Market Orchestrators:

The Effects of Certification on Complementor Behavior and Performance

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Abstract: Multisided platforms serve two or more sets of users who are connected via an indirect network effect. Beyond pricing, the extent and scope of the interactions between the platform's users depend on various other factors including product quality, exclusivity and users' heterogeneous preferences. Platforms, thus, have to carefully balance the needs of its users through the enactment of governance strategies. Selective promotion of a subset of the platform's users through certification is often part of this "market orchestration" process. We study how certification of complementors affects the bundle of products offered by those complementors as well as how it affects the platform's demand-side users. We use a unique dataset of Kiva's microfinance platform to take advantage of a quasi-exogenous shock: Kiva's unexpected introduction of the Social Performance badging program in late 2011. We show that Kiva's certification leads badged microfinance institutions to reorient their loan portfolio composition and that the extent of portfolio reorientation varies across microfinance institutions, depending on demand and supply-side factors. We further show that certified microfinance institutions who reorient their loan portfolios along the dimension of the certification gain greater demand-side benefits than certified microfinance institutions who do not reorient their loan portfolios.

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

1. INTRODUCTION

Firms in many industries today are organized around multisided platforms serving two or more sides of a market, including search engines such as Google and Bing, online dating sites such as eHarmony and Match.com, cable TV networks such as TimeWarner and Comcast, credit card networks such as Visa, Mastercard and American Express, video game consoles such as Nintendo, PlayStation and Xbox, and sharing economy firms such as Uber, Airbnb, Kickstarter, and Kiva, among other examples. In all these cases, the platform connects users on both sides of the market (e.g., drivers on one side to riders on the other side of the Uber platform). The two sides are connected via an indirect network effect (Parker and Van Alstyne, 2005; Rochet and Tirole, 2003), meaning that the number of users on one side of the market affects the pricing and product strategies used on the other side of the market. Beyond pricing, platforms must also carefully manage their ecosystems by setting the rules for participation and enacting governance frameworks on both sides of the market (Cegganoli, Forman, Huang and Wu, 2012; Gawer, 2014; Huber, Kude and Dibbern, 2017; Jacobides, Cennamo and Gawer, 2018). However, a challenge is that the platform cannot "tell" a user what to do, but instead needs to provide cues and incentives that reward users for doing what the platform wants (Huang, Tafti and Mithas, 2018; McIntyre and Srinivasan, 2017; Tiwana, Konsynski and Bush, 2010).

One of the tools frequently used by platforms to govern the behavior of its supply-side users is the selective promotion of complements through certification.[2] For example, there are over 1,500 "apps" submitted by developers to the Apple App Store daily. To help highlight high

[2] 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, microfinance institutions (or, 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 loans offered by microfinance institutions.

quality applications, Apple promotes a small subset of apps via App Store features such as "Editor's Pick" and "Apps we love." There are many examples of such selective promotion of complementors on other platforms, including Kickstarter's "Projects We Like," Spotify's "Curated Playlists," Airbnb's badge for "Superhosts," PlayStation's "Platinum Games," and eBay's "Top Rated Sellers." Not only does selective promotion help end-users find high quality complements, it also sends a powerful signal to complementors about the product categories the platform deems important. While a nascent literature on platform governance has highlighted the important role of certification in platform settings (e.g., Huang, Ceccagnoli, Forman and Wu, 2013; Elfenbein, Fisman and McManus, 2015; Hui, Saeedi, Shen and Sundaresan, 2016), many questions remain, particularly around the operationalization of certification, and its effects on subsequent complementor behavior and performance. In this paper we therefore address the following questions: *How does certification affect complementor behavior on the platform? How do these effects vary across different types of complementors?* And, *what is the effect of complementor certification on end-users on the other side of the platform?*

We study these questions in the context of Kiva's microfinance platform, for the time period 2010–2013. Kiva, established in 2005, allows lenders from around the world to provide small loans to borrowers, primarily in developing countries, who need these loans to fund projects that can serve several functions such as agricultural (purchasing a buffalo to increase milk sales) and educational (paying for a child's tuition fees). Borrowers' projects are offered and facilitated by local microfinance institutions (MFIs), also known as Kiva Field Partners. MFIs often pre-fund the loan to the borrower and use Kiva's lenders to support the loan. Therefore, while lenders choose which loans to support, their loans are managed by the MFI, who is ultimately responsible for making sure that the loan is repaid to the lender. In late 2011, Kiva started to certify selected sets of MFIs via a multidimensional badging program whereby these MFIs received one or more of seven newly introduced "Social Performance" badges. We study the effects of this Social Performance badging program on MFIs' loan portfolio composition, the limits to these effects, and the effect of badging on MFI performance.

We choose to study certification and platform governance using data from Kiva for several reasons. First, this is a setting in which information asymmetries are high—this is an online setting that involves lending money across large geographic distances to strangers—and so the need for certification as a way to provide quality signals to lenders is important. Second, Kiva implemented the certification initiative partway through our study period—in December 2011—allowing us to trace out changes in MFI and lender behavior over time. Moreover, the certification scheme was unanticipated by these parties, suggesting that any changes we observe following the certification scheme are arguably causal. Third, Kiva is active in multiple countries around the world, suggesting that our findings are likely generalizable. Finally, we benefit from very rich data made available by Kiva. For our time period, we have every single loan that appeared on Kiva, including MFI, borrower, lender, and loan characteristics.

Our study contributes to several literatures. First, we contribute to the literature on platform governance, and more broadly to the literature on multisided markets. While this literature has predominantly focused on platforms' pricing strategies for unlocking network externalities (Parker and Van Alstyne, 2005; Rochet and Tirole, 2003; Seamans and Zhu, 2014), there is a growing awareness that platforms must also implement non-pricing strategies to increase the overall value created in the ecosystem and capture a portion of that value (Ceccagnoli et al., 2012; Huang et al., 2013; Huber et al., 2017; Rietveld, Schilling and Bellavitis, 2018). Platforms are in a strong position to direct and exert power over their complementors due to the platform's central position in the ecosystem and its high levels of architectural control (Tiwana et al., 2010), yet we still know relatively little about how complementors respond to such incentives, or how this affects their subsequent behavior on the platform (Huang et al., 2018; Jacobides et al., 2018; McIntyre and Srinivasan 2017).

Second, our theoretical arguments and empirical findings around complementors' responses to a platform's selective promotion contribute to research on certification. The certification literature has primarily concerned itself with how demand changes in response to a firm receiving certification of some type (e.g., Jin and Leslie, 2003), or how firms *ex ante* adjust their behavior in an effort to receive certification (e.g., Forbes, Lederman and Tombe, 2015). However, in some cases, firms may *ex post* adjust their behavior after receiving certification (e.g., Lu, 2012; Sufi, 2007). Our paper is closest to this last set of literature in that we document how a platform's certification of complementors results in a reorientation of those complementors' product portfolios. Additionally, we describe supply-side and demand-side factors that drive heterogeneous responses to the platform's certification program. Lastly, while the performance benefits of certification have been well-documented, our results suggest that certified complementors who more closely align their product portfolio composition with the objectives of the platform enjoy a greater increase in performance than certified complementors who align their product portfolio composition less closely with the platform's objectives.

Third, our study also contributes to research on Kiva and the sharing economy more broadly. Kiva's microfinance platform has been the subject of study by several other researchers (e.g., Allison, Davis, Short and Webb, 2015; Burtch, Ghose and Wattal, 2014; Galak, Small, Stephen, 2011; Ly and Mason, 2012a; 2012b; Bollinger and Yao, 2018). Our study of how Kiva's Social Performance badging program affects MFI-level outcomes is complementary to this existing work, given that most of these studies focus on loan-level outcomes as a function of lenders' and borrowers' individual characteristics, and the interaction between these factors. One exception is Ly and Mason (2012a) who study competition between MFIs and find that it negatively affects their performance. Our paper differs from theirs in our focus on the role of platform governance, and our focus on complementor repositioning following certification.

The paper proceeds as follows. In the next section we first review the related literatures, and then draw from these literatures to develop our hypotheses. We then describe our context and Kiva's certification program, after which we describe the data that we obtain from Kiva. In section five we discuss our results, including robustness tests (some of which are presented in an Online Appendix for parsimony). In our last section (section six) we summarize our results and conclude with implications for managers of platforms and complementor firms.

2. RELATED LITERATURE AND HYPOTHESES

2.1. Platform Governance Literature

In order to grow and successfully compete, platforms must attract users to both sides of their market. An indirect network effect between both sides of the market 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; Rochet and Tirole 2003). For example, all else equal, the more developers there are that create applications for the Apple iPhone, the more end-users there are that will want to purchase an iPhone. And, the more end-users there are for the iPhone, the more app developers will want to develop apps. This interaction across the two sides creates a well-known "chicken-or-the-egg" problem (Rochet and Tirole, 2003), in which the platform needs to decide on which side it should focus more attention.

However, “more” of users on each side is not necessarily always beneficial. Research has shown that the scope of indirect network effects is additionally contingent on heterogeneous supply-side factors such as complement quality, complement diversity, and complement exclusivity (Cennamo and Santalo, 2013; Corts and Lederman, 2009; Lee, 2013). On the demand-side, too, there exists heterogeneity in end-users’ preferences, affecting the scope of indirect network effects for complements (Dou, Niculescu and Wu, 2013; Rietveld and Eggers, 2018). More generally, platforms need to set rules for user participation on both sides of the market, that might involve quality, price, conveyance of information, or other attributes (Boudreau and Hagiu, 2009; Huang et al., 2018; Huber et al., 2017; Tiwana et al., 2010). Heterogeneous users may prefer platforms with relatively high quality complements spread over a broad range of product categories, even if there are fewer of them, and so platforms must undertake actions to ensure participation from high quality complementors.

