# Market orchestrators:

# The effect of platform certification on complementor performance and behavior in the context of kiva (2010-2013)


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**This version:** February 28, 2018


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**Acknowledgements:** We thank the following persons for their feedback on our study: Sebastian Hoenen, Mallory Flowers, Daniel Sands, and Manav Raj. We thank Georgi Nikolov and Karan Chaudhari for their assistance in collecting data, and five MSc students at the Rotterdam School of Management for additional research assistance. Finally, we are grateful for Kevin O'Brien at Kiva for sharing with us his insights on Social Performance Badges.

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**Abstract:** Platforms need to carefully balance the needs of their customers and complementors. Certification of complementors is often used as part of this complex "market orchestration" process. We study how a platform's use of certification affects complementors' behavior, as pertains to the bundle of products offered. We use a unique dataset of Kiva's microfinance platform to take advantage of a quasi-exogenous shock: Kiva's unexpected introduction of a certification program in late 2011. We show that Kiva's certification leads microfinance institutions to experience positive performance effects and reorient their loan portfolio composition. We further show that these effects vary across complementors depending on demand-side and supply-side factors. We interpret our results to suggest that there are limits to the extent platforms can influence the behavior of complementors.

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

**Running head:** *Market orchestrators*

## INTRODUCTION

Firms in many industries today can be characterized as digital 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 and Mastercard, video game consoles such as 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 of the market are connected via an indirect network effect (Cennamo and Santalo, 2013; Parker and Van Alstyne, 2005; Rochet and Tirole, 2003), implying that the number of users on one side of the market can affect the pricing strategy used on the other side of the market. Thus, the platform's relationship with each set of users has direct implications for the platform's overall success.

To be successful, however, platforms also need to manage their users by setting the rules for participation and enacting governance frameworks on both sides of the market (Gawer, 2014; Wareham, Fox and Giner, 2014). The challenge for the platform is that it cannot "tell" a user on one side of its platform what to do, but instead needs to provide cues and incentives that reward the users for doing what the platform wants (McIntyre and Srinivasan, 2017; Rietveld, Schilling and Bellavitis, 2017; Yoffie and Kwak, 2006). A critical issue for the platform is that it not only needs to determine what its optimal strategy is, and how to achieve success via different governance mechanisms, but also how complementors will interpret and respond to different governance mechanisms. There are many different mechanisms a platform could use to govern the behavior of its complementors, including platform openness (Boudreau, 2010; Schilling, 2009), platform entry (Gawer and Henderson, 2007; Wen and Zhu, 2017), and platform complexity. For example, a platform might consider making its technology relatively complex, in an effort to increase the probability that a complementor specializes its product for the platform, rather than producing a more general product that can be used across multiple platforms (Anderson, Parker and Tan, 2014; Cennamo, Ozalp and Kretschmer, 2018).

One of the tools commonly used by platforms to govern the behavior of its complementors is the selective promotion of complements through certification. For example, there over 1,500 "apps" submitted by complementors to the Apple app store daily. In order to help highlight high quality apps for consumers, Apple promotes a small subset of them via App Store features such as "Editor's Pick" and "Apps we love." There are many examples of this on other platforms, including Kickstarter's "Projects We Like," Spotify's "Curated Playlists," Airbnb's badge for "Superhosts," PlayStation's "Platinum Rereleases," and eBay's "Top Rated Sellers." As we explain in more detail below, in late 2011, Kiva, a peer-to-peer online lending platform, started to certify selected sets of microfinance institutions (MFIs) on its platform via a new badging program whereby these MFIs received one or more of seven newly introduced "Social Performance Badges." While a nascent literature has highlighted the important role of certification in platform settings (e.g., 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. For example, *how does certification affect complementor behavior and performance on the platform, on average, and how do these effects vary across different types of complementors?*

We study these platform governance and certification issues in the context of Kiva, for the time period 2010 – 2013. Kiva was established in 2005, and allows lenders from around the world to provide funds to borrowers, primarily in developing countries, who need small 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). As we describe below, borrowers' projects are offered and facilitated by local intermediaries known as MFIs, or 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 ultimately managed by the MFI which is responsible for making sure that the loan is repaid. Kiva has been the subject of study by several other researchers (e.g., Allison et al., 2005; Burtch, Ghose and Wattal, 2014; Galak, Small, Stephen, 2011; Snihur, Reiche and Quintane, 2016; Ly and Mason, 2012a; 2012b; Bollinger and Yao, 2016). Our project is complementary to this existing work because most of these papers focus on loan-level outcomes as a function of lenders' and borrowers' individual characteristics (e.g., geographic location, gender, loan orientation), and the interaction between these features (e.g., does geographic or cultural proximity between the lender and borrower lead to a faster time to fund a loan). An exception is Ly and Mason (2012a) who study competition between MFIs and find that it negatively affects loans' funding speed and that the effect is stronger for loans that can be considered close substitutes. Our paper differs from theirs in our focus on the role of platform governance on MFI-level outcomes.

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—the transactions involve sending money across large geographic distances—and so the need for certification as a way to provide quality signals to lenders is important. Second, Kiva adopted a certification scheme partway through our study period—in December 2011—allowing us to trace out changes in lender, borrower, and MFI behavior over time. Moreover, the certification scheme was unanticipated by these parties, suggesting that any changes we observe following the certification scheme are likely 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 (i.e., 374,320 loans) that appeared on Kiva, including MFI, borrower, lender, and loan characteristics.

Our study contributes to the literature on platform ecosystem 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), there is a growing awareness that platforms must also implement non-pricing strategies to increase the value created by the overall ecosystem and capture a portion of that value (Boudreau and Hagiu, 2009; Ceccagnoli et al., 2012; Claussen, Kretschmer and Mayrhofer, 2013; Rietveld et al., 2017). Platforms are in a strong position to exert power over complementors due to high levels of architectural control (Yoffie and Kwak, 2006), yet we know little about how complementors respond to such incentives, or how this affects their subsequent behavior and outcomes (Jacobides, Cennamo and Gawer 2017; McIntyre and Srinivasan 2017). We document how platform governance in the form of a multidimensional badging program results in increased performance for badged complementors and a reorientation of their product portfolio that aligns with the overall objectives of the platform. Additionally, we describe supply-side and demand-side dimensions along which complementors vary, and show that these dimensions drive heterogeneous responses to the platform's certification program.

Our study also has implications for managers of firms operating in platform markets. Technology platforms are entering more and more markets (in some cases raising antitrust concerns (e.g., Khan 2017)), gradually turning firms in different industries into complementors for these platforms (Altman, 2015). While there often exist strong interdependencies between platforms and complementors, there may also exist structural misalignment in their objectives, resulting in divergent strategies. Complementors have to inform themselves about the platform's objectives, and their strategies will vary as the actions of platforms change over time (Gawer and Henderson, 2007; Wen and Zhu, 2017; Zhu and Liu, 2016). Our results underscore the impact platform governance mechanisms can have on how complementors compete and perform. Furthermore, our results suggest that complementors who align their product portfolio composition with the objectives of the platform are more likely to receive preferential treatment in the form of certification, which in turns boosts their performance on the platform.

## THEORY AND HYPOTHESES

In order to grow and successfully compete, platforms need to 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; 2006). For example, all else equal, the more app developers there are that create apps for the Apple iPhone, the more consumers there are that will want to purchase an iPhone. And, the more consumers 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; 2006) in which the platform needs to decide on which side it should focus more attention (e.g., should Apple focus first on getting more developers, or on getting more consumers).

However, “more” of users on each side is not necessarily always beneficial. Research has shown that the scope of indirect network effects is strongly contingent on heterogeneous supply-side factors such as complement quality, complement diversity, and complement exclusivity

(Binken and Stremersch, 2009; Cennamo and Santalo, 2013; Corts and Lederman, 2011; Doshi, 2014; Lee, 2013). On the demand-side, too, there typically exists heterogeneity in consumers affecting the scope of indirect network effects for complementors (Eggers, Grajek and Kretschmer, 2012; Gupta, Jain and Sawhney, 1999; Rietveld and Eggers, 2017). 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; Gawer, 2014; Kretschmer and Claussen, 2016; Wareham et al., 2014). Consumers may prefer platforms with relatively high quality complementors, even if there are fewer of them, and so platforms may want to undertake actions to ensure entry by high quality complementors.

