Does FinTech Improve Financial Inclusion? Evidence from Crowdfunded Microfinance Institutions*

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Abstract

We identify a set of financial technology (FinTech) shocks to developing economies' microfinance institutions (MFIs) and study its influence on financial inclusion. Via crowdfunding FinTech, the treated MFIs obtain subsidized debt capital from global atomic creditors when they produce and publish information about their clients on the platform, Kiva. We show in a triple-difference framework that Kiva participation benefits the MFIs, and the benefits concentrate on the MFIs that crowdfund large shares of their assets. Relative to low-stake counterparts, the MFIs that receive crowdsourced capital at a large scale expand in asset size and become more labor-intensive to facilitate information production. More importantly, financial inclusion improves as (i) they reach 5.7% more borrowers, (ii) the borrowers' estimated income is 9% lower, and (iii) the percentage of female borrowers increases by 5.1 percentage points. However, the improvements in financial inclusion come at a cost: these MFIs also have lower asset utilization rates and more non-performing loans.

JEL: D64, G21, G51, L31, N30, O16, O35, O57, R51

Keywords: Entrepreneurship, Household Finance, Financial inclusion, Microfinance institutions, Financial technology (FinTech).

*We appreciate constructive comments from seminar participants from The University of Hong Kong. All errors are ours.

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1 Introduction

The microfinance literature largely supports the notion that access to credit is productivity improving.[1] Prior experimental studies provide robust evidence of the benefits of microfinance interventions, ranging from business activities to household consumption.[2] However, these interventions are relatively small-scale and thus plausibly susceptible to "voltage drops" (List, 2024). In particular, microfinance may not have the same benefits when it is intermediated by authorities and institutions; when it scales up to the extent that general equilibrium effects occur, potentially countervailing the observed partial equilibrium effect; or when it embeds new technology to facilitate its upscaling and deviates from its original form in experimental settings.

The policy scale of microfinance, and more generally financial inclusion, is large. 1.4 billion adults around the world do not have a bank account in 2021, and many more have no formal access to credit (World Bank, 2022). To avoid voltage drops when administering microfinance to such a large and diverse demographic, more work is needed to have a better understanding of microfinance institutions (MFIs), the key intermediaries of microfinance. In this paper, we analyze a large sample of MFIs in developing economies to gauge their role in scaling microfinance. For causal identification, we utilize a set of financial technology (FinTech) shocks to examine if funding the MFIs can lead to improvements in financial inclusion.

The financial technology shocks that we analyzed are from Kiva, a digital marketplace for crowdfunded loans. As of 2023, lenders on Kiva have funded 2.3 million loans worth over $2 billion U.S. dollars, connecting two million charitable lenders to five million borrowers across 77 countries. Kiva pitches itself as a crowdfunding platform for entrepreneurs, with their Google search snippet stating "for as little as $25 you can lend to an entrepreneur around the world". Major destinations of Kiva loans include developing countries across Asia, Africa, and South America. Kiva partners with MFIs in these developing countries, where the MFIs make loans to borrowers, post the loans on

[1] Banerjee, Karlan, and Zinman (2015) and Buera, Kaboski, and Shin (2020) review the literature comprehensively. Both teams of authors summarize that microfinance development has a positive impact on business activities and a modestly positive impact on income and consumption.

[2] Banerjee et al. (2015) overview six microfinance experiments conducted in six countries on four continents. They find an overall positive (albeit statistically imprecise) effect of microfinance on borrowers' investment, business size, and profits.

Kiva for access to interest-free credit, and service the collection of interest and principal. From the MFI's perspective, the partnership with Kiva represents a technology adoption that requires more intensive production of loan- and borrower-level information, which the Kiva lenders consume to make loans. With sufficient information provided, the MFIs can obtain interest-free debt capital from Kiva lenders to fund their operations.

The Kiva partnership requires the partnering MFIs to produce and publish extensive information about their clients. In return, it enables the MFIs to obtain subsidized debt capital from global atomic creditors. We show in a triple-difference framework that Kiva participation benefits MFIs, and the benefits concentrate among MFIs that crowdfund larger shares of their assets. Compared with the low-stake counterparts, the MFIs that receive crowd-sourced capital at large scale expand in asset size and become more labor intensive to facilitate information production. These MFIs also show improvements in financial inclusion that are modest in statistical power but economically meaningful.

Our empirical work first matches the MFIs that take up the financial technology with similar MFIs that do not. We use the coarsened exact matching (Iacus, King, & Porro, 2012) method to match the treated MFIs and the control MFIs on quartiles of six variables that prior research shows to predict Kiva partnership, including (i) five-year average assets growth, (ii) return on assets, (iii) percentage of female borrowers, (iv) inflation-adjusted portfolio yield, (v) 30-day portfolio at risk, and (vi) operational self-sufficiency. The treatment group ($N = 112$ MFIs) and the control group ($N = 962$ MFIs) appear to be well-matched on the outcome variables that we analyze in our regression analyses.

We then develop a triple-differences framework to analyze the effect of Kiva partnership on MFI outcomes. The triple-differences regression exploits three sources of variations in outcome variables: outcome variation before and after the Kiva partnership, outcome variation between the MFIs taking up the partnership and those that do not, and outcome variation between the high take-up MFIs and the low counterparts. We define take-up rate as the average percentage of an MFI's assets crowdfunded by Kiva throughout the partnership, and classify an MFI as a high take-up MFI if its take-up rate is in the top quintile of the take-up rate distribution, i.e., if the MFI crowdfunds over

22% of its assets. Partnering MFIs that do not meet such criterion are classified as low take-up MFIs.

Separating the high take-up and the low take-up MFIs is important in our setting because we would like to focus not on the nominal part of the partnership but on the actual action of crowdfunding. The empirical distribution of the Kiva take-up rate is heavily right-skewed: for many MFIs, Kiva only funds a small fraction of their assets. By running a triple-differences regression, we establish a dosage effect of crowdfunding and raise the hurdle for alternative explanations. For example, one may be concerned that MFIs partner with Kiva to symbolically signal their organizational health, which is already in good shape before the partnership. If such concern is true, Kiva is the outcome, not the cause, of MFIs' improvements. We reject this Kiva-as-a-trophy hypothesis with our triple-differences estimate: trophy-waving MFIs need not actually seek funding from Kiva, so if they drive the effects we should see larger improvements among the low take-up MFIs. We show empirically that the opposite is true: Kiva partnership leads to improvements in MFI outcomes *particularly* among the high take-up MFIs that receive proportionally higher Kiva fund flows.

To organize our empirical results on the effectiveness of the Kiva partnership, we develop a stylized model that captures the key appeal of crowdfunding. The model modifies Lee and Parlour (2022) to account for the fact that Kiva lenders do not charge interest and display behaviors similar to warm-glow giving (Andreoni, 1990). We present four blocks of findings:

(1) *Crowdfunded projects have higher default rates than intermediary funded projects at similar investment levels.* We show that the high take-up MFIs have more non-performing loans. For these MFIs, loans are 1.9% more likely to become overdue by a month, 3.3% more likely to be written off, and 3.8% more likely to eventually default after the Kiva partnership. The sample averages of these statistics are 4.9%, 1.5%, and 1.3%, respectively. Hence, the loan performance effects are large relative to the low baseline non-performing rates. The increase in overdue loans is transient and recovers two years after the take-up, whereas the increase in defaults and more severe delinquencies is persistent in the three-year post-intervention period. Therefore, while temporary factors may explain some of the loan overdue variations, the persistence of higher default rates suggests a more permanent shift in the MFIs' clientele riskiness.

(2) *Crowdfunded projects overcome the underinvestment of projects initiated by entrepreneurs of under-represented demographics.* Contemporaneous with increased labor input, MFIs reach a larger number of borrowers, who on average earn lower incomes and are more likely to be female. These financial inclusion effects are particularly strong for the MFIs that receive large Kiva fund flows. All estimates of the financial inclusion effects are statistically noisy but economically sizable. For the high take-up MFIs, the number of active borrowers grows by 5.7%, borrower average income drops by 9%, and female borrower share grows by 5.1 percentage points, all relative to the low take-up MFIs, which in turn outperform the no take-up MFIs on all three measures. While the lack of statistical power advises us against making substantial claims based on these findings, the body of results is collectively coherent with the view that the Kiva partnership leads to local financial inclusion improvements.

(3) *Crowdfunded projects incur high information production costs that are reflected in overheads expenses.* Following the Kiva partnership, the high take-up MFIs become significantly more labor-intensive, and their payrolls expand substantially as a result. Unconditionally in our sample, an average loan officer services 333 borrowers and 357 loans every year. However, conditional on the high take-up intensity, an average loan officer only services 235 borrowers and 241 loans. Assuming a constant per-officer labor supply, each loan (borrower) becomes 32% (30%) more time-consuming to service. Presumably in response to such an increase in workloads, the high take-up MFIs increase their payrolls by nearly 50%. These statistics are consistent with the prediction that Kiva loan projects require more intensive information production efforts.

(4) *Crowdfunded projects face high matching friction that results in low asset utilitzation rates.* The high take-up MFIs have higher total assets, but their gross loan portfolios do not increase one-to-one with total assets. These MFIs' total assets grow by 36%, whereas their asset utilization ratios (gross loan portfolio divided by total assets) drop by 17.4 percentage points. Dynamically, the asset utilization ratio drops sharply in the year of the Kiva partnership for the high take-up MFIs and remains depressed two years after the partnership.

We perform two robustness checks. First, we vary the cutoffs used to define the high Kiva take-up MFIs. We report that the triple-differences effect size generally increases with the cutoff. Hence, this dosage effect indicates that it is likely the actual Kiva fund inflow, rather than the nominal partnership, that drives our results. In addition, lowering the cutoff significantly skews the distribution of take-up rates in the high take-up group. Setting the threshold at 22%, as we do in the baseline specification, ensures that we cover a wide range of take-up rates in the high take-up group of MFIs, without some particular take-up rate values dominating the distribution. In the second robustness check, we partition the sample into two sub-samples, one containing only non-profit MFIs and the other containing only for-profit MFIs. Sub-sample estimates indicate that our results are not entirely driven by either type of MFIs.

