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How do monetary incentives influence giving? An empirical investigation of matching subsidies on kiva

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How do monetary incentives influence giving? An empirical investigation of matching subsidies on kiva

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Abstract
Matching subsidies, through which third-party institutions provide a dollar-for-dollar match of private contributions made through selected campaigns, have served as effective tools to boost fundraising. We utilize a quasi-experiment on a prosocial crowdfunding platform to examine the effectiveness of matching subsidies in shaping funding outcomes and lender behaviors. Although matching subsidies offer matched loans competitive advantages over unmatched loans, we find that total private contributions made to both matched and unmatched loans increase compared to their prematching counterparts, suggesting a positive *spillover effect* on unmatched loans. However, matching subsidies lead to decreased private contributions made on the platform after a matching event, revealing an *intertemporal displacement effect* on existing loans. Furthermore, we find that matching subsidies effectively encourage previously inactive lenders to contribute to matched loans, leading to a motivational *crowding-out effect* on active lenders' contributions to unmatched loans. These findings shed new light on the overall effectiveness of matching subsidies provided through online crowdfunding platforms.

Keywords Monetary incentives · Crowdfunding · Prosocial lending · Matching subsidies · Generalized difference-in-difference

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1 Introduction

Online crowdfunding has become increasingly important for helping small entrepreneurs gain alternative access to capital, alleviate poverty, and improve social welfare in recent years. The global transaction value of crowdfunding reached US$5.8 billion in 2019 (Statista 2020). Despite the popularity of crowdfunding platforms, many campaigns using these platforms still have difficulty raising sufficient funding (Zhao et al. 2017). To address this issue, several platforms such as Kiva, Kickstarter and Donorchoose.org provide monetary incentives to attract funders and increase their contributions. The most popular monetary incentives are matching subsidies, whereby third-party institutions provide a dollar-for-dollar match of private contributions from individual funders on selected campaigns. According to a recent survey of more than 300 of the world's largest companies, approximately 92% of these companies together have offered 285.6 million funds through matching subsidies, accounting for 12% of total corporate cash contributions made to nonprofits (CECP Coalition 2018).

The existing literature has provided competing theories on the effectiveness of matching subsidies for matched campaigns. On the one hand, matching subsidies make private contributions (contributions from funders excluding matching grants) highly rewarding. Compared to campaigns without matching subsidies, individual funders can double their funding impact on matched campaigns with the same contribution (or achieve the same impact with half the contribution). This is also known as the *relative price effect,* where the volume or intensity of an activity increases when it becomes essentially less costly to pursue (Andreoni 2006). On the other hand, matching subsidies have a *crowding-out effect* that decreases private contributions by reducing donors' intrinsic motivation (Andreoni 1990; Frey and Oberholzer-Gee 1997). Given opposing theoretical perspectives, prior research provides mixed empirical evidence—matching subsidies either increase (Karlan and List 2007; Rondeau and List 2008) or do not affect (Karlan et al. 2011) private contributions made to matched projects.

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

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 matching subsidies for fundraising. Second, matching subsidies, as effective monetary incentives designed to improve funding outcomes, have not received much attention in the crowdfunding literature. Most of the existing literature focuses on traditional prosocial funding such as donations and charitable giving. Online crowdfunding platforms significantly differ from traditional fundraising as they are much larger in scale, favor shorter projects, and provide more transparent information. Meanwhile, the large-scale and high-intensity nature of matching subsidies may lead to different impacts on funding outcomes and lending behavior on crowdfunding platforms. The available information online also makes it possible to trace lenders' lending histories and 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 provided through crowdfunding platforms.

In this paper, we utilize a quasi-experiment of an exogenous event occurring on a prosocial crowdfunding platform to examine the effects of matching subsidies on funding outcomes and lender behaviors. Specifically, we address the following research questions. How do matching subsidies affect private contributions made to matched and unmatched loans during the event? How do matching subsidies affect private contributions made on the platform after the event? What are the effects of matching subsidies on lenders' behaviors 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 worldwide, on September 12, 2018. During this event, Kiva partnered with Google, Grameen-Jameel, and the Richard Brindle Foundation to provide one-for-one matching funds for thousands of selected loans through Kiva. We collected two weeks of transaction-level data for a period surrounding the event running from September 3, 2018, to September 16, 2018 as well as data on all loans and lenders involved. Using this comprehensive dataset and quasi-experimental setting, we explore the effects of matching subsidies on loan-level funding outcomes and lender-level 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 contributions made 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 that matching subsidies bring *positive spillover* effects for unmatched loans soliciting funds simultaneously, resulting in an increased number of contributing lenders and total private contributions made to unmatched loans during the event compared to pre-event levels. This runs contrary to the spatial displacement effect (Scharf et al. 2017). In addition, for active loans made on the platform after the event, we find evidence of *intertemporal displacement*. That is, once the "flash match" event was over, open loans made on the platform were, on average, less likely to receive any funding.

