlan and List 2007). Besides, although rebate (tax deduction) have similar discount effect with matching effect, Eckel and Grossman (2003) found that *matching gift* had a significantly higher positive effect on response rate and average contribution amount compared with rebate. Except for the price effect, donors will view matching as a signal of quality, especially in threshold public goods, which will also increase the response rate and donation amount (Heutel 2014).

However, *matching gift* programs may also cause a downside effect that it may crowd out the donation of private donors, from theoretical analysis (Andreoni 1990). Besides, Rondeau and List (2007) also provided empirical evidence that *matching gift* programs significantly increased the response rate of lenders but reduced the average contribution amount per lender. Overall, *matching gift* programs will definitely increase the response rate of lenders, but they may have an uncertain influence on the average contribution amount of lenders.

Besides, *matching gift* programs also have spillover effects for unmatched loans. Some scholars stated that *matching gift* programs could not only increase the contribution amount of matched projects but also had behavior spillover effects, inducing donors to make higher contributions to unmatched loans (Krieg and Samek 2017). Conversely, other studies also found that *matching gift* programs would exacerbate competition, leading to donation shift from unmatched projects to matched projects, increasing the contribution amount of matched projects and decreasing the contribution amount of unmatched projects (Scharf et al. 2017; Deck and Murphy 2019). What's more, *matching gift* programs will also affect the subsequent donation solicitation significantly. Meier (2006) found that *matching gift* programs increased the contribution amount in the short run, but the contribution amount would decrease after the program ceased. In summary, *matching gift* programs will definitely have a spillover effect for unmatched projects competing for funds simultaneously or subsequently.

The literature about how *matching gift* programs influence funding outcome on crowdfunding and online microfinance platforms is very scarce. Meer (2017) used the daily aggregation data from Donorchoose.org and found that *matching gift* programs increased giving to eligible requests, and they didn't appear to crowd out giving to similar ones, either contemporaneously or over time.

Methods

Research Context

Launched from October 2005, Kiva has become one of the largest prosocial microfinance platforms. In Kiva, people from any corner of the world can make lending to small entrepreneurs. And most of these entrepreneurs are from developing countries. They will post their loans description and target amount in Kiva, trying to get funding from the public. And lenders who are interested in the projects can choose to lend to the loans with at least $25 and zero interest before the loans get fully funded. The funded capital will be delivered to the entrepreneurs if loans are fully funded, while the loans don't receive full funding until the due will be returned to the lenders. Besides, Kiva is working with local microfinance field institution (MFI) who help screen the borrowers and deliver funds, in order to reduce the risk and make sure lenders get repayment on time. In Kiva, 96.8% of loans will get repayment, which is a relatively high repayment rate. Starting from 2005, Kiva has facilitated 1.8 million lenders to lend $1.25 billion to 3.1 million borrowers from 81 countries. These loans help the small entrepreneurs run their business, build their house and pay for tuitions.

Loans in Kiva are all threshold loans. Each loan in Kiva has a target amount. Once the lending amount reaches the target, the loan is fully funded and no more lending will be accepted. In other crowdfunding platforms, such as GoFundMe, lenders can continue lending money to loans even the funding amount of these loans exceed the target amount. The threshold nature of loans in Kiva make these loans have more equal funding since lenders cannot lend all of their money to popular loans. Besides, lenders in Kiva can get back their principal after certain time periods, which increase the participation rate of lenders. The threshold nature and repayment mechanism make it easier for projects in Kiva to get fully funded. Approximately 94.7% of loans get fully funded, which is significantly above the mean success rate of Donorchoose.org (68.3%).

Although loans in Kiva already have an extremely high success rate, Kiva still works hard to boost funding and improve funding outcomes. In order to increase the success rate of loans, Kiva works with some prestigious partners, like Google, VMware, and PayPal, to provide matching gift programs for selected loans. The matching partners at first define the criteria about which loans should be matched, and then an x2 badge with matching partners' name will be displayed on borrower profiles. However, Kiva does not public the matching criteria for each matching gift program. Kiva just states that matching partners can "define exactly where you want the dollars to go to – the countries, sectors, and causes that are most important to you". But Kiva does not provide detail information about which countries, sectors or causes of loans are selected.

On July 10, 2014, Kiva launched the program "matching day", where three foundations provide at least one million dollars to match part of loans. This event is an intervention to help us evaluate how *matching gift* programs influenced matched loans and unmatched loans.