There are a range of actions that platforms can take to manage the quality of their complementors, including the use of license fees and 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 new 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 incentives of other complementors (e.g., Gawer and Henderson, 2007; Wen and Zhu, 2017; Zhu and Liu, 2016). For example, when Microsoft decided to enter the video game console business, it developed some of its own games in-house, and also acquired 3rd party developers so as to ensure that enough variety of high quality games were available for end-users. In this example, Microsoft's entry helped to stimulate end-user demand, and this in turn helped to stimulate game developer demand. However, platform owners that enter and directly compete with complementors risk scaring off those same complementors, who fear that the platform will appropriate their innovations. Gawer and Henderson (2007) provide an interesting case study of Intel, which uses various mechanisms—including subsidies and organizational structure—to signal to complementors that it will not appropriate their innovations (see also Wen and Zhu (2017) for a more modern example).

Another action that can be used to maintain complementor quality is the platform's use of selective promotion of complements through certification (Elfenbein et al., 2015; Hui et al., 2016; Rietveld et al., 2017). For example, video game consoles will often promote some games via special releases or other marketing (e.g., PlayStation's "Platinum" rereleases), eBay certifies high quality sellers through its "Top Rated Seller" badging program, and smartphone companies promote some of their apps over others (e.g., Apple promotes a small subset of its apps via App Store features such as "Editor's Pick" and "Apps we love" and Samsung promotes a small subset of its gaming apps via "Exclusive Game Offers"). While sometimes the goals of these promotions are purely financial—for example, the app developer may provide some payment to the platform—in many cases the platform's goal is to help match its end-users to high quality apps and create the perception of a well-rounded portfolio of complements. End-user satisfaction helps drive additional app sales, and leads to upgrades to new generations of the platform (Cennamo, 2016; Kapoor and Agarwal, 2017). Thus, the platform's certification of high-quality complementors is a useful tool to govern the quality of complements, which ultimately is beneficial to the platform's entire ecosystem. All of these activities are attempts by the platform to manage their complementors and orchestrate their markets. While we acknowledge that platforms have many forms of governance mechanisms at their discretion, for our study we focus on the use of certification because it is visible and widely used across different settings.

**Effect of certification on complementor performance**

The literature on quality certification has consistently found a positive effect on performance of certification programs meant to differentiate high quality products from others (Dranove and Jin, 2010). In this context, much attention has been devoted to customers' responses to certification—i.e., demand-side effects of certification. In general, customers appear to respond by purchasing more products 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 signal argument is often made to explain customers' preference for certified firms, and the consequent increase in performance of the latter (e.g., Elfenbein et al., 2015; Hui et al., 2016; Stanton and Thomas, 2016). In line with previous literature, as a baseline hypothesis, we expect a positive effect of certification on a complementor's performance.

> *Hypothesis 1: Those complementors that receive certification will perform better than they would have if they did not receive certification.*

In general, a certification program provides both a quality certification and also specifies a *category* for which the recipient has reached top quality. This is particularly germane when certifiers apply multidimensional schemes not only to distinguish high quality recipients from others, but also to use the certification to identify areas of excellence (e.g., Apple's App Store features for newly released games "New games we love" versus features for games with certain genres "Unbelievably cute"). A certification program, such as the one we will examine in the case of Kiva, is both signaling that the recipient is of highest quality and also groups the recipient into different categories with other recipients that received the same certification. According to the organizational theory literature, customers will apply these categories to set the boundaries of the competition space (Durand and Paolella, 2013; Cattani, Porac and Thomas, 2017; Hsu, Hannan and Kocak, 2009), and organizations competing in the market will make use of these categories to identify their competitive arena (Porac, Thomas and Baden-Fuller, 1989; 2011). Thus, we expect that once the categories have been clearly defined, and a complementor has been assigned to a specific category as a result of receiving a category-specific certification, the complementor will be motivated to align to the category so as to meet customer expectations.

In some cases, complementors have a range of product types that they offer on a platform—which we will 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 projects with different scopes and goals, such as projects aimed at supporting women, implementing innovation, or supporting entrepreneurship. What happens when one type of a complementor's product receives certification but the others do not? We expect that following the assignment of badges or other type of certification to complementors will cause them to increase their identification with the category they have been certified for, and this will lead complementors to reorganize their portfolio of products to align with that category.

*Hypothesis 2: Certification of a complementor causes it to reorient its portfolio to align with the specifications of the certification*

**Heterogeneous effects of certification on complementor behavior**

Our second hypothesis predicts *average* effects of platform certification on complementor reorientation as pertains to the bundle of products offered. However, in practice, one might expect there to be heterogeneity across complementors along a number of dimensions. In order to better understand the sources and effects of this heterogeneity, we focus on a demand-based factor and a supply-based factor that could affect the complementor's response to certification.

We next 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 categories addressed by the certification. As tested in the second hypothesis, the complementor will want to cater to this increase in demand by reorienting its portfolio. However, multiple certifications may have an ambiguous effect as it requires the complementor to reorient its portfolio across several categories (Hannan, 2010; Hsu, 2006; Hsu et al., 2009). Indeed, in the presence of multiple certifications, the complementor will want to increase its focus on all certified categories, hence reducing its reorientation potential. To see how excess of certified categories potentially decreases portfolio reorientation, imagine that, in the limit, certification is provided for each product in the complementor's portfolio. Then the complementor will have no incentive to reorient its portfolio, and will want to keep the portfolio the same over time.[2]

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

[2] 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. We test and find support for this assumption in one of the robustness tests reported in our results section below.

A second limit to reorientation is the degree of the comlementor's specialization—a supply-side factor. That is, complementors vary in the extent to which they pursue specialist versus generalist strategies, as is the case in most industries (Chatain and Zemsky, 2011). Complementors that are specialists likely have a very concentrated portfolio of products; these specialized complementors are taking advantage of deep sectoral knowledge, but at the tradeoff of little diversity. We expect that platform certification of a given category will have a negative effect on portfolio reorientation 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 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 category, thus not having to go as far down the quality distribution compared to specialist complementors. The alternative proposed in hypothesis four is that rational complementors will balance the level of quality provided against the increase in demand, and they will avoid offering low quality products to the detriment of portfolio reorientation.

*Hypothesis 4: The positive effect of certification on 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 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 entrepreneurship, 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, which Kiva refers to as a "Field Partner."[3] MFIs 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—namely, these types of intermediaries help signal to

[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.

lenders about the quality of the borrowers (Stanton and Thomas, 2016). The loan process for MFIs on Kiva is as follows (Bollinger and Yao, 2016): 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 instalments and pay interest to the MFI. Only when borrowers have fully repaid their loans, lenders will receive their money back.

The number of MFIs on Kiva has increased exponentially. 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 in a geographical area is limited, there is competition 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] 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

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

from Agriculture to Wholesale.[5] Previous studies found that lenders are quicker to fund loans in some sectors (e.g., education and health), and slower to fund loans in other sectors (e.g., clothing and transportation) (Heller and Badding, 2012; Ly and Mason, 2012b). Besides these, there also exist systematic 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 scheme that rewards 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 a multidimensional certification scheme 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 a unique focus. The *Entrepreneurial Support* badge, for example, rewards MFIs that offer training and support to help people start, manage and grow their businesses. An internal team at Kiva monitors MFI behavior 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 section 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 particular loan.[7]

Our empirical analysis exploits the introduction of Kiva's social performance badging program. It is likely that the introduction of the badges was largely unanticipated as the certification scheme was announced on the same day as it was implemented. Thus, the certification was arguably exogenous with respect to behavior of MFIs, lender, and borrowers, and is useful to us from a research design point of view as arguably any changes we observe are likely causal. Furthermore, there is variation in terms of how many badges MFIs received, permitting us to identify the effect of badging relative to some baseline category of not getting badged (or receiving fewer or more badges). Finally, the certification scheme allows us to assess whether different badges have different outcomes on MFI behavior.