At the lender level, we examine how lenders' behaviors drive the funding outcomes of loans. We find that matching subsidies make lenders more likely to contribute, leading to more contributing lenders. In particular, matched loans attract more previously inactive lenders. However, the average contribution made per lender to matched loans decreases relative to the prematching counterpart, supporting the *crowding-out effect* of matching subsidies on individual lenders' average contributions to matched loans. At the same time, unmatched loans attract more active lenders with a higher average contribution made per lender. In contrast to inactive lenders who are mainly attracted to matched loans, active lenders are less influenced by matching subsidies, showing different patterns of behavior change across lenders. These findings provide new insights into the effectiveness of matching subsidies made on online prosocial crowdfunding platforms.

The rest of this paper is organized as follows. Section 2 provides a brief review of the related literature. Section 3 describes the study context and data. Section 4 provides the loan-level analysis of our empirical model. Section 5 presents our transaction-level analysis and results. Finally, Sect. 6 concludes the paper.

2 Literature review

With the rapid development of information technologies, many online crowdfunding platforms have emerged as alternative financing channels (Galak 2011). Such platforms enable small entrepreneurs who lack access to traditional financing tools to obtain funding from a large pool of individual investors. Agrawal et al. (2014) classify crowdfunding platforms into four types: equity-, reward-, loan-, and donation-based crowdfunding platforms. We are interested in loan-based crowdfunding platforms in this study.

Despite the popularity of crowdfunding, many crowdfunding campaigns suffer from a lack of support from funders (Massolution, 2015). Previous studies have investigated a number of campaign factors that influence funding outcomes, including the personal narratives and social entrepreneurship of borrowers (Sinanan 2009), provision points (Burtch et al. 2018), crisis shocks (Yang et al. 2016), borrower race (Younkin and Kuppuswamy 2017), and borrower friendship networks (Lin et al. 2013). Furthermore, for lenders, herding behavior (Zhang and Liu 2012), cultural and geographic differences (Burtch 2014), home biases between funders and fundraisers (Lin and Viswanathan 2016), social network structures of advocating individuals (Hong et al. 2018), the design of team communities (Chen et al. 2017), and characteristics of lenders (Liu et al. 2012) influence their funding behaviors. These prior findings provide important insights into ways in which platform design can improve funding success.

According to the theory of relative price, dollar-for-dollar matching is equivalent to reducing the price of contributions by half, which can significantly increase the fund solicitation response rate (Chen et al. 2006; Frey 2017; Meier 2007a, b; Karlan and List 2007). In addition to the price effect, donors view matching subsidies as a signal of quality, which also increases the response rate and funding amount (Heutel 2014). On the other hand, matching subsidies may impose a negative effect by crowding out private contributions (Andreoni 1990). This motivational crowding-out theory suggests that external monetary incentives, including matching subsidies, reduce intrinsic motivation, which may decrease individual contributions (Meier 2007a).

There are mixed empirical findings on the effects of matching subsidies on private contributions made to matched loans. Using field experiments, most previous studies show that matching subsidies increase the private contributions 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). However, Karlan et al. (2011) find that matching subsidies have no significant effect on private contributions, and Rondeau and List (2008) find that 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) identify spatial displacement between matched and unmatched campaigns soliciting funds simultaneously. The authors argue that matching subsidies exacerbate competition and shift funding from unmatched projects to matched ones, increasing contributions made to matched campaigns while decreasing those made to unmatched campaigns. Through lab experiments, Krieg and Samek (2017) find slightly positive spillover effects of matching subsidies on unmatched campaigns. Based on daily aggregated data from an online microfinance platform, Donorchoose.org, Meer (2017) provides empirical evidence that matching subsidies increase giving to eligible requests without crowding out giving to similar others either contemporaneously or overtime. However, Meier (2007b) finds intertemporal displacement where matching subsidies increase contributions in the short run, but contributions decrease after the program.

In terms of the effects of matching subsidies on lender behaviors, Eckel and Grossman (2008) find that continuing funders (i.e., funders who make regular contributions) decrease their contributions to matched campaigns while lapsed (i.e., funders who contribute occasionally) and prospect funders (i.e., funders who have not contributed before) do not respond to matching subsidies. Meer (2017) also finds that matching subsidies cause funders to consider other similar campaigns, increasing contributions made to unmatched loans. Different from these prior studies, we find evidence that matching subsidies motivate previously inactive lenders to contribute to matched loans while active lenders shift their contributions to unmatched loans. These findings provide new insights into the overall effectiveness of matching subsidies made through crowdfunding platforms.

3 Research context and data description

3.1 Research context

This study focuses on Kiva.org, the world's largest online peer-to-peer lending platform. The website has raised more than $1.37 billion funds for more than 3.4 million borrowers from 1.8 million lenders since its inception in October 2005 as an online microfinance (Morduch 1999) platform for the poor, unbanked and underserved. Most loans made through Kiva are donation-based with a 0% interest rate available for borrowers who are mostly located in developing countries. Kiva collaborates with local microfinance institutions (MFIs) to screen potential borrowers and select eligible ones. Local MFIs then help eligible borrowers create their profiles, which include biographical information, loan amounts, repayment schedules, and loan purposes. After the profiles are posted on Kiva, potential lenders around the world can provide funds in US$25 increments. Fundraising for these loans follows the "all or nothing" model where borrowers receive nothing until the targeted loan amount is achieved. That is, the full loan amount must be raised within the fundraising period for funds to be sent to borrowers; otherwise, the loan expires, and any funds raised are returned to the lenders.

