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Market Orchestrators: The Effects of Certification on Platforms and Their Complementors

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Abstract. We study how a multisided platform's decision to certify a subset of its complementors affects those complementors and ultimately the platform itself. Kiva, a microfinance platform, introduced a social performance badging program in December 2011. The badging program appears to have been beneficial to Kiva—it led to more borrowers, lenders, total funding, and amount of funding per lender. To better understand the mechanisms behind this performance increase, we study how the badging program changed the bundle of products offered by Kiva's complementors. We find that Kiva's certification leads badged microfinance institutions to reorient their loan portfolio composition to align with the certification and that the extent of portfolio reorientation varies across microfinance institutions, depending on underlying demand- and supply-side factors. We further show that certified microfinance institutions that do align their loan portfolios enjoy stronger demand-side benefits than do certified microfinance institutions that do not align their loan portfolios. We therefore demonstrate that platforms can influence the product offerings and performance of their complementors—and, subsequently, the performance of the ecosystem overall—through careful enactment of governance strategies, a process we call "market orchestration."

Keywords: multisided platforms • platform governance • complementors • certification • sharing economy

Introduction

Firms in many industries today are organized around multisided digital platforms serving two or more sides of a market (Adner et al. 2019), including, among other examples, search engines such as Google and Bing; video game consoles such as Nintendo Switch, Sony PlayStation, and Microsoft Xbox; and sharing economy firms such as Uber, Kickstarter, and Kiva. In all these cases, the platform connects users on both sides of the market (e.g., drivers on one side, with riders on the other side of the Uber platform). The two sides are connected via an indirect network effect (Parker and Van Alstyne 2005), meaning that the number of users on one side of the market affects the platform's pricing on the other side of the market (Caillaud and Jullien 2003). Beyond pricing, platforms also need to carefully manage their ecosystems by setting rules for participation and enacting governance strategies on both sides of the platform (Ceccagnoli et al. 2012, Williamson and De Meyer 2012, Wareham et al. 2014, Koo and Eesley 2021). A key challenge, however, is that the platform cannot "tell" its users what to do but instead needs to provide cues and incentives that reward users for behaving in accordance with the platform's intent (Tiwana et al. 2010, Rietveld et al. 2019, Hukal et al. 2020).

One of the tools frequently used by platforms to govern their supply-side users is selective promotion of complements through certification.[1] For example, there are over 1,500 applications ("apps") submitted by developers to Apple's iOS App Store daily. To help consumers find high-quality applications that match their tastes, Apple promotes a small subset of these apps through digital storefront features such as "Editor's Pick" and "Apps We Love." There are many examples of such certification programs on other platforms, including Kickstarter's "Projects We Love," Spotify's curated playlists, Airbnb's badge for "Superhosts," PlayStation's "Platinum Games," and eBay's "Top Rated Sellers." In many cases such certification plays a role in vertical differentiation that helps consumers locate the highest-quality complements on a platform. However, another function of selective promotion is to highlight specific complements or complementors that may otherwise go unnoticed, thereby reducing consumers' search costs in crowded markets. In doing so, platforms can use certification as a tool to signal to complementors and end users the products or product categories that the platform sponsor considers important. That is, certification can also play a role in horizontal differentiation whereby differentiated complementors are guided by the platform into areas that the platform believes to be high value. In this way, the platform can increase the ecosystem's overall value creation through certification (Rietveld et al. 2019, Hukal et al. 2020). Although a nascent literature on platform governance strategy has highlighted the importance of certification in platform settings (e.g., Elfenbein et al. 2015, Hui et al. 2016, and Aguiar and Waldfogel 2018), many important questions remain, particularly around the operationalization of certification and its heterogeneous effects on complementor behavior and performance—and, ultimately, on the performance of the platform itself.

We study these questions in the context of Kiva's microfinance platform. Kiva, established as a nonprofit organization in 2005, allows lenders from around the world to fund "microloans" to borrowers located primarily in developing countries. Borrowers use these loans for projects that can serve several functions, such as purchasing a buffalo to increase milk sales (agricultural) or paying for a child's tuition fees (educational). The loans are offered by local microfinance institutions (MFIs), also known as Kiva Field Partners. MFIs often prefund the loan to the borrower and use Kiva's lenders to finance the loan and carry the risks. Therefore, although lenders choose which loan projects to support on Kiva, the loans are managed by an MFI, which deals with the borrower to ensure that the loan principal is repaid.

In December 2011, Kiva certified a subset of its MFIs via an unanticipated badging program whereby these MFIs received one or more of seven "social performance" badges. Social performance badges recognize MFIs for offering loans in areas that Kiva considers important, such as facilitating entrepreneurship or empowering women. The badging program appears to have been beneficial to Kiva, as the number of borrowers, the number of lenders, the total amount paid to MFIs, and the amount paid per lender all increased in the period following the introduction of the certification program. To better understand why these changes occurred, we follow a set of MFIs from 2010 to 2013 to study the effects the badging program had on their loan portfolio composition, the limits to these effects, and the subsequent effects of the certification program on end-user demand for the MFIs' loans. Thus, we raise the following research questions:

- Why do platforms certify complementors?
- How does the platform's certification affect complementor behavior and performance?
- How do these effects vary across complementors?
- What is the effect of certification on end users on the other side of the platform?

Our results suggest that a platform's certification causes complementors to reorient their product portfolios. Specifically, MFIs that receive the Family and Community Empowerment badge (one of the seven social performance badges) adjust their loan portfolio to include a greater share of female borrowers—in line with Kiva's intentions for this badge. We also note, however, that complementors are constrained in their responses to certification. On the demand side, we find that MFI recipients of more than one social performance badge reorient their loan portfolios less extensively than MFIs that receive only one social performance badge. Similarly, on the supply side, we find that MFIs are constrained by the extent that their loan portfolios are tightly clustered within one or a few industry sectors rather than more evenly spread across multiple sectors. Finally, we find that Kiva's end users respond positively to MFIs that reorient their loan portfolios: certified MFIs that reorient their loan portfolios attract more lenders and a higher loan amount per lender than certified MFIs that do not reorient their loan portfolios. We conduct several robustness checks to validate these findings and to rule out alternative explanations.

Our study makes two contributions. First, we contribute to the literature on platform governance and more broadly to the literature on multisided markets. There is growing awareness that platforms need to enact governance strategies to create and capture value—which includes attracting the right type of complementors and structuring their behavior on the platform (Ceccagnoli et al. 2012, Williamson and De Meyer 2012, Wareham et al. 2014). That said, we still know little about how complementors respond to the platform's governance and what drives complementors' heterogeneous responses. To the extent that certification can change complementor behavior postcertification, then certification is potentially a way to structure complementors' roles and ultimately manage the overall ecosystem.[2] We document that complementors who more closely align their product portfolio with the objectives of the platform's certification program benefit more from increased end-user demand than complementors who align their product portfolio less closely with the platform's objectives. Additionally, we identify supply- and demand-side factors that limit or constrain complementors' responses to certification. Our findings thus help explain how governance strategies enable platforms' market orchestration and where the platform sponsor's efforts can be best deployed toward increasing the ecosystem's overall value creation.

Second, our findings on complementors' responses to receiving a platform badge contribute to the literature on certification.[3] This literature has primarily concerned itself with how demand changes in response to a firm's receiving a certification (e.g., Jin and Leslie 2003 and Lanahan and Armanios 2018) or how firms ex ante adjust their behavior in an attempt to receive certification (e.g., Forbes et al. 2015). However, in some cases, firms may ex post adjust their behavior after receiving a certification (e.g., Sufi 2007 and Lu 2012). Platforms are an ideal context to study the effects on ex post behavior resulting from certification: whereas in most traditional settings firms proactively solicit certification, in a multisided platform setting, the platform sponsor *chooses* which products or firms should receive a certification. Moreover, a platform's selective promotion typically is based on criteria that are neither fully disclosed nor exclusively based on a complementor's ex ante behavior on the platform (Rietveld et al. 2019, Hukal et al. 2020). Put differently, a platform's certification will likely be unanticipated by complementors and therefore not based on prior "gaming" behavior. Our paper thus extends the nascent literature on the effects of certification on ex post behavior by illustrating how an unanticipated certification program results in a reorientation of firms' product portfolio.

Theoretical Background

Platform Governance Literature

To grow and successfully compete, platforms need to attract users on both sides of the market. An indirect network effect between both sets of users means that the more users there are on one side of the market, the more users will be willing to join the platform on the other side of the market (Parker and Van Alstyne 2005). For example, all else equal, the more app developers there are creating applications for the iOS App Store, the greater the number of consumers who will want to purchase an iPhone. And the more consumers there are with an iPhone, the greater the number of app developers who will want to develop apps. This interaction between the two sides creates the well-known "chicken-and-egg" problem (Caillaud and Jullien 2003), requiring the platform to decide which side it should focus more attention on.

However, having *more* users on each side is not necessarily always *better*. Research has shown that the scope of indirect network effects is contingent on heterogeneous supply-side factors, such as complement quality, complement diversity, and complement exclusivity (Corts and Lederman 2009, Cennamo and Santalo 2013, Park et al. 2021). On the demand side, too, heterogeneity in end users' preferences for complements affects the scope of indirect network effects (Rietveld and Eggers 2018, Panico and Cennamo 2020). More generally, platforms need to set rules for user participation and engagement on both sides of the market; these might involve quality, price, conveyance of information, or other attributes (Tiwana et al. 2010, Wareham et al. 2014). Heterogeneous users may prefer platforms with relatively high-quality complements spread over a wide range of product categories, even if there are fewer of them. Complementors therefore need to supply the platform with the types of products that the ecosystem needs to attract demand-side users (Rietveld et al. 2019). Thus platforms need to carefully orchestrate their ecosystems to ensure participation and engagement by the *right* complementors.