Hypothesis Development

Drawing on the previous literature, we build a series of hypothesis relating to how *matching gift* programs will affect the funding outcome of matched loans and unmatched loans. The funding outcomes of a project examined include (1) lender arrival rate (i.e., the number of lenders who make the lending action per unit time), (2) funding time (i.e., the time between a loan is posted and fully funded or expired), (3) funding success (i.e., indicator of whether the project gets fully funded), and (4) average contribution per lender (i.e., the average amount that the lenders loan to the project).

Economic theory suggests that monetary incentives can increase prosocial behavior (Meier 2006). Since the *matching gift* program can double the impact of giving, the multiplier effect will increase people's willingness to behave prosaically. Studies on traditional offline donations show that *matching gift* programs will increase the response rate among donors (Karlan and List 2007; Rondeau and List 2008). And empirical evidence from online fundraising (Chen et al. 2006) and crowdfunding (Meer 2017) also demonstrate that *matching gift* programs will increase the response rate of donors. In Kiva, the higher response rate of lenders equals to the higher arrival rate of lenders. Consequently, *matching gift* programs will increase the arrival rate of lenders for matched loans.

Theories of prosocial behavior are based on the notion that people care about the wellbeing of others, and thus an individual's utility depends on the utility of others (Meier 2006). The impure altruism theory (Andreoni 1990) predicts that people will partially reduce their own contributions when others increase their share to the public good. Kingama (1989) finds that matching funds partially crowd out the private donation. In crowdfunding, Burtch et al. (2013) find that others' prior contribution to a project will partially crowd-out the contribution of subsequent donors because their contribution is less important for the recipient. Consequently, *matching gift* programs will decrease the average contribution per lender for matched loans. We thus propose the following hypothesis:

> *H1a (Effect on Matched Loans): The matching gift programs will make matched loans have higher arrival rate but lower average contribution per lender.*

The total lending amount per unit time for the loan equals the product of arrival rate and average contribution per lender. Matched loans have higher arrival rate but lower average contribution, which make it hard to determine the value of total lending amount per unit time from theoretical analysis. However, most of the empirical evidence supports that *matching gift* programs will increase the total contribution for matched loans (Bekkers 2015). Many nonprofits have also witnessed the power of matching programs. Taylor (2015) reported that, on the microfinance site Kiva (kiva.com), loan volume on a matching day could go up to 9-10 times more than a standard day. On charitable organization I'm ME (imme.org), matching promotions have successfully induced existing donors to increase their donations, and at the same time attract new donors to make contributions. Consequently, matched loans will have a higher total lending amount per unit time, which will make these loans have shorter funding time and a higher possibility to get fully funded. We thus propose the following hypothesis:

> *H1b (Effect on Matched Loans): The matching gift programs will make matched loans have shorter funding time and a higher possibility to get fully funded.*

Matched loans and unmatched loans are competing for funds. For charity competition, Krieg and Samek (2017) demonstrated that competition between matched loans and unmatched loans will have two major effects: *behavior spillover* and *expenditure substitution*. *Behavior spillover* indicates that lenders may follow the behavior of other lenders (Bednar et al. 2012). Thus, more lending action to matched loans will make other lenders be more likely to lend to loans competing for funds simultaneously. Besides, *matching gift* programs will make matched loans easier to get successfully funded, and the success of matched loans will induce more lenders to make contributions to similar competing projects (Aldashev and Verdier 2010; Meer 2017; Sulaeman 2019). Overall, *matching gift* programs will not only benefit for matched loans but also attract more lenders for their competitors. Matched loans and unmatched loans are competitors. Consequently, unmatched loans will have higher arrival rate of lenders.

Expenditure substitution indicates that the decrease(increase) of contribution to matched loans will lead to higher(lower) contributions to unmatched loans since the lenders have a pre-set budget to lend. In traditional donation, usually, donors will increase their contribution to matched projects and decrease their contribution to unmatched projects (Scharf et al. 2017). The reason is that these loans are all non-threshold projects, and lenders can continuously make lending to matched loans without limit. A key difference between Kiva and other charitable donations is that Kiva loans are threshold loans. Once the lending amount reaches the target amount, the project is fully funded and no more lending will be accepted. Matching funds decrease the required capital and average contribution per lender for matched loans, leaving more remaining funds to unmatched projects for each lender. Thus, these lenders will make higher contributions to unmatched loans, leading to higher average contribution per lender for unmatched loans.