To help more small enterprises achieve their funding goals, Kiva often partners with prestigious companies such as Google, VMware, and PayPal, providing matching subsidies for selected loans. With the slogan "be a part of this day of impact by choosing a borrower to support," Kiva organizes "flash match" events whereby a large number of loans are matched on chosen event days. Through such programs, the matching partner defines the criteria on which loans are to be matched, and the qualified loans are then displayed with a "×2" badge with the partner's name. If any lender makes contributions to matched loans, the matching partner lends the same amount to these loans. With these programs, approximately 94.7% of loans are fully funded through Kiva. This success rate is much higher than those of other prosocial crowdfunding platforms such as Donorchoose.org (68.3%), Kickstarter (43%) and Indiegogo (less than 10%) (Massolution 2015; Meer 2017).

3.2 Quasi-experiment setting and data collection

Our study utilizes one "flash match" event held on 12 September 2018, as a quasi-experiment to examine the impacts of matching subsidies on the funding outcomes of matched and unmatched loans. Through this event, US$1 million matching grants were provided for approximately 2000 loans through Kiva. Figure 1 shows how daily aggregated lending changed before and after the event.

As shown in Fig. 1a, the daily number of new loans made did not change significantly on the match day relative to days before the event, whereas the number of active loans decreased significantly after the event, suggesting that more loans were fully funded because of the event. According to Fig. 1b, the number of matched loans made on the match day exceeded 2000 and dropped sharply on the following day, as many matched loans were funded fully on the event day while the rest were no longer matched after the event day. More than 4000 active loans made on the event day were unmatched. The total daily contribution from lenders increased considerably on the match day and the day after as shown in Fig. 1c. Figure 1d shows a jump in total contributions made to matched loans on the event day and an increase in contributions made to unmatched loans on the day after the event.

To examine the influence of the "flash match" event held on September 12, we collected granular transaction-level data on funding activities from September 3 to 16, 2018. The data contain detailed information for each lending activity, including information on lenders, borrowers, lending amounts, and timestamps. Our final dataset consists of 49,031 lending actions made during the study period taken by

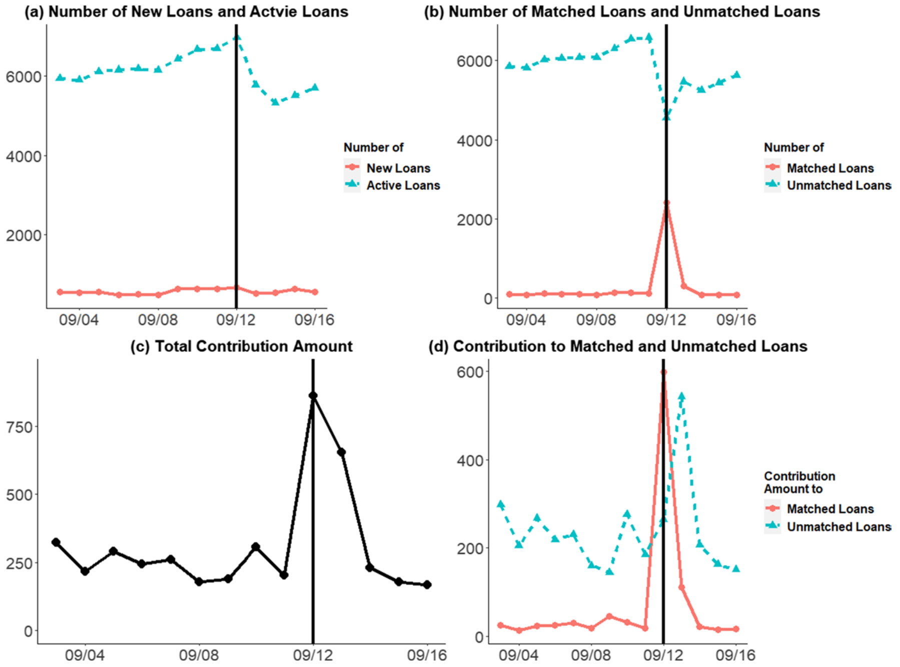

Fig. 1 Daily aggregated loan and lender level data. **a** Total number of new and active loans; **b** total number of active matched and unmatched loans; **c** total contribution to all active loans; **d** total contribution to all active matched and unmatched loans. The x-axis denotes dates. The black vertical line denotes the match day (September 12, 2018)

24,404 lenders for 6246 loans. Among these 6246 loans, 1994 were matched loans. These 1994 loans were matched by 15 third-party institutions or funders with different matching criteria (Table 7 in the Appendix).

At the loan level, we also collected data on the funding outcomes of these sample loans, including information on total funds raised, the amount of time involved to reach full funding, the number of lenders, average contribution amounts made 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 in terms of both loan outcomes and lender activities.