## DATA AND VARIABLE DEFINITIONS

### 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.[8] For the purpose of this study we collected data on all MFIs with at least one loan posted in every quarter (i.e., three 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 social performance badging program (Q4-2010 – Q3-2011) and sufficient time periods following the

[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] Data on which MFIs received social performance badges was collected by conducting periodic web scrapes of Field Partners' profile pages on Kiva.org. 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.

introduction of the badging program (Q1-2012 – Q4-2013).[9,10] We focus only on those MFIs with at least one loan posted in every time period in order to minimize *ex-ante* heterogeneity between the group of MFIs who eventually receive a social performance badge and those who do not. Minimizing *ex-ante* heterogeneity is important as the empirical design for our results 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 homogenous sample of successful and financially stable MFIs; a number of additional checks described below document that our results are robust to alternate sample refinements.[11] After collapsing the loan-level data into MFI-quarter observations, we arrive at a balanced panel dataset of 70 MFIs who collectively posted 245,998 loans (an average of 270 loans per MFI-quarter) over 13 quarterly time periods (910 observations).[12] We further restrict the sample by removing MFIs who received their first badge at some point after Q4-2011 (we worry about endogenous efforts by these MFIs to be awarded a badge), or who had a badge revoked by Kiva (we worry about bias from any "badge revoking" effects, which is not the theoretical construct we are studying). As a robustness test we estimate our main results on the full sample of MFIs, including those with later badges and those with badges revoked.

[9] We use Q4-2011, the period in which badges were introduced, as the base period for our estimates.

[10] Using a longer post-treatment time period allows us to better explore changes and potential lagged effects of the treatment over time (Autor, 2003). As a robustness test we have estimated results on an expanded sample including seven pre-treatment observations and the results are fully consistent with those reported in our results section.

[11] While our sample of 70 MFIs includes 28% of all MFIs who were active (i.e., at least one loan posted between Q4-2010 and Q4-2013) during our study period, it comprises 66% of all the loans posted by active MFIs.

[12] Over six million lenders made loans to 481,694 borrowers (26 lenders per loan, 2 borrowers per loan) in our sample. The sum of these loans approximates $200 million ($1,280 per loan, $30 per lender, $412 per borrower).

**Dependent variables**

We identify the effects of receiving social performance badges on MFI performance by estimating a series of outcome variables (H1). On the lender side, we measure performance by counting the number of individuals lending money to a MFI. *Lenders* face a choice in terms of which loans to support when they evaluate their options on Kiva and we expect badging to have a positive effect on individuals' lending decisions. The MFI managing a loan is a key decision factor for lenders, and a large part of a loan's page on Kiva is devoted to details about the MFI, including an overview of its badges. Relatedly, we estimate the *amount paid to borrowers* (in USD) by a MFI as another outcome of interest. While we suspect a strong correlation between *lenders* and the *amount paid to borrowers*, we identify the effect on both measures separately as lenders can decide how much money they ultimately want to contribute to a loan (as a robustness test—reported in the appendix—we estimate the *amount paid per lender*). On the borrower side, we estimate the number of individuals requesting loans from a MFI. We expect badged MFIs to receive greater attraction from *borrowers* in their regions as they will enjoy a stronger reputation (e.g., for better loan terms). Furthermore, given the positive effect of certification on lenders, we expect that badged MFIs will exploit the increased supply of lenders willing to make loans by offering bigger loans, from a larger number of borrowers.[13]

To test the effect of badging on complementor portfolio composition (H2-H4), we focus our attention on one of the social performance badges, the *Family and Community Empowerment* (FCE) badge, and a specific outcome, the variable *female borrower ratio* which is the ratio of female borrowers to all borrowers (female and male). We focus on this badge and outcome for

[13] 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 loans funded 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.

three reasons. First, the aim of the FCE badge is unidimensional and clear: it has a strong focus on promoting loans by women borrowers. In a document we 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 (i.e., attract more female borrowers). From internal Kiva documentation we learned that the majority of the other badges aim to reward behavior on more than one dimension. The *Entrepreneurial Support* badge, for example, aims to reward MFIs for promoting business loans *and* 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. For example, Kiva does not provide any information about the extent to which a MFI offers non-financial services support to its borrowers, let alone for specific loans, 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 70 MFIs we note good variation in terms of which MFIs were awarded the FCE badge and which were not. Figure 1 shows that 37 out of 70 MFIs were awarded the FCE badge in Q4-2011, with the remaining 33 MFIs either receiving one (or more) of the other six badges, or no badge at all.

--- INSERT FIGURE 1 ABOUT HERE ---

**Independent variables**

We further predict that the degree to which MFIs adjust their portfolio composition in reaction to receiving a badge is moderated by two factors. The first moderator testing H3, called *non-FCE badge received*, simply indicates whether a MFI received any of the other badges alongside the FCE badge. We expect that for these MFIs the degree of loan portfolio reorientation, as measured by the female borrower ratio, will be less than for those MFIs that exclusively receive the FCE badge. The second moderator testing H4, 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 evenly distributed. (Recall that there are 15 pre-defined sectors on Kiva and that each loan is categorized into one distinct sector.) We expect that MFIs with loan portfolios evenly spread across a larger number of sectors will find it easier to adjust their loan portfolios than those with loan portfolios strongly clustered in one or only a few sectors. We resort to a commonly used statistic for measuring concentration (Besanko et al., 2009), the $CR_4$. Here, the $CR_4$ 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 one or a few sectors, thus being more concentrated, while a lower $CR_4$ means that loans are more diffuse and spread across multiple sectors.[14] In the appendix, we also 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 loans rather than the count.

[14] Note that our sample of 70 MFIs exclusively includes MFIs with large loan portfolios, and we only note a weak negative correlation ($\rho$ = -0.09) between the number of loans posted and sector-level portfolio concentration.

**RESULTS**

We have two sets of results. We first study the effect of badging on portfolio performance measures (H1). We next study the effect of badging on portfolio repositioning (H2), and moderators of this repositioning (H3, H4). For both sets of results, we rely on 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. In the first set of results, the treated MFIs are those who received any badge and the untreated MFIs are those who did not receive a badge. In the second set of results, the treated MFIs are those who received a FCE badge and the untreated MFIs are those who received some other badge, or no badge at all. In both cases, the model takes the following functional form:

$$Y_{it} = \alpha_i + \eta_t + \beta D_{it} + X_{it}\delta + \beta D_{it} * X_{it}\delta + \varepsilon_{it}$$

where $Y_{it}$ are our dependent variables, $\alpha_i$ is a vector of MFI fixed effects, $\eta_t$ is the vector of year-quarter fixed effects, $\beta D_{it}$ is the vector of badging treatments (i.e., *any badge*, *number of badges*, *FCE badge*), $X_{it}\delta$ is a vector of time varying control variables (i.e., *non-FCE badge received*, *portfolio concentration ratio*), which we interact with the treatment dummies to test the moderation effects (H3, H4), and $\varepsilon_{it}$ is the error term. MFI fixed effects control for any unobserved and systematic differences between MFIs in our sample, while quarter-year fixed effects control for macroeconomic and platform-level trends (e.g., growth in registered lenders on Kiva) that affect all MFIs equally. The coefficients of our treatment dummies should be interpreted as the quarterly difference in our dependent variables between treated and control MFIs as a result of getting badged. We estimate robust standard errors clustered at the MFI-level to control for autocorrelation between observations (Bertrand, Duflo and Mullainathan, 2004).

**Summary statistics**

Table 1 provides summary statistics for both estimation samples broken out by treatment and control MFIs. The top panel lists summary statistics for the estimation sample used for testing whether badging has any effect on MFI performance (H1), while the bottom panel lists summary statistics for the estimation sample used for testing whether receiving the FCE badge leads to a reorientation in loan portfolio composition (H2-H4).