Our paper adds to the literature on financial inclusion. One stream of these studies focuses on the welfare implications of financial inclusion, which is well-documented.[3] Another stream of studies investigates the causes of financial inclusion, to which we are more related. The theoretical work of He, Huang, and Zhou (2023) and Parlour, Rajan, and Zhu (2022), as well as the empirical study by Erel and Liebersohn (2022), analyze financial inclusion outcomes when FinTech entrants compete with banks. We contribute to this line of work by providing evidence that financial inclusion improves after a novel financial technology injects crowdfunded capital into microfinance institutions.

Our paper also adds to the literature on microfinance. Prior studies of microfinance programs have provided robust evidence regarding the positive effects of microfinance interventions. We consider a more institutional approach to utilize microfinance and argue that to avoid voltage drops when scaling microfinance, MFIs need to be more systematically incorporated into the framework. Our findings suggest that while the degree of success can vary across individual cases, crowdfunding MFIs is overall a viable pathway to expand microfinance. By focusing our triple-difference framework on MFIs that receive large injections of crowdfunded capital, we provide empirical support for the validity of leveraging crowdfunding as a significant source of microfinance, as well as some evidence on the validity of leveraging MFIs to scale up financial inclusion.

[3] Using the staggered rollout of branches of the Freedman's Savings Bank after the American Civil War, Stein and Yannelis (2020) show that families with accounts are more likely to have children in school, be literate, work, earn higher occupational income, own a business, and accumulate real estate wealth. Célerier and Matray (2019) report similar results on household wealth accumulation using the U.S. interstate branching deregulation between 1994 and 2005. Brown, Cookson, and Heimer (2019) studies Native American reservations, whose degree of financial market development vary as an unintended result of Congressional legislation. They report that individuals growing up in financially underdeveloped reservations face a worse credit market in their adulthood, possibly due to their lower financial literacy and lower trust in financial institutions. Hacamo (2021) relates inclusion in the mortgage market to economy-wide fertility rates using the 2004 U.S. mortgage market deregulation.

Our investigation of Kiva is also related to studies that examine crowdfunding platforms. Goldstein, Jiang, and Karolyi (2019) review crowdfunding as one of the central applications of FinTech. Lee and Parlour (2022) compare crowdfunding to conventional intermediary funding and show that crowdfunding can improve efficiency by funding projects with positive consumption utility but negative net present value (NPV). These projects would not be funded by intermediaries because consumers cannot credibly commit to paying more than the market price, and the market price implies negative NPV and no participation from the intermediaries. From a theoretical perspective, crowdfunding is a commitment device that is more effective for short-duration, low-markup, and innovative projects.[4] Kiva is a crowdfunding platform for one-year, zero-interest, and financial inclusive entrepreneurial loans, and we indeed find that it is effective in partnering with intermediaries and funding these projects. The body of empirical evidence, which we obtain in a triple-difference setup, contributes to the understanding of crowdfunding's efficiency implications.

2 Institutional Details

2.1 Platform Overview

Kiva is founded in 2005 in San Francisco, the United States as a 501(c)3 non-profit organization. It is a crowd-sourced online lending platform that aims to connect individual borrowers and charitable lenders around the world. As of 2023, lenders on Kiva have funded 2.3 million loans worth over $2 billion U.S. dollars, connecting two million charitable lenders to five million borrowers across 77 countries. As an illustration, Figure 1 plots the Kiva fund flow map for the year 2020, in which 58% of Kiva's charitable fund originates from the United States. Major destinations of Kiva fund flow include developing countries across Asia, Africa, and South America.

Kiva partners with MFIs in developing countries. The MFIs screen the borrowers, disburse the loan, post the loan on Kiva for access to interest-free credit, and service the subsequent collection of

[4] Liquidity discount and entrepreneur's market power both reduces the efficiency of crowdfunding, so short-lived and low-markup projects are more suitable for crowdfunding. Innovative projects disrupts the market power of vertically differentiated firms by altering their endogenous pricing function, which also transfers market power to consumers and makes the projects suitable for crowdfunding.

interest and principal. To become a field partner, an MFI needs to pass Kiva's on-site due diligence on its stability, governance, and risk profile. Once it becomes a Kiva partner, it can post loans online to solicit funding from Kiva lenders, who have access to several categories of information provided by the MFI.

As shown in Figure 2, Kiva lenders can see the borrower's portrait, nationality, and name; the funding progress of the loan on Kiva; and a brief description of the purpose of the loan. Lenders can click on the loans that they are interested in and explore more details on a separate web page, where they can learn about the MFI that intermediates the loan, read a short biography of the borrower, and get other information such as the repayment schedule, loan term, and whether the exchange rate risk is covered. Once the lenders decide to fund the loan, they can check out and transfer the funds to Kiva via PayPal (PayPal, in partnership with Kiva, does not charage a fee on such transfer). By default, lenders lend in $25 increments and can choose to donate some extra money (e.g., $5) to keep Kiva running.

As intermediaries, the MFIs benefit from the participation of Kiva users in three ways. First and perhaps the most obvious, Kiva users lend at zero interest. Second, MFIs can recover the principal much faster by funding their loans on Kiva. On average, Kiva users fund a loan in around 13 days, and the proceeds are transferred to the MFIs on a monthly or quarterly basis. It is thus much faster to recover the principal by posting the loan on Kiva than by waiting until its maturity, which for the average loan takes about 13 months. Third, MFIs can pass on the default risk to Kiva lenders. During the checkout phase of funding a loan, Kiva lenders need to agree to absorb the loss in the event of default, which shields MFIs from potential default losses.[5]

While Kiva users lend charitably and do not receive interest on their loans, MFIs do charge interest from the borrowers to cover their costs and, in the cases of commercial MFIs, profit from their operations. While interest rates charged for individual loans are usually not made available, MFIs often report the percentage yield at the portfolio level, which is an aggregate proxy for the interest rates charged for each loan in the portfolio. For MFIs that partner with Kiva, Kiva reports that the average percentage yield on the MFI level is 27% per year. In Appendix A, we compare Kiva with other fundraising platforms, and review more studies related to them.

[5] Kiva also recruits and sends volunteers (Kiva Fellows) to partnering MFIs. See Appendix B for more details.

3 Model

We present a stylized model that captures the key appeal of crowdfunding. The model modifies Lee and Parlour (2022) to account for the fact that Kiva lenders do not charge interest and display behaviors similar to warm-glow giving (Andreoni, 1990). Crowdfunding – a funding mode in which the consumer is also the financier – challenges the Fisher (1930) separation theorem that firms and consumers are separate entities. To zoom in on the Fisher separation and clearly illustrate the effect of crowdfunding, we follow Lee and Parlour (2022) and abstract from other important frictions related to the interaction of principals and agents, such as moral hazard, adverse selection, and asymmetric information.

Time is discrete and there are three types of agents: an entrepreneur, a bank, and a continuum of households of unit measure. At $t = 0$, the penniless entrepreneur is endowed with a project with a fixed cost $I > 0$. The bank and the households have deep pockets and consider funding the project. All agents are risk neutral, time discount rate is zero, and both the bank and the households have zero outside options.

Production. In each period $t = 1, 2, ...$, the project continues with probability $\delta \in (0, 1)$ and produces output of utility v when consumed. With probability $1 - \delta$ the project fails and produces nothing going forward. The expected present value of the infinite-horizon project, denoted by $\mathbf{V}$, is given by $\mathbf{V} = \Sigma_{t=1}^{\infty} \delta^t v = \frac{\delta}{1-\delta} v$. In this scenario, the first-best outcome is to fund the project whenever $\mathbf{V} > I$.

Allocation without crowdfunding. The output v is shared by the entrepreneur with bargaining power $\alpha \in [0, 1]$ and the bank with bargaining power $1-\alpha$. The bank and the entrepreneur negotiate a constant periodic interest p, so that the bank gets p and the entrepreneur keeps $v - p$. Under generalized Nash bargaining, p is selected to maximize

$$(v - p)^{\alpha} \, p^{1-\alpha},$$

and the solution is

$$p = (1 - \alpha)\, v.$$

The project's expected present value to the bank, denoted by $\mathbf{V}^b$, is given by $\mathbf{V}^b = \Sigma_{t=1}^{\infty} \delta^t p = (1 - \alpha)\, \mathbf{V}$. If the entrepreneur has any bargaining power, the bank cannot extract the full surplus and values the project at $\mathbf{V}^b < \mathbf{V}$. In this case, the first-best is not achieved because the bank suboptimally rejects the project when $\mathbf{V} > I > \mathbf{V}^b$, i.e., when the project's NPV is negative. The underinvestment becomes more severe when enterpreneur's bargaining power, α, grows large.

Allocation with crowdfunding. Crowdfunding allows the households to directly fund the project. Introducing crowdfunding is beneficial if it funds any project with negative NPV ($\mathbf{V}^b - I < 0$) but positive utility ($\mathbf{V} - I > 0$). Essentially, crowdfunding is an improvement over intermediary funding if the households can internalize a larger fraction of $\mathbf{V}$ than the bank. When the households internalize the entire consumption benefit of the project, the first-best is restored and all productive projects are funded. This can be achieved via setting $\alpha = 0$ for crowdfunding, i.e., the crowdfunded entrepreneurs produce under perfect competition and the households consume everything. Our empirical setting provides a more realistic way to model this full internalization of $\mathbf{V}$: let households derive warm glow utility $w = v$ from funding the project *without* claiming any of its output. Denote by $\mathbf{V}^c$ the samaritan households' expected present value of the project. The entrepreneur's consumption utility v is fully internalized by the household's warm glow utility w,

$$\mathbf{V}^c = \frac{\delta}{1-\delta} w = \frac{\delta}{1-\delta} v = \mathbf{V}.$$

More generally, crowdfunding is an improvement over intermediary funding for any $w \in [(1-\alpha)\, v, v]$. It is reasonable to assume that Kiva lenders have $w \geq (1-\alpha)\, v$, because they are willing to lend to borrowers typically excluded from the formal credit system. They are also unlikely to have $w > v$ (which creates overinvestment problems), because such a high level of warm glow would imply that the household derives more utility than the entrepreneur who actually consumes the output. In aggregate, as long as w does not greatly exceed v, we should predict crowdfunding to produce a net benefit by alleviating the intermediary's underinvestment problem.