3.3 Key variables and summary statistics

Key variables are defined in Table 1, and summary statistics are shown in Table 2. Now_t, $Post1_t$, and $Post2_t$ are time dummies for September 12 (the event day), September 13, and September 14 to 16, respectively.[1] A total of 1994 matched loans

[1] We split the time window into four time periods according to the number of active matched loans made each day. Before the event, no loans were matched yet. We found that the number of active matched loans on September 12 and September 13 was significantly higher than the number on subsequent days. Therefore, we divide the time window following the event day into three time periods: September 12 (the event day), September 13, and September 14 to 16.

Table 1 Definitions 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 made per lender for loan j on day t
	$FundAmount_{jt}$	Funding amount for 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 competing with loan j on day t
	$AccuAmount_{jt}$	Funding amount that loan j raised at the start of day t
Transaction Level	$Lend_{ij}$	1 if lender i lent to loan j and 0 otherwise
	$LendAmount_{ij}$	Lending amount from lender i to loan j
	$Match_{ij}$	1 if loan j was matched when lender i lent to it
	$Active_{i}$	1 for active lender i and 0 otherwise
	$AccuAmount_{ij}$	Funding amount that loan j raised before lender i lent to loan j
	$Competition_{ij}$	Number of other active loans available when lender i lent to loan j

Table 2 Descriptive statistics

Variables	Obs	Min	Max	Mean	SD
$LendArrRate_{jt}$	67,227	0	757	0.79	4.84
$AveContr_{jt}$	67,227	0	2825	7.02	28.59
$FundAmount_{jt}$	67,227	0	29,075	27.91	187.69
$Match_{jt}$	67,227	0	1	0.03	0.17
$Competition_{jt}$	67,227	1	519	109.5	119.77
$AcuumAmount_{jt}$	67,227	0	77,600	109.5	741.1
$Lend_{ij}$	309,092	0	1	0.33	0.47
$LendAmount_{ij}$	309,092	25	5750	33.98	73.95
$Match_{ij}$	309,092	0	1	0.09	0.28
$Active_{i}$	309,092	0	1	0.39	0.49
$AccumAmount_{ij}$	309,092	0	81,275	708.3	3843.74
$TotalComp_{ij}$	309,092	1	488	85.77	108.18

were made in the *Now* period, 204 of which remained matched in the *Post1* period. For the *Post2* time period, all loans were unmatched. Using these 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 allows us to study temporary treatment effects of the matching subsidies over time. As some matched loans became unmatched after the event day, we use this reversal to study the effects of treatment removal in addition to the treatment effect.

To examine how the loan-level funding outcomes are affected by matching subsidies, we first construct loan-daily level panel data. Loans posted after the event or fully funded before the event were removed to avoid the systematic difference between these loans and loans active both before and after the event (Geva et al. 2019). Three variables measuring funding outcomes are chosen as 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 made 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 for 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 subsidies affect lenders' selection of loans at the transaction level. To model the lender's selection of loans, we use dummy variable $Lend_{ij}$ to indicate lender i's decision to lend to loan j. Lenders' lending decisions where $Lend_{ij}$ equals 1 are directly observed. However, lenders' no-lending decisions where $Lend_{ij}$ equals 0 are not observed directly but rather assumed on all other active loans made under the "potential dyads" approach (Liu et al. 2015; Lin and Viswanathan 2016). It is impossible to include all potential lender-loan dyads given the large number of sample lenders and loans. It is unrealistic to assume that 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 among all 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 lending loan and two for no-lending loans. For the two dyads for no-lending loans, both $Lend_{ij}$ and $LendAmount_{ij}$ are valued at 0. Overall, the dyadic data contain 309,092 observations for 43,175 lenders lending to 12,333 loans.

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

4 Loan-level analysis

4.1 Empirical model

At the loan level, we use 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. DID estimation identifies the treatment effect by comparing the difference of the treated group before and after treatment to 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 a context in which the treated group remains treated once the treatment starts. However, in our research setting, some matched loans reverted to being unmatched after the event day. Therefore, instead of using 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:

$$Outcome_{jt} = \beta_0 + \beta_1 Match_{jt} + \emptyset X_{jt} + \mu_j + w_t + \varepsilon_{jt} \tag{1}$$

In Eq. (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 the three time period dummies of Now_t, $Post1_t$, and $Post2_t$ instead of daily dummies. $\boldsymbol{X}_{jt}$ denotes 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 matched and unmatched loans are fundamentally different due to the nonrandom selection of matched loans. To address this issue, we use PSM to construct a control group of unmatched loans that resemble the matched loans for all observables except for the treatment condition (Dehejia and Wahba 2002). As stated in our description of the data, third-party institutions select matched loans based on the following loan characteristics: *LoanAmount*, the target amount of the loan; *RepayTerm*, the number of months over which the borrower repays the loan; *IsGroup*, whether the loan has more than one borrower; *IsFemale*, whether the borrower is female; *Country*,[2] the country of the loan; and *Sector*,[3] the sector of the 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 based on the nearest neighbor without replacement. The propensity score matching procedure generated a sample of 1425 control (unmatched) loans for the 1425 treated (matched) loans. The balance check after PSM is presented in Table 3.