--- INSERT TABLE 1 ABOUT HERE ---

The top panel of Table 1 documents mean values for all three performance measures for (eventually-) badged and control-group MFIs. For all measures we observe higher values for (eventually-) badged MFIs. For example, (eventually-) badged MFIs received loans from 7,269 lenders per quarter whereas control-group MFIs received loans from 3,733 lenders per quarter (the quarterly mean difference between these groups of 3,537 lenders is significant at $p = 0.00$).

--- INSERT FIGURES 2-4 ABOUT HERE---

Additionally, in Figures 2 to 4 we document both groups' average performance measures before and after Kiva's introduction of the social performance badges. The figures show that 1) both subsamples had similar pre-treatment trends, though eventually-badged MFIs had higher overall performance even before the introduction of the badging program; 2) badged MFIs enjoy an increase in performance which manifests itself from the first quarter after the introduction of the badges, and this increase appears to uphold throughout our study period; and, 3) for two out of three performance measures (*borrowers, amount paid to borrowers*) we note that the difference in performance is widening over time implying not only a positive effect of getting treated, but also a negative effect of not receiving any badges that increases over time.

The bottom panel of Table 1 further shows that 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 $p = 0.00$). We further note that FCE-badged MFIs had a 9 percentage points higher probability of receiving any of the other social performance badges ($p = 0.10$), but that there are no significant differences in terms of how concentrated MFIs' portfolios were.

**The effect of certification on MFI performance**

In Table 2 we test the effect of receiving any social performance badge on MFI performance. Lending support to our baseline hypothesis (H1), in all models we find that MFIs enjoy a significant boost in performance after they receive any of the social performance badges, compared to MFIs that did not receive any such badges. In Model 1, for example, we find that badged MFIs attract 2,455 additional lenders per quarter compared to un-badged MFIs. Not only is this difference in performance statistically significant ($p = 0.01$), it is also relevant considering the overall average of 7,058 lenders per quarter for the MFIs in our estimation sample. We further find that receiving any social performance badge increases performance also on the borrower-side: In Model 2 we find that badging leads to a quarterly increase of 230 borrowers ($p = 0.00$). In Model 3 we also document that badged MFIs pay out $98,238 more to borrowers compared to MFIs who did not receive any social performance badges ($p = 0.00$).

--- INSERT TABLE 2 ABOUT HERE---

In Models 4-6 we replicate our results, but instead of using a binary treatment measure we estimate the effect of a multi-level treatment variable (Abadie, 2005), namely the *number of badges received*. This alternative operationalization of the treatment allows us to see if there is any effect to receiving multiple badges and whether the returns to badging for MFIs vary with additional badges. In this alternative test we again note support for hypothesis 1, as we find that every additional badge received results in 595 additional lenders per quarter ($p$ = 0.02), 80 additional borrowers per quarter ($p$ = 0.10), and an extra $24,585 paid to borrowers per quarter ($p$ = 0.06). Unreported supplementary analyses suggest that the returns to badging are constant for lenders, while they are increasing for borrowers and the amount paid to borrowers, lending some preliminary support to the existence of *super-additive* returns to certification.

**The effect of certification on loan portfolio composition**

We next focus on the effects of platform certification on complementor portfolio composition and the contingency factors underlying this effect (H2-H4). In Table 3 we test whether MFIs reoriented their loan portfolio compositions following the receipt of the FCE badge. In Model 1 we test the main effect of FCE badging on portfolio composition (i.e., *female borrower ratio*), and in Models 2 and 3, we test whether receiving any of the other social performance badges and the extent of MFI sector-level portfolio concentration moderate the effect of badging on portfolio composition, respectively. In Models 4-12 we impose different lags on our independent variables allowing us to explore the dynamics of the treatment (Autor, 2003).

--- INSERT TABLE 3 ABOUT HERE ---

In Model 1 of Table 3 we find support for the portfolio reorientation hypothesis (H2), as MFIs increased their female borrower ratio by 3 percentage points per quarter as a result of receiving the FCE badge compared to MFIs who did not receive this badge ($p = 0.09$). Model 2 tests whether receiving additional badges alongside the FCE badge moderates the effect on portfolio reorientation (H3). Here, we fail to support H3 as the coefficient for the interaction between FCE badge received and non-FCE badge received is not statistically significant, albeit directionally consistent with the stated hypothesis ($p = 0.13$). 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 (H4). We find support for this hypothesis as the interaction between *FCE badge received* and *portfolio concentration* is negative and significant ($p = 0.00$), 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 15 percentage points more than control-group MFIs, 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 MFIs are unable to change their portfolio composition overnight, 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 trend model (Autor, 2003). The relative time trend 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. We model the relative time trend 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 (Greenwood and Wattal, 2017; Seamans and Zhu, 2013). The omitted category against which our coefficients are estimated is Q4-2011, in which we also group all observations for control-group

MFIs. The results, visualized in Figure 5, show that 1) 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)), and 2) 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 make sense. Portfolio reorientation takes time to implement as MFIs will need to seek out additional women borrowers with interesting projects and good creditworthiness in their region.

--- INSERT FIGURE 5 ABOUT HERE ---

Second, in Models 4-12 of Table 3 we re-estimate our main results by imposing lags of one, two, and three time quarterly periods on our independent variables. While our results are largely consistent with those reported in Models 1-3, we note two differences in these lagged models. First, and consistent with the relative time trend model discussed above and presented in Figure 5, 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 FCE badge on female borrower ratio increases by 5 percentage points when we lag the treatment variable by three time periods ($p$ = 0.01). The second change is that we note strong support for H3 in all lagged models as the interaction between FCE badge and non-FCE badge is negative and significant, implying that MFIs who received additional badges reorient their portfolios less than those MFIs who exclusively received the FCE badge ($p < 0.05$ for models 4-12). Analyzing the marginal effects, we further find 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.

**Falsification, mechanism, and robustness tests**

As reported in the prior subsection, we find strong supporting evidence for all four hypotheses. Across two sets of analyses we find that the introduction of social performance badges results in increased performance on both the lender and the borrower side for certified MFIs. We further find that MFIs who receive the FCE badge reorient their portfolios to include a greater share of female borrowers, fully in line with Kiva's intended consequences for this badge. Lastly, we find that the effect of the FCE badge on portfolio orientation was attenuated for MFIs who received additional badges from Kiva and for those with more concentrated loan portfolios.

There are a number of features of 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 restrict our sample to MFIs with loans posted in every time period to create a balanced sample of MFIs and rule out any bias from MFI attrition or entry. Nevertheless, we also undertake a number of additional robustness tests and falsification exercises to further rule out alternative explanations. We report the results of these additional tests in this section.[15]

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, 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

[15] Results for tests that we do not directly report in the main text are reported in the appendix.

with the number of loans posted at the MFI-quarter level as the outcome variable; we find that the treatments did not lead to an absolute increase in the number of loans posted. These results confirm that badging leads to a *relative increase* in performance as well as a *shift* in the composition of portfolios, across both models. In similar fashion, we estimate our performance models with the *amount paid per lender* as an alternative outcome measure and find that badging leads to an increase of $3.25 paid per lender for loans posted by treated MFIs.