Proposition 1. *If the household derives warm glow utility $w \in [(1-\alpha)\,v, v]$ from funding the entrepreneur's project, crowdfunding is an improvement over intermediary funding towards the first-best, as illustrated in Figure 3.*

3.1 Testable predictions from the model

We develop three testable predictions from the stylized model to organize our empirical analyses. First, since crowdfunding is introduced after intermediary funding, it only funds projects rejected by the bank. In these projects, entrepreneurs are likely to have higher bargaining power that supresses the bank's valuation of the project. One relevant and widely observable metric here is the default rate of the project. We relate the observed default rate to the bargaining power parameter α to allow a more general interpretation of it.[6] Higher observed default rates indicate higher bargaining power of the entrepreneur, which makes crowdfunding an appealing choice over intermediary funding.

Hypothesis 1. *Crowdfunded projects have higher default rates than intermediary funded projects at similar investment levels.*

Next, we model the bank's prior about the entrepreneur's bargaining power and derive statistical discrimination. We demonstrate that households with warm glow utility overcome the underinvestment caused by bank's incomplete information. With warm glow, crowdfunding bootstraps the financial inclusion of discriminated demographics.

In the model, the bank encounters the entrepreneur at $t = 0$ and obtains a signal about the entrepreneur's bargaining power α. To have a simple formulation of this signal, we assume that the bank observes the entrepreneur's gender and poverty status and perceive the entrepreneur to have α_m^+ (male above poverty line), α_f^+ (female above poverty line), α_m^- (male below poverty line), or

[6] We assume that the observed default rate is not related to δ in the model, because in the microfinance industry the project's failure may be insured by a joint liability contract or simply unverifiable (de Quidt, Fetzer, & Ghatak, 2018). Observed defaults can also be simply due to diverting, which relates less to the projects failure probability and more to the bargaining power dynamics.

α_f^- (female below poverty line). The bargaining power order of these four types of entrepreneurs is $0 \leq \alpha_m^+ < \alpha_f^+ < \alpha_m^- < \alpha_f^- \leq 1$. A microfoundation for this order is that the bank has encountered more above-poverty male entrepreneurs in the past and can exploit them more effectively. On the other hand, it has rarely encountered below-poverty female entrepreneurs, so it rejects their loans as if α_f^- is large. The household derives warm glow utility and is insensitive to α. As a result, crowdfunding bootstraps the financial inclusion of discriminated demographics.

Hypothesis 2. *Crowdfunded projects overcome the underinvestment of projects initiated by entrepreneurs of discriminated demographics.*

We make a final prediction based on the institutional details of our data. Since Kiva does not have the capacity to directly engage entrepreneurs in the developing economies, it relies on partnerships with local MFIs to allocate the crowdfunded capital. In these partnerships, Kiva use zero-cost crowdfunded capital to incentivize MFIs to profile underpriviliged entrepreneurs and include them in the credit system. Profiling these entrepreneurs should be more costly than profiling the average entrepreneur due to under-representation. This friction predicts higher overhead expenses for MFIs that partner with Kiva.

Hypothesis 3. *Crowdfunded projects incur high information production costs that are reflected in overheads expenses.*

Matching with these entrepreneurs should also be more difficult, similarly due to under-representation. This friction predicts that for MFIs that partner with Kiva, their loan portfolios do not grow one to one with their assets, i.e., they utilize their assets at a lower rate.

Hypothesis 4. *Crowdfunded projects face high matching friction that results in low asset utilitzation rates.*

4 Data

We obtain data on MFI financial performance from MIX Market, the leading data provider for fundamentals of global microfinance institutions. We collect information on partnerships between

MFIs and Kiva from Kiva's API.[7] MIX and Kiva use different sets of codes to identify MFIs and no crosswalk file is readily available to merge the two datasets. Below we describe the name matching procedure that we use to match 133 MFIs exactly, 30 MFIs fuzzily, and 69 MFIs from archival sources.

We start from a cleaned set of MFI names provided by Kiva, which contain the full names of the MFIs and/or the acronyms associated with the full names. We attempt to match either the full names or the acronyms to the cleaned set of MFI names provided by MIX, which similarly may record the MFIs in either their full names, their acronyms, or both. The first step returns 133 matches. Unmatched MFI names from Kiva are then each paired with the MFI name from MIX to which it has the shortest edit distance, also known as the Levinstein distance. We manually review the pairs of names generated and retain 30 pairs, of which we have strong confidence that the two names in each pair actually refer to the same entity. We also utilize online archives of Kiva's webpages as another source of information to map MFIs from Kiva to MIX. Old versions of the profiles of Kiva partner MFIs contain links to the MFIs' profiles on the MIX platform, but the links were later removed. We manually recovered the links from archival webpages provided by the Internet Archive, a third-party online archive initiative.[8] We are able to link another 69 MFIs from Kiva to MIX with this procedure.

Less than 10% of the MFIs in the MIX dataset ever enters a Kiva partnership. To ensure that the MFIs in the treatment group and the MFIs in the control group are comparable in their ex-ante likelihood to partner with Kiva, we perform coarsened exact matching (CEM) to match never-treated MFIs with treated MFIs in the same CEM strata. We match on six variables, each coarsened into quartiles and evaluated at the year before Kiva partnership: five-year average assets growth, return on assets, percentage of female borrowers, inflation-adjusted portfolio yield, 30-day portfolio at risk, and operational self-sufficiency.[9] In all our regressions, we include strata-specific fixed effects to

[7] As an advantage of our empirical setup, Kiva maintains a relatively consistent level of data transparency throughout our sample period. This is often not the case for non-charitable lending platforms such as Prosper and Lending Club. Vallée and Zeng (2019) discuss the theoretical motives (e.g., mitigating adverse selection) behind lending platforms' decisions to reduce information transparency.

[8] https://archive.org/web/

[9] These characteristics are shown to predict a Kiva-MFI partnership: Dorfleitner, Oswald, and Rohe (2020) show that Kiva is more likely to partner with MFIs that lend to females, charge non-predatory interest rates, and have low-risk portfolios, and relatively not self-sufficient.

identify the intervention effect on a within-strata basis, i.e., while the treated MFIs and the control MFIs differ in their take-up of Kiva partnership, they are ex-ante similar in key charateristics that predicts the partnership.

Table 1 reports summary statistics of the outcome variables that will be used in the regressions in Section 4. We tabulate the summary statistics separately for the treatment group ($N = 112$) and the control group ($N = 962$). The two groups appear to be well-matched on the outcome variables that we run regressions on.

We proceed with the matched sample for our regression analyses in the next section.

5 Results

Starting in 2006, Kiva partners with new MFIs every year, so the take-ups of financial technology in our sample are staggered. We address this issue with a stacked regression approach (Baker, Larcker, and Wang, 2022; Cengiz, Dube, Lindner, and Zipperer, 2019). Specifically, treated units are grouped into cohorts based on their timing of treatment, denoted by $d = \{2006, 2007, ..., 2015\}$. Within each cohort, treatment units are paired with control units that are similar in key characteristics (see Section 3 for details), forming a cohort-specific dataset d. For example, all MFIs that partnered with Kiva in 2006 would be paired with comparable MFIs that never partnered with Kiva, forming a dataset indexed by $d = 2006$. This cohort-specific dataset would be a MFI-by-year panel that covers the period $t = [d-3, d+2] = \{2003, 2004, 2005, 2006, 2007, 2008\}$.

After generating datasets for all treatment cohorts, all datasets are combined for a single DiD regression. This regression is standard except for the fact that it now includes *cohort-specific* time and unit fixed effects. We choose to use never-treated units as control units since plenty are available. The regression equation is

$$\begin{aligned} Y_{itd} \quad = \quad & \beta_1 \cdot (\text{Treat}_{id} \times \text{Post}_{td} \times \text{High\_Kiva\_Flow}_{id}) + \\ & \beta_2 \cdot (\text{Treat}_{id} \times \text{Post}_{td}) + \text{FE}_{id} + \text{FE}_{ctd} + \epsilon_{itd}, \end{aligned} \tag{1}$$

where Y_{itd} is one of the outcome variables of MFI i, Treat_{id} is a dummy variable that evaluates to one if MFI i is a Kiva partner, Post_{td} is a dummy that takes one if $t \geq d$, $\text{High\_Kiva\_Flow}_{id}$ takes one if the MFI's annual average percentage of assets funded by Kiva is above 22% (i.e., within the top quintile of the Kiva take-up rate distribtution), FE_{id} and FE_{ctd} are cohort-strata-specific MFI and country-year fixed effects, and ϵ_{itd} is the error term.

Our considerations in choosing the threshold is twofold. First, from the data we only observe outcome variations for the MFI as a whole, and not outcome variations for the business segment funded by Kiva. Therefore, for Kiva to actually drive the MFI-level variations and for us to observe it from the data, the Kiva take-up rate threshold cannot be low. Second, the empirical distribution of Kiva take-up rates are heavily right skewed: the top quintile of it contains more variation than the other four quintiles combined. If we conjecture the equilibrium distribution of the take-up rates to be more symmetric than what we observe (for example, by expecting Kiva to grow as the crowdfunding technology becomes more well-known), we should focus more on the observations at the right tail of the distribution.[10]

Regression (1) is a triple-difference regression that exploits three sources of variations in outcome variables: outcome variation before and after the Kiva partnership (Post_{td}), outcome variation between MFIs taking up the partnership and MFIs that do not (Treat_{id}), and outcome variation between high take-up MFIs and low take-up MFIs ($\text{High\_Kiva\_Flow}_{id}$). Our prediction is that $\beta_1 \neq 0:$ the impact that Kiva partnership has on MFI outcomes should be even stronger among MFIs that intensively adopt the technology.

An equally important prediction is, for a unobserved confounding variable to explain our findings, it must generate outcome variation not across the take-up line (β_2; Treat_{id}) but across the intensity line (β_1; $\text{High\_Kiva\_Flow}_{id}$). For example, a critic may argue that Kiva is a trophy: MFIs partner with Kiva to symbolically signal their organizational health, which is already in good shape before the partnership. Therefore, the critic may argue, Kiva partnership is the outcome, not the cause, of the

[10]This is akin to giving larger weights to survey responses from subgroups that are under-represented in the survey than in the population, in order to restore population representativeness. We do not establish a set of weights formally for two reasons. First, the regression already employs analytical weights from the CEM procedure. Second, while we draw from our findings to suggest that the equilibrium empirical distribution should be less skewed, without specifying the counterfactual distribution parameters we cannot pin down the weights.