As a general rule, the standardized mean deviation (SMD) of variables between matched and unmatched loans should be no larger than 0.2 (or preferably 0.1) if the two loan groups are well balanced (Rosenbaum 2010). As shown in Table 3, most of the SMDs are less than 0.1, and only the SMD of *Country* is 0.17. The distribution of propensity scores presented in Table 7 in the Appendix also shows that the matching procedure produced balanced samples. Finally, we create a sample containing 29,381 loan-daily observations of the 2850 selected loans for further analysis.

[2] Borrowers from 74 countries publish their projects and raise funds. Most of these countries are developing countries in Africa, Asia, and South America.

[3] Kiva supports projects in 15 sectors: Construction, Clothing, Education, Agriculture, Food, Services, Retail, Health, Entertainment, Arts, Transportation, Personal Use, Wholesale, Housing, and Manufacturing.

Table 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

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) measures the balance of variables between treated and control groups

For the matched and unmatched loans selected by PSM, we use zero-inflated models to estimate the effect of matching subsidies for two reasons. First, our dependent variables of funding outcomes such as funding amounts and the number of lenders are nonnegative variables. Second, according to Table 2, these variables are also overdispersed with many zero observations. In fact, only 20% of the observations have nonzero funding outcomes. The zero-inflated model is suitable for nonnegative data with overdispersion and excess zeros assuming that the positive values are generated according to a nonnegative distribution and the excess zeros are generated by a separate inflation process of a binary distribution. The separate data generating process for excess zeros is appropriate in our context, as an absence of funding given by lenders for many loans can be attributable to either lenders' no-lending decisions made after consideration or to a lack of consideration from lenders.

A zero-inflated model can be specified as:

$$\Pr\left(Y_i = y_i\right) = \begin{cases} \phi + (1-\phi)f(y_i = 0|\theta) & y_i = 0 \\ (1-\phi)f(y_i|\theta) & y_i > 0 \end{cases}. \tag{2}$$

In Eq. (2), Y_i is the outcome variable, ϕ is the probability of obtaining zero values in the logit distribution, $\boldsymbol{f}$ is the distribution function for the positive values, and $\boldsymbol{\theta}$ is the vector of parameters that affect the distribution function $\boldsymbol{f}$. Because *LendArrRate* and *FundAmount* measure count data, we use the negative binomial distribution function for $\boldsymbol{f}$ and thus zero-inflated negative binomial (ZINB) models. As *AveContr* is continuous, we use the truncated Gaussian distribution function for $\boldsymbol{f}$ and thus the zero-inflated Gaussian model.

4.2 Estimation results

The estimation results are presented in Table 4. Since all three dependent variables have the same occurrence pattern of zeros, the estimation results for their inflation

Table 4 Loan-daily level estimation of zero inflated models

Variable	(1)	(2)	(3)	(4)
	Logit	Negative binomial		
		LendArrRate	AveContr	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
#Observations	29,381	29,381	29,381	29,381

Standard errors are provided in parentheses. The zero-inflated model with the fixed effect is estimated with maximum likelihood estimation, instead of least squared estimation. The maximum likelihood estimation doesn't provide clustered standard errors. Consequently, we use standard errors, instead of clustered standard errors here

***$p<0.01$; **$p<0.05$; *$p<0.10$

process are the same as those shown in column (1) and are estimated using a logit model with the dependent variable set to one for zero observations. For ease of interpretation, we present all coefficients in column (1) in log odds ratios for the relative probability of receiving zero funding (Bland and Altman 2000). According to column (1), the odds ratio of zero funding given 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.

The coefficients of the three time dummies show how matching subsidies affect loans made (both matched and unmatched) during the three periods compared to loans made 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 on the match day. However, on the day following the event, loans are more likely to be considered by potential lenders as shown by the negative 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 matching subsidies cease, showing evidence of intertemporal displacement—loans are less likely to receive funding when the matching program is over. The observed intertemporal displacement may be explained by the shift in the timing of lending. Potential lenders who expect to contribute to loans after the event may make their contributions earlier because of the event, rendering loans less likely to receive funding after the event.

Columns (2)–(4) present the estimation results for the nonzero outcomes of the three dependent variables. The coefficient estimates of *Match* show that conditional on being considered by lenders, matched loans receive more total funding from more lenders than unmatched loans. This finding is consistent with the intuition that receiving matching subsidies makes matched loans more attractive for lenders. This result supports the relative-price effect whereby the reduced price of contributions increases total contributions by attracting more lenders. However, as shown in column (3), an average lender contributes 5% less ($=\exp(-0.05)-1$) to a matched loan relative to his contribution to an unmatched loan. This finding supports the crowding-out effect of matching subsidies whereby the average private contribution decreases when contributions from other sources increase (Adena and Huck 2017; Bekkers 2015; Rondeau and List 2008).