Second, we conduct a number of falsification tests to rule out false positive associations for the portfolio reorientation effect. In Table 4 we estimate the effect of receiving any of the non-FCE badges on female borrower ratio. Since increasing the number of women 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 4 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 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 4 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 that relate to the outcome variable, we conduct two additional tests to validate that the control group MFIs in our sample are indeed a representative counterfactual for our tests. In the first of these tests, for our performance results we create a restricted sample of 10 badged MFIs using the coarsened exact matching (CEM) procedure (Blackwell et al., 2009; Iacus, King and Porro, 2012). CEM allows for matching based on pre-treatment observables and thereby further minimizing *ex-ante* differences between treated and control group observations (Bettis, Gambardella, Helfat and Mitchell, 2014). Minimizing such differences strengthens the causal claim that badging leads to a positive effect on MFI performance. We match based on four criteria as observed in the year prior to the implementation of the badging program: MFI return on assets, whether Kiva had conducted a full due diligence check, MFI age, and whether a MFI was based in Asia, Africa, or outside either of these continents.[16] We then re-estimate our main results and find consistent and significant support (i.e., $p < 0.05$) that badging positively affects all three outcome variables (see Table 5). In the second of these tests, since we observe that FCE-badged MFIs are slightly more likely to also receive any of the other social performance badges compared to MFIs who did not receive the FCE badge (see 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, MFI portfolio concentration ratio, and MFI age using a probit estimator. The results in Table 6 show that the only significant predictor (i.e., $p < 0.10$) of receiving the FCE badge is *female borrower ratio*. Model 2 further shows that female borrower ratio does not predict whether MFIs receive any of the other badges. Combined, these results suggest that the only determinant of receiving the FCE badge is MFIs' prior female borrower ratio and that this factor did not determine receiving any of the other badges. Relatedly, our main results are consistent when we exclude the subsample of MFIs without any of the other badges from our portfolio reorientation estimations.

--- INSERT TABLES 5 AND 6 ABOUT HERE ---

[16] In our sample of 70 MFIs, 27% are based in Africa, 31% in Asia and the remaining 42% in other continents. Note that the multivariate L1 distance between the unmatched and matched samples decreases from 0.78 to 0.30, implying that our matching criteria successfully reduced differences between treatment and control groups.

Fourth, to rule out that support for H4 is driven by measurement error we re-estimate our results with a number of alternative operationalizations of the MFI portfolio concentration measure. Specifically, instead of using the sector-level $CR_4$, we use MFIs' quarterly sector-level Herfindahl-Hirschman Index (HHI) as well as their sector-level Mean Absolute Deviation (MAD). Furthermore, rather than measuring concentration based on loan counts, we also look at loans' dollar value as an alternative way to estimate the three different concentration ratios. Our results are fully consistent when using these alternative, well-established measures.

Fifth, we re-estimate our results with the inclusion of treatment specific time-trends. Treatment specific time-trends are an alternative way of controlling for unobserved heterogeneity in time trends between observations in the control and treatment groups (Besley and Burgess, 2004). Results are fully consistent with the main results presented in the text.

Sixth, we re-estimate results using additional variations in the sample set of MFIs and years. In the first sample variation, we used the full sample of 70 MFIs, including those who were treated in time periods after the introduction of the badging program and those who had any badges revoked during our study period (for which we code accordingly) and find results similar to our main results. In the second sample variation, we run models with an expanded sample that includes three additional pre-treatment time periods. Here, too, our results are 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). 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 competition (Ly and Mason, 2012a), as well as controlling for portfolio concentration ratio in our first set of models estimating the effect on performance. In all these tests our findings are fully consistent with those reported as our main findings, thus lending further support to our hypotheses.

## CONCLUSION

We use a unique dataset of Kiva's microfinance loans to study how a platform's use of certification affects its complementors' performance and behavior. Our setting allows us to use a quasi-exogenous shock—Kiva's unexpected introduction of a MFI certification program in late 2011—to identify the causal effects of certification on complementor performance and portfolio composition. We show that Kiva's adoption of the social performance badging program leads certified MFIs to experience positive performance effects and also leads them to reorient their loan portfolios to align with the dimensions specified by the certification. We further show that these average effects vary across MFIs depending on the number of other certifications the MFIs receive and depending on the pre-existing sector-level concentration of the MFIs' portfolio of loans. 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.

There are a number of limitations to our study. First, we limit our focus to the effect of the platform's governance choices on the platform's 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 certification. The introduction of the 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.

Another limitation is that, while we observe Kiva engaging in platform governance decisions by adding a badging program, and also observe changes on the part of complementors, we do not know Kiva's ultimate objective as pertains to its certification program. We thus cannot speak to whether Kiva's decision was successful from a platform governance point of view. In particular, our findings highlight an interesting tradeoff: we find that more badges lead to improved complementor performance but at the same time lead to less complementor portfolio reorientation. Depending on the "mix" that Kiva wanted to achieve between increasing complementor performance and realigning complementors' loan portfolios, it may have wanted to introduce more or less badges, or be more or less stringent in its award of badges. The lesson from this tradeoff that we observe is that platforms need to think carefully about what they aspire to accomplish and how they allocate their resources accordingly. Future research may want to investigate these tradeoffs in platform governance in greater detail and in other contexts.

These limitation aside, our study contributes to existing platform ecosystem 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 multidimensional badging program, to control its ecosystem (Jacobides, Cennamo and Gawer 2017). Second, we also document important supply-side and demand-side dimensions along which complementors vary, and show that these dimensions drive heterogeneous reactions from complementors in response to the platform's governance mechanisms (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., Pope and

Sydnor 2011; Agrawal et al., 2011), though recent studies of the sharing economy have contributed some cross-national comparisons (e.g., 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 and the potentially misaligned objectives between platforms and complementors. While MFIs on Kiva are profit-driven organizations, Kiva itself is a non-profit organization whose 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 a profit maximizing rationale—from the MFIs' perspective. It may well be that other types of loans are less costly to manage or justify charging higher interest rates, thus better serving the MFIs' objectives. In selecting the platforms to enter, complementors have to be aware of the platform's overall 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., 2017), or whether and which categories the platform may decide to enter and head-on compete with its complementors (Gawer and Henderson, 2007; Wen and Zhu, 2017; Zhu and Liu, 2016). Overall, our study highlights the challenges of market orchestration faced by platforms as they seek to carefully balance the needs of their customers and complementors.

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**Table 1. Descriptive statistics**

| | *Any badge received (n=819)* | | | | *No badge received (n=52)* | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** | **Mean difference** |
| *Lenders* | 7,269.42 | 5,665.19 | 98.00 | 41,072.00 | 3,732.54 | 2,004.16 | 82.00 | 9,260.00 | -3,536.88 [789.10] |
| *Borrowers* | 566.53 | 759.44 | 4.00 | 6,434.00 | 209.06 | 132.07 | 5.00 | 747.00 | -357.48 [105.47] |
| *Amount paid to borrowers* | 228,131 | 204,179 | 2,700 | 1,690,271 | 100,248 | 52,502 | 2,000 | 264,000 | -127,883 [28,388] |
| *Any badge received* | 0.62 | 0.49 | 0.00 | 1.00 | | | | | |
| *Number of badges received* | 2.13 | 1.98 | 0.00 | 6.00 | | | | | |
| | *FCE badge received (n=442)* | | | | *FCE badge not received (n=416)* | | | | |
| **Variable** | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** | **Mean difference** |
| *Female borrower ratio* | 0.80 | 0.22 | 0.18 | 1.00 | 0.65 | 0.23 | 0.07 | 1.00 | -0.15 [0.02] |
| *Non-FCE badge received* | 0.60 | 0.49 | 0.00 | 1.00 | 0.52 | 0.50 | 0.00 | 1.00 | -0.09 [0.03] |
| *Portfolio concentration ratio* | 0.86 | 0.10 | 0.52 | 1.00 | 0.86 | 0.10 | 0.55 | 1.00 | 0.002 [0.007] |
| *FCE badge received* | 0.62 | 0.49 | 0.00 | 1.00 | | | | | |

*Note*. Mean differences [standard errors] are derived from a two-sample t test. Data source: Kiva.org.