There are a range of actions that platforms can take to manage the quality of their complementors, including the use of licensing fees, restrictive rules for complementor entry, threat of platform entry, certification and other rules for participation. For example, Hagiu (2007) describes Microsoft’s decision to set royalty rates for 3rd party game developers of its Xbox video game console. While each developer would prefer a low royalty rate for itself, they each also realize that a higher royalty rate for everyone helps keep developer quality high, and ensures success of the platform. Another action is that platform owners can themselves enter into certain categories as a way to spur investment and demand in that category, while being mindful of the effects of their entry on complementors (e.g., Foerderer, Kude, Mithas and Heinzl, 2018; Gawer and Henderson, 2007; Wen and Zhu, 2018; Zhu and Liu, 2018). For example, when Microsoft decided to enter the video game console business with its Xbox console, it developed some of its games in-house, and also acquired 3rd party developers such as Bungie to ensure that enough variety of high quality games were available for consumers. Microsoft's entry therefore helped to stimulate end-user demand, and this in turn helped to stimulate game developer demand.

An alternative action to govern complementor quality and diversity is the platform's use of selective promotion of complements through certification (Rietveld et al., 2018). For example, video game consoles promote a subset of their games via special releases (e.g., PlayStation's "Platinum" rereleases), eBay certifies high quality sellers through its "Top Rated Seller" badging program, Spotify promotes selected artists via curated playlists, and Apple promotes a small subset of its apps via storefront features such as "Editor's Pick" and "Apps we love". Oftentimes, the platform's objective is to help solve asymmetric information between the complementor and its end-users and to reduce adverse selection. Selective promotion of complements can also help to create the perception of a well-rounded portfolio of complements, which is beneficial to the entire ecosystem of the platform and its demand- and supply-side users.

2.2. Certification Literature

Findings from the literature on certification can be broadly classified into three categories. The first category involves performance effects arising from a firm's certification (see Dranove and Jin, 2010 for a review). 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 (Akerlof, 1970). A quality signal argument is often made to explain customers' preference for certified firms, and the consequent increase in performance of the latter. For example, Jin and Leslie (2003) find that report cards on a restaurant's hygiene (which act to certify restaurants as providing high quality food) lead to customers purchasing more food from cleaner establishments (also see: Jin and Leslie, 2009). In the context of platforms, Elfenbein et al. (2015) and Hui et al. (2016) find that eBay's "Top Rated Seller badges" act as a signal of quality leading to increased sales and higher prices for certified sellers on the platform. Much of this literature holds the actions of the certified firm constant, in an effort to study the demand-side effects of certification.

A second category involves firms' change in behavior in an effort to receive certification. The idea is that when there are gains from receiving certification (as argued in the first category), firms will have an incentive to seek certification. 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 student's performance on the test (e.g., Jacob and Levitt, 2003), and airlines focusing on on-time arrivals (Forbes, Lederman, and Tombe, 2015). This stream highlights many 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 flights that have a chance to be on-time.

A third category—and the one that is closest to our study—involves firms changing their behavior *after* receiving certification. This research seeks to understand how certification affects a firm's subsequent behavior. Conceptually, it is easy to imagine that it does. A firm which receives performance benefits from its certification (as argued in the first category), but is also a strategic actor (as argued in the second category), may therefore adjust its behavior because it does not want to lose its certification. Lu (2012) studies these issues in the context of quality certification of nursing homes. She argues and finds support for the idea that when a nursing home receives a quality certification for a specific type of service, the nursing home will subsequently increase effort along that dimension of service, to the detriment of other dimensions. As another example, Sufi (2007) finds that the introduction of loan ratings leads to an increase in supply of debt finance (i.e., evidence of the first category) and that firms receiving these ratings adjust their portfolio of debt (i.e., evidence of the third category).

2.3. Hypotheses on the Effect of Certification on Complementor Behavior

2.3.1. Post-certification portfolio reorientation

Complementors typically have a range of products they offer on a platform—which we refer to as the complementor's portfolio of products. For example, a video game producer's portfolio of video games might span multiple genres (e.g., racing games and first-person shooter games) that are produced for the same console, or a MFI on Kiva may finance loan projects with different scopes and goals, such as projects aimed at supporting women, implementing innovation, or supporting entrepreneurship. Certification provides a quality signal about what types of products the platform values. This may cause the complementor to shift resources along the dimension certified. What happens when a complementor receives certification for one type of its products but not others? Firms use cues from the changing environment to define their strategies (Mithas, Tafti, and Mitchell, 2013). Indeed, after receiving a certification for a specific product, complementors know how valuable that product is to them relative to other complementors in the market, and also relative to the other products in the complementor's own portfolio. We therefore expect that complementors will react to certification by allocating more of their resources toward products in the categories that received certification. In other words, we expect that following the assignment of badges or other types of certification, complementors will reorient their portfolio of products to align with the dimension certified:

Hypothesis 1: Certification of a complementor causes it to reorient its portfolio to align with the dimensions of the certification

2.3.2. Heterogeneous effects of portfolio reorientation

Our first hypothesis predicts *average* effects of certification on product portfolio reorientation. However, in practice, one might expect there to be heterogeneity across complementors along a number of factors. In order to better understand the sources and effects of this heterogeneity, we focus on two factors that could affect the complementor's response to certification.

We first investigate the limits of portfolio reorientation brought about by excessive certification, which affects the complementor via expectations from its current and potential customers—a demand-side effect. Each additional certification brings prominence to the complementor in the form of customers' interest focused on the dimension addressed by the certification. As tested in the first hypothesis, the complementor will want to cater to this increase in demand by reorienting its portfolio along this dimension. However, multiple certifications may have an ambiguous effect as it requires the complementor to reorient its portfolio across several dimensions (also see Lanahan and Armanios, 2018). Indeed, in the presence of multiple certifications, the complementor will want to increase its focus on all certified dimensions, hence reducing its reorientation potential in any given dimension. To see how excess of certified dimensions potentially decreases portfolio reorientation, imagine that, in the limit, certification is provided for each dimension represented in the complementor's portfolio of products. Then the complementor will have no incentive to reorient its portfolio, and will want to keep the portfolio the same over time. Note, our argument relies on the assumption that complementors are limited in the amount of products (or, loans in our Kiva example) they are able to manage. Hence, portfolio reorientation happens through *shifting* current resources to a different product category, rather than by *adding* more products to the portfolio. Lu (2012) also finds that reorientation occurs via shifting rather than adding. Thus, we predict the following:

Hypothesis 2: The positive effect of certification on 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 reorientation. That is, complementors vary in the extent to which they pursue specialist versus generalist strategies, as is the case in most industries (Porter, 1996; Chatain and Zemsky, 2007). Complementors that are specialists likely have a very concentrated portfolio of products; these complementors are taking advantage of deep sectoral knowledge, but at the tradeoff of little diversity. We expect that certification of a given dimension will have a less positive effect for complementors with higher levels of portfolio concentration. In reorienting its portfolio (i.e., offering a greater share of products that align with the platform's certification), the complementor is deciding, case by case, whether the new product has positive profit potential. Starting from the highest potential product, the complementor will add new products to the portfolio (and forego others), but the estimated profit potential will be decreasing to the point that the complementor may judge it to be counterproductive to undertake another product within the same category. (The assumption in this case is that the environment itself is constrained in the amount and quality of resources that can be used by the complementor.)

Specialist complementors, those with more concentrated product portfolios pooled in only one or a few industry sectors, will thus have to go further down the quality distribution to offer more products in the same sector to meet the increased demand from lenders. Generalist complementors, those with less concentrated product portfolios spread over multiple industry sectors, on the other hand, will be able to draw from more than one sector to find promising projects that fit the certified dimension, thus not having to go as far down the quality distribution compared to specialist complementors. The alternative proposed in hypothesis 3 is that rational complementors will balance the level of quality provided against the increase in demand, and will avoid offering low quality products to the detriment of portfolio reorientation.

> *Hypothesis 3: The positive effect of certification on portfolio reorientation will decrease with portfolio concentration.*

2.3.3. Effects of portfolio reorientation on end user behavior

As noted above, one mechanism through which certification helps increase performance is by reducing information asymmetry for both complementors and end users—that is, certification showcases the top complementors for each dimension valued, and subsequently certified, by the platform. Hence, certification not only reduces asymmetric information about complementors' quality, but also reduces uncertainty about their quality within each product category. While prior research shows that a complementor's performance increases after receiving certification (Elfenbein et al., 2015; Hui et al., 2016), we argue that, by strategizing on their portfolio composition, complementors can further increase their performance. Indeed, by reorienting their portfolio along the certified dimension, thus reducing their presence in non-certified categories, complementors will be able to gain more from receiving the platform's certification:

Hypothesis 4: Those certified complementors that better align with the dimensions of the certification will perform better than those certified complementors that do not align with the dimensions of the certification.

3. 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 micro-lending transactions between borrowers (located mostly in developing countries) and lenders (located mostly in developed countries). Kiva is an online platform on which lenders can inspect and support one or more projects proposed in the form of loans, requested by group or individual borrowers. The purpose of these loans varies and ranges from entrepreneurial activity (purchasing cattle for milk production) to supporting education (paying for a child's tuition). Bearing all risks while earning no financial interest, lenders mostly fund loans for philanthropic or altruistic reasons, such as promoting entrepreneurial activity, empowering the disenfranchised, or other personal values. A typical loan on Kiva supports between one and three borrowers and has a principal of $800. Roughly 25 lenders support each loan, contributing approximately $32 each. 97% of the loans posted on Kiva are funded and most loans get funded within a week from posting and take around 300 days to be fully repaid.