A platform sponsor can take a range of actions to manage the products of its complementors, including the use of licensing fees and restrictive rules for complementor entry, threat of platform sponsor entry, certification, and others. For example, Hagiu (2007) describes Microsoft's decision to set royalty rates for third-party developers of games for its Xbox video game console. Whereas each developer would prefer a low royalty rate for itself, they each also realize that a higher royalty rate for everyone helps keep overall video game quality high and ensures the platform's success. Another action platform sponsors can take is to vertically integrate into certain complement categories as a way to spur investment and demand in that category (Zhu 2019) while being mindful of the effects their entry has on complementors (e.g., Gawer and Henderson 2007, Zhu and Liu 2018, and Wen and Zhu 2019). For example, when Microsoft decided to enter the video game console business with its Xbox console, it developed some of its games internally and acquired third-party game developers such as Bungie to ensure that consumers had access to a big enough variety of exclusive video games. Microsoft's entry therefore helped to stimulate end-user demand, and this, in turn, helped to stimulate third-party game developer entry.

Another important way to govern complementor quality and diversity is for the platform to use selective promotion of complements and complementors, which includes certification. For example, video game console manufacturers promote a subset of their games via endorsed rereleases (e.g., Microsoft's "Classics" rereleases) (Rietveld et al. 2019), eBay certifies high-quality sellers through its "Top Rated Seller" badging program (Elfenbein et al. 2015, Hui et al. 2016), Spotify promotes selected artists and songs via curated playlists (Aguiar and Waldfogel 2018), Airbnb highlights experienced hosts by giving them a "Superhost" badge, and Apple promotes a small subset of its apps via storefront features such as "Editors' Picks" and "Apps We Love." Oftentimes, the platform's objective is to help resolve asymmetric information between complementors and end users and to reduce search costs. Certification can also help create the perception of a well-rounded portfolio of complements and complementors and highlight some of the platform's distinguishing features, which ultimately benefits the entire ecosystem of users.

Certification Literature

Findings from the literature on certification can be broadly classified into three groups (see Dranove and Jin (2010) for a review). The first group addresses performance benefits arising from a firm receiving certification. In general, customers respond by purchasing more products from firms that have received certification. The literature highlights several mechanisms leading to this result, including a search effect and a reduction in asymmetric information. A quality-signaling argument is often made to explain customers' preference for certified firms and the consequent increase in performance of the latter (Akerlof 1970). For example, Jin and Leslie (2003) find that favorable report cards on a restaurant's hygiene—which imply that restaurants provide high-quality food—lead to customers purchasing more food from those establishments (also see Bollinger et al. (2011)). Much of this literature holds the behavior of the certified firm constant, in an effort to study the demand-side effects of certification.

A second group of studies documents firms' change in behavior in an effort to receive certification. When there are gains from receiving certification (as argued in the first category), firms will have an incentive to seek it. This is sometimes referred to as "gaming" behavior. Examples of how incentives can change behavior include teachers "teaching to the test" if they are rewarded for their students' performance on the test (e.g., Jacob and Levitt 2003) and airlines focusing on on-time arrivals (Forbes et al. 2015). This literature highlights some of the downsides from certification. For example, in the case of airlines, if a flight is delayed enough that it will not be on time, then the airline may have a perverse incentive to delay that flight even more in favor of other flights that have a chance to be on time.

A third line of research studies firms that change their behavior *after* receiving certification. This research seeks to understand how certification affects a firm's subsequent behavior. In addition to benefiting from greater demand for its products or services as a result of certification, the firm may also act strategically to adjust its behavior to avoid *losing* its certification. In the context of nursing homes, for example, Lu (2012) finds that when a nursing home receives a quality certification for a specific type of service, it will subsequently devote more effort to that service, to the detriment of other services. Sufi (2007) similarly finds that the introduction of loan ratings leads to an increase in the supply of debt finance and that firms receiving these ratings subsequently adjust their portfolio of debt. Our study contributes to this third category of the literature by illustrating how a platform's unanticipated introduction of a certification program results in a reorientation of its complementors' product portfolio.

Hypotheses

Postcertification Portfolio Reorientation

Complementors typically offer a range of products on a platform, which we refer to as the complementor's portfolio of products. For example, a video game developer's portfolio of games might span multiple genres (e.g., racing games and first-person shooter games) that are produced for the same video game console. Similarly, an MFI on Kiva might finance loans with different scopes and goals, such as loan projects aimed at supporting women, fostering innovation, or supporting entrepreneurship. A platform's certification of some of a complementor's products may cause the complementor to shift its resources along the dimension certified. What happens when a complementor receives certification for one of its products but not others? After receiving a certification for a specific product, a complementor will learn how valuable that product is relative to the other products in its portfolio and also relative to other complementors on the platform. We therefore expect complementors to react to certification by allocating more of their resources to products in the categories that received certification. In other words, we expect that, after receiving a selective promotion or other types of certification by the platform, complementors will reorient their product portfolio to align with the dimension certified.

Hypothesis 1. *Certification of a complementor causes it to reorient its product portfolio by offering a greater share of its products in the dimension certified.*

Heterogeneous Effects of Portfolio Reorientation

Our first hypothesis predicts an *average* effect of certification on product portfolio reorientation. In practice, however, one might expect complementors to react differently from each other in a number of ways that are either unexpected or counterproductive for the platform. To better understand the sources and effects of these reactions, we focus on two factors (one demand-side factor and one supply-side factor) that could constrain the complementor's response to certification.

We first investigate a demand-side effect: the limits of portfolio reorientation brought about by excessive certification. Each certification brings additional prominence to the complementor in the form of customer interest and expectations. As argued in the first hypothesis, the complementor will want to cater to this increase in interest, and demand, by refocusing its product portfolio on the certified dimension. However, multiple certifications may have a less positive effect by causing the complementor to reorient its product portfolio across several dimensions (also see Lanahan and Armanios (2018)). Indeed, dispersion of a complementor's product portfolio across multiple dimensions can negatively affect demand for its products (Hansen and Haas 2001, Hsu 2006, Hsu et al. 2009, Pontikes 2012). To see how certifications in several dimensions can potentially constrain portfolio reorientation, imagine that, in the limit, certification is provided for every dimension represented in the complementor's portfolio of products. Then the complementor will have no incentive to reorient its portfolio; instead, it will want to keep the portfolio the same. Note that our argument relies on the assumption that complementors offer a finite number of products (or loan projects in our Kiva example). Therefore, portfolio reorientation requires them to *shift* existing resources to a different product category, rather than *adding* more products to the portfolio (also see Lu 2012 and Tae et al. 2020). We therefore expect the following.

Hypothesis 2. *The positive effect of certification on the complementor's product portfolio reorientation will decrease with additional certifications.*

We propose the degree of the complementor's specialization—a supply-side factor—as a second limit to portfolio reorientation. That is, in most industries, there are both specialist and generalist complementors (Adner et al. 2016). Complementors that are specialists likely have a more concentrated portfolio of products; these complementors take advantage of deep sectoral knowledge, but at the expense of diversity. We expect that certification of a given dimension will have an attenuated effect on complementors with higher levels of portfolio concentration. In reorienting its product portfolio (i.e., offering a greater share of products that align with the certification), the complementor decides, case by case, whether the new product has the potential to increase demand. Starting with the highest-potential product, the complementor will add new products to the portfolio (and forgo others), but the estimated demand potential will decrease to the point that the complementor may judge it to be counterproductive to undertake another product in the same category. The assumption is that the environment itself can only accommodate a limited quantity and quality of resources.

Specialist complementors, those with product portfolios in only one or a few sectors, will thus have to search extensively to offer more quality products in the same sector to meet the increased demand from customers. Generalist complementors, those with product portfolios spread over multiple industry sectors, on the other hand, will be able to draw from more than one sector to find promising products in the certified dimension without sacrificing quality. The alternative proposed in Hypothesis 3 is that rational complementors will balance the level of quality against the increase in demand and will avoid offering low-quality products for the sake of portfolio reorientation. We thus predict the following.

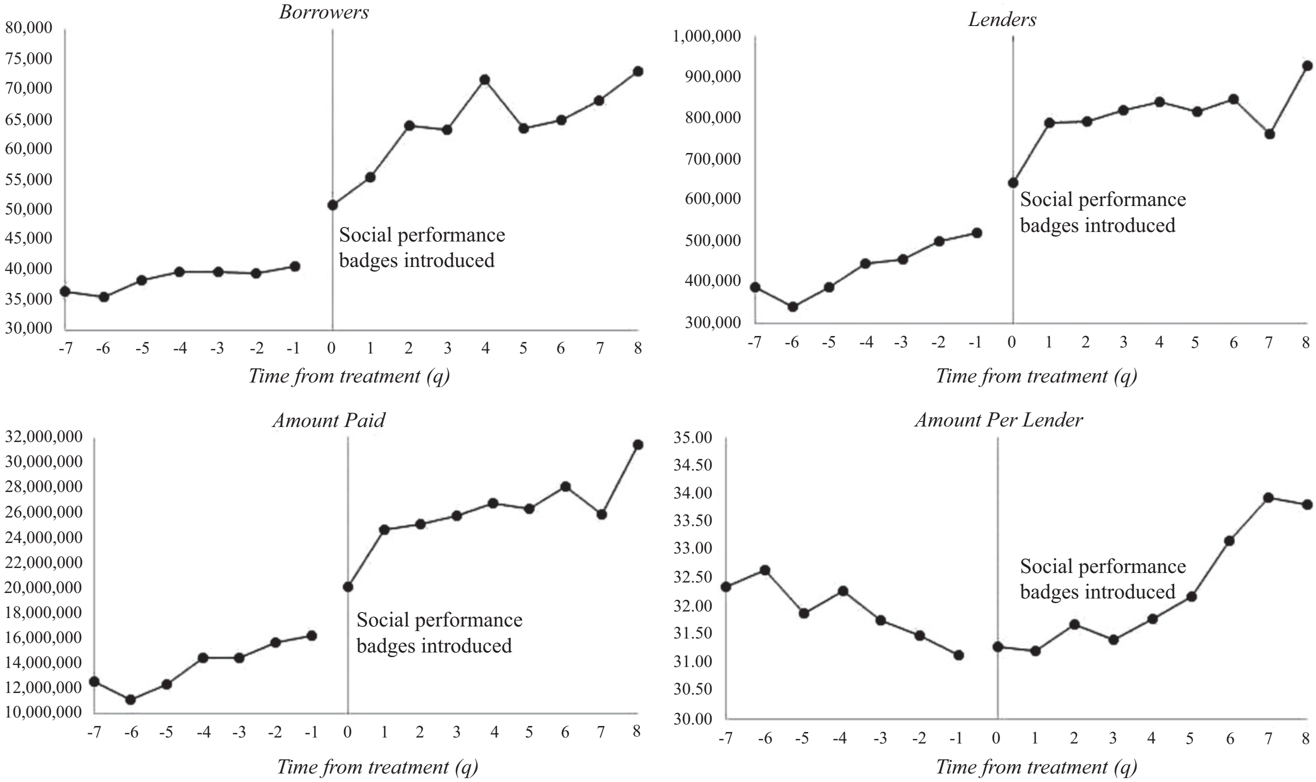
Hypothesis 3. *The positive effect of certification on the complementor's product portfolio reorientation will decrease with portfolio concentration.*