**Table 2. The effect of badging on complementor performance (H1)**

| **Model** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| Dependent variable | *Lenders* | *Borrowers* | *Amount paid* | *Lenders* | *Borrowers* | *Amount paid* |
| *Any badge received* | 2,455.70<br>[960.40] | 230.32<br>[72.01] | 98,238.04<br>[26,807.48] | | | |
| *Number of badges received* | | | | 594.59<br>[264.17] | 79.74<br>[47.80] | 24,584.79<br>[12,665.11] |
| Constant | 6,421.19<br>[324.35] | 486.82<br>[31.50] | 200,005.90<br>[10,185.90] | 6,421.19<br>[322.30] | 486.82<br>[32.38] | 200,005.90<br>[10,006.70] |
| Quarter-year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| MFI fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 871 | 871 | 871 | 871 | 871 | 871 |
| MFIs | 67 | 67 | 67 | 67 | 67 | 67 |
| R-squared (within) | 0.21 | 0.12 | 0.20 | 0.22 | 0.15 | 0.22 |

*Note*. Fixed effects OLS panel regressions with heteroscedasticity robust standard errors clustered at the MFI-level.

**Table 3. The effect of badging on complementor portfolio reorientation (H2-H4)**

| **Model** | **1 (no lag)** | **2 (no lag)** | **3 (no lag)** | **4 (lag$_{t+1}$)** | **5 (lag$_{t+1}$)** | **6 (lag$_{t+1}$)** | **7 (lag$_{t+2}$)** | **8 (lag$_{t+2}$)** | **9 (lag$_{t+2}$)** | **10 (lag$_{t+3}$)** | **11 (lag$_{t+3}$)** | **12 (lag$_{t+3}$)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent variable | | | | | | *Female borrower ratio* | | | | | | |
| *FCE badge received* | 0.03 | 0.07 | 0.35 | 0.03 | 0.08 | 0.32 | 0.04 | 0.11 | 0.33 | 0.05 | 0.12 | 0.32 |
| | [0.02] | [0.02] | [0.12] | [0.02] | [0.02] | [0.13] | [0.02] | [0.03] | [0.14] | [0.02] | [0.03] | [0.13] |
| *Non-FCE badge received* | | 0.02 | | | 0.03 | | | 0.03 | | | 0.04 | |
| | | [0.02] | | | [0.02] | | | [0.03] | | | [0.03] | |
| *FCE badge * Non-FCE badge* | | -0.04 | | | -0.06 | | | -0.07 | | | -0.08 | |
| | | [0.02] | | | [0.03] | | | [0.03] | | | [0.04] | |
| *Portfolio concentration ratio* | | | 0.06 | | | -0.05 | | | -0.04 | | | 0.12 |
| | | | [0.12] | | | [0.10] | | | [0.08] | | | [0.08] |
| *FCE badge * Portfolio concentration* | | | -0.37 | | | -0.34 | | | -0.34 | | | -0.32 |
| | | | [0.13] | | | [0.14] | | | [0.15] | | | [0.15] |
| Constant | 0.71 | 0.71 | 0.65 | 0.71 | 0.71 | 0.75 | 0.71 | 0.71 | 0.67 | 0.71 | 0.71 | 0.60 |
| | [0.01] | [0.01] | [0.10] | [0.01] | [0.01] | [0.09] | [0.01] | [0.01] | [0.07] | [0.01] | [0.01] | [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.

**Table 4. Falsification tests for portfolio reorientation**

| **Model** | **1 (no lag)** | **2 ($lag_{t+1}$)** | **3 ($lag_{t+2}$)** | **4 ($lag_{t+3}$)** | **5 (no lag)** | **6 ($lag_{t+1}$)** | **7 ($lag_{t+2}$)** | **8 ($lag_{t+3}$)** |
|---|---|---|---|---|---|---|---|---|
| Dependent variable | *female borrower ratio* | | | | | | | |
| *Non-FCE badge received* | 0.04<br>[0.04] | 0.05<br>[0.03] | 0.001<br>[0.02] | 0.01<br>[0.02] | | | | |
| *No badge received* | | | | | -0.04<br>[0.03] | -0.05<br>[0.03] | -0.05<br>[0.04] | -0.07<br>[0.04] |
| Constant | 0.70<br>[0.01] | 0.70<br>[0.01] | 0.70<br>[0.01] | 0.70<br>[0.01] | 0.71<br>[0.01] | 0.71<br>[0.01] | 0.71<br>[0.01] | 0.71<br>[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.

**Table 5. Coarsened exact match of badging on complementor performance**

| **Model** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| Dependent variable | *Lenders* | *Borrowers* | *Amount paid* | *Lenders* | *Borrowers* | *Amount paid* |
| *Any badge received* | 2,588.67<br>[1,063.42] | 93.90<br>[40.30] | 74,525.89<br>[33,867.50] | | | |
| *Number of badges received* | | | | 637.66<br>[239.18] | 39.66<br>[12.99] | 17,007.40<br>[7,404.49] |
| Constant | 6,920.87<br>[662.56] | 335.93<br>[39.39] | 216,123.30<br>[22,467.52] | 6,920.87<br>[671.86] | 335.93<br>[37.32] | 216,123.30<br>[22,615.95] |
| Quarter-year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| MFI fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 195 | 195 | 195 | 195 | 195 | 195 |
| MFIs | 15 | 15 | 15 | 15 | 15 | 15 |
| R-squared (within) | 0.17 | 0.09 | 0.16 | 0.17 | 0.12 | 0.16 |

*Note.* Fixed effects OLS panel regressions with heteroscedasticity robust standard errors clustered at the MFI-level Restricted estimation sample based on coarsened exact matching procedure.

**Table 6. Determinants of badging**

| **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.