The vast majority of loans on Kiva are posted and managed by a local MFI, also known as a Kiva Field Partner.[3] The MFIs in our sample are mostly 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—namely, these types of

[3] Direct loans were introduced in 2011 and are exclusively available to borrowers in the U.S. Direct loans are the only type of loans on Kiva that enable borrowers to manage their loans directly, without an intermediary MFI. This study does not use data from borrowers in U.S., thus all loans in our dataset are managed by an MFI.

intermediaries help signal to lenders about the quality of the borrowers (Stanton and Thomas, 2016). The loan process for MFIs on Kiva is as follows (Bollinger and Yao, 2018): a borrower requests a loan from a MFI who, after checking their creditworthiness, either rejects the borrower or accepts the loan and relays the loan terms. If the borrower accepts the terms, the loan is granted and the MFI posts the loan on Kiva (including a description consisting of information about the borrower, the loan's intended purpose and timeframe). Lenders can then decide whether they want to finance the loan. When the loan is fully funded the principal is transferred to the MFI. Borrowers repay the principal in monthly arrears and pay interest to the MFI. Lenders will receive their money back, only when borrowers have fully repaid their loans.

While the sourcing and monitoring activities performed by MFIs help solve some of the asymmetric information between borrowers and lenders, there still remains considerable uncertainty on the lender-side. Particularly, the number of loans and MFIs on Kiva increased exponentially over time, making it harder for lenders to identify the best MFIs. Kiva started with a single MFI posting 36 loans in 2005. In 2009, the number of MFIs had grown to more than one hundred, and between October 2010 and December 2013, there were 247 active MFIs posting 374,320 loans. Notwithstanding growth rates on the lender side, it is evident that competition between MFIs is fierce. Competition between MFIs mostly revolves around two dimensions: First, MFIs typically source loans from the same subnational region or country in which they are based. Since the supply of loans is limited, there is competition for loan projects between MFIs from the same region (Ly and Mason, 2012a). Location further affects the likelihood of attracting lenders as both the geographical and the cultural distance between MFIs and prospective lenders have been found to negatively affect the number of people making loans (Burtch et al., 2014).[4]

[4] MFIs in our sample are based in 38 countries spread over six contents, ranging from Armenia to Yemen.

The second dimension of competition pertains to the sectoral orientation of the loan. Based on its description, each loan project is classified into one of 15 pre-defined industry sectors ranging from Agriculture to Wholesale (Heller and Badding, 2012; Ly and Mason, 2012b).[5] Besides these, there also exist structural differences between MFIs that affect their competitiveness. These differences are mostly reflected in MFIs' risk rating (Burtch et al., 2014), and revolve around the potential risk of bankruptcy, fraud, and operational difficulties they might be facing.

In order to facilitate lender selection of MFIs, on December 11 2011, Kiva introduced 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 increase the amount of information available to lenders by providing "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's Social Performance badges are multidimensional with seven distinct categories including: *Anti-Poverty Focus*, *Vulnerable Groups Focus*, *Client Voice*, *Family and Community Empowerment*, *Entrepreneurial Support*, *Facilitation of Savings*, and *Innovation*. MFIs can earn more than one badge and each badge has its own unique focus. The *Entrepreneurial Support* badge, for example, rewards MFIs that offer training and support to help people start, manage and grow their own businesses. An internal team at Kiva monitors MFIs over time, and when a MFI has demonstrated a commitment to any of these areas (as reflected by a sufficient score on the Social

[5] The full list of loan sectors is composed of: Agriculture, Arts, Clothing, Construction, Education, Entertainment, Food, Health, Housing, Manufacturing, Personal Use, Retail, Services, Transportation, and Wholesale. A loan can only have one sector and we observe loans in all sectors for the MFIs that compose 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 (February, 2018)

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.[7]

Our empirical strategy exploits the introduction of Kiva's badging program. It is likely that the introduction of the badges was unanticipated as the badging scheme was announced to the public as well as to MFIs on the same day as it was implemented. This was confirmed by the Senior Director of Social Performance at Kiva, who on the day the badges were implemented, 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."*[8] Thus, the certification was exogenous with respect to the behavior of MFIs as well as lenders, and is useful from a research design point of view as arguably any changes we observe are likely causal. The unexpected introduction of the badges allows us to identify the effect of receiving a badge relative to the baseline category of not receiving a badge. Furthermore, there is variation in terms of how many badges MFIs receive, which also allows us to identify the effect of receiving more than one badge.

4. DATA AND VARIABLE DEFINITIONS

4.1. Data Sample

Our main data source is Kiva's public Application Programming Interface (API) which allows the collection of loan-level data going back to the start of the platform.[9] For the purpose of this study we collected data on all MFIs with at least one loan posted in every quarter (i.e., three

[7] Note that while Kiva followed this protocol during our study period, it no longer features the badge on the loan page. Social performance badges are still featured prominently on the MFI profile page on Kiva.
[8] Source: https://www.brighttalk.com/webcast/6575/39243/introducing-social-performance-badges (October, 2018)
[9] Data on which MFIs received social performance badges was collected by conducting periodic web scrapes of Field Partners' profile pages on Kiva. Furthermore, through private communication with managers at Kiva we obtained some internal company documentation relating to the social performance badges that we use to motivate our choices in terms of variable operationalization and why we specifically focus on certain badges.

month period) from the fourth quarter of 2010 until the fourth quarter of 2013. We chose this timeframe so as to include sufficient time periods preceding the introduction of the badging program and sufficient time periods after its introduction.[10,11] We focus on those MFIs with at least one loan posted in every time period to minimize *ex-ante* heterogeneity between the group of MFIs who eventually received a badge and those who did not. Reducing *ex-ante* heterogeneity is important as our empirical design requires that there are no meaningful differences between badged and un-badged MFIs that relate to the stated outcomes of our hypotheses (Angrist and Pischke, 2008). With this restriction we thus aim to arrive at a relatively homogenous sample of successful and financially stable MFIs. For example, while our sample of 70 MFIs includes just 28% of all MFIs who were active during our study period, it comprises 66% of all loans posted in the same timeframe. A number of additional checks described below document that our results are robust to alternate sample refinements. After collapsing the loan data into MFI-quarter observations, we arrive at a balanced panel of 70 MFIs who collectively posted 245,998 loans (an average of 270 loans per MFI-quarter) over 13 quarterly periods (910 observations).[12] We call this our “expanded sample.” For most of our analyses, we further restrict the sample by removing four MFIs who received their badge at some point after Q4-2011. We worry about endogenous efforts by these MFIs to be awarded a badge, whereas our focus is on how behavior changes following certification. Our final sample for estimation therefore includes 66 MFIs over 13 quarterly time periods (858 observations). We call this our “estimation sample.” As a robustness test we also estimate our results on the “expanded sample” of 70 MFIs.

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[10] We use Q4-2011, the period in which badges were introduced, as the base period for our estimates.
[11] Using a longer post-treatment time period allows us to better explore changes and potential lagged effects of the treatment over time (Autor, 2003). In robustness tests we estimate results on alternate time windows and the results are fully consistent with those reported in our results section.
[12] Over six million lenders made loans to 481,694 borrowers (26 lenders per loan, 2 borrowers per loan, on average) in our sample. The sum of these loans is about $200 million ($1,280 per loan, $30 per lender, $412 per borrower).

4.2. Dependent Variables

To identify the effect of certification on complementor behavior (H1-H3), we focus our attention on one of the social performance badges, the *Family and Community Empowerment* (FCE) badge, and one specific outcome, the variable *female borrower ratio* which is the ratio of female borrowers to all borrowers (female and male). Per H1, if a MFI receives the FCE badge, we expect it will adjust its behavior in by increasing its share of female borrowers.

We focus on this specific badge and outcome 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. In a document obtained from Kiva it is stated that: "*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 clarity implies that if badging triggers MFIs to change their loan portfolios, it will be obvious how to adjust their portfolio composition. The majority of the other badges aim to reward behavior on more than one dimension. The *Entrepreneurial Support* badge, for example, rewards MFIs for promoting business loans *and* for offering non-financial services.

Second, the indicator that MFIs are scored on for the FCE badge is observable in our data as we can trace how many female borrowers are part of a group of borrowers requesting a loan. From this information we can derive the overall *female borrower ratio* at the MFI-quarter level. Similar information is mostly absent for many 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."*[13] For example, Kiva does not provide information about whether a MFI offers non-financial services to support its borrowers, which would be needed to study whether a MFI reorients itself in response to receiving the *Entrepreneurial Support* badge.

Third, within our estimation sample of 66 MFIs we note good variation in terms of which MFIs were awarded the FCE badge and which were not. Figure 1 shows that 34 out of 66 MFIs were awarded the FCE badge in Q4-2011, with the remaining 32 MFIs either receiving one (or more) of the other six badges (27 MFIs), or no badge at all (5 MFIs). Note that because several MFIs received more than one badge, the sum of badges in Figure 1 is greater than 66.