Since the total contribution of a loan is the product of the number of lenders and the average contribution made per lender, our result demonstrates that the relative-price effect dominates the crowding-out effect in the crowdfunding context, leading to a higher total contribution made to matched loans each day. In previous work using laboratory experiments to study the effect of matching subsidies, the number of contributors usually cannot increase too much due to a limited number of potential contributors. However, on crowdfunding platforms, millions of potential lenders have easy access to information regarding matching subsidies with the help of social media and discussion forums. Consequently, matching subsidies provided through crowdfunding platforms may attract a much larger pool of lenders. From our estimation results, matching subsidies not only significantly increase the probability of matched loans receiving funding from any lender but also increase their number of contributing lenders by 285% ($=\exp(1.35)-1$) relative to simultaneous unmatched loans.

The coefficients of *Now* are significant and positive in columns (2)–(4), suggesting that unmatched loans receive funding from more lenders, more funding per lender, and more total contributions. In total, contributions made to unmatched loans increase by 41.9% ($=\exp(0.35)-1$) 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 the spatial displacement effect (Scharf et al. 2017) of the flash match event for unmatched loans. It may be that most crowdfunding platforms such as Kiva follow the "all or nothing" model, also known as the provision point mechanism (Burtch et al. 2018). Under this model, a loan is closed when funds raised achieve the funding target. Consequently, when matched loans receive full funding quickly and are then closed, many potential lenders can only lend to unmatched loans, leading to higher contributions from lenders to unmatched loans.

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 contributions made per lender suggest that the effect of motivating more contributions from a lender is only temporary. Therefore, our results indicate that the event had a persistent effect in promoting the platform and attracting more lenders to the platform but only a temporary effect in changing lender behavior.

The coefficients of the control variables are mostly as expected. *AccuAmount* has a significant and positive coefficient in columns (2)–(4), consistent with the herding effect whereby loans with more accumulated funding receive more contributions

Table 5 Robustness check using alternative models

Variables	(1) ArrRate Negbin	(2) AveContr OLS	(3) Amount Negbin
Match	0.93*** (0.05)	−0.06** (0.03)	1.21*** (0.05)
Now	0.44*** (0.05)	0.06** (0.03)	0.27*** (0.05)
Post1	0.87*** (0.04)	0.02 (0.02)	0.57*** (0.04)
Post2	−0.13*** (0.04)	0.02 (0.02)	−0.5*** (0.04)
AccuAmount	0.55*** (0.01)	0.06* (0.03)	0.67*** (0.01)
#Competition	−0.11*** (0.02)	0.05*** (0.01)	−0.1*** (0.01)
Fixed-effect	Y	Y	Y
#Observation	24,377	7342	24,377
Adjusted R^2		0.018	

In column (1), the dependent variable is the lender arrival rate. Since the variable is a count variable and its distribution shows overdispersion, we use a negative binomial model for the estimation. In column (2), the dependent variable is the average contribution made per lender conditional on a positive contribution. Since the variable is a continuous variable and highly skewed, we use a log transformed OLS model for estimation. In column (3), the dependent variable is the total contribution amount. Since the variable is a count variable and its distribution shows overdispersion, we use a negative binomial model for the estimation. Standard errors are provided in parentheses in the negative binomial model while robust standard errors clustered by loan are provided in parentheses in the OLS regression. The negative binomial model with fixed effects is estimated using the maximum likelihood method, which does not provide clustered standard errors. Consequently, we report standard errors rather than clustered standard errors in the negative binomial model

***$p<0.01$; **$p<0.05$; *$p<0.10$

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 lender and total funding for each loan.

4.3 Robustness check

Our use of a zero-inflated model is appropriate for the employed dataset. The overdispersion ratios calculated from the negative binomial model with dependent variables *LendArrRate* and *FundAmount* are 1.75 and 9.25, respectively, which suggests an overdispersion of the count-dependent variables. In addition, we used the Vuong closeness test (Vuong 1989) to check whether the zero-inflated model is preferred among the negative binomial models. 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, the zero-inflated negative binomial model is preferred.

We also conduct robustness checks using the negative binomial models for dependent variables *LendArrRate* and *FundAmount* and the OLS model conditional on positive contributions for dependent variable *AveContr*. The estimation results are presented in Table 5. We find that the matching subsidies program increases the number of contributing lenders and the total contribution made to matched loans and decreases the average contribution made to matched loans. In addition, the matching subsidies program has positive spillover effects for unmatched loans, and the positive effect disappears when matching grants cease. These results are consistent with those obtained through zero-inflated negative binomial model estimations.

5 Lender-level analysis

A loan-level analysis of the effects of matching subsidies on funding outcomes provides an initial understanding of the change in lending behavior occurring 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 direct incentives that motivate lenders, they are likely to be more effective for lenders with fewer incentives to contribute without the program. That is, lenders with sufficient self-motivation may be less likely to change their lending behaviors in response to matching subsidies. In this section, we further explore how the different types of lenders are affected by the program differently. We differentiate lenders according to their activity levels prior to the event ($PreLend_i$). We define active lenders as those whose $PreLend_i$ value is greater than the sample median and the rest as inactive lenders. In our sample, active lenders not only made more frequent contributions but also made higher average contributions than inactive lenders (\$35.5 vs. \$30.9).