Kiva and the Introduction of Social Performance Badges

Kiva was founded in 2005 as a nonprofit organization with the aim of alleviating poverty by facilitating microlending transactions between borrowers (located mostly in developing countries) and lenders (located mostly in developed countries). Kiva is an online platform on which lenders can browse and support projects in the form of small loans, as requested by group and individual borrowers. The purpose of these loans varies and ranges from entrepreneurial activity (e.g., purchasing cattle for milk production) to supporting education (e.g., paying for a child's tuition). Bearing all risks while earning no financial interest, most lenders fund loans for philanthropic or altruistic reasons, such as promoting entrepreneurial activity, empowering the disenfranchised, and fostering other personal values. The average loan on Kiva supports between one and three borrowers and has a principal of US$800. Roughly 25 lenders support a typical loan, contributing approximately $32 each. Ninety-seven percent of the loans posted on Kiva are funded, and most loans are funded within a week of posting and are fully repaid in around 300 days.

The vast majority of loans on Kiva are sourced and offered by a local MFI, also known as a Kiva Field Partner.[4] Most of the MFIs in our sample are profit-driven organizations that act as intermediaries between lenders and borrowers. MFIs provide a service similar to the outsourcing agencies used in online markets for remote labor services—that is, they send a signal to lenders about the quality of the borrowers (Stanton and Thomas 2016). The loan process for MFIs on Kiva is as follows: A borrower requests a loan from an MFI, which, after checking the borrower's creditworthiness, either rejects the borrower's request or accepts the loan and relays the loan terms. If the borrower accepts the terms, the loan is granted, and the MFI submits the loan to Kiva, including information about the borrower, the loan's intended purpose, and time frame. If Kiva approves the loan, the loan is posted on the platform. Lenders can then decide whether they want to finance the loan. Once the loan is fully funded, the principal is transferred to the MFI. The borrower repays the principal in monthly installments and pays interest to the MFI. Lenders receive their money back only when the borrower has fully repaid the loan principal. If either the borrower or MFI defaults, lenders lose their money. When the loan is fully repaid and lenders have received their money back, lenders can decide to relend their money, donate the money to Kiva, or withdraw their

Figure 1. Borrowers, Lenders, Amount Paid, and Amount per Lender Before and After Kiva's Introduction of Social Performance Badges



Notes. Data include all MFIs active on Kiva from January 1, 2010, to December 31, 2013. Time from treatment is measured in quarters (i.e., three-month increments) and is centered on Q4 2011, when Kiva introduced its social performance certification program. Amounts are in U.S. dollars.

money from the platform (see Appendix Figure A.1 for a visual representation of Kiva's business model).

Although the sourcing and monitoring activities performed by MFIs help to resolve some of the search frictions that lenders face in selecting loans, there remains considerable uncertainty in this regard. In particular, the number of loans and MFIs on Kiva have increased exponentially over time, making it harder for lenders to identify the best match. Kiva started with a single MFI posting 36 loans in 2005. In 2009, the number of MFIs had grown to more than 100, and in our study period 2010–2013, there were 257 active MFIs posting 424,142 loans. Competition between MFIs mostly revolves around two dimensions. First, MFIs typically source loans from the region in which they are located. Because the supply of loans is limited, there is competition over loans between MFIs from the same region (Ly and Mason 2012a). Location further affects the likelihood of attracting lenders, as both the geographic and cultural distance between MFIs and lenders have been found to negatively affect the number of lenders making loans (Burtch et al. 2013). The second dimension of competition pertains to the sectoral orientation of a loan. Based on its description, a loan is classified into one of 15 predefined industry sectors ranging from agriculture to wholesale (Ly and Mason 2012b).[5] In addition, there are systematic differences between MFIs that affect their attractiveness. These differences are mostly reflected in MFIs' risk rating, and they are related to the potential risk for bankruptcy, fraud, and operational difficulties. We use variation in MFIs' loan portfolios to test Hypothesis 3, because MFIs' location and risk rating are fixed across time periods, and we include MFI fixed effects in our models to control for firm-level variation.

To facilitate lenders' selection of MFIs and loans, on December 11, 2011, Kiva introduced Kiva Social Performance badges, a certification program rewarding MFIs that "are going above-and-beyond in serving the needs of their communities."[6] Kiva's social performance badging program is intended to provide "insight into the positive impact a Field Partner is attempting to have within their community," allowing lenders to "easily find Field Partners that are working in areas that speak to" them. Kiva Social Performance badges are awarded in seven categories: Anti-Poverty Focus, Vulnerable Group Focus, Client Voice, Family and Community Empowerment, Entrepreneurial Support, Facilitation of Savings, and Innovation. MFIs can receive more than one badge, and each badge has a unique focus. The Entrepreneurial Support badge, for example, rewards MFIs for offering training and support to help borrowers start, manage, and grow their own businesses. An internal team at Kiva monitors MFIs over time and, when an MFI has demonstrated a commitment to any of these areas (as reflected by a sufficient score on Kiva's internal social performance scorecard), Kiva confers the corresponding badge, which is then prominently featured on the MFI's profile page as well as on the "Field Partner" section of a loan. Kiva also publishes stories about some of the MFIs that received social performance badges on its website[7] and has repeatedly pointed to the badges as a way to generate trust with its lenders.[8]

The implementation of the Kiva Social Performance badges appears to be linked to improvements in the platform's overall performance on multiple dimensions. Figure 1 illustrates that the introduction of the badging program was followed by an increase in the number of both lenders and borrowers on the platform. The total amount paid by lenders and the average amount paid per lender increased as well.

To better understand the mechanisms underlying this performance improvement, our empirical strategy exploits the unexpected introduction of the social performance badging program on Kiva. It is likely that the introduction of the social performance badges was unanticipated because the badges were announced to MFIs and to the public on the same day they were implemented. This was confirmed by the senior director of social performance at Kiva, who, on the day the badges were introduced, noted, "We only just announced which badges were given to which MFIs. I imagine we're going to hear quite a bit over the next couple of months from our partners who want to earn more badges and figure out how to do this effectively."[9] Thus the certification was exogenous with respect to the prior behavior of both MFIs and lenders, and therefore we can assume that any subsequent changes we observe are likely causal.

Kiva's microfinance platform has been the subject of studies by several other researchers. Most of these studies focus on loan-level outcomes (e.g., Galak et al. 2011, Ly and Mason 2012b, Burtch et al. 2013, and Bollinger and Yao 2018). One exception is Ly and Mason (2012a), whose analysis of competition between MFIs finds that it negatively affects their performance. Our study differs from theirs in our focus on Kiva's governance strategies and MFIs' loan portfolio composition as the outcome of interest. In addition to loan-level and MFI-level factors, we thus show that Kiva's actions importantly affect which loans are likely to receive funding and which MFIs are best positioned to attain success.

Data and Variable Definitions

Data Sample

Our main data source is Kiva's public application programming interface, which allows the collection of loan-level data going back to the start of the platform. Data on which MFIs received social performance badges were collected from MFIs' profile pages on Kiva. We focused our data collection on all MFIs with at least one loan posted from the first quarter (i.e., three-month period) of 2010 through the fourth quarter of 2013. We chose this time frame to ensure we include enough time before and after the introduction of the social performance badging program for our analysis to be meaningful.

We restrict our estimation sample by keeping only those MFIs with at least one loan posted in every quarter during our study's time frame. We focus on this subset of MFIs to minimize ex ante heterogeneity between the group of MFIs that did eventually receive a badge and those MFIs that did not. Reducing such ex ante heterogeneity is important because our empirical design requires that there are no meaningful differences between badged and unbadged MFIs that relate to the stated outcomes of our hypotheses (Angrist and Pischke 2008). With this sample restriction, we thus aim to retain a relatively homogeneous set of MFIs. For example, although our sample for analysis includes just 27% of all MFIs that were active during our data collection period, it includes 66% of all the loans posted during the same time frame. Put differently, we exclude a large number of smaller MFIs (i.e., those with fewer loans, borrowers, and lenders). Several robustness checks described in a subsequent section confirm that our results are robust to alternative sample refinements and counterfactuals. After collapsing the data into MFI-quarter observations, we obtain a balanced panel of 70 MFIs that collectively posted 279,195 loans (an average of 249 loans per MFI-quarter) over 16 quarters (1,120 observations). In this sample, more than 6.8 million lenders made loans to 567,910 borrowers (24 lenders per loan, 2 borrowers per loan, on average). The sum of these loans is \$223 million (\$798 per loan, \$33 per lender, \$392 per borrower).

Dependent Variables

We focus our attention on one of the Kiva Social Performance badges, the Family and Community Empowerment (FCE) badge, and one specific outcome, the variable *female borrower ratio*, which measures the ratio of female borrowers to all borrowers (female and male). Per Hypothesis 1, if an MFI receives the FCE badge, we expect that it will adjust its loan portfolio by increasing its share of female borrowers.

We focus on this specific badge and outcome variable for three reasons. First, the aim of the FCE badge is unidimensional and clear: it has a strong focus on promoting loans by female borrowers. A document that we obtained from Kiva states, "In order to serve families and communities, a Field Partner should be reaching women. In most markets, serving women means offering loans without material guarantee requirements or otherwise reaching out to poorer clients with fewer assets." This statement implies that if badging triggers MFIs to change their loan portfolios, it will be obvious how to adjust their portfolio composition. Most of the other badges reward behavior on more than one dimension, which makes it less obvious to MFIs how to adjust their loan portfolios. The Entrepreneurial Support badge, for example, rewards MFIs for promoting business loans *and* for offering nonfinancial services.