--- INSERT FIGURE 1 ABOUT HERE ---

We study the effect of portfolio reorientation on MFI performance by estimating a series of outcome variables on the lender side (H4).[14] First, we measure performance by counting the number of individuals lending money to a MFI (*lenders*). Lenders face a choice in terms of which loans to support when they evaluate their options on Kiva, and we expect the combination of badging and portfolio reorientation to have a positive effect on lenders' decisions. The MFI managing a loan is a key decision factor for lenders, and a large part of a loan's profile on Kiva is devoted to details about the MFI, including an overview of its badges. We suspect that badged MFIs offering loans who align with the dimension of their certification will be more successful in attracting lenders for their loans than badged MFIs who do not reorient their loan portfolios, and MFIs without any certification. Second, we estimate the *amount paid to borrowers* (in USD) by a MFI's lenders as another outcome of interest. While we suspect a strong correlation

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

[14] Similar to other studies using Kiva as empirical setting (e.g., Burtch et al., 2014; Galak et al., 2011; Ly and Mason, 2012a; 2012b), we do not use the number of funded loans as a measure of performance given that 97% of all loans on Kiva are funded. This measure therefore does not exhibit sufficient variation for identification.

between *lenders* and the *amount paid to borrowers*, we identify the effect on both measures separately as lenders can decide how much money they want to contribute to a loan. Third, we estimate the average *amount paid per lender* (in USD) as a final outcome. Collectively, these measures will give us a good understanding of the mechanisms underpinning a possible increase in performance; i.e., whether a MFI attracted more lenders, whether the sum of money for its loans increased, and/or whether the average amount paid per individual lender increased.

4.3. Independent Variables

We predict that the degree to which MFIs adjust their portfolio composition in reaction to being certified is moderated by two factors. The first moderator, called *non-FCE badge received*, indicates whether a MFI received any of the other badges alongside the FCE badge. Per H2, we expect that for these MFIs the degree of loan portfolio reorientation, as measured by the female borrower ratio, will be less than for MFIs that exclusively receive the FCE badge.

The second moderator, called *portfolio concentration ratio*, measures the extent to which MFIs' loan portfolios are concentrated by industry sector. We operationalize loan portfolio concentration by looking at the number of different sectors a MFI's loans are spread across and the degree to which this spread is even. (Recall that there are 15 pre-defined sectors and that each loan is categorized into one distinct sector.) Per H3, we expect that MFIs with portfolios evenly spread across a larger number of sectors find it easier to adjust their portfolios than those with portfolios strongly clustered in one or a few sectors. We resort to a commonly used metric for measuring concentration (Besanko, Dranove, Shanley and Schaefer, 2009), the concentration ratio, or CR_4. Here, CR_4 measures the combined share of the four largest sectors, in terms of number of loans, at the MFI-quarter level. A higher CR_4 implies that loans are more strongly pooled in the four largest sectors that the MFI offers loans in, while a lower CR_4 means that loans are more diffuse and spread across multiple sectors.[15] In the Online Appendix, we assess the robustness of our findings to alternative measures of portfolio concentration, including the Herfindahl-Hirschman Index (HHI) and the Mean Absolute Deviation (MAD), as well as estimating these ratios based on the dollar value of a MFI's loans rather than based on the count.

5. RESULTS

5.1. Methods

We test our hypotheses using difference-in-difference models that estimate the outcomes of interest before and after the introduction of the badging program for treated MFIs, relative to untreated MFIs, where the treated MFIs are those who received the FCE badge and the untreated MFIs are those who received one or more of the remaining badges, as well as MFIs who received no badge at all. To test H1-H3, our estimation models take the following functional form (1):

$$F_{it} = \alpha_i + \eta_t + \beta D_{it} + \beta \delta_{it} + \beta (D_{it} \delta_{it}) + \varepsilon_{it} \ (1)$$

where F_{it} is the female borrower ratio, α_i is a vector of MFI fixed effects, η_t is the vector of year-quarter fixed effects, βD_{it} is the vector of badging treatments testing the main effect of receiving the FCE badge (i.e., H1), $\beta \delta_{it}$ is a vector of time varying control variables, which we interact with the treatment dummies to test for moderation effects (i.e., H2 and H3), and ε_{it} is the error term. To test H4, our estimation models take the following functional form (2):

$$Y_{it} = \alpha_i + \eta_t + \beta D_{it} + \beta \delta_{it} + \beta (D_{it} F_{it}) + \varepsilon_{it} \ (2)$$

where Y_{it} is the number of lenders, total amount paid, or amount paid per lender, βD_{it} indicates receipt of the FCE badge, βF_{it} is the female borrower ratio, which we interact with the indicator

[15] Note that our sample of 66 MFIs exclusively includes MFIs with large loan portfolios, and we only note a weak negative correlation (ρ = -0.09) between the number of loans posted and sector-level portfolio concentration.

for receipt of the FCE badge to test for performance effects. 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.

Across both models (1) and (2), MFI fixed effects control for any unobserved, time invariant, differences between the MFIs in our sample, while quarter-year fixed effects control for macroeconomic and platform-level trends (e.g., growth in number of lenders on Kiva) that affect all MFIs equally. The coefficients of our treatment dummies in should be interpreted as the quarterly difference in our dependent variables between treated and control MFIs as a result of receiving certification. We estimate robust standard errors clustered at the MFI-level to control for autocorrelation between observations (Bertrand, Duflo and Mullainathan, 2004). It is worth noting that we use a restricted sample of 66 MFIs, all of which that have large portfolios of loans spread across multiple industry sectors and the majority of which that have received at least one badge, which makes it easier to compare between them. We conduct several robustness checks to further guarantee the comparability of our treatment and control group, as described below.

5.2. Summary Statistics

Table 1 provides summary statistics broken out by treatment and control group MFIs. MFIs who received the FCE badge had, on average, a higher share of female borrowers to all borrowers, which is in line with the stated selection criteria and intended outcome for this badge. MFIs who (eventually) received the FCE badge had an average female borrower ratio of 80% whereas those in the control group had an average female borrower ratio of 65% (the mean difference of 15 percentage points is significant at $p < 0.01$). We further note that FCE-badged MFIs had a 9 percentage points higher probability of receiving any of the other social performance badges ($p < 0.05$), but that there are no significant differences in terms of how concentrated their portfolios were. The table further shows that FCE-badged MFIs attracted more lenders ($p < 0.01$), received a greater amount of money from their lenders ($p < 0.01$), and enjoyed a greater amount of money per lender ($p < 0.01$). Figure 2 displays MFIs' average female borrower ratios per quarter broken out by MFIs treated with the FCE badge and control group MFIs. The figure shows that while both groups had similar trends prior to the introduction of the social performance badges, the average share of female borrowers by MFIs that eventually received the FCE badge gradually increased after the introduction of the badges, as compared to control group MFIs.

--- INSERT TABLE 1 AND FIGURE 2 ABOUT HERE ---

5.3. The Effect of Certification on Loan Portfolio Composition

In Table 2 we test the degree to which MFIs reoriented their loan portfolio compositions after Kiva awarded them with the FCE badge. In Model 1 we test the main effect of FCE badging on portfolio composition (i.e., *female borrower ratio*) (H1), and in Models 2 and 3, we test whether receiving any of the other (i.e., non-FCE) social performance badges and the extent of MFI sector-level portfolio concentration moderate the effect of badging on portfolio composition, testing H2 and H3, respectively. In Models 4-12 we impose different lags on our independent variables allowing us to explore the temporal dynamics of the treatment (Autor, 2003).

--- INSERT TABLE 2 ABOUT HERE ---

In Model 1 of Table 2 we find support for the main effect of portfolio reorientation (H1), as MFIs increased their female borrower ratio by an average of 3 percentage points per quarter as a result of receiving the FCE badge compared to MFIs who did not receive this badge ($p < 0.10$). Model 2 tests whether receiving additional badges alongside the FCE badge moderates the effect on portfolio reorientation (H2). Here, we fail to support H2 as the coefficient for the interaction between *FCE badge received* and *non-FCE badge received* is directionally consistent with the stated hypothesis, albeit not statistically significant ($p = 0.13$). Model 3 tests the hypothesis that focused MFIs, those with more concentrated loan portfolios, will reorient their portfolios less than those with diversified loan portfolios (H3). We find support for this hypothesis as the interaction between *FCE badge received* and *portfolio concentration* is negative and significant ($p < 0.01$), meaning that the effect of receiving the FCE badge depends on the extent of MFI portfolio concentration. Analysis of the marginal effects for treated and control-group MFIs shows that, at low values of portfolio concentration (*portfolio concentration* = 0.5), treated MFIs increased their female borrower ratio by 16 percentage points more than control-group MFIs ($p < 0.01$), while at high values of portfolio concentration (*portfolio concentration* = 1), there was no difference in the change in female borrower ratio between treated and control-group MFIs.

Since we suspect that it takes time for MFIs to change their 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 estimating a relative time model (Greenwood and Wattal, 2017). The relative time model estimates the main treatment effect for different lags and leads relative to the treatment and provides insight into the dynamics of the treatment effect (Autor, 2003). We model the relative time model by replacing the FCE dummy with a series of time dummies that indicate the relative distance 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 estimated results are presented in Figure 3. The results show that there are no differences during pre-treatment time periods between MFIs that eventually receive the FCE badge and those that do not (providing further support that the key identifying assumption of the difference-in-difference estimator was met (Angrist and Pischke, 2008). The results also indicate that there is a lagged effect of receiving the FCE badge on changes in female borrower ratio that does not fully manifest itself until after the third quarter following the treatment. We believe that these results are intuitive: Portfolio reorientation takes time for MFIs to implement, as they will need to seek out additional female borrowers with interesting projects and good creditworthiness.