MFIs' improvements. We can directly test this hypothesis in our framework: the Kiva-as-a-trophy hypothesis would predict that MFIs taking up the partnership at low intensity sees the strongest improvement in outcomes, since these are the trophy-waving, already-healthy MFIs that need not seek actual funding from Kiva. As we will report in the remaining part of this section, this is most often not the case: the empirical findings largely support our hypothesis that Kiva partnership leads to improvements in MFI outcomes *particularly* among MFIs that intensively adopt the technology and receive higher fund flows.

5.1 FinTech Adoption and Loan Performances

We run two regressions related to the MFIs' loan performances. The first regression uses the outcome variable of 30-days portfolio at risk, defined as the value of loans overdue by more than 30 days divided by the value of gross loan portfolio. The second regression uses the outcome variable of loan write-off ratio, the value of written-off (but potentially still recoverable) loans divided by gross loan portfolio. The third regression uses a related outcome variable, loan loss rate, defined as the value of loans written off and considered unrecoverable divided by the value of gross loan portfolio. As is well known in the literature, the sample average of these statistics are low: the average 30-days portfolio at risk is 4.9%, the average loan written-off ratio 1.5%, and the average loan loss rate 1.3%. We again cluster standard errors at the MFI level to account for serially correlated errors.

Table 2 reports the regression results. Relative to low-takeup MFIs, high take-up MFIs have more non-performing loans. For these MFIs, loans are 1.9% more likely to become overdue by a month, 3.3% more likely to be written off, and 3.8% more likely to eventually default after the Kiva partnership. The dynamics plotted in Figure 5 suggests that the increase in overdue loans is transient and recovers at $t = d + 2$, i.e., two years after the take-up, whereas the increase in loan write-offs and loan defaults is more persistent and does not revert in the three-year post-intervention period. Therefore, while it is likely that loan overdues are partially driven by temporary factors (e.g., loan officer shortages, which we investigate later), the persistence of more severe deliquencies suggest a more permanent shift in the MFIs' clientele riskiness.

These results support the loan performance hypothesis from our stylized model, as illustrated in

Figure 4. We bin MFIs according to their 30-days portfolio at risk with the bin width of one percentage point. The solid dashed line overlays the intermediary's underinvestment problem. As predicted by the model, high-takeup MFIs are more concentrated in the region of less performant loans, i.e., they pick up loans rejected by intermediaries when they receive crowdfunded capital from Kiva.

5.2 FinTech Adoption and Financial Inclusion

Kiva makes an ambitious claim on its front page to "make a loan, change a life." Does it do what it says, or fail to deliver on the promise of financial inclusion? We analyze, again using regression 1, three commonly reported measures of financial inclusion to see if MFIs improve on these measures after partnering with Kiva. The measures are the natural log of the number of active borrowers, the average loan size (a proxy for borrower income, assuming that borrowers only get access to loans proportional to their income), and the percentage of female borrowers. The results are reported in Table 3.

Regression results indicate that following Kiva partnership, MFIs reach a larger number of borrowers, who on average earn lower income and are more likely to be female. These financial inclusion effects are particularly strong for MFIs that receive large Kiva fund flows. All estimates in Table 3 are imprecise, as is often the case when evaluating the impact of microfinance (Banerjee et al., 2015). The point estimates are nevertheless economically sizable: for high take-up MFIs, the number of active borrowers grow by 5.7%, borrower average income drop by 9%, and female borrower share grow by 5.1%, all relative to low take-up MFIs, which in turn outperform no take-up MFIs on all three measures. While the lack of statistical power advises us against making substantial claims based on these findings, the body of results reported in Table 3 is collectively coherent with the view that Kiva partnership leads to local financial inclusion improvements.

5.3 FinTech Adoption and Payrolls

To analyze how Kiva partnership affects the workers employed by the MFIs, we choose four variables as the outcome of regression 1: Number of loans handled per year per loan officer, number of borrowers handled per year per loan officer, the natural log of MFI's total number of employees, and the natural log of MFI's number of loan officers. Following definition by the MIX, loan officers are client-facing employees that directly handle the loans. We again reported standard errors clustered at the MFI level. Results are in Table 4.

Following Kiva partnership and relative to low take-up MFIs, high take-up MFIs become significantly more labor intensive, and their payrolls substantially expand as a result. Unconditionally in our sample, an average loan officer services 333 borrowers and 357 loans every year. For high take-up MFIs, an average loan officer now services 235 borrowers and 241 loans, so assuming constant per-officer labor supply each loan (borrower) now becomes 32% (30%) more time-consuming to service.

The increase in workload per borrower aligns with the institutional details we covered in Section 2. Kiva requires MFIs to produce detailed information about the borrowers and the loans before funding the loans online. The requirement includes standard information about the borrowers and the loans, as well as some information that are less standard and is likely to require extra effort. For example, Kiva emphasizes that having a well-taken photo of both the borrowers and their means of subsistence (such as livestocks, village stores, and farmlands) helps to accelerate the loan funding process. Even for the standard information that the MFIs may have already collected, more work is needed for translation into English and posting them online. We see, likely in response to such increase in workloads, that MFIs substantially increase their payrolls by nearly 50% (Column 3 and 4, Table 4; see also Figure 6 for the effect dynamics).

5.4 FinTech Adoption and Asset Utilization

We run three regressions related to asset utilization, each with a different outcome variable. The three outcomes are the natural log of total assets, the natural log of gross loan portfolio, and the ratio of gross loan portfolio to total assets (i.e., the asset utilization ratio). Standard errors are clustered at the MFI level, so we account for the potential error correlation within MFI across years.

Table 5 reports the regression results. Relative low take-up MFIs, high take-up MFIs have higher total assets, but their gross loan portfolios do not increase one-to-one with total assets. These MFIs' total assets grow by an average of 36%, whereas their asset utilization ratio drop by 17.4% from the sample average of 81.5%. The under-utilization of crowdfunded capital is consistent with the prediction that crowdfunded projects are more likely to have limited capacity.

We plot the dynamic version of regression (1) in Figure 7 to see how the asset utilization ratio changes over time. For completeness, the dynamics of log assets and log gross loan portfolio are also plotted. Assets and gross loan portfolios both increase sharply at the year of Kiva partnership and remain at high levels up to two years after the partnership for high take-up MFIs. As a result, asset utilization is persistently low throughout the post-intervention periods.

6 Robustness

6.1 Different cutoffs to separate high and low Kiva take-up MFIs

In our baseline specification, we define high Kiva take-up MFIs to be the top 20% of MFIs ranked by percentages of assets funded by Kiva. We choose this cutoff for two reasons. First, considering the empirical distribution of Kiva take-up rates, this cutoff indicates that all MFIs in the high take-up group have at least 22% of assets funded by Kiva. This threshold appears more reasonable to us than, for example, using the median take-up rate of 5% as the cutoff. Since our outcome variables are measured for the whole institution and not just the part that Kiva funds, setting a high threshold helps to reduce estimation noise.

For completeness, we vary the cutoffs used to define $\text{High\_Kiva\_Flow}_{id}$ from 12% of MFI's total assets (the sample's average and 70th percentile) to 22% of MFI's total assets (our baseline specification) at two percent increments. We repeat regression (1) with six different cutoffs $\{12\%, 14\%, 16\%, 18\%, 20\%, 22\%\}$ and nine different outcome variables, producing $6 \times 9 = 54$ estimates of β_1.[11] Figure A1 organizes these estimates by outcome variables and by cutoffs.

[11] Four outcome variables $\{ln\,(GLP)\,, ln\,(NumBorrowers)\,, LoanPerBorrower, PercentFemale\}$ have statistically insignficant β_1 in the main specification; they also have statistically insignficant β_1 across the range of cutoffs and are not reported in Figure A1 for brevity.

We have two observations. First, with a few exceptions, the triple-differences effect size generally increases with the cutoff. This dosage effect indicates that it is the actual Kiva fund inflow, rather than the nominal partnership or some unobserved confounders, that drives the results. Second, the results on payroll and labor intensity show a spike in effect size and statistical significance at the 22% cutoff. Since the top quintile of a right-skewed distribution contains the largest variation (the take-up rate varies from 22% to 73% for 19 different MFIs), observations there are relatively thin. Lowering the threshold to 18% adds another 6 MFIs to the high take-up group, so the four-percent range $[18\%, 22\%]$ is heavily over-represented in the high take-up group. We more formally make this point in Figure A2: the take-up rates are more uniformly distributed in the region $[22\%, 73\%]$, but extending the region leftward significantly skews the distribution. Setting the threshold at 22%, as we do in the baseline specification, ensures that we cover a wide range of take-up rates in the high take-up group of MFIs, without some particular take-up rate values dominating the distribution.

6.2 Do non-profit MFIs differ from for-profit MFIs?

Not systematically. We partition the sample into two sub-samples, one containing only non-profit MFIs and the other containing only for-profit MFIs. The MFI profit status data is a snapshot as of 2020 (the latest MIX data release) and we cannot observe whether the MFIs switched profit status at some point in the past. With this caveat in mind, we rerun regression (1) and report the triple-differences estimates β_1 for all outcome variables in Figure A3. There are instances where the effects of large Kiva capital injection lose statistical significance at conventional levels when we partition the sample, but no instance where we observe an opposite (yet still significant) effect in the partitioned sample. The sub-sample estimates in Figure A3 indicate that while partitioning the sample by MFI profit status reduces the precision of our estimates, our results are not entirely driven by either type of MFIs.

7 Conclusion

We study the effectiveness of crowdfunding MFIs to scale up financial inclusion. We use a triple-difference framework to analyze the effects of Kiva partnerships on MFI outcomes, particularly distinguishing between high take-up and low take-up MFIs. We find that MFIs receiving larger inflows of crowdfunded capital through Kiva experience significant changes in four aspects, which we organize in a stylized model. First, they have more non-performing loans, consistent with crowdfunding alleviating the intermediary's underinvestment problem in projects where entrepreneurs have high bargaining power. Second, they show economically large yet statistically imprecise improvements in financial inclusion outcomes, as their clienteles shift towards low-income and female entrepreneurs. Third, they become more labor-intensive as their loans become more time-consuming to service and journal. Fourth, their asset utilization rates (gross loan portfolio divided by total assets) drops sharply in the year of the Kiva partnership and remains depressed two years into the partnership, indicating a high matching friction for crowdfunded loans.