Second, the dimension MFIs are scored on for the FCE badge is observable in our data; we can trace how many female borrowers are part of a group of borrowers requesting a loan. From this, we can calculate the overall *female borrower ratio* at the MFI-quarter level. Similar information is absent for most of the other social performance badges. This was confirmed by the senior director of social performance at Kiva: "[Social performance badges] identify characteristics about our Field Partners. … They are supposed to reward social good of different variety being accomplished by our Field Partners. These are things that may not be evident in a loan profile."[10] For example, Kiva does not provide data about whether an MFI offers nonfinancial services to borrowers, which would be needed to study whether an MFI reorients its portfolio in response to receiving the Entrepreneurial Support badge.

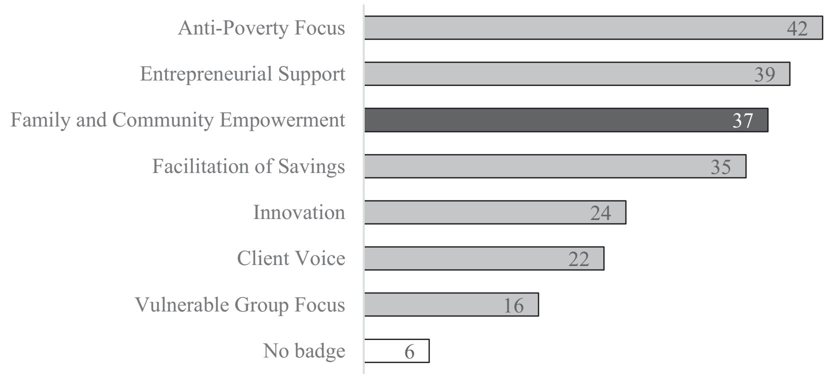
Third, within our estimation sample we observe sufficient variation in terms of which MFIs were awarded the FCE badge and which were not. Figure 2 shows that 37 MFIs received the FCE badge in Q4 2011 (our treatment group), with the remaining 33 MFIs (our control group) either receiving one or more of the remaining six social performance badges (27 MFIs) or no badge at all (6 MFIs). Despite these features that facilitate our identification strategy, we acknowledge that our focus on only one of the social performance badges is also a shortcoming that potentially limits the generalizability of our findings.

Independent Variables

We predict that the degree to which MFIs adjust the share of female borrowers in their loan portfolio in response to receiving the FCE badge is moderated by two factors. The first moderator, called *additional badge received*, indicates that an MFI received any of the other six badges in addition to the FCE badge. Per Hypothesis 2, we expect that for these MFIs, the extent of loan portfolio reorientation, as measured by the share of female borrowers, will be less than for those MFIs that received exclusively the FCE badge.

The second moderator, called *portfolio concentration ratio*, measures the degree that MFIs' loan portfolios are concentrated by industry sector. We operationalize *loan portfolio concentration* by looking at the number of distinct industry sectors an MFI's loans are spread across and the degree to which this spread is evenly distributed. Per Hypothesis 3, we expect that MFIs with loans evenly spread across a larger number of sectors will find it easier to adjust their loan portfolios than those with loans clustered in one or a few sectors. We use a widely accepted metric for measuring concentration, the concentration ratio, or CR_4 (Besanko et al. 2009). Here, the CR_4 refers to the combined share of an MFI's four largest industry sectors each quarter. A higher CR_4 implies that an MFI's loans are more strongly clustered in the four largest sectors, whereas a lower CR_4 means that its loans are more diffuse and spread across multiple sectors. Our reported findings are directionally consistent when we use alternative measures of portfolio concentration, such as the Herfindahl–Hirschman index and the mean absolute deviation.

Figure 2. Distribution of Social Performance Badges for MFIs in Estimation Sample



Results

Methods

We test our hypotheses using difference-in-difference models that estimate the outcome of interest before and after the introduction of the badging program for treated MFIs (*FCE badge received*) relative to control group MFIs (*FCE badge not received*). Our models take the functional form shown in (1):

$$F_{it} = \alpha_i + \eta_t + \beta_1 D_{it} + \beta_2 \delta_{it} + \beta_3 (D_{it}\delta_{it}) + \varepsilon_{it}, \qquad (1)$$

where F_{it} is the *female borrower ratio*; α_i is a vector of MFI fixed effects; η_t is the vector of quarter-year fixed effects; D_{it} is the vector of badging treatments estimating the main effect of an MFI receiving the FCE badge per Hypothesis 1; δ_{it} is a vector of time-varying control variables, some of which (i.e., *additional badge received* and *portfolio concentration*) we further interact with the treatment dummies to test for the hypothesized moderation effects stated in Hypotheses 2 and 3 (i.e., $(D_{it}\delta_{it})$); and ε_{it} is the error term.

MFI fixed effects control for any unobserved and time-invariant differences between the MFIs in our sample, and quarter-year fixed effects control for macroeconomic factors and platform-level trends (e.g., growth in the number of lenders on Kiva, competitive crowding between MFIs) that affect all MFIs equally. We also include the number of *borrowers* at the MFI-quarter level to control for variation in the denominator of our outcome variable and capture the relative change in female borrowers.

The coefficients of our treatment dummies should be interpreted as the quarterly difference in MFIs' female borrower ratio between treated and control group MFIs as a result of receiving the FCE badge. We treat Q4 2011, the period in which the social performance badging program was introduced, as the base period for our estimates. We estimate robust standard errors clustered at the MFI level to control for autocorrelation between observations (Bertrand et al. 2004). It is worth reiterating that we use a restricted sample of 70 MFIs, all of which have large loan portfolios spread across multiple industry sectors and the majority of which that have received at least one badge, which makes it easier to compare them. We conduct several robustness checks as well as a synthetic control analysis to further guarantee the comparability of our treatment and control group, as described in the following subsections.

Summary Statistics

Table 1 provides summary statistics broken out by treated and control group MFIs. FCE-badged MFIs have on average a 15-percentage-point-higher share of female borrowers than do control group MFIs ($p < 0.01$), which is in line with Kiva's stated selection criteria and intended outcome for this badge. We further note that FCE-badged MFIs have a 7-percentage-point-higher probability of receiving any of the other social performance badges ($p < 0.05$) but that there are no significant differences in how concentrated their loan portfolios are. Table 1 further shows that FCE-badged MFIs attract more borrowers ($p < 0.01$) and lenders ($p < 0.01$), and they also receive more money ($p < 0.01$) and a larger amount of money per lender ($p < 0.01$) than do control group MFIs. Figure 3 displays the quarterly average female borrower ratio broken out by treatment group MFIs and control group MFIs. The figure shows that although the groups had parallel trends prior to the introduction of the social performance badges (Angrist and Pischke 2008), the average share of female borrowers for MFIs that received the FCE badge increased with each quarter after the introduction of the badges relative to control group MFIs.

The Effect of Certification on Loan Portfolio Reorientation

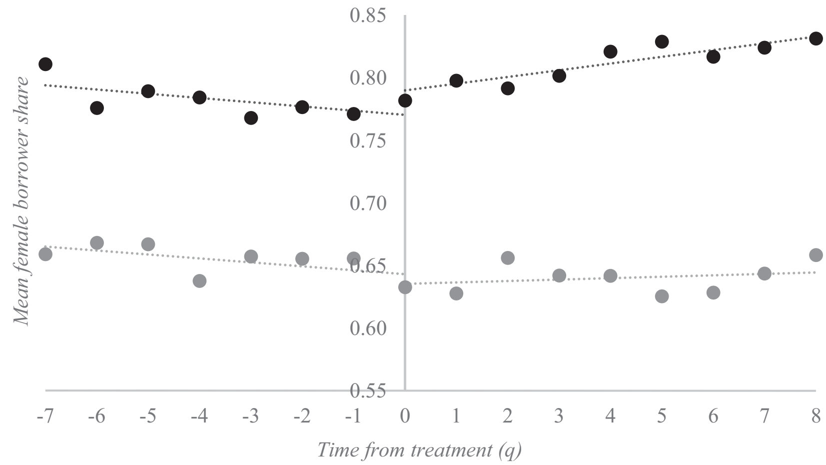
In Table 2 we test the extent that MFIs reoriented their loan portfolios after Kiva awarded them the FCE badge. We start by estimating a controls-only model

Table 1. Descriptive Statistics (Based on Estimation Sample of 70 MFIs)

	FCE badge received (n = 592)				FCE badge not received (n = 528)				
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean difference
Female borrower ratio	0.80	0.22	0.15	1.00	0.65	0.23	0.07	1.00	−0.15**
Additional badge received	0.49	0.50	0.00	1.00	0.42	0.49	0.00	1.00	−0.07*
Portfolio concentration ratio	0.86	0.11	0.52	1.00	0.87	0.10	0.55	1.00	0.01
Borrowers	634.52	854.77	9.00	6504.00	364.16	389.15	3.00	3162.00	−270.36**
Lenders	6,807.28	6,164.74	98.00	41,072.00	5,277.97	3,340.71	49.00	20,270.00	−1,529.31**
Amount paid	227,877.70	230,860.20	2,700.00	1,672,650.00	166,607.90	106,877.90	1,725.00	617,350.00	−61,269.75**
Amount per lender	32.23	5.72	26.22	103.54	31.69	3.48	27.92	68.39	−0.53+
FCE badge received	0.50	0.50	0.00	1.00					

Notes. Mean differences are derived from a two-sample t-test. The source of the data is Kiva.org.
**Significant at 1; *significant at 5%; +significant at 10%.

Figure 3. Average Female Borrower Ratio by Treatment and Control Group MFIs



Notes. Black dots measure the average quarterly female borrower ratio for MFIs that (eventually) received the FCE badge, and gray dots measure the quarterly female borrower ratio for MFIs that did not receive the FCE badge. Dotted lines depict linear trend lines.