--- INSERT FIGURE 3 ABOUT HERE ---

Second, in Models 4-12 of Table 2 we re-estimate our main results by imposing lags of one, two, and three quarterly time periods on our independent variables. While our results are largely consistent with those reported in Models 1-3, we note two important differences in these models. First, and consistent with the relative time model in Figure 3, we find that the main effect on portfolio reorientation becomes more pronounced with greater time lags. In Model 10, we find that the effect of receiving the FCE badge on female borrower ratio increases from 3 to 5 percentage points when we lag the treatment by three time periods ($p < 0.01$). The second change is that we note support for H2 in all lagged models as the interaction between *FCE badge* and *non-FCE badge* is negative and significant ($p < 0.05$ in models 5, 8 and 11), implying that MFIs who received additional badges alongside the FCE badge reoriented their portfolios less than those MFIs who exclusively received the FCE badge. Analyzing the marginal effects from Model 11, we conclude that the *difference* in female borrower ratio between MFIs who exclusively received the FCE badge and those who received additional badges is 4 percentage points ($p < 0.05$), to the detriment of MFIs receiving additional badges. Taken all together, the results present in Table 2 and Figure 3 are consistent with our predictions in H1-H3.

5.4. The Effect of Certification and Portfolio Reorientation on Performance

We next discuss results for H4, that FCE-badged MFIs, who reorient their loan portfolios to include a greater share of female borrowers, will enjoy greater performance benefits. Our results are reported in Table 3: Models 1 and 2 take the *number of lenders* as the outcome of interest, Models 3 and 4 look at the *amount paid* by lenders, and Models 5 and 6 direct attention to the average *amount per lender*. Odd-numbered models include only the first-order effects of *FCE badge received* and *female borrower ratio*, while the even-numbered models include the covariate of interest, the interaction between the two independent variables.

--- INSERT TABLES 3 AND 4 ABOUT HERE ---

In Model 2, we find that the interaction between *FCE badge* and *female borrower ratio* is positive, albeit not significantly different from zero (p = 0.25). Thus, the combination of receiving a badge and including a greater share of female borrowers does not appear to increase the *number of lenders*. In Model 4, we find that the interaction between *FCE badge* and *female borrower ratio* has a positive effect on the total *amount paid* by lenders ($p < 0.05$). We find that FCE-badged MFIs gain an additional $103,114 per quarter ($p < 0.05$) if they have loan portfolios composed predominantly of female borrowers (*female borrower ratio* = 1). FCE-badged MFIs with few female borrowers in their loan portfolios (*female borrower ratio* = 0.5), however, do not enjoy any significant increases in the amount paid by lenders. In Model 6, we find that the interaction between *FCE badge* and *female borrower ratio* has a positive effect on the *amount paid per lender* ($p < 0.05$). Similar to the previous outcome variable, we find that FCE-badged MFIs receive an additional $3.05 per lender per quarter ($p < 0.05$) if they have loan portfolios mostly composed of female borrowers. Table 4 replicates these analyses by restricting the counterfactual exclusively to those MFIs that received the FCE badge (variation comes from the extent of *female borrower ratio*). These results are largely consistent with Table 3. The results in Tables 3 and 4 provide support for H4. MFIs which receive the FCE badge and respond to that badge by increasing their share of female borrowers have better performance. The specific mechanism appears to be through an increase in the amount paid per lender.

5.5. Falsification, Mechanism, and Robustness Tests

To summarize, we find that MFIs who receive the FCE badge reorient their portfolios to include a greater share of female borrowers, a result that is fully in line with Kiva's intended consequences for this badge. We also find that the effect of the FCE badge on portfolio orientation is attenuated for MFIs who received additional badges from Kiva and for those with more concentrated loan portfolios. Additionally, we find that the benefits of receiving the FCE badge primarily accrue to MFIs who reorient their loan portfolios to include more female borrowers. FCE-badged MFIs with a greater share of female borrowers in their loan portfolios benefit from larger average and cumulative dollar amounts paid by lenders, while FCE-badged MFIs with a smaller share of female borrowers do not enjoy these benefits.

There are a number of features in our econometric approach that help rule out alternative explanations. The inclusion of MFI fixed effects controls for unobserved idiosyncratic differences across 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 MFIs with at least one loan posted in every time period in order to create a balanced sample of MFIs and rule out bias from MFI attrition or entry. By restricting our sample to badged-only MFIs (Table 4), we further aim to establish that the performance related effects were driven by variation in *female borrower ratio*, rather than exclusively by MFIs without badges. Nevertheless, as reported below we also undertake a number of additional robustness tests and falsification exercises to further rule out alternative explanations.

First, as a mechanism check, we explore the role of the number of loans posted pre- and post-treatment. If the number of loans increases after a MFI receives the FCE badge from Kiva, it may be that the portfolio repositioning is being accomplished by adding more women owned loans, but not dropping other types of loans. Also, if the number of loans increases, it may be that the MFIs are adding more high performing loans (if anything, we would expect that the loans would be lower quality, but admit the possibility of better loans, and so feel the need to check). To test this, we estimate our models with the number of loans posted at the MFI-quarter level as the outcome variable. The results reported in the Online Appendix Table A1 show no evidence that the badging treatment leads to an absolute increase in the number of loans posted. These results confirm that badging leads to a *shift* in the composition of portfolios.

Second, we conduct a number of falsification tests to rule out false positive associations for the portfolio reorientation effect. In Table 5 we estimate the effect of receiving any of the non-FCE badges on female borrower ratio. Since increasing the number of female borrowers is the exclusive objective of the FCE badge, we should expect the other badges *not* to have any effect on female borrower ratio. Models 1-3 in Table 5 indeed show that receiving any of the non-FCE badges does not lead to a (lagged) increase in female borrower ratio. We conduct another test by reversing our coding to identify MFIs who did not receive any badge during our study period. Again, since these MFIs are not treated by the badging program we should expect to observe no significant change in female borrower ratio. Here, too, we find that there was no (lagged) effect on portfolio composition. Combined, these falsification tests instill confidence that the change we observed in portfolio composition can indeed be linked to the FCE badge.

--- INSERT TABLE 5 ABOUT HERE ---

Third, since one of the key assumptions of the difference-in-difference estimator is that there are no systematic differences between the treatment and control groups which are related to the outcome variable, we conduct an additional test to validate that the control MFIs in our sample are indeed a representative counterfactual for our tests. Since we observe that FCE-badged MFIs are marginally more likely to also receive any of the other badges compared to MFIs who did not receive the FCE badge (Table 1), we conduct a test of the determinants of the FCE badge. We regress receiving the FCE badge (in Q4-2011) on MFIs' female borrower ratio, MFIs' portfolio concentration ratio, and MFIs' age. The results reported in Table 6 show that the only significant predictor of receiving the FCE badge is *female borrower ratio*. Model 2 further shows that *female borrower ratio* does not predict whether MFIs received any of the other badges. Relatedly, our results are consistent when we exclude the subsample of MFIs without any of the other badges from our portfolio reorientation estimations (Appendix Table A2).

--- INSERT TABLE 6 ABOUT HERE ---

Fourth, to further assess our results for H2, that excessive badging is detrimental to the extent of portfolio reorientation, we run a robustness test in which we split the non-FCE badge variable into three categories: *no additional badges received* (base), *one non-FCE badged received*, and *multiple non-FCE badges received*. If our argument underlying H2 is correct, we should expect to find that receiving one non-FCE badge has a negative effect on MFIs' female borrower ratio compared to the base of receiving no additional badges, and that receiving multiple non-FCE badges has an even more negative effect. The results, reported in Appendix Table A3, are directionally consistent with this argument, providing further support for H2.

Fifth, to further assess our results for H3, and to rule out that support is driven by measurement error, we re-estimate our results with a number of alternative operationalizations for MFI portfolio concentration. Specifically, instead of using the sector-level concentration ratio, we use MFIs' quarterly sector-level Herfindahl-Hirschman Index (HHI) as well as their sector-level Mean Absolute Deviation (MAD) as alternative measures for loan portfolio concentration. Furthermore, rather than measuring concentration based on loan counts, we look at loans' dollar value as an alternative way to estimate the three different concentration ratios. Our results in Appendix Table A4 are consistent when using any of these alternative measures.

Sixth, we re-estimate results using additional variations in the sample set of MFIs and years. In the first sample variation (Appendix Table A5), we used the full sample of 70 MFIs, including those who were treated in time periods after the introduction of the badges and find results that are consistent with our main results. In the second sample variation (Appendix Table A6), we use an expanded sample that includes three additional pre-treatment time periods (one period gets dropped due to the lagged specification). Here, too, our results are fully consistent.

Seventh, we check the robustness of our main results to alternate specifications. These robustness tests include models in which we estimated results by fitting the model with AR(1) disturbances to further control for potential serial correlation (Bertrand et al., 2004), as reported in Appendix Table A7. We also fit the models with the inclusion of additional control variables, such as the number of active MFIs in the same country and quarter as the focal MFI as a measure of market-level competition (Ly and Mason, 2012a), as reported in Appendix Table A8. In all these additional tests our findings are either fully or directionally consistent with those reported in our main results section, thus lending additional support to our hypotheses.

6. CONCLUSION

We study how a platform's use of complementor certification affects complementors' behavior on the platform. In so doing, our paper joins a small but growing literature on how certification affects *ex post* firm behavior. We find that complementors who receive certification re-orient their portfolio of products to more closely align with the dimension on which they are certified. However, these effects are attenuated by complementor (supply-side) and end-user (demand-side) characteristics. We interpret these results to suggest that there are limits to the extent to which platforms are able to influence the behavior of their complementors: from the complementor's point of view, demand-side and supply-side factors enable and constrain their response. Lastly, we find that certified complementors that re-align their portfolios perform better compared to certified complements that do not re-align their portfolios.