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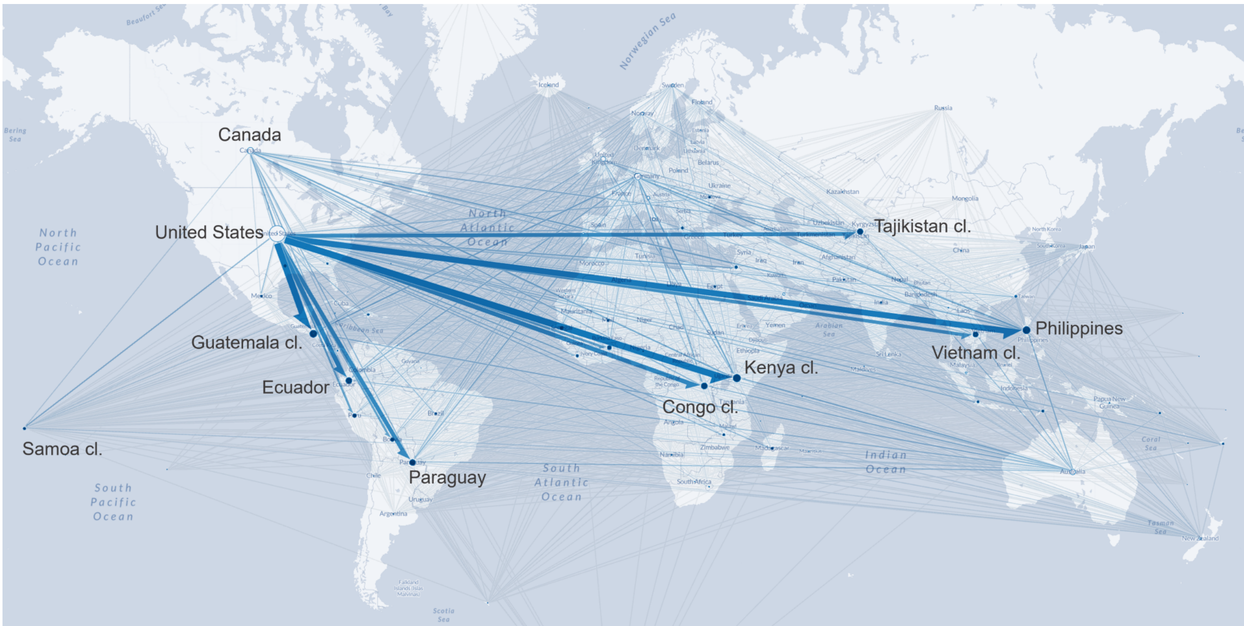

Figure 1: *Kiva Fund Flow Map in 2020.* The thickness of the arrows represents the amount of charitable fund flow between two countries. "cl." indicates that the dot on the graph is a cluster of several countries. An interactive version of this map is available here.

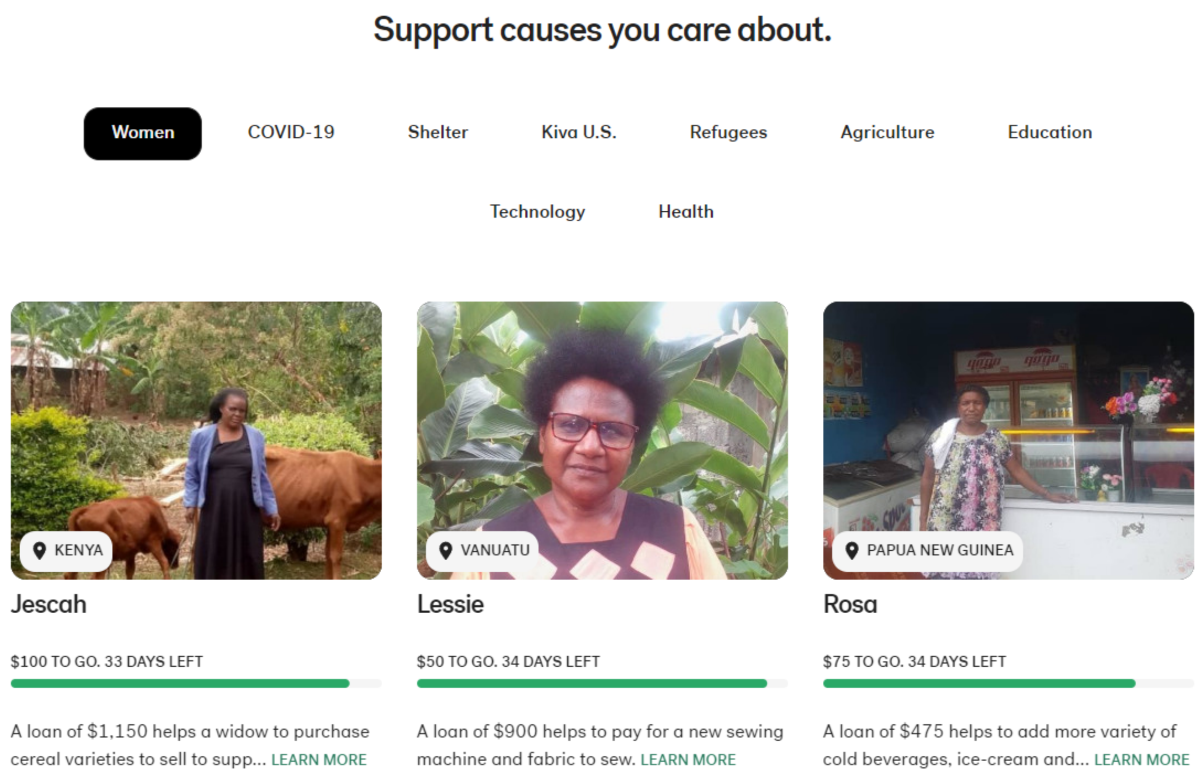

Figure 2: *A Snapshot of the Kiva Website.* Kiva lenders have access to several categories of information: the portrait, nationality, and name of borrowers, the funding progress, and a short description of the purpose of the loan. Lenders can click on the loans that they are interested in and explore more details on a separate web page, where they can learn about the MFI that intermediates the loan, read a short biography of the borrower, and get other information such as the repayment schedule, loan term, and whether the exchange rate risk is covered.

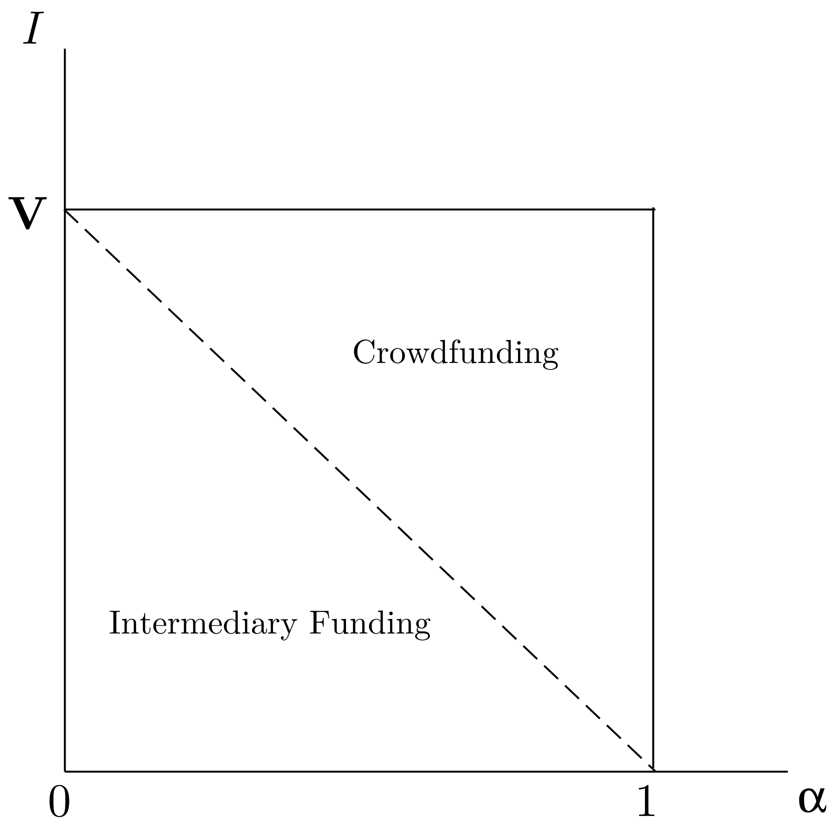

Figure 3: *A Stylized Model of Crowdfunding.* When the entrepreneur's bargaining power (α, horizontal axis) grows large, the intermediary's underinvestment problem becomes more severe, as it rejects a larger number of projects with positive utility ($\mathbf{V} > I$) but negative NPV ($I > \mathbf{V}^b = (1 - \alpha)\,\mathbf{V}$). Crowdfunding is an improvement towards the first-best if it funds additional positive utility projects, which are located towards the top right and bounded by $\mathbf{V} = I$ and $\alpha = 1$.