(model 1). In model 2 we test the main effect of FCE badging on portfolio reorientation (i.e., *female borrower ratio*) (Hypothesis 1), and in models 3 and 4 we test whether receiving any of the additional badges and the extent of MFIs' sector-level portfolio concentration modify the effect of FCE badging on portfolio reorientation (Hypotheses 2 and 3). In models 5–13 we impose different leads on our outcome variable to explore the temporal dynamics of badging.

In model 2 we find support for the main effect of receiving a certification on portfolio reorientation (Hypothesis 1). FCE-badged MFIs increased their female borrower ratio by an average of 4% points per quarter relative to MFIs that did not receive the FCE badge ($p < 0.05$). Model 3 tests whether receiving any additional badges moderates the effect on portfolio reorientation (Hypothesis 2). Here, we initially fail to reject the null hypothesis because the coefficient for the interaction between *FCE badge received* and *additional badge received* is not statistically different from 0, although it is directionally consistent with the hypothesis. Model 4 tests the hypothesis that specialist MFIs, those with concentrated loan portfolios, reorient their portfolios less than those with more dispersed loan portfolios (Hypothesis 3). Support for this hypothesis is found in the interaction between *FCE badge received* and *portfolio concentration*, which is negative and significant ($p < 0.05$), meaning that the effect of receiving the FCE badge is modified by the extent of MFI portfolio concentration. Analysis of the marginal effects for treated MFIs suggests that FCE-badged MFIs with low values of portfolio concentration (*portfolio concentration* = 0.5) increased their female borrower ratio by 14% points more than FCE-badged MFIs with high portfolio concentration (*portfolio concentration* = 1). Notably, MFIs with a highly concentrated loan portfolio showed no increase in their female borrower ratio after receiving the FCE badge.

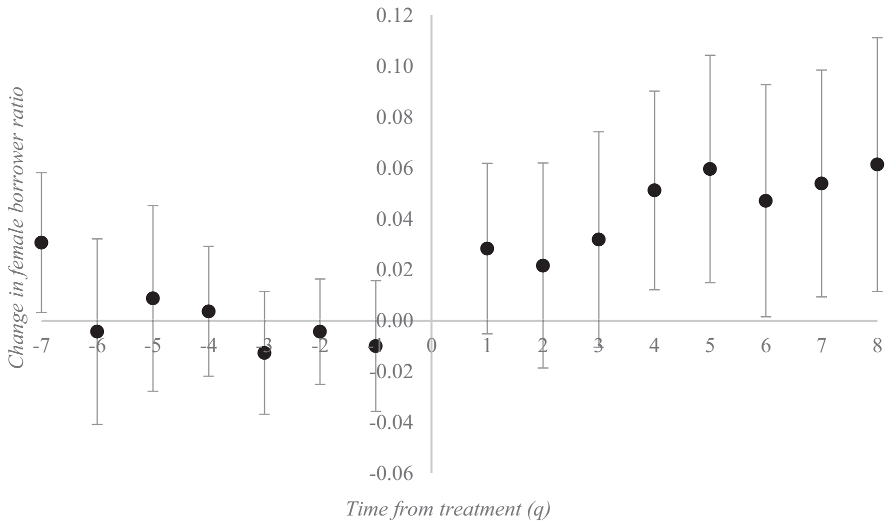
Because we suspect that it takes time for MFIs to adjust their loan portfolio composition, we assess the effects of FCE badging at different points in time. First, we explore the main effect of FCE badging on portfolio reorientation by fitting a relative time model (Greenwood and Wattal 2017). The relative time model estimates the effects of badging for different lags and leads relative to the treatment period and provides insight into the temporal dynamics of the treatment effect (Autor 2003). We model the relative time model by replacing the FCE dummy with a vector of dummies that indicate the relative distance (in quarters) between period t and the introduction of the FCE badge. The omitted category against which our coefficients are estimated is Q4 2011, in which we also group all observations for control group MFIs (Seamans and Zhu 2014). The results presented in Figure 4 suggest that during any of the pretreatment periods there were no meaningful differences between MFIs that received the FCE badge and those that did not. This finding provides additional support that the assumption of parallel trends has been met (Angrist and Pischke 2008). The results further suggest that there is a lagged effect of receiving the FCE badge on MFIs' portfolio reorientation that does not fully manifest until after the third quarter following the treatment. All coefficients from the fourth period after the treatment are statistically significant ($p < 0.05$), and the effect of badging on MFIs' female borrower ratio becomes more pronounced over time. We believe that these results are intuitive: portfolio reorientation takes time to implement, given that MFIs will need to seek out additional female borrowers with interesting projects and good creditworthiness.

Table 2. The Effects of Certification on Complementor Portfolio Reorientation

Model	1	2	3	4	5 (t + 1)	6 (t + 1)	7 (t + 1)	8 (t + 2)	9 (t + 2)	10 (t + 2)	11 (t + 3)	12 (t + 3)	13 (t + 3)
Dependent variable	*Female borrower ratio*												
Additional badge received	0.02	0.003	0.004	0.01	0.01	0.02	0.02	0.02	0.03	0.03	0.03	0.05	0.05
	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]	[0.03]	[0.02]	[0.03]	[0.03]	[0.03]
Portfolio concentration ratio	−0.01	−0.01	−0.01	0.06	−0.09	−0.09	−0.03	−0.06	−0.07	0.004	0.08	0.07	0.14
	[0.10]	[0.10]	[0.10]	[0.10]	[0.09]	[0.09]	[0.08]	[0.07]	[0.07]	[0.05]	[0.08]	[0.08]	[0.08]
Borrowers	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
FCE badge received (H1)		0.04*	0.05**	0.28**	0.04*	0.07**	0.27*	0.04*	0.10**	0.28*	0.04*	0.11**	0.28*
		[0.02]	[0.01]	[0.10]	[0.02]	[0.01]	[0.11]	[0.02]	[0.02]	[0.13]	[0.02]	[0.03]	[0.12]
FCE badge received × *Additional badge received* (H2)			−0.01			−0.03			−0.06*			−0.08*	
			[0.02]			[0.02]			[0.03]			[0.04]	
FCE badge received × *Portfolio concentration ratio* (H3)				−0.27*			−0.28*			−0.28*			−0.28*
				[0.11]			[0.12]			[0.14]			[0.13]
Constant	0.71**	0.72**	0.72**	0.66**	0.79**	0.79**	0.73**	0.78**	0.78**	0.72**	0.66**	0.66**	0.60**
	[0.09]	[0.09]	[0.09]	[0.09]	[0.08]	[0.08]	[0.07]	[0.06]	[0.06]	[0.05]	[0.07]	[0.07]	[0.07]
Quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,120	1,120	1,120	1,120	1,050	1,150	1,150	980	980	980	910	910	910
MFIs	70	70	70	70	70	70	70	70	70	70	70	70	70
R^2 (within)	0.02	0.04	0.04	0.06	0.05	0.05	0.07	0.05	0.05	0.07	0.05	0.06	0.08

Note. Fixed effects ordinary least squares panel regressions with heteroskedasticity robust standard errors clustered at the MFI level are shown.
**Significant at 1%; *significant at 5%

Figure 4. Estimated Effects of Receiving an FCE Badge on MFIs' Female Borrower Ratio



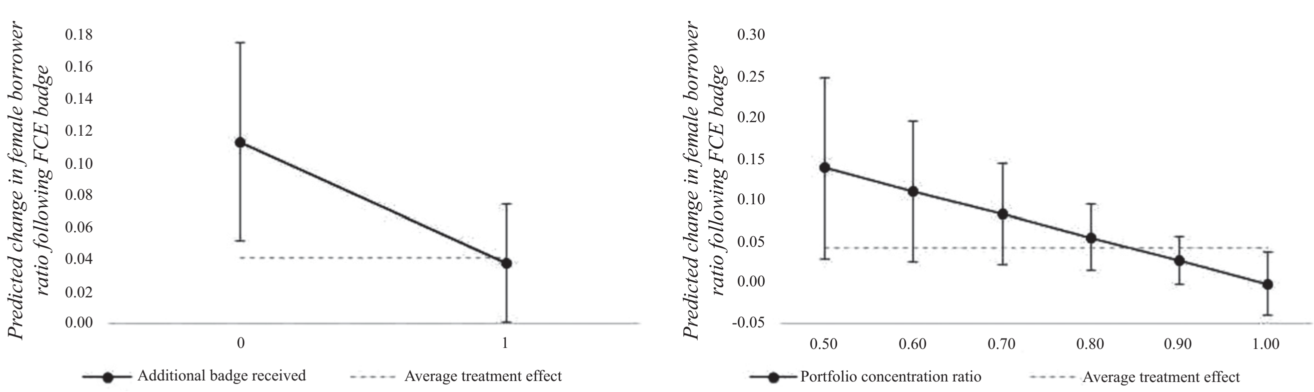
Notes. Point estimates from relative time model. The only pretreatment period that is significantly different from 0 is period −7 ($p < 0.05$). Post-treatment period estimates 4–8 are statistically significant at $p < 0.05$. Error bars denote the 95% confidence interval range.

Second, in models 5–13 of Table 2 we reestimate our main results by imposing leads of one, two, and three time periods (i.e., quarters) on our outcome variable. Although our results are largely consistent with those reported in models 2–4, we note support for Hypothesis 2 when we impose leads of two quarters or more. The interaction between *FCE badge* and *additional badge* is negative and significant in models 9 and 12 ($p < 0.05$), implying that MFIs that received any additional badges alongside the FCE badge reoriented their portfolios less extensively than MFIs that received only the FCE badge. Analyzing the marginal effects from model 12, we find that the difference in the female borrower ratio between MFIs that received only the FCE badge and those that received any additional badges is 7.54% points per quarter ($p < 0.01$). We plot the marginal effects in Figure 5 to visualize the heterogeneous treatment effects described for Hypotheses 2 and 3. Taken together, the results presented in Table 2 and Figures 4 and 5 are fully consistent with our hypotheses, though empirical support is stronger for Hypotheses 1 and 3 than for Hypothesis 2.