Our study contributes to existing platform governance and multisided markets literature in a number of ways. First, the literature has focused predominantly on pricing strategies across different sides of the market (Parker and Van Alstyne, 2005; Rochet and Tirole, 2003), whereas we demonstrate how platforms can use other strategies, in the form of a badging program, to orchestrate its ecosystem (Jacobides et al., 2018; Tiwana et al., 2010). Second, we document important supply-side and demand-side factors along which complementors vary, and show that these dimensions drive heterogeneous reactions from complementors in response to the platform's governance mechanisms (Huang et al., 2018; McIntyre and Srinivasan 2017). Finally, we provide a study of a peer-to-peer lending platform that is international in scope. In contrast, existing studies of peer-to-peer lending are mostly U.S.-centric (e.g., Agrawal, Catalini and Goldfarb, 2011), though more recent studies of the sharing economy have contributed some cross-national comparisons (e.g., Burtch et al., 2014; Uzunca, Rigtering and Ozcan 2018).

Our results also hold implications for managers of firms operating in platform markets. Our findings underscore the power that platforms have in shaping the behavior of actors on both sides of their market. Certification is a powerful tool that platforms can use to elicit specific actions from complementors and end-users. However, in our setting the platform's tools come with tradeoffs, including those arising from potentially misaligned objectives between the platform and its complementors. While the MFIs in our sample are mostly profit-driven organizations, Kiva itself is a non-profit organization whose overall goal it is to alleviate poverty. Kiva's focus on women borrowers for its badging program aligns with its mission as women borrowers reinvest, on average, 80% of their income in the wellbeing of their children, thus directly serving their families and the wider community. On the other hand, we do not know if this focus on female borrowers is justified from the (profit-maximizing) MFIs' perspective. It may well be that other types of loans are less costly to manage or justify charging higher interest rates, therefore better serving the MFIs' financial goals. In selecting the platforms to enter, complementors must be aware of the platform's strategic objectives and how these align with their own. The platform's goals likely drive the preferential treatment of complementors as reflected in which complements the platform chooses to selectively promote (Rietveld et al., 2018). Overall, our study highlights the challenges of market orchestration faced by platforms as they seek to carefully balance the needs of users on both sides of their market.

There are several limitations to our study. Primarily, we limit our focus to the effect of the platform's governance choices on its complementors, but do not investigate the ultimate effects of these choices on the platform itself. We intentionally limit our focus in this way to take advantage of the quasi-exogenous shock (from the MFIs, lenders, and borrowers points of view) of the introduction of the Social Performance badges. The introduction of this certification program itself is of course an endogenous choice on the part of the platform; we thus lack a similarly clean "experiment" from the point of view of the platform. Future research, however, may want to probe how certification programs affect platforms themselves.

As we have highlighted, one critical issue for any platform is that it needs to determine how complementors will interpret and respond to different governance mechanisms. While we have focused on the use of badging, there are many different mechanisms a platform could use to govern the behavior of its complementors and orchestrate its ecosystem, including platform openness (Boudreau, 2010; Schilling, 2009), platform entry (Foerderer et al., 2018; Wen and Zhu, 2018; Zhu and Liu, 2018), and platform complexity (Anderson, Parker and Tan, 2014; Cennamo, Ozalp and Kretschmer, 2018). Future research may want to investigate how platforms decide between different governance mechanisms, and how these governance mechanisms differently affect the portfolio of products offered by the platforms' complementors.

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TABLES AND FIGURES

Table 1. Descriptive Statistics (based on Estimation Sample of 66 MFIs)

	FCE badge received (n=442)				*FCE badge not received (n=416)*				**Mean**
Variable	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**difference**
Female borrower ratio	0.80	0.22	0.18	1.00	0.65	0.23	0.07	1.00	-0.15**
Non-FCE badge received	0.60	0.49	0.00	1.00	0.52	0.50	0.00	1.00	-0.09*
Portfolio concentration ratio	0.86	0.10	0.52	1.00	0.86	0.10	0.55	1.00	0.002
Lenders	7,435.83	6,531.42	98.00	41,072.00	6,010.99	3,428.96	82.00	19,357.00	-1,424.83**
Amount paid	240,346.30	245,414.50	2,700.00	1,690,271.00	177,015.20	105,154.00	2,000.00	583,275.00	-63,331.15**
Amount per lender	30.79	6.35	20.82	100.90	29.60	4.45	1.57	68.39	-1.19**
FCE badge received	0.62	0.49	0.00	1.00					

Note. Mean differences are derived from a two-sample t test. Data source: Kiva.org.
** significant at 1%, * significant at 5%, + significant at 10%.

Table 2. The Effects of Certification on Complementor Portfolio Reorientation

Model	**1**	**2**	**3**	**4 ($_{t+1}$)**	**5 ($_{t+1}$)**	**6 ($_{t+1}$)**	**7 ($_{t+2}$)**	**8 ($_{t+2}$)**	**9 ($_{t+2}$)**	**10 ($_{t+3}$)**	**11 ($_{t+3}$)**	**12 ($_{t+3}$)**
Dependent variable	*Female borrower ratio*											
FCE badge received	0.03+ [0.02]	0.07** [0.02]	0.35** [0.12]	0.03 [0.02]	0.08** [0.02]	0.32* [0.13]	0.04* [0.02]	0.11** [0.03]	0.33** [0.14]	0.05* [0.02]	0.12** [0.03]	0.32* [0.13]
Non-FCE badge received		0.02 [0.02]			0.03 [0.02]			0.03 [0.03]			0.04 [0.03]	
*FCE badge * Non-FCE badge*		-0.04 [0.02]			-0.06* [0.03]			-0.07* [0.03]			-0.08* [0.04]	
Portfolio concentration ratio			0.06 [0.12]			-0.05 [0.10]			-0.04 [0.08]			0.12 [0.08]
*FCE badge * Portfolio concentration*			-0.37** [0.13]			-0.34* [0.14]			-0.34* [0.15]			-0.32* [0.15]
Constant	0.71** [0.01]	0.71** [0.01]	0.65** [0.10]	0.71** [0.01]	0.71** [0.01]	0.75** [0.09]	0.71** [0.01]	0.71** [0.01]	0.67** [0.07]	0.71** [0.01]	0.71** [0.01]	0.60** [0.07]
Quarter-year fixed effects	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
Observations	858	858	858	858	858	858	858	858	858	858	858	858
MFIs	66	66	66	66	66	66	66	66	66	66	66	66
R-squared (within)	0.06	0.06	0.10	0.06	0.07	0.10	0.07	0.08	0.10	0.07	0.08	0.10

Note. Fixed effects OLS panel regressions with heteroskedasticity robust standard errors clustered at the MFI-level.
** significant at 1%, * significant at 5%, + significant at 10%.

Table 3. The Effects of Certification and Portfolio Reorientation on Complementor Performance

Model	**1**	**2**	**3**	**4**	**5**	**6**
Dependent variable	*Lenders*		*Amount paid*		*Amount per lender*	
FCE badge received	1,273.64	-1,192.67	63,836.83*	-103,177.50	1.45	-5.36*
	[825.70]	[1,863.28]	[31,735.24]	[62,997.57]	[1.21]	[2.01]
Female borrower ratio	328.44	179.52	-8,609.63	-18,694.10	-0.18	-0.59
	[1,722.24]	[1,790.93]	[49,073.35]	[54,364.58]	[1.82]	[1.85]
*FCE badge * Female borrower ratio*		3,046.32		206,292.10*		8.41*
		[2,622.49]		[100,194.70]		[3.41]
Constant	5,885.74**	5,991.87**	196,890.90**	204,077.70**	30.54**	30.83**
	[1,215.30]	[1,254.54]	[36,268.83]	[39,494.44]	[1.32]	[1.32]
Quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	858	858	858	858	858	858
MFIs	66	66	66	66	66	66
R-squared (within)	0.22	0.23	0.21	0.23	0.07	0.09

Note. Fixed effects OLS panel regressions with heteroskedasticity robust standard errors clustered at the MFI-level. ** significant at 1%, * significant at 5%, + significant at 10%.

Table 4. The Effects of Portfolio Reorientation on Certified Complementors' Performance

Model	**1**	**2**	**3**
Dependent variable	*Lenders*	*Amount paid*	*Amount per lender*
Female borrower ratio	-3,081.23	-173,127.10	-6.47*
	[3,856.10]	[108,853.60]	[3.11]
*FCE badge * Female borrower ratio*	3,146.04	207,105.10*	8.38*
	[2,568.63]	[99,110.90]	[3.78]
Constant	8,841.96**	338,786.60**	35.62**
	[2,761.17]	[79,039.97]	[2.07]
Quarter-year fixed effects	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes
Observations	442	442	442
MFIs	34	34	34
R-squared (within)	0.23	0.23	0.13

Note. Fixed effects OLS panel regressions with heteroskedasticity robust standard errors clustered at the MFI-level. ** significant at 1%, * significant at 5%, + significant at 10%.