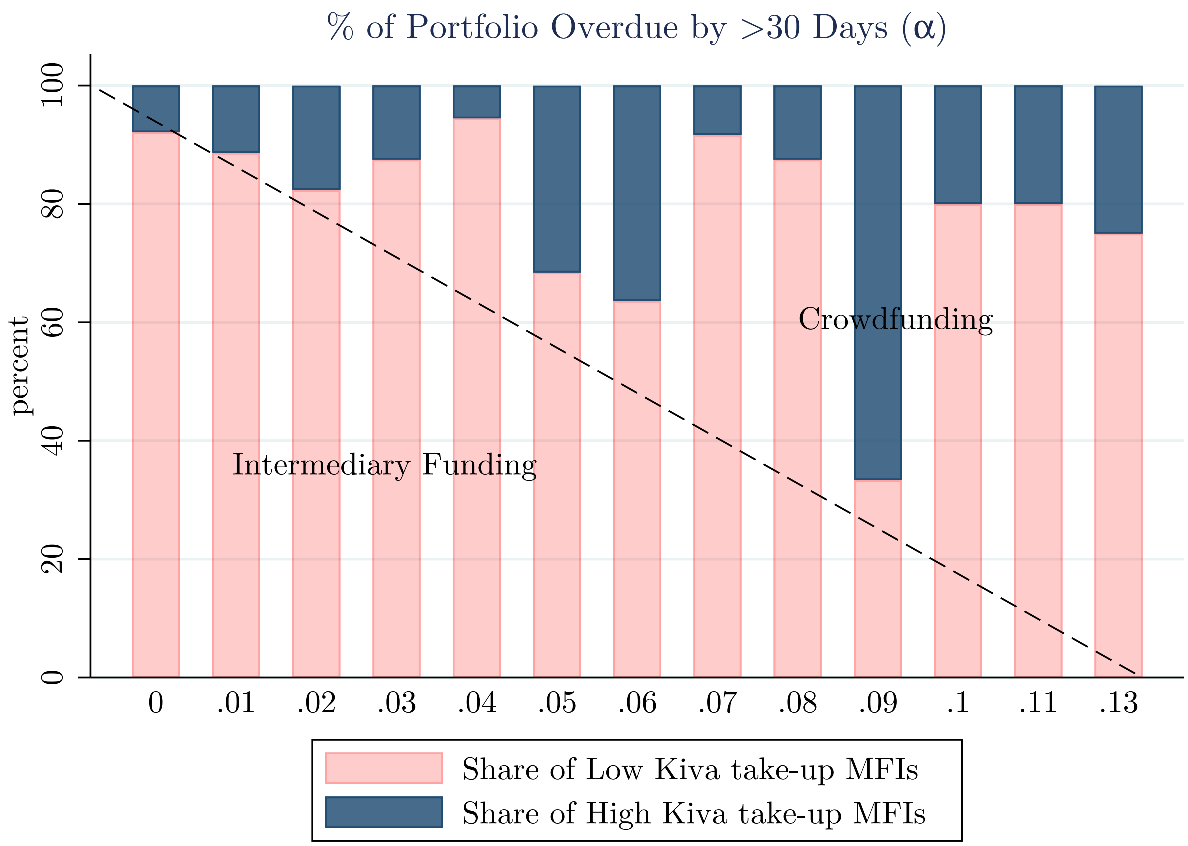

Figure 4: *Crowdfunding and Loan Performance.* We bin MFIs according to the overdue rates of their loan portfolios. Each bin is a 1% increment in overdue rates. Within each bin, the share of high Kiva take-up MFIs is colored in dark blue, and the share of low Kiva take-up MFIs is colored in light red. High Kiva take-up MFIs have a larger share of their loan portfolios funded by crowdfunders on Kiva. The solid dashed line overlays the intermediary's underinvestment problem as suggested by the stylized model.

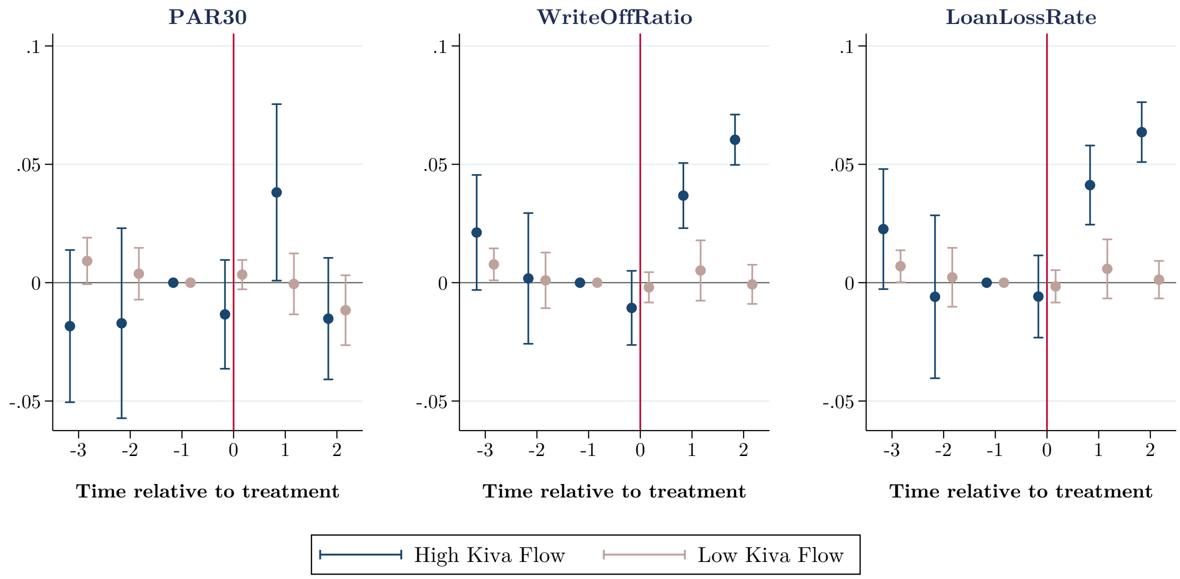

Figure 5: *Triple-differences loan performance regression.* The outcome variable is 30-days portfolio at risk in the left panel, loan write-off ratio in the middle panel, and loan loss rates in the right panel. 30-days portfolio at risk is the value of loans overdue by more than 30 days divided by gross loan portfolio. Loan write-off ratio is the value of written-off (but potentially still recoverable) loans divided by gross loan portfolio. Loan loss rate is value of unrecoverable loans divided by gross loan portfolio. The reference time period is the year before treatment. High Kiva share (plotted in dark blue) refers to the top 20% of Kiva-partnering MFIs, ranked by percentages of assets funded by Kiva. Low Kiva share (plotted in light brown) refers to the bottom 80% of Kiva-partnering MFIs.

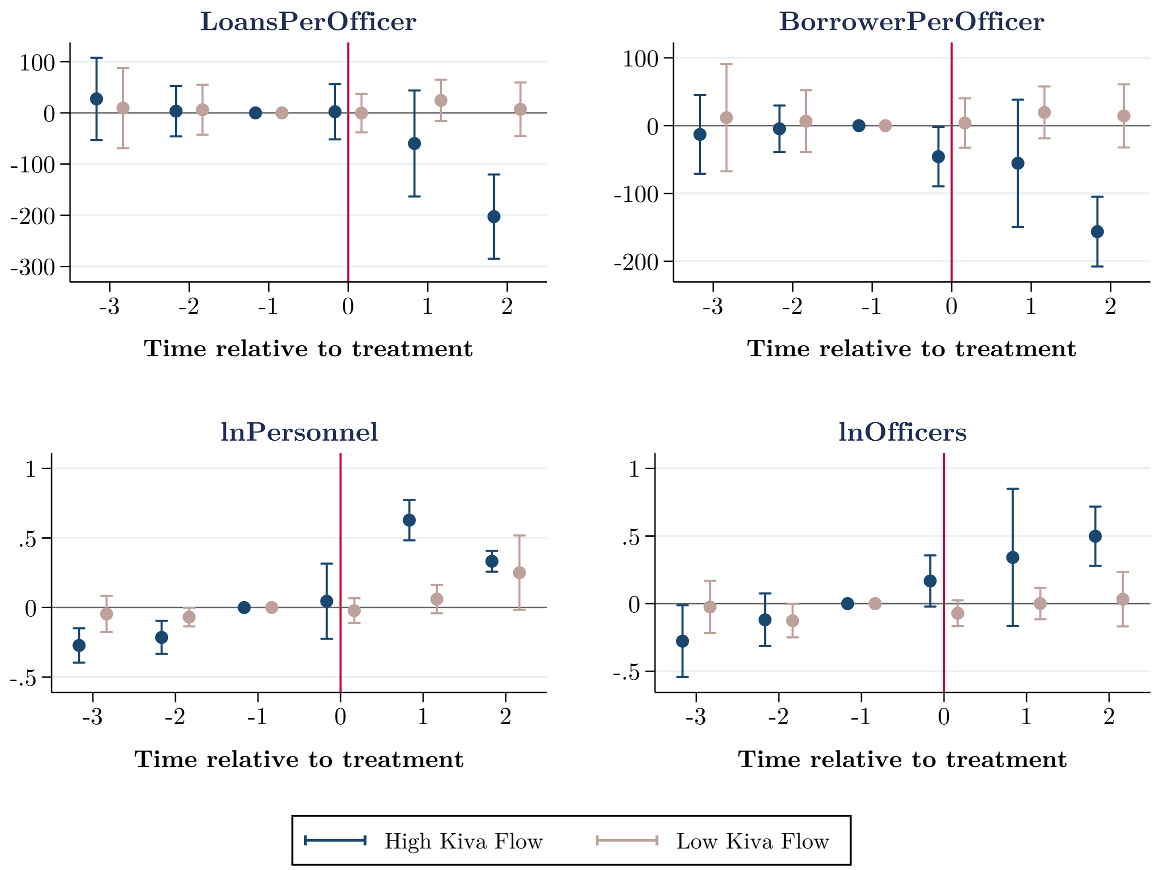

Figure 6: *Triple-differences MFI payroll regression.* The outcome variable is the number of loans serviced per loan officer in the top left panel, the number of borrowers served per loan officer in the top right panel, the natural log of the number of employees in the bottom left panel, and the natural log of the number of loan officers in the bottom right panel. The reference time period is the year before treatment. High Kiva share (plotted in dark blue) refers to the top 20% of Kiva-partnering MFIs, ranked by percentages of assets funded by Kiva. Low Kiva share (plotted in light brown) refers to the bottom 80% of Kiva-partnering MFIs.