Post Hoc Analyses on Mechanisms

The results presented in the previous section are consistent with our predictions that complementors respond to receiving certification by adjusting the portfolio of products that they offer on the platform and that there exists heterogeneity in the extent of the portfolio reorientation. Complementors' actions could

Figure 5. Heterogeneous Treatment Effects of Receiving an FCE Badge



Notes. Predicted change in MFIs' female borrower ratio as a result of receiving the FCE badge, modified by whether MFIs received any additional badges (left panel) and the extent of portfolio concentration (right panel). Error bars denote the 95% confidence interval range.

be motivated by supply- or demand-side effects (or both). We conduct several post hoc analyses to investigate which of these effects are driving complementors' responses to certification.

There are reasons to expect that both potential borrowers and lenders react to the changes made by the MFI. Borrowers need to decide whether to request a loan from an MFI and, conditional on wanting to do so, which MFI to request a loan from. We expect the combination of badging and portfolio reorientation to have a positive effect on borrowers' decisions, as these would indicate that the MFI is high quality. Lenders similarly need to choose which loans to support on Kiva, and we expect the combination of badging and portfolio reorientation to also have a positive effect on lenders' decisions. We expect that badged MFIs offering loans that align with the badge will be more successful in attracting lenders than will badged MFIs that do not reorient their loan portfolios and MFIs without any badges.

To assess these supply- and demand-side mechanisms, we investigate how portfolio reorientation affects MFIs' performance by estimating a series of outcome variables on the borrower (supply) and lender (demand) sides. The variables we consider are the number of loans posted by the MFI (*loans posted*), the number of borrowers (*borrowers*), the number of lenders (*lenders*), the amount paid (*amount paid*), and the amount paid per lender per loan (*amount per lender*).[11] Although we suspect a strong correlation between *lenders* and the *amount paid to borrowers*, we estimate the effect on both measures separately because lenders can decide how much money they want to contribute to a loan. Collectively, these measures give us a good understanding about the mechanisms underpinning Kiva's overall increase in performance—that is, whether badged MFIs attracted more borrowers and/or more lenders, whether the amount paid to MFIs increased, and/or whether the average amount paid per lender increased.

To study the effects of loan portfolio reorientation on these various demand- and supply-side measures of MFI performance, our estimation models take the functional form shown in (2):

$$Y_{it} = \alpha_i + \eta_t + \beta_1 D_{it} + \beta_2 F_{it} + \beta_3 (D_{it} F_{it}) + \varepsilon_{it}, \qquad (2)$$

where Y_{it} is the number of *loans posted*, *borrowers*, *lenders*, total *amount paid*, or *amount paid per lender* (we estimate log transformations to account for the skewness in these measures); D_{it} is the treatment of *FCE badge received*; and F_{it} is the *female borrower ratio*, which we further interact with *FCE badge received* for our mechanism tests (to check for the combined effects of badging *and* reorientation). As in (1), α_i is a vector of MFI fixed effects, η_t is the vector of year-quarter fixed effects, and ε_{it} is the error term.

The results of these post hoc analyses are reported in Table 3: models 1 and 2 predict *loans posted* as the outcome variable, models 3 and 4 estimate the number of *borrowers*, models 5 and 6 predict the number of *lenders*, models 7 and 8 estimate the total *amount paid*, and models 9 and 10 look at the *amount paid per lender*. Odd-numbered models estimate the first-order effects on *FCE badge received* and *female borrower ratio*, whereas even-numbered models include the interaction between these two covariates. In all models, we lag our independent variables by one time period (i.e., quarter).

Table 3. Supply-Side and Demand-Side Mechanism Checks

Model	1	2	3	4	5	6	7	8	9	10
Dependent variable	ln(*Loans posted*)		ln(*Borrowers*)		ln(*Lenders*)		ln(*Amount paid*)		ln(*Amount per lender*)	
FCE badge received	0.01	0.09	0.11	−0.02	0.16	−0.15	0.17	−0.24	0.02	−0.09*
	[0.13]	[0.29]	[0.13]	[0.29]	[0.12]	[0.21]	[0.12]	[0.21]	[0.03]	[0.04]
Female borrower ratio	0.06	0.07	0.33	0.32	0.15	0.12	0.16	0.12	0.008	0.001
	[0.37]	[0.36]	[0.37]	[0.36]	[0.33]	[0.34]	[0.34]	[0.35]	[0.03]	[0.03]
FCE badge received × *Female borrower ratio*		−0.10		0.16		0.38+		0.51*		0.13+
		[0.32]		[0.29]		[0.23]		[0.23]		[0.07]
Constant	5.20**	5.20**	5.57**	5.58**	8.53**	8.55**	11.95**	11.98**	3.42**	3.43**
	[0.25]	[0.25]	[0.26]	[0.26]	[0.23]	[0.24]	[0.24]	[0.24]	[0.03]	[0.03]
Quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050
MFIs	70	70	70	70	70	70	70	70	70	70
R^2 (within)	0.20	0.20	0.25	0.25	0.26	0.26	0.26	0.27	0.08	0.10

Notes. Fixed effects ordinary least squares panel regressions with heteroskedasticity robust standard errors clustered at the MFI level are shown. Independent variables are lagged by one quarterly period. Reported results are consistent with using no lags or larger lags as well as with estimating untransformed outcome variables.

**Significant at 1%; *significant at 5%; +significant at 10%.

In model 2, we find that the interaction between *FCE badge* and *female borrower ratio* is negative but not statistically significant. Thus the combination of receiving a badge and including a greater share of female borrowers does not seem to affect the number of *loans posted*. In model 4, we further find that the interaction term has a positive but not statistically significant effect on the number of *borrowers*. Combined, these findings suggest that FCE-badged MFIs *shift* their portfolio composition to include a larger share of female borrowers rather than *adding* loans or borrowers to their portfolios. This finding is consistent with our theoretical arguments (and with Lu 2012 and Tae et al. 2020).

In model 6, we note an increase in the number of lenders for FCE-badged MFIs that reorient their loan portfolios. We find that FCE-badged MFIs attract 19% more lenders when they have loan portfolios consisting exclusively of female borrowers (*female borrower ratio* = 1) than loan portfolios with an equal split between female borrowers and male borrowers (*female borrower ratio* = 0.5) ($p < 0.10$). In model 8, we further find that FCE-badged MFIs that reorient their loan portfolios enjoy financial performance benefits: the sum of money received by FCE-badged MFIs is 26% larger when they have loan portfolios consisting exclusively of female borrowers than loan portfolios with an equal split between male and female borrowers ($p < 0.05$). Moreover, model 10 results suggest that FCE-badged MFIs receive 6% more money per lender per loan when they feature loan portfolios consisting exclusively of female borrowers instead of loan portfolios with an equal split between male and female borrowers ($p < 0.10$). Combined, these results suggest that portfolio reorientation following the receipt of a platform's certification increases complementor performance via a demand-side response.

Robustness Tests

We found that MFIs that receive the FCE badge shift their loan portfolios to include a greater share of female borrowers, a result that is consistent with Kiva's intended purpose for this badge. We also found that the effects of receiving the FCE badge on portfolio reorientation are attenuated for MFIs that receive any additional badges and for those with concentrated loan portfolios. In addition, we found that the benefits of receiving the FCE badge primarily accrue to those MFIs that reorient their loan portfolio to include a greater share of female borrowers. These MFIs benefit from demand-side performance increases, whereas FCE-badged MFIs that do not adjust their loan portfolios do not enjoy such benefits.

There are several features in our econometric approach that help us rule out alternative explanations. The inclusion of MFI fixed effects controls for unobserved and time-invariant differences between MFIs. The use of time-period fixed effects controls for macroeconomic and platform-level trends affecting all MFIs on the platform at the same time. We intentionally restricted our sample to those MFIs with at least one loan posted in every time period to create a balanced sample of MFIs and rule out biases arising from posttreatment MFI attrition or entry. Nevertheless, as reported in what follows, we undertake several additional robustness tests to further rule out some potential alternative explanations.

First, because one of the key assumptions of the difference-in-difference estimator is that there are no systematic differences between treatment and control observations that are related to the outcome variable, we conduct an additional check to verify that the control MFIs in our sample are indeed a suitable counterfactual for our tests. Because we observe that FCE-badged MFIs are slightly more likely to also receive any of the other badges than MFIs that did not receive the FCE badge (Table 1), we conducted a test of the determinants of receiving the FCE badge. We regress MFIs' *female borrower ratio*, MFIs' *portfolio concentration ratio*, the number of *borrowers*, MFIs' *default rates*, and *MFI age* (in months) on receiving the FCE badge. The results reported in Table A.1 in the appendix suggest that the only significant predictor of receiving the FCE badge is *female borrower ratio*. Models 2 and 3 further show that *female borrower ratio* does not predict whether MFIs receive any of the other badges or no badge at all.

Second, we reestimate our results by applying alternative considerations to our sample construction. In the first sample variation, we further restrict our estimation sample by applying a matching algorithm via coarsened exact matching (CEM). The CEM algorithm reduces the imbalance in the empirical distribution of our covariates between FCE-badged and control group MFIs (Iacus et al. 2011). Based on a set of variables (in our case, *female borrower ratio*, *loans posted*, and MFIs' *default rates*), the CEM matching algorithm prunes observations from the sample so that the remaining data exhibit a better balance between the treatment and the control groups. For each FCE-badged MFI, the algorithm finds at least one control group MFI that is similar on the matching covariates. The restricted sample of 54 matched MFIs can be used by subsequent estimators to improve the quality of the inferences made (Blackwell et al. 2009). One consequence of pruning the sample is that we can no longer test Hypothesis 2, because all remaining FCE-badged MFIs also received at least one additional badge. Table A.2 in the appendix reports the results from the CEM restricted sample, which are consistent with our main results.