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 lending to loan j is modeled as follows:

$$\begin{aligned} Prob\left[Lend_{ij}\right] = \beta_0 + \beta_1 Match_{ij} + \beta_2 Active_{ij} + \beta_3 Active_{ij} * Match_{ij} \\ + \delta \boldsymbol{Time_t} + \theta \boldsymbol{Time_t} * Active_{ij} + \emptyset \boldsymbol{X_{ij}} + \mu_j + \varepsilon_{ij} \end{aligned} \tag{3}$$

In Eq. (3), $Match_{ij}$ is used to capture the effect of matching subsidies on the lending decision, $Active_{ij}$ is the binary indicator for active lenders, and $Active_{ij} * Match_{ij}$ captures the differential impact of matching subsidies on active lenders. $\boldsymbol{Time_t}$ is the vector including time dummy variables Now_t, $Post1_t$, and $Post2_t$ where t refers to the day on which $Lend_{ij}$ is set. $\boldsymbol{Time_t} * Active_{ij}$ is used to examine how the three time periods affect active lenders' lending decisions for both matched and unmatched loans relative to inactive lenders. $\boldsymbol{X_{ij}}$ denotes control variables including competition and accumulated funding amounts. μ_j denotes 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:

$$\begin{aligned} LendAmount_{ij} = \beta_0 + \beta_1 Match_{ij} + \beta_2 Active_{ij} + \beta_3 Active_{ij} * Match_{ij} \\ + \delta \boldsymbol{Time_t} + \theta \boldsymbol{Time_t} * Active_{ij} + \emptyset \boldsymbol{X_{ij}} + \mu_j + \varepsilon_{ij} \end{aligned} \tag{4}$$

Table 6 Estimation of Lenders' individual choices

Variables	(1) Lend LPM	(2) Lend amount 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

Model (1) is estimated with the linear probability model with fixed effects. Model (2) is estimated with a fixed effects model with a log form dependent variable. Robust Standard errors are provided in parentheses

***$p < 0.01$; **$p < 0.05$; *$p < 0.10$

5.2 Estimation results

The estimation results of the lender-level models are presented in Table 6. 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 the funding amount. According to the coefficient estimates for *Match*, lenders are more likely to contribute to matched loans but contribute less than they do to unmatched loans, consistent with the results of our loan-level analysis. The positive and significant coefficients for *Active* shown 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 the control variables are consistent with those from the loan-level estimation.

We are most interested in the coefficients of the interaction terms. The negative and significant coefficients of *Match*Active* shown 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 lower amounts. The positive and significant coefficients of *Now*Active* further suggest that compared to inactive lenders, active lenders are more likely to fund unmatched loans, and they contribute to unmatched loans with higher amounts on the event day. Compared to inactive lenders who are motivated to fund matched loans, active lenders fund more unmatched loans with higher contributions while decreasing their contributions to matched loans. This finding supports motivational crowding-out theory by confirming that extrinsic monetary incentives reduce intrinsic motivation, especially for more prosocial individuals. According to the coefficients of *Post1*Active* and *Post2*Active*, active lenders' inclination to select unmatched loans is persistent throughout the postevent period whereas their contributions to unmatched loans lower to less than those of inactive lenders shortly after the event.

6 Conclusion

Matching subsidies have been widely used by online crowdfunding platforms to boost funding. Large-scale, short-duration, and high-intensity online matching subsidies are distinct from matching subsidies provided through traditional offline fundraising. Leveraging a quasi-experiment of a prosocial crowdfunding platform, Kiva, we examine the effects of matching subsidies on funding outcomes and lender behaviors. We find that matching subsidies have overall positive effects on all campaigns of the crowdfunding platform. Consistent with previous research, this finding suggests that monetary incentives can increase the total prosocial contributions made to fundraising campaigns (Lacetera et al. 2014). However, in contrast to most previous studies that document a positive effect on matched campaigns and a negative effect on unmatched campaigns, 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 a positive spillover effect. As a result, unmatched loans also benefit from a matching event.

Furthermore, we find that matching subsidies negatively affect fundraising after the event, suggesting an intertemporal displacement effect – loans are less likely to receive funding when the matching event is over. We find that the effect of matching subsidies, although strong on the event day, is only temporary – lenders tend to make their contributions on the event day, leading to decreased funding activity after the event. Similar to the existing findings for traditional matching subsidies, our findings suggest a short-term, time-shifting effect of matching subsidies for online fundraising campaigns.

We find that matching subsidies attract a large number of inactive contributors, most of who would have remained inactive if not for the matching program. These contributors are mostly interested in matched loans, crowding out active contributors who then shift their contributions to unmatched loans. In addition, we find that the average contribution made per lender per matched 7loan decreases relative to the prematching average, suggesting a negative effect of matching subsidies on lenders' intrinsic motivations to contribute to matched loans. At the same time, unmatched loans receive a higher average contribution per lender than their prematching counterparts. This is mainly due to active lenders who tend to make higher average contributions per loan shifting their contributions to unmatched loans. Compared to inactive lenders who are mainly attracted to matched projects due to matching subsidies, active lenders are influenced reversely by matching subsidies, showing different patterns of behavior change induced by monetary incentives.