Table 5. Falsification Tests

Model	1	2 ($_{t+1}$)	3 ($_{t+2}$)	4 ($_{t+3}$)	5	6 ($_{t+1}$)	7 ($_{t+2}$)	8 ($_{t+3}$)
Dependent variable				*female borrower ratio*				
Non-FCE badge received	0.04	0.05	0.001	0.01				
	[0.04]	[0.03]	[0.02]	[0.02]				
No badge received					-0.04	-0.05	-0.05	-0.07
					[0.03]	[0.03]	[0.04]	[0.04]
Constant	0.70**	0.70**	0.70**	0.70**	0.71**	0.71**	0.71**	0.71**
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	845	845	845	845	871	871	871	871
MFIs	65	65	65	65	67	67	67	67
R-squared (within)	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.07

Note. Fixed effects OLS panel regressions with heteroskedasticity robust standard errors clustered at the MFI-level.
** significant at 1%, * significant at 5%, + significant at 10%.

Table 6. Determinants of Complementor Certification

Model	1	2
Dependent variable	*FCE badge received*	*Non-FCE badge received*
Female borrower ratio	1.72*	-0.80
	[0.77]	[0.94]
Portfolio concentration ratio	-1.65	3.43
	[1.88]	[2.29]
MFI age	0.01	-0.22
	[0.01]	[0.02]
Constant	-0.04	-0.22
	[1.62]	[1.90]
MFIs	70	70
R-squared	0.07	0.08

Note. Probit regression with robust standard errors.
** significant at 1%, * significant at 5%, + significant at 10%.

Figure 1. Distribution of Social Performance Badges for MFIs in Estimation Sample

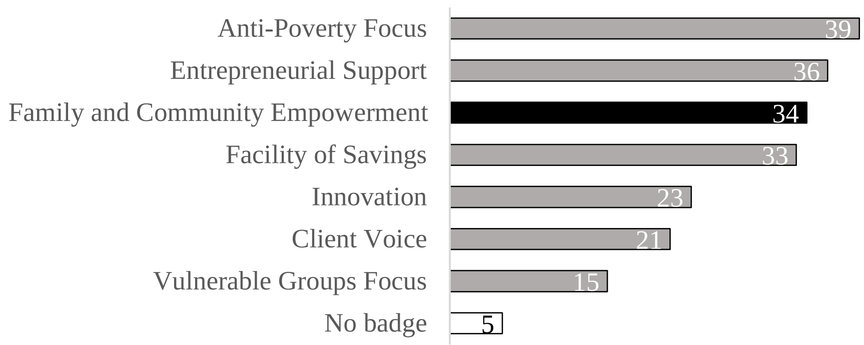


Figure 2. Average Female Borrower Ratio for Treatment and Control MFIs, over Time

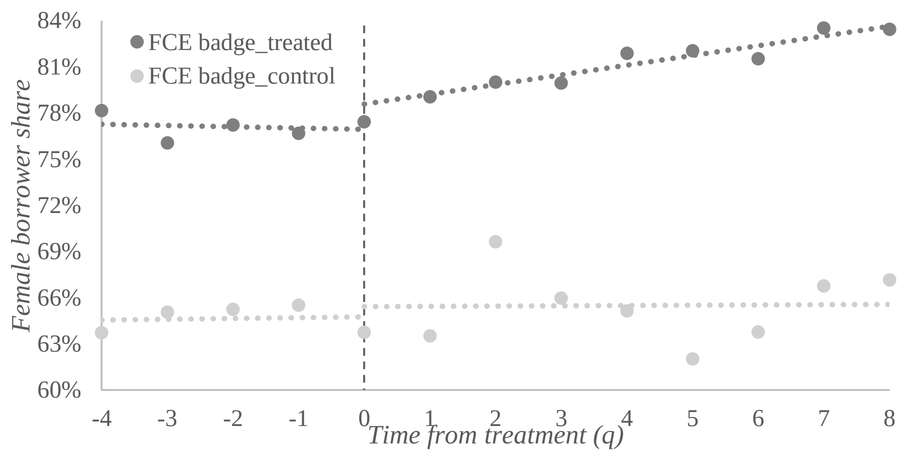
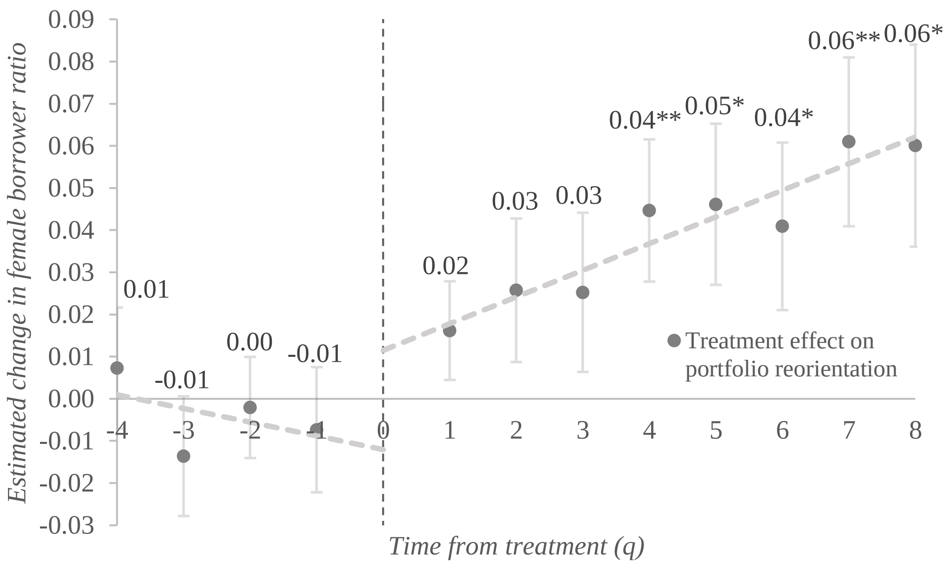


Figure 3. Effect of Certification on Complementor Portfolio Reorientation, over Time



Online Appendix

Table A1. Mechanism Check, Estimating the Number of Loans Posted as a Function of Receiving the FCE Badge

Model	**1**	**2$_{(t+1)}$**	**3$_{(t+2)}$**	**4$_{(t+3)}$**
Dependent variable		*Number of loans posted*		
FCE badge received	44.05	48.57	52.69	60.56
	[54.27]	[56.74]	[55.88]	[59.00]
Constant	233.59**	233.59**	233.59**	233.59**
	[14.50]	[14.50]	[14.49]	[14.49]
Quarter-year fixed effects	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes
Observations	858	858	858	858
MFIs	66	66	66	66
R-squared (within)	0.11	0.12	0.12	0.12

Note. Fixed effects OLS panel regressions with heteroskedasticity robust standard errors clustered at the MFI-level.
** significant at 1%, * significant at 5%, + significant at 10%.

Table A2. Main Results Estimated on a Restricted Sample of 61 MFIs with at Least One Badge Received in Q4, 2011

Model	**1**	**2**	**3**	**4**	**5**	**6**
Dependent variable		*Female borrower ratio*		*Lenders*	*Amount paid*	*Amount per lender*
FCE badge received	0.04*	0.07**	0.32*	-1,514.07	-113,609.00+	-5.63**
	[0.02]	[0.02]	[0.14]	[1,858.44]	[62,816.41]	[2.04]
Non-FCE badge received		0.02				
		[0.02]				
*FCE badge * Non-FCE badge*		-0.04+				
		[0.02]				
Portfolio concentration ratio			0.14			
			[0.09]			
*FCE badge * Portfolio concentration*			-0.33*			
			[0.15]			
Female borrower ratio				-478.33	-47,869.10	-1.46
				[1,937.19]	[57,748.51]	[1.94]
*FCE badge * Female borrower ratio*				3,064.32	206,097.00*	8.33*
				[2,611.24]	[99,831.75]	[3.41]
Constant	0.70**	0.70**	0.57**	6,603.35**	229,392.10**	31.48**
	[0.01]	[0.01]	[0.08]	[1,332.06]	[41,190.16]	[1.37]
Quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	793	793	793	793	793	793
MFIs	61	61	61	61	61	61
R-squared (within)	0.08	0.07	0.11	0.24	0.25	0.11

Note. Fixed effects OLS panel regressions with heteroskedasticity robust standard errors clustered at the MFI-level. Model 1 replicates Table 2's Model 10; Model 2 replicates Table 2's Model 11; Model 3 replicates Table 2's Model 12; Model 4 replicates Table 3's Model 2; Model 5 replicates Table 3's Model 4; Model 6 replicates Table 3's Model 6.
** significant at 1%, * significant at 5%, + significant at 10%.

Table A3. The Moderating Effect of Receiving Additional Badges, broken out by the Number of Additional Badges Received

Model	**1**	**2$_{(t+1)}$**	**3$_{(t+2)}$**	**4$_{(t+3)}$**
Dependent variable		*Female borrower ratio*		
FCE badge received	0.09**	0.10**	0.11**	0.12**
	[0.02]	[0.02]	[0.03]	[0.03]
One non-FCE badge received	0.03	0.06*	0.04	0.05
	[0.03]	[0.03]	[0.03]	[0.03]
Multiple non-FCE badges received	0.01	0.02	0.02	0.04
	[0.02]	[0.02]	[0.03]	[0.03]
*FCE badge * One non-FCE badge*	-0.02	-0.04	-0.04	-0.05
	[0.03]	[0.03]	[0.04]	[0.04]
*FCE badge * Multiple non-FCE badges*	-0.06+	-0.07*	-0.08*	-0.09*
	[0.03]	[0.03]	[0.03]	[0.03]
Constant	0.71**	0.71**	0.71**	0.71**
	[0.01]	[0.01]	[0.01]	[0.01]
Quarter-year fixed effects	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes
Observations	858	858	858	858
MFIs	66	66	66	66
R-squared (within)	0.08	0.08	0.08	0.09

Note. Fixed effects OLS panel regressions with heteroskedasticity robust standard errors clustered at the MFI-level. Model 1 replicates Table 2's Model 2; Model 2 replicates Table 2's Model 5; Model 3 replicates Table 2's Model 8; Model 4 replicates Table 2's Model 11.
** significant at 1%, * significant at 5%, + significant at 10%.