In the second sample variation, we create a synthetic control MFI that closely resembles FCE-badged MFIs during the pretreatment periods (Abadie et al. 2010). The synthetic control method simulates MFIs' quarterly female borrower ratio during the posttreatment periods for a synthetic control MFI by taking the weighted average of pretreatment outcomes from selected control MFIs, based on a data-driven procedure. We use our sample of 33 control group MFIs as the potential donor pool and select donor MFIs and weights based on the lagged dependent variable (*female borrower ratio*), *portfolio concentration ratio*, *borrowers,* and *default rate*. The difference in *female borrower ratio* in the posttreatment periods between a treated MFI and its synthetic control is the estimate of interest. Because we observe more than one treated MFI, we repeat the synthetic control procedure for all 37 MFIs that received the FCE badge in our sample and then calculate the average treatment effect across the set of treated MFIs and their synthetic controls. In addition, we follow procedures in Abadie et al. (2010) for conducting placebo tests, from which we calculate an average placebo effect. Figure A.2 in the appendix plots the average quarterly difference in the female borrower ratio between the 37 FCE-badged MFIs and their synthetic controls. The figure shows that the FCE badge had an impact on MFIs' portfolio composition and that the average treatment effect increased over time (similar to Figure 4). During posttreatment periods, FCE-badged MFIs increased their female borrower ratio by an average of four percentage points per quarter. The average placebo estimates, on the other hand, show no tangible treatment effect. Taken together, these results suggest that our main results are consistent with this alternative synthetic control approach.

Discussion and Conclusion

In this paper, we study how a platform's use of certification affects complementors' behavior on the platform and ultimately the platform itself. In so doing, we document heterogeneous reactions of complementors that depend on both demand- and supply-side factors. In line with our expectations, we find that complementors that receive a certification reorient their portfolio of products to align with the dimension on which they are certified. However, these effects are attenuated by end-user (demand-side) and complementor (supply-side) characteristics. Specifically, our results suggest that complementors that receive multiple certifications are less likely to reorient their portfolios. We further find that specialist complementors (those with concentrated product portfolios) reorient their product portfolios less than generalist complementors (those with dispersed product portfolios). We interpret these results to suggest that there are limits to the extent that platforms can influence the behavior of their complementors: from the complementor's point of view, demand- and supply-side factors enable and constrain their response to the platform's certification—a set of results that we believe is generalizable across most platforms (also see Tae et al. (2020)). The mechanism through which certified complementors that realign their portfolios benefit is driven primarily by the demand side; these complementors benefit from more lenders, more money paid, and more money paid per lender. Finally, we provide suggestive evidence that the introduction of a certification program for complementors increases the overall value for the platform, though we leave it to future research to study the causal link between certification and platform value.

Our study contributes to the platform ecosystem and multisided markets literature in a number of ways. First, we extend a recent literature that identifies ecosystem orchestration as an important driver of value creation in multisided platforms by demonstrating how platforms can use governance strategies, in the form of a certification program, to orchestrate their ecosystem (Ceccagnoli et al. 2012, Wareham et al. 2014). We demonstrate that a platform's selective promotion of complementors can "structure complementors' roles" (Williamson and De Meyer 2012) in a way that ultimately creates value for the platform itself. In this sense, the platform's certification provides not just a means for complementors to engage in vertical differentiation but also horizontal differentiation. Second, we document important variations in the supply- and demand-side factors considered by complementors and show that these dimensions drive heterogeneous responses to the platform's certification program. Finally, our paper is one of only a few papers to identify certification as an important strategic governance tool for platform sponsors. Whereas Rietveld et al. (2019) describe *which* complements platforms selectively promote to increase the ecosystem's overall value creation and capture (also see Hukal et al. (2020)), our paper documents *how* such selective promotion changes complementors' subsequent behavior on the platform.

Our study also contributes to the literature on certification. Much of this literature has focused on either how demand changes in response to a firm receiving a certification of some type or how firms ex ante adjust their behavior in an effort to receive certification. With a few exceptions (i.e., Sufi 2007 and Lu 2012), this literature has not considered how firms adjust their behavior after receiving certification. Hence we contribute to the literature by looking at the effect of certification on firms' product portfolio composition. Our setting is an ideal one in which to study such behavior because Kiva's badging program was introduced unexpectedly, and thus there was no anticipatory change in behavior. We also add to a small literature documenting the potential downsides to firms receiving multiple certifications (e.g., Lu 2012 and Lanahan and Armanios 2018). The firms in our sample that received more than one badge from the platform displayed attenuated alignment with the dimension of at least one of those badges.

We believe our study also has implications for the literature on how market "categories" affect performance (e.g., Zuckerman 1999 and Cattani et al. 2017). First, given that in our setting a platform badge effectively assigns a complementor to a category, our finding that complementors with one badge benefit more strongly than complementors with multiple badges is consistent with the well-documented idea that spanning categories hurts performance (e.g., Hsu et al. 2009 and Paolella and Durand 2016). In our setting, the mechanism through which performance is hurt comes through a demand-side response—consistent with other findings in this literature (e.g., Hansen and Haas 2001 and Hsu 2006). Second, our results suggest that platforms can act as mediators through their use of certification—by certifying the products of some complementors but not others, platforms can increase the legitimacy of those complementors receiving certification (Cattani et al. 2017, Lee et al. 2017). However, whereas typically mediators are viewed as neutral third parties, in our case the platform sponsor is also a strategic actor. The introduction of badges thus is an example of "category strategy," where a powerful firm shapes or creates market categories to its own benefit (Pontikes and Kim 2017, Pontikes 2018). The strategic role of platforms as "market makers" (Pontikes 2012, 2018)—they create categories, legitimize participants in these categories, and ultimately benefit from any performance increases—should be a rich area for future work at the nexus of the platforms and categories literatures. Finally, complementors appear to heed the direction given to them by the platform, as this market orchestration improves their performance. By contrast, the organizational sociology literature has found that, in some cases, firms engage in only nominal compliance with corporate governance policies (e.g., Westphal and Zajac 2001 and Fiss and Zajac 2006). Further explicating conditions under which firms actively or nominally heed policy directives may be another rich area for future work.

Our results have important implications for managers of firms in platform markets. Our findings underscore the power platforms have in influencing the behavior of their users on both sides of the market (Adner et al. 2019). However, although platforms can use certification to steer complementors' behavior on the platform, not all complementors respond equally well to the platform's selective promotion. In the case of Kiva, complementors displayed a stronger reaction to the platform's certification when they received only one certification and when their portfolios were spread across multiple product categories. Thus, when introducing a certification program to better orchestrate the behavior of their complementors, platforms should carefully consider the potentially heterogeneous effects of certification on complementors. Furthermore, a platform's orchestration comes with trade-offs, including those arising from potentially misaligned objectives between the platform and its complementors. Although the MFIs in our sample are predominantly profit-driven organizations, Kiva itself is a nonprofit organization whose objective it is to alleviate poverty. Kiva's focus on female borrowers in its social performance badging program aligns with this mission, given that female borrowers reinvest, on average, 80% of their income in the well-being of their children, thus directly serving their families and the wider community. That said, we do not know if such a focus on female borrowers is justified from the MFIs' perspective. It may well be that other types of loans are less costly to manage or allow for charging higher interest rates, therefore better serving the MFIs' financial goals. In selecting the platforms to enter, complementors thus need to carefully evaluate the platform's strategic objectives and how these align with their own.

There are several limitations to our study. We focus primarily on the effect of the platform's governance strategies on its complementors, but we do not investigate the ultimate effects of these choices on the ecosystem itself, for example, by considering how Kiva fared vis-à-vis competing microfinance platforms. We do, however, document improvement in Kiva's performance on multiple dimensions: the number of users on both the borrower side and lender side, the amount of money invested on the platform, and the average amount of money invested per lender. We intentionally limited our focus on complementors to take advantage of the quasi-exogenous shock to field partners from Kiva's introduction of the social performance badging program. We lack a similarly clean "experiment" at the platform level because the introduction of the certification program itself is, of course, an endogenous choice by the platform. Future researchers may want to study further how certification programs affect the platforms themselves.

One critical issue for any platform is that it needs to determine how complementors will interpret and respond to different governance mechanisms. Although we have focused on the use of certification through badging, there are many different strategies a platform could use to influence the behavior of its complementors and orchestrate its ecosystem, including increasing platform openness, entering the complement market, and building architectural complexity. Future researchers may want to investigate how platforms decide between different governance strategies and how these governance strategies differently and collectively affect the portfolio of products offered by complementors on the platform.

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Appendix

Table A.1. Determinants of Receiving a Social Performance Badge

Model	1	2	3
Dependent variable	*FCE badge received*	*Non-FCE badge received*	*No badge received*
Female borrower ratio	0.62*	−0.22	0.21
	[0.30]	[0.18]	[0.17]
Portfolio concentration ratio	−0.64	0.70^{+}	−0.24
	[0.64]	[0.39]	[0.37]
Borrowers	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]
Default rate	−1.67	0.09	0.01
	[1.84]	[1.12]	[1.07]
MFI age	−0.00	−0.04	0.03
	[0.06]	[0.04]	[0.04]
Constant	0.61	0.51	0.11
	[0.55]	[0.33]	[0.32]
MFIs	70	70	70
R^2	0.12	0.10	0.06

Notes. A limited probability model is used. All covariates (except for *MFI age*) take the quarterly average of the pretreatment period at the MFI level.
*Significant at 5%; $^{+}$significant at 10%.