Overall, our research has several practical implications for the application of matching subsidies through crowdfunding platforms. First, unlike traditional matching subsidies that mostly benefit matched loans but hurt unmatched loans, matching subsidies provided through crowdfunding platforms have positive effects on both matched and unmatched loans. This alleviates concerns about the negative effects of matching subsidies on unmatched loans and thus supports the use of monetary incentives in boosting online fundraising. Second, our analysis of lender behavior reveals different contribution preferences across contributors. Matching subsidies effectively motivate previously inactive lenders to contribute. An online crowdfunding platform can offer matching subsidies as an effective mechanism to stimulate contributors and keep them active on the platform. Finally, maintaining high-level private contributions over the long run is of particular importance to increasing the overall effectiveness and sustainability of online crowdfunding platforms. Due to data limitations, we were unable to examine the long-term effects of matching subsidies, though this would be an interesting avenue for future research (Table 6).

Appendix 1: The matching preferences of matching fund providers

On 12 September 2018, 15 third-party institutions provided matching subsidies for 1994 loans through Kiva. These third-party matching fund providers selected matched loans based on several major criteria: the target loan amount, the number of months over which the borrower was to repay the loan, whether the number of borrowers was larger than 1, whether the borrower of the loan was female, the country of the loan, and the sector of the loan. These characteristics are important in determining whether a loan should be matched. In Table 7, we present the preferences of matching fund providers in terms of their selection criteria. For each institution, Column #Loans shows the number of loans an institution provided matching subsidies; Column Country shows the preferred countries if the number of selected loans from the top two countries accounted for more than 50% of the total number of selected loans. Similarly, Column Sector presents the preferred sectors of an institution if the number of selected loans from the top two sectors accounted for more than 50% of the total number of selected loans. Column Group presents institutions' preferences for single or group borrowers. A preference for a single borrower denotes that an institution only matched loans for a single borrower while a

Table 7 The matching preferences of matching fund providers

Institutions	#Loans	Country	Sector	Group	Gender
Anonymous supporter	1112	No	Agriculture, 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	Agriculture, food	No	No
Bank of America	257	No	Agriculture, 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

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

preference for group borrowers denotes that an institution only matched loans for more than one borrower. Finally, Column Gender shows institutions' preferences for the borrower's gender. A preference for female borrowers means that an institution only matched loans for female borrowers.

Appendix 2: The distribution of propensity scores before and after the matching procedure

The histogram of propensity scores is presented in Fig. 2. The horizontal axis shows propensity scores while the vertical axis denotes the density of propensity scores.

From Fig. 2a, b, we observe that the propensity scores of treated and controlled loans have different distributions before matching. Nevertheless, Fig. 2c, d show that the propensity scores of treated and controlled loans have similar distributions after propensity score matching.

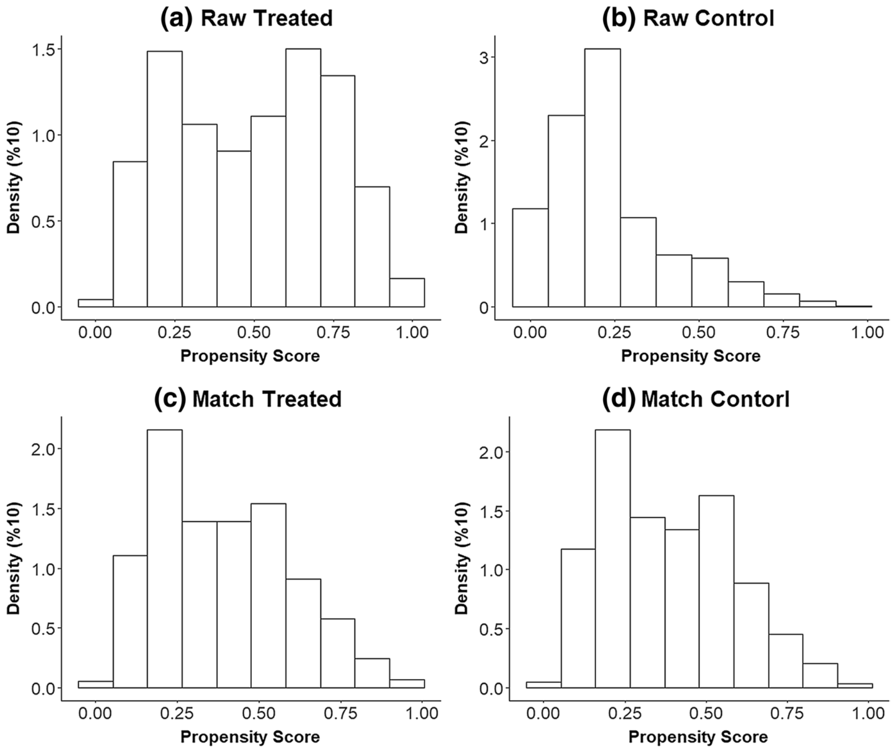

Fig. 2 The distribution of propensity scores

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