Table A4. The Moderating Effect of Portfolio Concentration Using Various Alternative Measures for Portfolio Concentration

Model	**1**	**2**	**3**	**4**	**5**
Dependent variable			*Female borrower ratio*		
FCE badge received	0.32*	0.23**	0.23*	0.08*	0.08*
	[0.13]	[0.08]	[0.09]	[0.03]	[0.03]
Portfolio concentration ratio	0.04	0.15	0.01	-0.04	-0.04
	[0.13]	[1.16]	[1.07]	[0.10]	[0.10]
*FCE badge * portfolio concentration*	-0.33*	-2.29*	-2.20*	-0.13+	-0.13+
	[0.14]	[0.90]	[0.93]	[0.07]	[0.07]
Constant	0.68**	0.70**	0.71**	0.72**	0.72**
	[0.11]	[0.10]	[0.09]	[0.03]	[0.03]
Quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	858	858	858	858	858
MFIs	66	66	66	66	66
R-squared (within)	0.10	0.10	0.10	0.09	0.08

Robustness tests estimating the effects of alternative measures for *portfolio concentration ratio.* All models in this table replicate Table 2's Model 12: Model 1 estimates the effect of portfolio concentration using the CR_4 based on loan amount; Model 2 estimates the effect of portfolio concentration using the mean absolute deviation based on loan count; Model 3 estimates the effect of portfolio concentration using the mean absolute deviation based on loan amount; Model 4 estimates the effect of portfolio concentration using the HHI based on loan count; Model 5 estimates the effect of portfolio concentration using the HHI based on loan amount.
** significant at 1%, * significant at 5%, + significant at 10%.

Table A5. Main Effects Estimated on an Expanded Sample of all 70 MFIs

Model	**1**	**2**	**3**	**4**	**5**	**6**
Dependent variable		*Female borrower ratio*		*Lenders*	*Amount paid*	*Amount per lender*
FCE badge received	0.05*	0.12**	0.27*	-1,578.77	-116,352.00+	-5.49**
	[0.02]	[0.03]	[0.12]	[1,884.32]	[63,855.08]	[2.00]
Non-FCE badge received		0.04				
		[0.03]				
*FCE badge * Non-FCE badge*		-0.09*				
		[0.04]				
Portfolio concentration ratio			0.11			
			[0.08]			
*FCE badge * Portfolio concentration*			-0.27*			
			[0.13]			
Female borrower ratio				292.23	-13,563.00	-0.67
				[1,787.20]	[53,611.11]	[1.89]
*FCE badge * Female borrower ratio*				3,446.78	214,276.70*	7.83*
				[2,524.70]	[95,919.84]	[3.30]
Constant	0.71**	0.71**	0.61**	6,175.59**	208,409.30**	30.91**
	[0.01]	[0.01]	[0.07]	[1,244.61]	[38,615.19]	[1.35]
Quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	910	910	910	910	910	910
MFIs	70	70	70	70	70	70
R-squared (within)	0.07	0.08	0.09	0.21	0.22	0.09

Note. Fixed effects OLS panel regressions with heteroskedasticity robust standard errors clustered at the MFI-level. Model 1 replicates Table 2's Model 10; Model 2 replicates Table 2's Model 11; Model 3 replicates Table 2's Model 12; Model 4 replicates Table 3's Model 2; Model 5 replicates Table 3's Model 4; Model 6 replicates Table 3's Model 6.

** significant at 1%, * significant at 5%, + significant at 10%.

Table A6. Main Effects Estimated on Expanded Sample Including Two Additional Pre-Treatment Time Periods (Q2'11-Q4'13)

Model	**1**	**2**	**3**	**4**	**5**	**6**
Dependent variable		*Female borrower ratio*		*Lenders*	*Amount paid*	*Amount per lender*
FCE badge received	0.03+ [0.02]	0.07** [0.02]	0.33* [0.13]	-1,308.45 [2,052.99]	-107,498.00+ [69,897.00]	-5.16* [2.07]
Non-FCE badge received		0.03 [0.02]				
*FCE badge * Non-FCE badge*		-0.05* [0.02]				
Portfolio concentration ratio			-0.04 [0.09]			
*FCE badge * Portfolio concentration*			-0.35* [0.14]			
Female borrower ratio				522.17 [1,828.89]	-2,091.38 [54,855.37]	-0.62 [1.65]
*FCE badge * Female borrower ratio*				3,075.22 [2,875.27]	209,273.10+ [110,565.40]	8.30* [3.52]
Constant	0.71** [0.01]	0.71** [0.01]	0.74** [0.08]	5,747.68** [1,288.43]	192,245.70** [40,023.04]	30.85** [1.22]
Quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	990	990	990	990	990	990
MFIs	66	66	66	66	66	66
R-squared (within)	0.05	0.06	0.09	0.28	0.27	0.09

Note. Fixed effects OLS panel regressions with heteroskedasticity robust standard errors clustered at the MFI-level. Model 1 replicates Table 2's Model 4; Model 2 replicates Table 2's Model 5; Model 3 replicates Table 2's Model 6; Model 4 replicates Table 3's Model 2; Model 5 replicates Table 3's Model 4; Model 6 replicates Table 3's Model 6. We estimate models with only one period time lag to take advantage of the additional pre-treatment time periods.
** significant at 1%, * significant at 5%, + significant at 10%.

Table A7. Main Effects Estimated Using an Alternative Estimation Technique: Autoregressive Disturbances (1)

Model	**1**	**2**	**3**	**4**	**5**	**6**
Dependent variable		*Female borrower ratio*		*Lenders*	*Amount paid*	*Amount per lender*
FCE badge received	0.04**	0.07	0.21**	-398.28	-58,246.60	-4.99**
	[0.01]	[0.06]	[0.07]	[1,432.81]	[45,367.24]	[1.91]
Non-FCE badge received		0.001				
		[0.01]				
*FCE badge * Non-FCE badge*		-0.04				
		[0.06]				
Portfolio concentration ratio			0.15			
			[0.06]			
*FCE badge * Portfolio concentration*			-0.19*			
			[0.08]			
Female borrower ratio				1,555.76	52,734.46	3.15*
				[1,215.40]	[37,462.03]	[1.58]
*FCE badge * Female borrower ratio*				2,033.54	103,332.50+	4.67*
				[1,720.60]	[54,516.84]	[2.30]
Constant	0.72**	0.72**	0.59**	5,924.62**	193,125.80**	28.49**
	[0.002]	[0.003]	[0.03]	[326.18]	[8,603.30]	[0.37]
Quarter-year fixed effects	No	No	No	No	No	No
MFI fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	792	792	792	792	792	792
MFIs	66	66	66	66	66	66
R-squared (within)	0.02	0.02	0.03	0.02	0.01	0.11

Note. Fixed effects regressions with AR(1) disturbances. Model 1 replicates Table 2's Model 10; Model 2 replicates Table 2's Model 11; Model 3 replicates Table 2's Model 12; Model 4 replicates Table 3's Model 2; Model 5 replicates Table 3's Model 4; Model 6 replicates Table 3's Model 6.
** significant at 1%, * significant at 5%, + significant at 10%.

Table A8. Main Effects Estimated with Added Control Variable: Country-MFI Level Competition

Model	**1**	**2**	**3**	**4**	**5**	**6**
Dependent variable		*Female borrower ratio*		*Lenders*	*Amount paid*	*Amount per lender*
FCE badge received	0.05*	0.12**	0.32*	-1,285.87	-101,303.00+	-4.82*
	[0.02]	[0.03]	[0.13]	[1,804.37]	[60,567.90]	[1.85]
Non-FCE badge received		0.04				
		[0.03]				
*FCE badge * Non-FCE badge*		-0.08*				
		[0.04]				
Portfolio concentration ratio			0.12			
			[0.08]			
*FCE badge * Portfolio concentration*			-0.32*			
			[0.15]			
Female borrower ratio				130.08	-17,699.60	-0.31
				[1,763.26]	[53,325.48]	[1.89]
*FCE badge * Female borrower ratio*				3,155.16	204,102.60*	7.79*
				[2,523.95]	[96,200.97]	[3.17]
Country-level competition	-0.002	-0.002	-0.002	81.37	-1,636.95	-0.47
	[0.004]	[0.004]	[0.004]	[191.93]	[6,715.77]	[0.28]
Constant	0.71**	0.71**	0.61**	5,810.10**	207,734.10**	31.87**
	[0.01]	[0.01]	[0.07]	[1,430.26]	[45,219.44]	[1.50]
Quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
MFI fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	858	858	858	858	858	858
MFIs	66	66	66	66	66	66
R-squared (within)	0.08	0.08	0.10	0.23	0.23	0.11

Note. Fixed effects OLS panel regressions with heteroskedasticity robust standard errors clustered at the MFI-level. Model 1 replicates Table 2's Model 10; Model 2 replicates Table 2's Model 11; Model 3 replicates Table 2's Model 12; Model 4 replicates Table 3's Model 2; Model 5 replicates Table 3's Model 4; Model 6 replicates Table 3's Model 6.
** significant at 1%, * significant at 5%, + significant at 10%.