Table A.2. Results Estimated on a Restricted Sample of Matched MFIs

Model	1	2	3 (t + 1)	4 (t + 1)	5 (t + 2)	6 (t + 2)	7 (t + 3)	8 (t + 3)
Dependent variable	*Female borrower ratio*							
Additional badge received	0.004	0.01	0.01	0.02	0.01	0.03	0.02	0.04
	[0.02]	[0.02]	[0.02]	[0.02]	[0.03]	[0.03]	[0.04]	[0.04]
Portfolio concentration ratio	−0.05	0.03	−0.16	−0.08	−0.08	0.00004	0.06	0.14
	[0.10]	[0.11]	[0.10]	[0.09]	[0.08]	[0.07]	[0.09]	[0.09]
Borrowers	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
FCE badge received	0.04+	0.25*	0.04+	0.24+	0.04+	0.27+	0.05*	0.27*
	[0.02]	[0.11]	[0.02]	[0.12]	[0.02]	[0.14]	[0.02]	[0.13]
FCE badge received × *Portfolio concentration ratio*		−0.24*		−0.24+		−0.27+		−0.26+
		[0.12]		[0.13]		[0.15]		[0.14]
Constant	0.77**	0.70**	0.87**	0.80**	0.81**	0.73**	0.70**	0.63**
	[0.09]	[0.10]	[0.08]	[0.08]	[0.07]	[0.06]	[0.08]	[0.08]

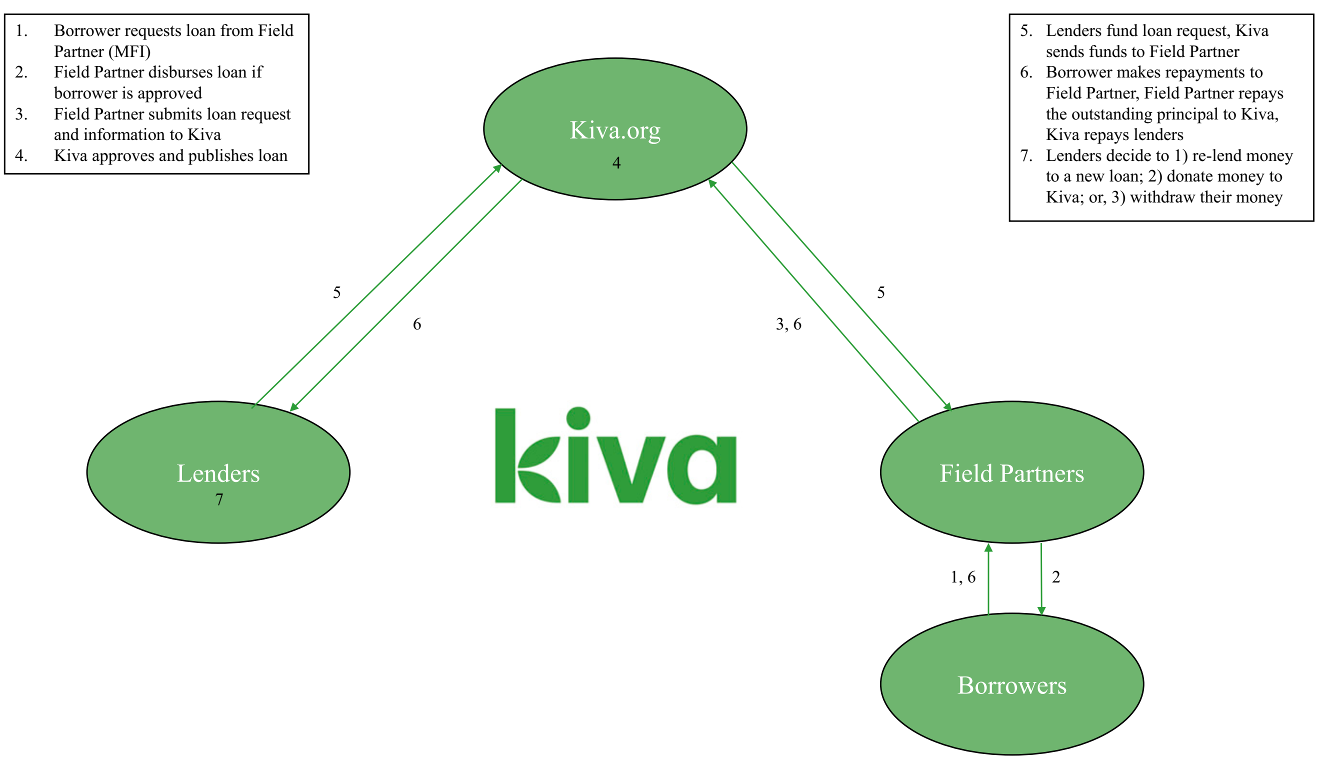
Table A.2. (Continued)

Model	1	2	3 (t + 1)	4 (t + 1)	5 (t + 2)	6 (t + 2)	7 (t + 3)	8 (t + 3)
Quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	864	864	810	810	756	756	702	702
MFIs	54	54	54	54	54	54	54	54
R^2 (within)	0.05	0.07	0.05	0.07	0.05	0.08	0.06	0.08

Notes. Fixed effects ordinary least squares panel regressions with heteroskedasticity robust standard errors clustered at the MFI level are shown. A matched sample using CEM based on MFIs' pretreatment quarterly *female borrower ratio*, the *number of loans posted*, and their *default rates* is used. The L_1 statistic improves from 0.36 to 0.28 as a function of the matching algorithm, implying a less imbalanced sample. The interaction between *FCE badge received* and *non-FCE badge received* is omitted from the model because all FCE-badged MFIs included in this sample have also received at least one other badge.

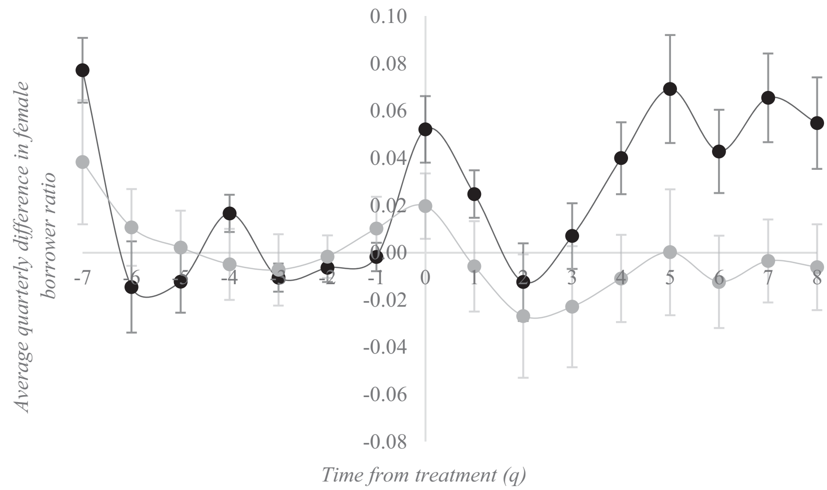
**Significant at 1%; *significant at 5%; $^+$significant at 10%.

Figure A.1. (Color online) Kiva Business Model



Notes. Borrowers pay interest to Kiva Field Partners, and field partners are charged a (small) fee by Kiva. Lenders assume the risks of default loans. Kiva, being a nonprofit organization, further generates income from grants, loans, and donations made by lenders and third-party institutions.

Figure A.2. Results from Synthetic Control Function



Notes. Shown are the average quarterly differences between FCE-badged MFIs and synthetic control MFIs, repeated for treated MFIs (black line) and placebo MFIs (grey line) following procedures in Abadie et al. (2010). The following treatment effects are statistically different from 0 ($p <$ 0.05): −7, −4, −3, 0, 1, and 4–8. None of the placebo effects is statistically different from 0. Error bars denote the 95% confidence interval range.

Endnotes

[1] We distinguish between the platform's supply-side users and its demand-side users. We refer to supply-side users as complementors and to their products and services as the platform's complements. In our empirical context of Kiva's microfinance platform, local microfinance institutions, also known as Kiva Field Partners, are the complementors, and their loans are the complements. We interchangeably refer to demand-side users as end users, consumers, or customers. In the context of Kiva, lenders are the demand-side users, who fund the loan projects that are offered by microfinance institutions.

[2] Several studies have highlighted the importance of certification in platform settings (e.g., Elfenbein et al. 2015, Hui et al. 2016, and Aguiar and Waldfogel 2018). However, to the best of our knowledge, only one other study has documented the strategic governance role that certification can play (Rietveld et al. 2019). That study examines *which* complements are selectively promoted via a platform's certification, but it does not study the effects of certification on complementors' behavior.

[3] A related literature in organizational theory studies the role of certification and the emergence of product market categories (e.g., Pontikes 2012 and Cattani et al. 2017). This literature is particularly interested in how categories emerge and the resulting effects on competition. A central tenet of this literature is that firms spanning multiple categories tend to suffer a competitive disadvantage as a result of impaired sensemaking on the demand side (e.g., Hsu 2006, Hsu et al. 2009). This literature further argues that third-party evaluators play an important role in facilitating transactions between firms and customers by conferring legitimacy through certification (Zuckerman 1999, Lee et al. 2017), and sometimes even by reshaping market categories to redefine existing submarkets and evaluation standards (Pontikes 2018). Although our focus on certification is related, the market transactions in our setting are relatively straightforward, and the categories are fixed. Nevertheless, in the discussion we identify some potentially interesting findings from our study for scholars in this literature.

[4] Direct loans (i.e., loans posted without the help of an MFI) were introduced in 2011 and are exclusively available to borrowers in the United States. This study does not use data from borrowers in the United States; thus all loans in our data set are managed by an MFI.

[5] The full list of loan sectors includes agriculture, arts, clothing, construction, education, entertainment, food, health, housing, manufacturing, personal use, retail, services, transportation, and wholesale. A loan can only list one sector, and we observe loans across all sectors for the MFIs that comprise our estimation sample.

[6] All quotes in this paragraph come from https://www.kiva.org/blog/kiva/2011/12/11/kiva-launches-social-performance-badges-and-increases-the-information-available-for-your-lending-decisions.html (accessed February 2018).

[7] See, for example, https://web.archive.org/web/20120424114201/http://www.kiva.org/updates/kiva/2012/04/13/social-performance-in-action-vulnerable.html (accessed November 2020).

[8] In addition to the quotes provided in the main text, in an interview with *Inc. Magazine* about the social performance badges, Kiva's senior director of social performance says, "We wanted to show lenders in an easy way the kind of impact they were having and the kind of partners we work with. When they hear about a negative story coming out of India, we want them to know that we're working with solid partners. These badges help us do that because we have such a broad network of fellows in the field who can keep us updated." See https://www.inc.com/esha-chhabra/catching-up-with-kiva.html (accessed November 2020).

[9] See https://www.brighttalk.com/webcast/6575/39243/introducing-social-performance-badges (accessed October 2018).

[10] See https://www.brighttalk.com/webcast/6575/46975/a-closer-look-at-social-performance-badges-part-1 (accessed October 2018).

[11] Similar to other studies using Kiva as empirical setting (e.g., Galak et al. 2011; Ly and Mason 2012a, b; and Burtch et al. 2013), we do not use the share of funded loans as a measure of performance given that 97% of all loans on Kiva are funded.

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