**Figure 1. Distribution of social performance badges for estimation sample**

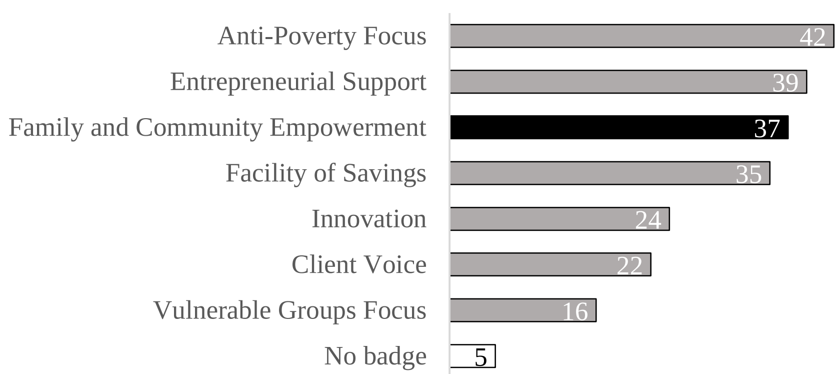



**Figure 2. Average effects of badging on number of lenders**

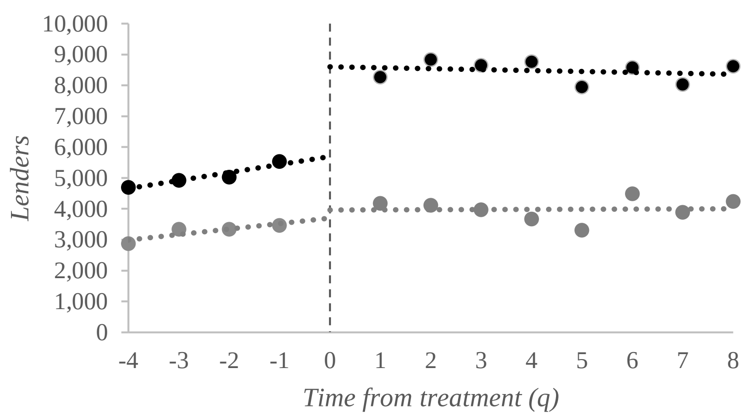


**Figure 3. Average effects of badging on number of borrowers**

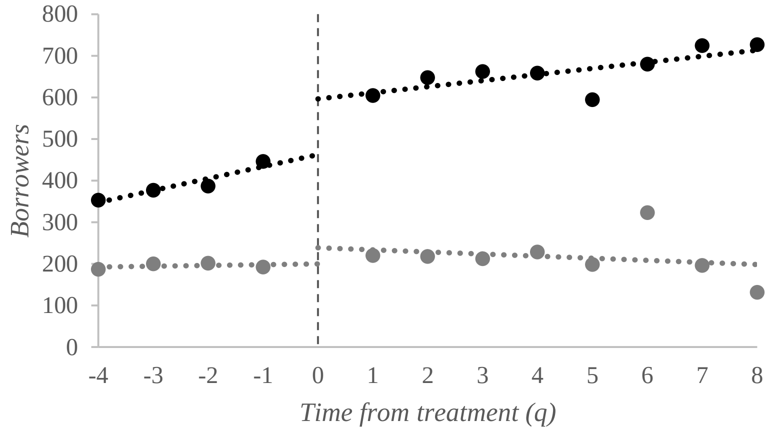



**Figure 4. Average effects of badging on amount paid to borrowers**

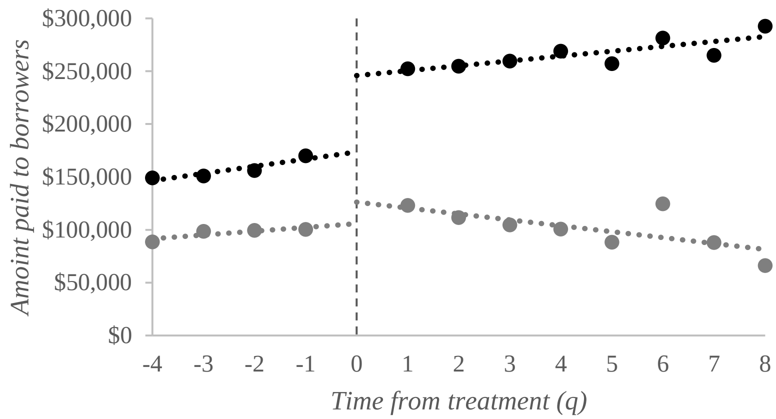
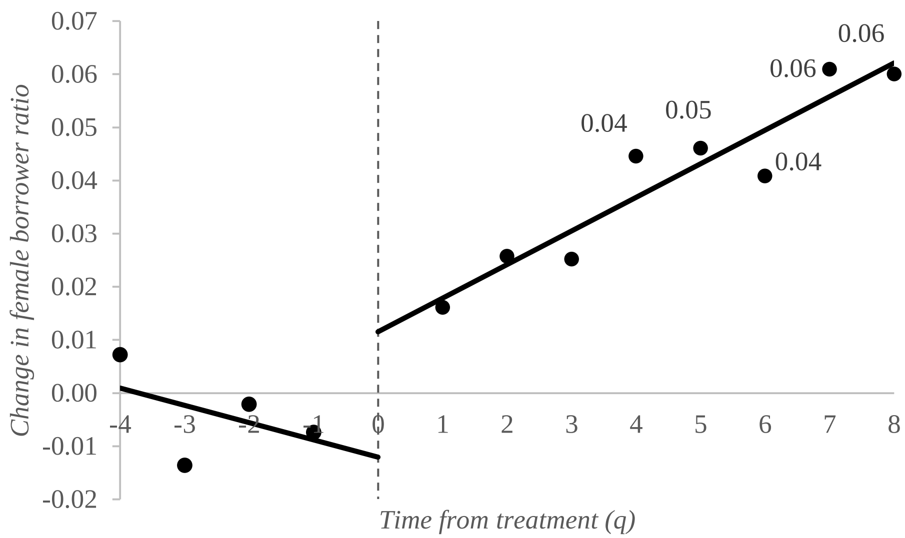



**Figure 5. Effect of badging on portfolio reorientation over time**[17]




[17] Effect sizes only shown for coefficients with p-values below 0.05.

## APPENDIX: FALSIFICATION, MECHANISM AND ROBUSTNESS TESTS

### Table A1. The effect of various treatments on the number of loans posted

| **Model** | **1** | **2** | **3** |
|---|---|---|---|
| Dependent variable | *Number of loans* | | |
| *Any badge received* | 56.37<br>[67.22] | | |
| *Number of badges received* | | 29.32<br>[16.76] | |
| *FCE badge received* | | | 44.05<br>[54.27] |
| Constant | 250.25<br>[14.84] | 250.25<br>[14.74] | 233.59<br>[14.50] |
| Quarter-year fixed effects | Yes | Yes | Yes |
| MFI fixed effects | Yes | Yes | Yes |
| Observations | 871 | 871 | 858 |
| MFIs | 67 | 67 | 66 |
| R-squared (within) | 0.11 | 0.12 | 0.11 |

*Note.* Mechanism tests estimating the effect of various treatments on the number of loans posted by MFIs per quarter.

### Table A2. The effect of badging on the amount paid per lender

| **Model** | **1** | **2** |
|---|---|---|
| Dependent variable | *Amount paid per lender* | |
| *Any badge received* | 3.25<br>[0.91] | |
| *Number of badges received* | | 0.14<br>[0.45] |
| Constant | 30.44<br>[0.37] | 30.44<br>[0.37] |
| Quarter-year fixed effects | Yes | Yes |
| MFI fixed effects | Yes | Yes |
| Observations | 871 | 871 |
| MFIs | 67 | 67 |
| R-squared (within) | 0.08 | 0.07 |

*Note.* Robustness tests estimating the effect of badging on the amount paid per lender.

**Table A3. The moderating effect of alternative measures for portfolio concentration**

| **Model** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Dependent variable | | | *Female borrower ratio* | | |
| *FCE badge received* | 0.37<br>[0.13] | 0.25<br>[0.08] | 0.24<br>[0.09] | 0.08<br>[0.04] | 0.07<br>[0.03] |
| *Portfolio concentration ratio* | 0.09<br>[0.13] | 0.41<br>[1.19] | 0.26<br>[1.10] | -0.04<br>[0.12] | -0.03<br>[0.11] |
| *FCE badge * portfolio concentration* | -0.39<br>[0.14] | -2.67<br>[0.91] | -2.56<br>[0.94] | -0.16<br>[0.09] | -0.14<br>[0.08] |
| Constant | 0.63<br>[0.11] | 0.67<br>[0.10] | 0.69<br>[0.09] | 0.72<br>[0.04] | 0.72<br>[0.04] |
| 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 | 0.08 | 0.08 |

*Note*. Robustness tests estimating the effects of alternative measures for *portfolio concentration ratio*
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.

**Table A4. Main results estimated with the inclusion of treatment specific time trends**

| **Model** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| Dependent variable | *Lenders* | *Borrowers* | *Amount paid* | *Female borrower ratio* | | |
| *Any badge received* | 1,424.10<br>[1,385.15] | 297.31<br>[112.62] | 128,514.30<br>[42,775.81] | | | |
| *FCE badge received* | | | | 0.03<br>[0.03] | 0.06<br>[0.03] | 0.35<br>[0.12] |
| *Non-FCE badge received* | | | | | 0.02<br>[0.02] | |
| *FCE badge * Non-FCE badge* | | | | | -0.04<br>[0.02] | |
| *Portfolio concentration ratio* | | | | | | 0.08<br>[0.11] |
| *FCE badge * Portfolio concentration* | | | | | | -0.38<br>[0.13] |
| Constant | 6,421.19<br>[325.28] | 486.82<br>[31.62] | 200,005.90<br>[10,211.92] | 0.71<br>[0.01] | 0.71<br>[0.01] | 0.64<br>[0.10] |
| Quarter-year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter-year-treated fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| MFI fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 871 | 871 | 871 | 858 | 858 | 858 |
| MFIs | 67 | 67 | 67 | 66 | 66 | 66 |
| R-squared (within) | 0.21 | 0.13 | 0.20 | 0.09 | 0.09 | 0.13 |

*Note*. Re-estimation of main effects with the inclusion of treatment specific fixed effects. The main effect of *FCE badge received* in Model 4 attains statistical significance with lags of two quarterly time periods or more.