> *H2a (Effect on Unmatched Loans): The matching gift programs will make unmatched loans have higher arrival rate and higher average contribution per lender.*

The higher arrival rate and average contribution per lenders will make the unmatched loan have higher total contribution per unit time, which will make these loans have shorter funding time and a higher possibility to get fully funded.

> *H2b (Effect on Unmatched Loans): The matching gift programs will make unmatched loans have shorter funding time and a higher possibility to get fully funded.*

We are also interested in how the intensity of matching among similar competitors will influence the matched loans and unmatched loans since third-party institutions have concerns that high intensity of matching in some days (matching day) will increase the competition between loans and bring negative effect. Thus, we want to learn whether the variety of matching intensity among competing loans will influence the funding outcome.

From the above statement, matched loans will make unmatched loans have higher lender arrival rate through *behavior spillover* effect and higher average contribution from *expenditure substitution* effect. Thus, higher intensity of matching among competing loans will make stronger *behavior spillover* and *expenditure substitution* effect, leading to higher arrival rate and average contribution for the loan, no matter whether they are matched loans and unmatched loans. And higher arrival rate and average contribution brought by the higher intensity of matching will make these loans have shorter funding time and a higher possibility to get fully funded.

> *H3a (Intensity Effect): The higher intensity of matching gift programs among similar competitors will bring a stronger positive effect, leading to higher arrival rate and average contribution for both matched loans and unmatched loans.*

> *H3b (Intensity Effect): The higher intensity of matching gift programs among similar competitors will bring a stronger positive effect, leading to shorter funding time and a higher possibility to get fully funded for both matched loans and unmatched loans.*

Data Description

To evaluate the intervention effect of "match day", we sample loans totally affected by the event (affected loans) and loans that are not affected by the event (baseline loans). We define affected loans as loans posted after the event day (10 July) and before 31 July. From the observation, the number of matched loans decrease significantly after 31 July, which means the influence of the matching event decrease dramatically in August. Consequently, we don't view loans posted after 31 July as affected loans.

However, it is more difficult to define the baseline loans since not all of the loans posted before the event are totally not affected by the event. Some loans posted before 10 July but not closed at that day are also matched. These loans are partially affected by the event, which will be dropped. In Kiva, loans will expire 30 days later after the loans are posted. Consequently, loans posted 30 days before the event day (10 June) are totally not affected by the event since they have already expired before the event. Consequently, we define loans posted from 1 April to June 10 as baseline loans.

We further group these loans into three categories: (1) loans posted and closed before the event day and thus not influenced by the event (baseline loans), (2) loans posted after the event day and matched (matched loans), and (3) loans posted after the event day but not matched (un-matched loans). We compare the performance of the matched and unmatched loans with baseline loans respectively, to identify the effect of *matching gift* programs.

The relevant variables are shown in table 1. From the table, we use four dependent variables to measure the performance of the loans, in order to study how *matching gift* influences the loan performance. At first, the variable *ArrRate* represents the arrival rate of lenders for the loan. We also use *FundTime* to measure the funding time of the loans, which represents the number of days between the posted time and end time (funded time or expiration time). Funding time can be used to measure the success level of the project (Ly and Mason 2012). Thus, projects more favored by lenders will be more quickly get fully funded. We also use a binary variable *Funded* to measure the success of projects, which indicates that the projects get fully funded finally. To measure the average contribution level of projects, we introduce the variable *AveContr*, measuring the average contribution per lender excluding matching funds.

The main independent variable we are interested in is *PostEvent*, indicating the loans are posted on and after the matching day. And we use variable *MatchInten* to measure the intensity of matching among similar competitors. For each loan, there are many matched loans and unmatched loans soliciting for funds simultaneously. And *MatchInten* represents the percentage of matched loans among similar competitors. We define similar competing loans as loans with the same location (country) and cause (sector) since usually, lenders prefer to lend in certain location and cause (Ly and Mason 2012; Meer 2017).

Finally, we also use loans characteristics to control the heterogeneity of loans. *LoanAmount* represents the target amount of loans. *RepayTerm* is the number of months scheduled to repay. Longer repay term means that lenders will need more time to get back the funding. *FemRatio* measures the percentage of female lenders among all of the lenders. If the loans have only one female lender, the value of FemRatio will be one. While *Bonus* is a binary variable to indicate whether the projects have received a bonus program to attract new lenders. From the previous literature, the competition will also influence the funding outcome (Ly and Mason 2012). Same with the Ly and Mason, we use the total number of loans soliciting for funds simultaneously with the loan(*CompAll*) to control the overall competition, and the total number of similar competing loans (*ComSim*) to control the level of similar competition. *CompAll* and *ComSim* are all time varying variables, which account for the competition level when the loans are active. We don't include time dummies because there is perfect multicollienarty between time dummies and *PostEvent*.We also use variable *Country* and *Sector* to control the country and sector characteristics of each loan.