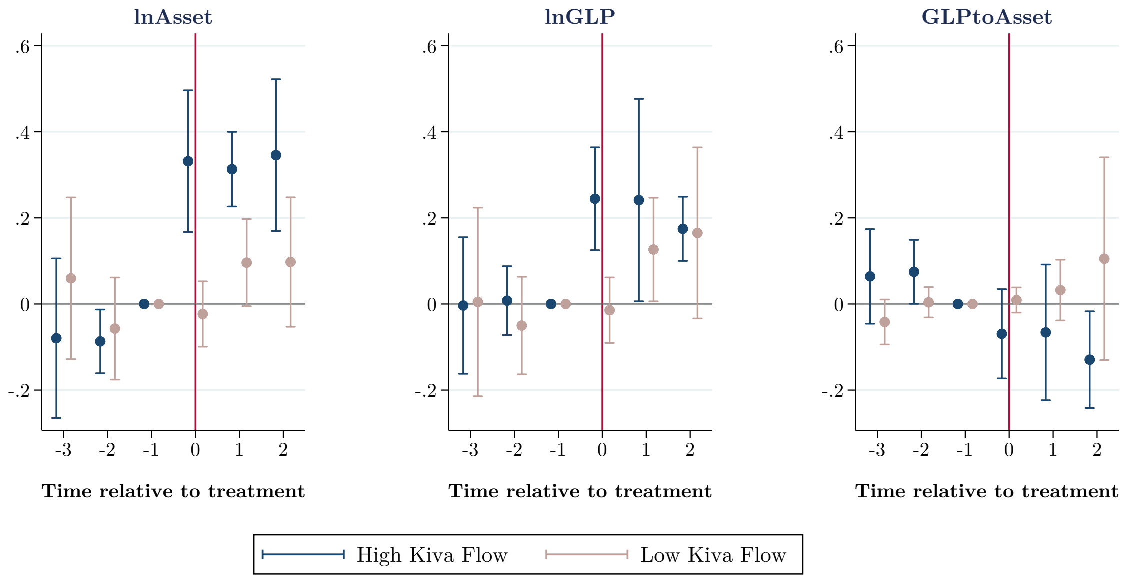

Figure 7: *Triple-differences MFI asset regression.* The outcome variable is the natural log of MFI assets in the left panel, the natural log of MFI gross loan portfolio in the middle panel, and the ratio of gross loan portfolio to assets in the right panel. The reference time period is the year before treatment. High Kiva share (plotted in dark blue) refers to the top 20% of Kiva-partnering MFIs, ranked by percentages of assets funded by Kiva. Low Kiva share (plotted in light brown) refers to the bottom 80% of Kiva-partnering MFIs.

	Treated MFIs (N=112)				Control MFIs (N=962)			
	Mean	SD	p5	p95	Mean	SD	p5	p95
lnAsset	15.88	1.37	13.53	17.95	16.48	1.89	13.57	19.79
lnGLP	15.61	1.37	13.39	17.66	16.23	1.91	13.30	19.63
GLPtoAsset	0.78	0.17	0.53	0.94	0.80	0.27	0.51	0.98
Portfolio at risk > 30 days	0.04	0.05	0.00	0.12	0.05	0.06	0.00	0.16
Loan loss rate	0.01	0.03	−0.00	0.05	0.01	0.03	−0.00	0.05
Loans per loan officer	323.48	182.76	106.00	674.00	352.55	271.67	91.00	837.00
Borrowers per loan officer	312.80	180.05	107.00	657.00	328.64	243.13	88.00	750.00
lnPersonnel	4.69	1.10	2.94	6.52	4.97	1.64	2.30	7.81
lnOfficers	3.93	1.14	2.08	5.78	4.13	1.74	1.39	7.05
lnNumBorrowers	9.54	1.22	7.49	11.41	9.72	1.88	6.44	12.76
Average loan balance per borrower	751.49	867.10	91.00	2,512.00	1,419.24	1,997.90	101.00	4,976.00
Percent of female borrowers	0.74	0.22	0.36	1.00	0.67	0.24	0.32	1.00

Table 1: *Summary Statistics.* This table summarizes all the outcome variables in our regression analyses separately for the treated MFIs (i.e., MFIs that partnered with Kiva, $N = 112$) and for the control MFIs ($N = 962$). GLP: gross loan portfolio.

	(1) PAR30	(2) WriteOffRatio	(3) LoanLossRate
Treat × Post	−0.006	−0.002	−0.001
	(−1.484)	(−0.565)	(−0.328)
Treat × Post × High Kiva Flow	0.019***	0.033***	0.038***
	(3.292)	(4.761)	(7.500)
Strata-cohort-MFI FE	Yes	Yes	Yes
Strata-cohort-country-year FE	Yes	Yes	Yes
Mean of Dep. Var.	0.049	0.015	0.013
R2	0.733	0.749	0.732
N	6,973	6,684	6,850

Table 2: *FinTech Adoption and Loan Performance.* Standard errors are clustered at the MFI level. t-statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) lnNumBorrowers	(2) LoanPerBorrower	(3) PercentFemale
Treat × Post	0.079	−51.187	0.006
	(1.138)	(−0.705)	(0.544)
Treat × Post × High Kiva Flow	0.057	−106.672	0.052
	(0.489)	(−0.536)	(1.259)
Strata-cohort-MFI FE	Yes	Yes	Yes
Strata-cohort-country-year FE	Yes	Yes	Yes
Mean of Dep. Var.	9.852	1203.249	0.713
R2	0.991	0.976	0.965
N	7,119	7,119	7,119

Table 3: *FinTech Adoption and financial inclusion.* Standard errors are clustered at the MFI level. t-statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) LoansPerOfficer	(2) BorrowerPerOfficer	(3) lnPersonnel	(4) lnOfficers
Treat × Post	5.778	6.999	0.116**	0.028
	(0.271)	(0.351)	(1.972)	(0.426)
Treat × Post × High Kiva Flow	−115.377***	−96.836***	0.371***	0.420**
	(−2.776)	(−2.945)	(5.757)	(2.533)
Strata-cohort-MFI FE	Yes	Yes	Yes	Yes
Strata-cohort-country-year FE	Yes	Yes	Yes	Yes
Mean of Dep. Var.	356.534	332.242	5.025	4.223
R2	0.854	0.859	0.983	0.986
N	6,946	6,972	7,095	6,986

Table 4: *FinTech Adoption and payrolls.* Standard errors are clustered at the MFI level. t-statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) lnAsset	(2) lnGLP	(3) GLPtoAsset
Treat × Post	0.053	0.098	0.054
	(0.816)	(1.607)	(1.174)
Treat × Post × High Kiva Flow	0.311***	0.116	−0.174***
	(4.537)	(1.453)	(−2.894)
Strata-cohort-MFI FE	Yes	Yes	Yes
Strata-cohort-country-year FE	Yes	Yes	Yes
Mean of Dep. Var.	16.434	16.206	0.815
R2	0.992	0.991	0.847
N	6,972	6,973	6,972

Table 5: *FinTech Adoption and Assets*. Standard errors are clustered at the MFI level. t-statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

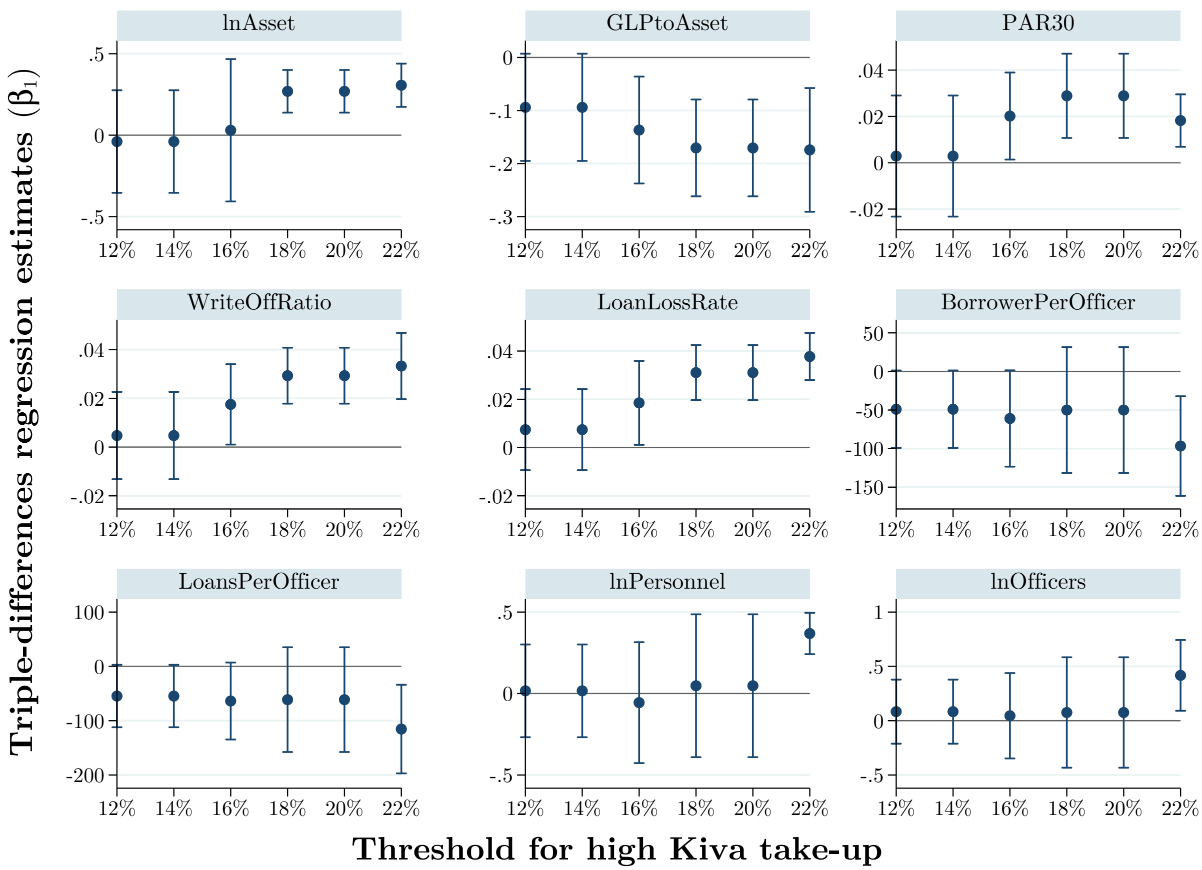

Figure A1: *Robustness to the choice of thresholds for high Kiva take-up.* Along the x-axis, we vary the threshold value that defines High_Kiva_Flow$_{id}$ from 12% of MFI's total assets to 22% of MFI's total assets. Point estimates of β_1 in (1) and corresponding 95% confidence intervals are plotted for different threshold values and for different outcome variables used in the paper.