**Table A5. Main results estimated with the full estimation sample of 70 MFIs**

| **Model** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| Dependent variable | *Lenders* | *Borrowers* | *Amount paid* | *Female borrower ratio* | | |
| *Any badge received* | 2,241.53<br>[679.74] | 194.92<br>[58.22] | 83,568.96<br>[21,323.05] | | | |
| *FCE badge received* | | | | 0.04<br>[0.02] | 0.07<br>[0.02] | 0.31<br>[0.11] |
| *Non-FCE badge received* | | | | | 0.02<br>[0.02] | |
| *FCE badge * Non-FCE badge* | | | | | -0.03<br>[0.02] | |
| *Portfolio concentration ratio* | | | | | | 0.05<br>[0.11] |
| *FCE badge * Portfolio concentration* | | | | | | -0.32<br>[0.12] |
| Constant | 6,385.16<br>[311.10] | 474.11<br>[30.11] | 198,682.50<br>[9,751.71] | 0.71<br>[0.01] | 0.71<br>[0.01] | 0.66<br>[0.10] |
| 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) | 0.20 | 0.12 | 0.19 | 0.07 | 0.07 | 0.10 |

*Note*. Re-estimation of main effects with the inclusion of MFIs who either get badged after the introduction of the badging program or have one of their badges revoked (coded as such). The moderation effect of *non-FCE badged received* in Model 5 attains statistical significance with one period lag or more.

**Table A6. Main results estimated with three additional pre-treatment time periods**

| **Model** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| Dependent variable | *Lenders* | *Borrowers* | *Amount paid* | *Female borrower ratio* | | |
| *Any badge received* | 2,783.71<br>[1,110.33] | 264.82<br>[82.58] | 109,170.50<br>[29,722.90] | | | |
| *FCE badge received* | | | | 0.03<br>[0.02] | 0.06<br>[0.01] | 0.35<br>[0.12] |
| *Non-FCE badge received* | | | | | 0.01<br>[0.02] | |
| *FCE badge * Non-FCE badge* | | | | | -0.02<br>[0.02] | |
| *Portfolio concentration ratio* | | | | | | 0.07<br>[0.10] |
| *FCE badge * Portfolio concentration* | | | | | | -0.37<br>[0.13] |
| Constant | 6,421.19<br>[309.81] | 486.82<br>[31.35] | 200,005.90<br>[9,452.99] | 0.71<br>[0.01] | 0.71<br>[0.01] | 0.65<br>[0.10] |
| Quarter-year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| MFI fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,072 | 1,072 | 1,072 | 1,056 | 1,056 | 1,056 |
| MFIs | 67 | 67 | 67 | 66 | 66 | 66 |
| R-squared (within) | 0.28 | 0.15 | 0.25 | 0.05 | 0.05 | 0.09 |

*Note.* Re-estimation of main effects with the inclusion of three additional pre-treatment time periods (Q1-2010 - Q3-2010). The main effect of *FCE badged received* in Model 4 is significant at $p < 0.10$ and the moderation effect of *non-FCE badged received* in Model 5 attains statistical significance with a one period lag or more.

**Table A7. Main results estimated using fixed effects regression with AR(1) disturbances**

| **Model** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| Dependent variable | *Lenders* | *Borrowers* | *Amount paid* | *Female borrower ratio* | | |
| *Any badge received* | 1,999.31<br>[348.32] | 110.90<br>[36.14] | 55,580.90<br>[11,318.05] | | | |
| *FCE badge received* | | | | 0.04<br>[0.01] | 0.03<br>[0.05] | 0.23<br>[0.07] |
| *Non-FCE badge received* | | | | | 0.005<br>[0.01] | |
| *FCE badge * Non-FCE badge* | | | | | 0.0005<br>[0.05] | |
| *Portfolio concentration ratio* | | | | | | 0.09<br>[0.06] |
| *FCE badge * Portfolio concentration* | | | | | | -0.22<br>[0.08] |
| Constant | 6,228.64<br>[143.02] | 536.40<br>[12.99] | 204,420.00<br>[4,256.24] | 0.72<br>[0.004] | 0.71<br>[0.004] | 0.64<br>[0.03] |
| MFI fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 804 | 804 | 804 | 792 | 792 | 792 |
| MFIs | 67 | 67 | 67 | 66 | 66 | 66 |
| R-squared (within) | 0.04 | 0.01 | 0.03 | 0.02 | 0.02 | 0.03 |

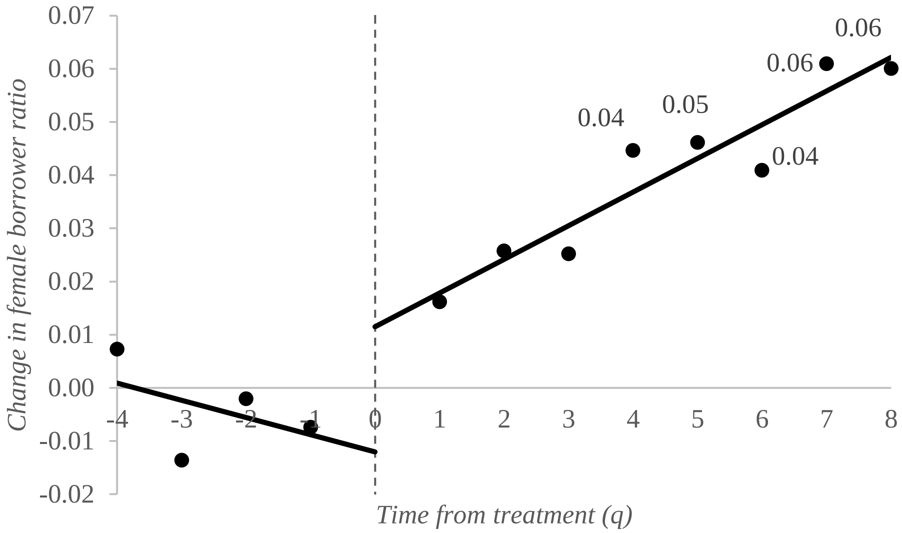
*Note*. Re-estimation of main effects using fixed effects regression with AR(1) disturbances. The moderation effect of *non-FCE badged received* in Model 5 attains statistical significance with a one period lag or more.

**Table A8. Main results estimated with the inclusion of additional control variables**

| **Model** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| Dependent variable | *Lenders* | *Borrowers* | *Amount paid* | | *Female borrower ratio* | |
| *Any badge received* | 2,255.23<br>[894.63] | 256.13<br>[92.77] | 98,118.26<br>[28,810.34] | | | |
| *FCE badge received* | | | | 0.03<br>[0.02] | 0.07<br>[0.02] | 0.35<br>[0.12] |
| *Non-FCE badge received* | | | | | 0.02<br>[0.02] | |
| *FCE badge * Non-FCE badge* | | | | | -0.04<br>[0.02] | |
| *Portfolio concentration ratio* | -3,824.51<br>[3,460.76] | 482.16<br>[416.06] | -2,983.57<br>[5,398.54] | | | 0.06<br>[0.12] |
| *FCE badge * Portfolio concentration* | | | | | | -0.36<br>[0.13] |
| *Within country competition* | 46.73<br>[164.57] | -15.78<br>[17.48] | -5,477.73<br>[113,702.80] | 0.004<br>[0.002] | 0.004<br>[0.002] | 0.003<br>[0.002] |
| Constant | 9,595.82<br>[2,933.51] | 114.20<br>[347.317] | 213,067.00<br>[95,982.96] | 0.70<br>[0.01] | 0.70<br>[0.01] | 0.65<br>[0.10] |
| Quarter-year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| MFI fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 871 | 871 | 871 | 858 | 858 | 858 |
| MFIs | 67 | 67 | 67 | 66 | 66 | 66 |
| R-squared (within) | 0.21 | 0.13 | 0.20 | 0.07 | 0.07 | 0.10 |

*Note*. Re-estimation of main effects with the inclusion of controls. Within country competition measures the number of active MFIs (at least one loan posted in focal time period) located in the same country as focal MFI. The moderation effect of *non-FCE badged received* in Model 5 attains statistical significance with a one period lag or more.

**Figure A1. Relative time trend results on portfolio reorientation on restricted sample of badged-only MFIs**[18]




[18] *Note*. Effect sizes only shown for coefficients with p-values below 0.05.