Table 1. Variables Description

Type	Variables	Definition
Dep Vars	*ArrRate*	The average number of lenders lend in the project per unit time (day).
	FundTime	The time between loans' posted time and funded time or expiration time
	Funded	A binary variable to indicate whether the project is fully funded
	AveContr	average lending amount per lender, excluding the matched amount
Indep Vars	*PostEvent*	The loan is posted on or after the matching day
	MatchInten	Percentage of the number of matched loans to the number of all loans in the same subgroup (country-sector)
Contr Vars	*LoanAmount*	The target amount of the project
	RepayTerm	Number of months the borrowers will repay the loan
	FemRatio	Percentage of female lenders among all of the lenders.
	Bonus	A binary variable to indicate whether the project has received a bonus program to attract new lenders
	CompAll	Total number of loans soliciting for funds simultaneously with the loan
	CompSim	Total number of loans soliciting for funds simultaneously and from the same subgroup with the loan

Table 2 presents the summary statistics of dependent and independent variables. From the table, the funding time of baseline loans is 9.81 days. Unmatched loans and matched loans all have lower funding time, and matched loans only have half funding time compared with baseline loans. Besides, both matched and unmatched fully influenced loans have a higher success rate. The summary statistics of funding time is consistent with the hypothesis that matched loans will bring benefit for all of the matched loans and unmatched loans.

Matched loans have lower average contribution per lender, but the unmatched loans have higher average contribution compared with baseline loans, which is also consistent with the hypothesis.

Table 2. Summary Statistics

Variables	Baseline Loans	Unmatched Loans	Matched Loans
Count	30497	8946	1998
ArrRate	1.792 (3.479)	1.872(3.601)	1.872(3.601)
FundTime	9.81(122)	9.63(131)	2.718(3.501)
Funded	0.946(0.051)	0.966(0.033)	0.97(0.029)
AveContr	3.538(0.291)	3.577(0.239)	3.194(0.111)
MatchInten	0(NA)	0.213(0.021)	0.448(0.0247)
LoanAmount	6.352(0.766)	6.231(0.989)	6.475(0.765)
RepayTerm	2.513(0.295)	2.51(0.268)	2.54(0.234)
FemRatio	0.775(0.168)	0.725(0.193)	0.855(0.12)
Bonus	0.599(0.24)	0.549(0.248)	0.666(0.223)
CompAll	8.498(0.102)	8.643(0.115)	8.624(0.062)
CompSim	3.521(2.406)	3.551(2.639)	3.495(3.808)
Note: The summary statistics use mean(variance) form for non-count variables. Besides, we use the log form for continuous data.			

Model Specification

To test the first and second hypothesis, we make a before and after analysis to compare the performance of matched funds and unmatched loans with baseline loans respectively. The model is shown in equation (1). $Performence_i$ represents four dependent variables to measure the funding outcome of matched loans and unmatched loans. $PostEvent_i$ represents that the loans are posted after the event day. And we will analyse matched loans and unmatched loans respectively.

$$Performence_i = f(PostEvent_i + Contrl_i + \varepsilon_i) \qquad (1)$$

To test the third hypothesis, I use $MatchRatio_i$ to measure how matching intensity will affect the funding outcome, as showed in equation (2). We also use $PostEvent_i$ to control the influence of the matching event. The coefficient of $MatchRatio_i$ will measure the effect of matching intensity on funding outcome, after controlling the event shock.

$$Performence_i = f(PostEvent_i + MatchRatio_i + Contrl_i + \varepsilon_i) \qquad (2)$$

Estimation Result

Direct Effect

At first, we compare all of the matched loans with the baseline loans. The estimation result is presented in Table 3. From the estimation result, the coefficient of *PostEvent* in column (1) is positive and significant. The result demonstrates that *matching gift* programs significantly increase the arrival rate of lenders. Besides, the magnitude of the coefficient indicates that the matching event attracts approximately 130% more lending actions per unit time, compared with baseline loans. The coefficient of *PostEvent* in column (2) is significant and negative, indicating that matched loans have a lower average contribution. The estimation result support H1a. The coefficient of *PostEvent* in column (3) is both statistically and magnitude significant, demonstrating that matched loans have shorter funding time. The value of the coefficient indicates that the *matching gift* programs decrease about 75% funding time for matched loans compared with baseline loans. Besides, the coefficient of *PostEvent* in column (4) is significant and positive, which means that matched loans have higher possibility to get fully funded. The result support H1b that matched loans will have shorter funding time and a higher possibility to get fully funded.