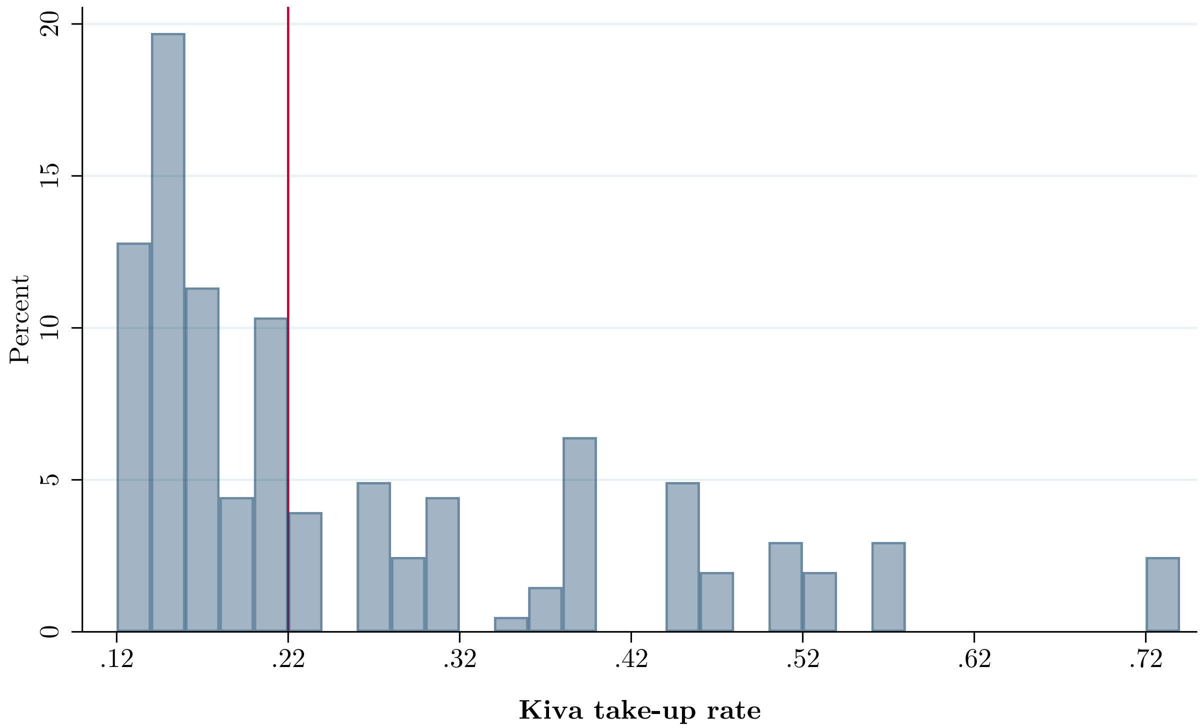

Figure A2: *Left-truncated distribution of Kiva take-up rates.* Kiva take-up rate is defined as the percentage of an MFI's assets funded by Kiva fund flows. The red vertical line marks the take-up rate of 22%, which we use as the threshold to define High_Kiva_Flow$_{id}$ in our main specification. Take-up rates below 12% (the sample average) are truncated; see Section 6.1 for details.

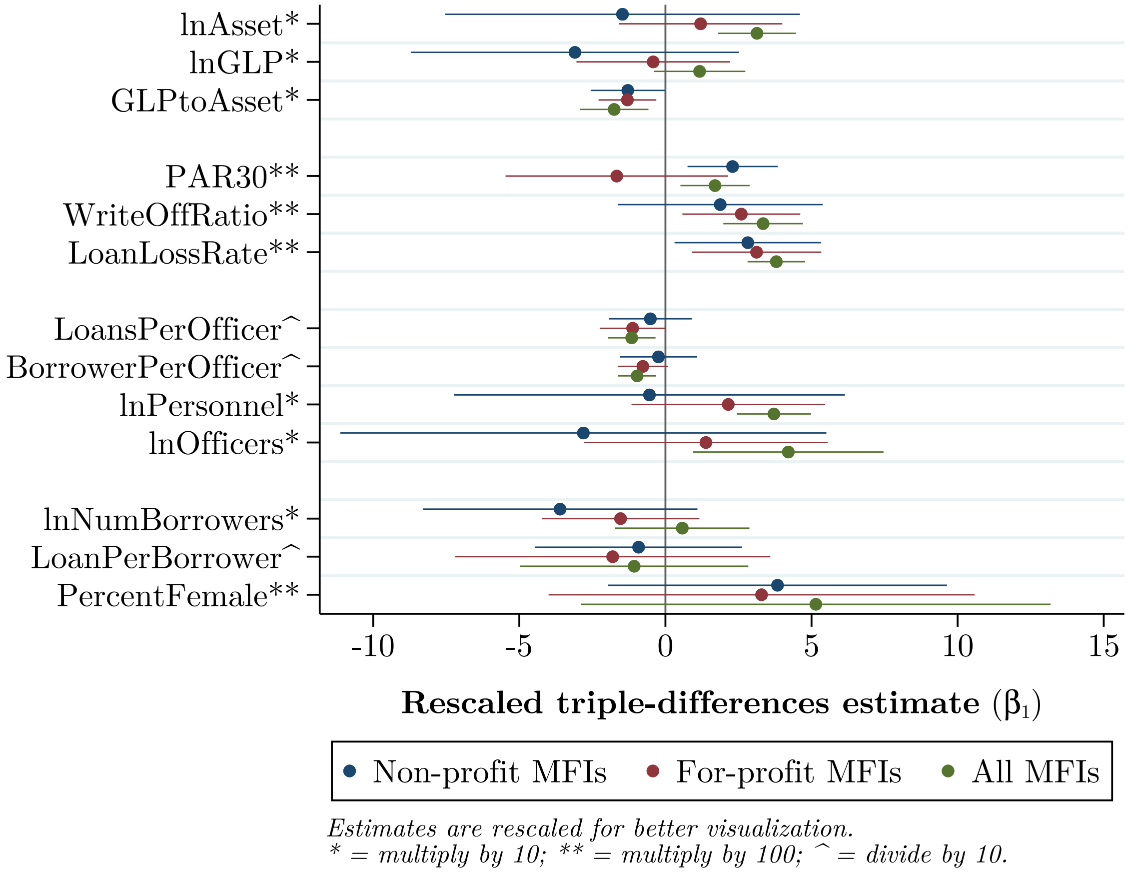

Figure A3: *Non-profit MFIs vs. for-profit MFIs.* We partition the sample into two sub-samples, one containing only non-profit MFIs and the other containing only for-profit MFIs. We rerun regression (1) and report the triple-differences estimates β_1 for all outcome variables. 95% confidence intervals are also plotted. Estimates from non-profit MFI sample are in blue; Estimates from for-profit MFI sample are in red; Estimates from the full sample (i.e., our baseline estimates) are in green, plotted here again for ease of comparison. Estimates are rescaled for better visualization.

A Comparison of Kiva with Other Crowd-based Fundraisers

Kiva enables charitable lenders to fund borrowers around the world at zero interest, which differentiates itself from other crowdfunding or peer-to-peer (P2P) lending platforms that allow the interest rate to float and primarily serve U.S. users. Some of the commercial crowdfunding and P2P lending platforms have received more attention from the economics and finance literature in the past. We summarize the difference between Kiva and these platforms below.

A.1 Other Crowdfunding Platforms

The leading donation-based crowdfunding platform in the U.S. is GoFundMe. The key distinction between Kiva and GoFundMe is that Kiva facilitates loans rather than donations. The twist with Kiva loans is that Kiva lenders do not demand a risk premium, so the pecuniary payoff is at best zero. Therefore, while Kiva is not an outright donation-based crowdfunding platform, Kiva lenders' incentive compatibility does hinge on charitable motives.[12]

A.2 Other Peer-to-Peer Lending Platforms

The leading commercial P2P lending platforms in the U.S. are Lending Club and Prosper. Studies that use Lending Club data include Hertzberg, Liberman, and Paravisini (2018) and Paravisini, Rappoport, and Ravina (2017). Studies that use Prosper data include Hildebrand, Puri, and Rocholl (2017), Iyer, Khwaja, Luttmer, and Shue (2016), Lin, Prabhala, and Viswanathan (2013), Lin and Viswanathan (2016), Wei and Lin (2017), and Zhang and Liu (2012). Vallée and Zeng (2019) use data from robo-advisors that invest on both Lending Club and Prosper. Chava, Ganduri, Paradkar, and Zhang (2021) use credit bureau data that includes credit history on both P2P lending platforms.

[12] Another popular form of crowdfunding is reward-based crowdfunding. The payoff for reward-based crowdfunders is in-kind rewards that are usually the output of the funded project. The leading reward-based crowdfunding platform in the U.S. is Kickstarter. Studies that use Kickstarter data include Burtch, Carnahan, and Greenwood (2018), Gafni, Marom, Robb, and Sade (2021), Lin and Pursiainen (2022, 2023), Xu and Ni (2022), and Younkin and Kuppuswamy (2018).

Kiva's key distinctions from these commercial P2P lending platforms are twofold. First, Kiva fund flow is zero interest out of the Kiva gate. The near shutdown of the pecuniary channel (no interest, small principal, and low probability of default) characterizes Kiva as a unique platform, where financial transactions are primarily governed by social considerations. Second, Kiva's fund flow is intermediated. Intermediation by MFIs around the world allows Kiva to distribute funds in underdeveloped regions, where P2P lending is not feasible in its modern flavor. Indeed, leading P2P lending platforms in the U.S. have gone through similar re-intermediation, presumably for the same reason that intermediaries, despite the moral hazard problem, have superior ability to evaluate and distribute the loans (Balyuk & Davydenko, 2023). Given Kiva's even higher demand for local intermediary expertise, intermediation has extra appeal over the P2P approach.

B The Kiva Fellow Program

In addition to fund transfers, Kiva also hosts a volunteer program that sends Kiva fellows to partner MFIs. Kiva fellows travel to, live near, and provide voluntary service to Kiva's partner MFIs. The typical stay lasts for three to twelve months, during which the fellow assists the MFI to collect and post online the borrowers' profiles, the loans' journal entries, and other related information that help to engage the Kiva users online. Working closely with the partner MFIs, the Kiva fellows exchange skills and best practices with the local staff.