Table 3. The Effect of Matching Gift Program on Matched Loans

Variables	(1) ArrRate	(2) AveContr	(3) FundTime	(4) Funded
LoanAmount	0.087***(0.011)	0.114***(0.004)	0.781***(0.011)	-1.768***(0.072)
RepayTerm	-0.732***(0.017)	-0.035***(0.007)	0.765***(0.017)	-1.858***(0.141)
FemRatio	0.580***(0.018)	-0.076***(0.007)	-0.457***(0.019)	1.578***(0.081)
Bonus	-0.304***(0.02)	0.020**(0.008)	0.296***(0.021)	-0.386***(0.12)
CompAll	-2.789***(0.025)	-0.143***(0.01)	2.838***(0.026)	-4.327***(0.143)
CompSim	-0.423***(0.008)	-0.003(0.003)	0.420***(0.009)	-1.107***(0.065)
PostEvent	1.261***(0.027)	-0.317***(0.011)	-1.483***(0.028)	1.246***(0.205)
#Observation	30,771	30,771	30,771	30,771
Adjusted R^2	0.639	0.111	0.692	0.364
Note: *p<0.1; **p<0.05; ***p<0.01				

Indirect Effect

And then, we compare unmatched loans posted after the event with baseline loans. The estimation result is showed in table 4.

Table 4. The Effect of Matching Gift Program on Unmatched Loans

Variables	(1) ArrRate	(2) AveContr	(3) FundTime	(4) Funded
LoanAmount	0.137***(0.009)	0.160***(0.004)	0.689***(0.009)	-1.618***(0.061)
RepayTerm	-0.749***(0.014)	-0.091***(0.006)	0.838***(0.015)	-1.816***(0.123)
FemRatio	0.579***(0.015)	-0.063***(0.007)	-0.474***(0.016)	1.668***(0.072)
Bonus	-0.344***(0.017)	0.008(0.008)	0.346***(0.018)	-0.389***(0.107)

CompAll	-2.908***(0.022)	-0.193***(0.01)	3.022***(0.023)	-4.170***(0.129)
CompSim	-0.418***(0.007)	-0.011***(0.003)	0.423***(0.007)	-0.948***(0.054)
PostEvent	0.463***(0.014)	0.093***(0.006)	-0.531***(0.015)	1.679***(0.086)
#Observation	39,445	39,445	39,445	39,445
Adjusted R^2	0.666	0.171	0.714	0.361
Note: *p<0.1; **p<0.05; ***p<0.01				

From the estimation result in table 4, unmatched loans posted after the matching day have significantly higher arrival rate and average contribution, which support H2a. Besides, these loans have shorter funding time and higher success possibility. The estimation result support H2b.When we compare the effect of matching gift programs on matched loans and unmatched loans, we find that matched loans receive a stronger benefit. The result makes sense that the direct effect of matching on matched loans should be stronger compared with an indirect effect on unmatched loans. However, the *matching gift* programs only make unmatched loans have about 9.3% higher average contribution per lender, but the average contribution to matched loan decrease about 31.7%.

Intensity Effect

We also study how the intensity of *matching gift* programs influence unmatched loans. Table 5 presents the estimation result of analysis for the effect of matching intensity on matched loans. From the estimation result, the higher matching intensity will lead to higher arrival rate and average contribution per lender. Thus, the result support H3a. Besides, higher matching intensity among similar competitors will make matched loans have shorter funding time and a higher possibility to get fully funded, which support H3b. Besides, although the total effect of the matching intensity and matching event on average contribution is still negative, matching intensity can moderate the negative effect of *matching gift* on average contributions of matched loans.

Table 5. The Effect of Matching Intensity on Matched Loans

Variables	(1) ArrRate	(2) AveContr	(3) FundTime	(4) Funded
LoanAmount	0.087***(0.011)	0.114***(0.004)	0.782***(0.011)	-1.768***(0.072)
RepayTerm	-0.733***(0.017)	-0.035***(0.007)	0.766***(0.017)	-1.858***(0.141)
FemRatio	0.579***(0.018)	-0.077***(0.007)	-0.455***(0.019)	1.577***(0.081)
Bonus	-0.302***(0.02)	0.020***(0.008)	0.293***(0.021)	-0.390***(0.12)
CompAll	-2.786***(0.025)	-0.142***(0.01)	2.834***(0.026)	-4.314***(0.143)
CompSim	-0.421***(0.008)	-0.002(0.003)	0.416***(0.009)	-1.096***(0.065)
PostEvent	0.894***(0.082)	-0.462***(0.033)	-0.890***(0.086)	0.494(0.414)
MatchInten	0.486***(0.103)	0.193***(0.041)	-0.786***(0.107)	1.896**(0.948)
#Observation	30,771	30,771	30,771	30,771
Adjusted R^2	0.641	0.121	0.693	0.546
Note: *p<0.1; **p<0.05; ***p<0.01				

We also study the effect of matching intensity on unmatched loans Table 6 presents the estimation result of analysis for the effect of matching intensity on unmatched loans. From the estimation result, unmatched loans with higher matching intensity will have higher arrival rate and average contribution per lender, which support H3a. Besides, the higher intensity of matching among similar competitors make unmatched loans have shorter funding time and a higher possibility to get fully funded. However, the estimation coefficient of *MatchInten* in column (4) is not significant. Thus, the result partially supports H3b.

From the estimation result about the effect of matching intensity on matched loans and unmatched loans, we find that high matching intensity among competitors will induce lenders to make higher contributions to the loan, making these loans have higher arrival rate and average contribution, which will make these loans have shorter funding time and higher possibility to get successfully funded.

Table 6. The Effect of Matching Intensity on Unmatched Loans

Variables	(1) ArrRate	(2) AveContr	(3) FundTime	(4) Funded
LoanAmount	0.141***(0.009)	0.160***(0.004)	0.685***(0.009)	-1.619***(0.061)
RepayTerm	-0.734***(0.014)	-0.090***(0.006)	0.822***(0.015)	-1.816***(0.123)
FemRatio	0.586***(0.015)	-0.062***(0.007)	-0.481***(0.016)	1.668***(0.072)
Bonus	-0.334***(0.017)	0.009(0.008)	0.336***(0.018)	-0.389***(0.107)
CompAll	-2.916***(0.022)	-0.193***(0.01)	3.031***(0.023)	-4.172***(0.13)
CompSim	-0.426***(0.007)	-0.012***(0.003)	0.432***(0.007)	-0.947***(0.054)
PostEvent	0.273***(0.017)	0.081***(0.007)	-0.330***(0.018)	1.661***(0.117)
MatchInten	1.411***(0.07)	0.091***(0.031)	-1.489***(0.074)	0.131(0.569)
#Observation	39,445	39,445	39,445	39,445
Adjusted R^2	0.669	0.169	0.717	0.517
Note: *p<0.1; **p<0.05; ***p<0.01				

Conclusion

In this research, we study how external monetary incentive will influence the contribution level and funding outcomes on the prosocial crowdfunding platform Kiva. We find that *matching gift* programs benefit both matched and unmatched loans. *Matching gift* programs will make both matched loans and unmatched loans have higher arrival rate, lower funding time and a higher possibility to get fully funded. But it will decrease the average contribution per lender for matched loans and increase the average contribution per lender for unmatched loans. Besides, we also find that the higher intensity of matching among similar competitors will induce lenders making higher contributions to both matched loans and unmatched loans.

Our study makes both academic and managerial contribution. First of all, this paper is the first research to study how money incentive will facilitate loan campaigns in IS literature. Money incentive is one of the most popular methods to help boost campaigns, but it receives scarce study previously in IS literature. Besides, we contribute to public economics since we provide evidence that *matching gift* can not only benefit matched loans but also bring a significantly positive effect on unmatched loans, which have never been found before.

Secondly, we provide empirical evidence that *matching gift* programs benefit both matched and unmatched loans. While the positive effect on matched loans is consistent with existing findings, the positive effect on unmatched loans has not been reported in the literature. Prior literature suggests that monetary incentives, including *matching gift* programs, would shift the contribution from unmatched projects to matched projects (Scharf et al. 2017). This raises the concern on the overall effectiveness of the campaign. However, we find that this applies to non-threshold projects only. For threshold fundraising projects with pre-determined target amount, *matching gift* programs bring a positive effect for both matched loans and unmatched loans. Our findings highlight the important difference in project types and support the use of *matching gift* programs on prosocial lending websites to increase overall funding.

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