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Diffusion of Mobile Banking among Rural Women

INCENTIVIZING LOCAL LEADERS VS. A MARKETING CAMPAIGN

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Abstract

Although mobile banking is seen as a solution to limited access to banking and financial services in the developing world, its adoption rates–especially among women–fall well below expectations. Hence, how can we promote its adoption among the socially and economically disadvantaged? We compare the effectiveness of two strategies, seeded diffusion via incentivised local leaders and a traditional marketing campaign, to promote the adoption of mobile banking among poor women in rural Peru. For the first one, we exploit the existence of local leaders who were trained by a local firm to promote the diffusion of a mobile banking application. For the second, we take advantage of an on-going regional marketing campaign. Our findings show that the personalized seeded diffusion via local leaders is an effective promotion strategy. It significantly outperforms the traditional campaign, during which adoption rates are statistically indistinguishable from zero and similar to those in our control areas. We additionally show that the seeded incentivised diffusion relies on features of the underlying community networks known to promote trust. Our results emphasize the necessity of personalized approaches to promote technological products such a mobile banking among vulnerable populations.

Keywords: mobile banking, field/natural experiments, network diffusion, marketing campaign, gender, innovation, word-of-mouth communication.

JEL Codes: C93, D85, G21, O10, O33.

Resumen

Aunque la banca móvil se considera una solución al acceso limitado a servicios bancarios y financieros en el mundo en desarrollo, sus tasas de adopción, especialmente entre las mujeres, están muy por debajo de las expectativas. Por lo tanto, ¿cómo podemos promover su adopción entre las personas social y económicamente desfavorecidas? En este artículo, comparamos la efectividad de dos estrategias: la difusión incentivada a través de líderes locales y una campaña de marketing tradicional, para promover la adopción de la banca móvil entre mujeres pobres en zonas rurales de Perú. Para la primera, aprovechamos la existencia de líderes locales capacitados por una empresa local para promover la difusión de una aplicación de banca móvil. Para la segunda, aprovechamos una campaña de marketing regional en curso. Nuestros resultados muestran que la difusión personalizada a través de líderes locales incentivados es una estrategia de promoción efectiva. Supera significativamente a la campaña tradicional, durante la cual las tasas de adopción son estadísticamente indistinguibles de cero y similares a las observadas en las áreas utilizadas como grupo control. Además, demostramos que la difusión incentivada se basa en características de las redes comunitarias subyacentes que promueven la confianza. Nuestros resultados subrayan la necesidad de enfoques personalizados para promover tecnologías como la banca móvil entre poblaciones vulnerables.

Palabras claves: Banca móvil, experimentos de campo, experimentos naturales, difusión en redes, campaña de marketing, género, innovación, comunicación de boca en boca.

Códigos JEL: C93, D85, G21, O10, O33.

Diffusion of mobile banking among rural women: Incentivizing local leaders vs. a marketing campaign*

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Abstract

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1 Introduction

Limited access to banking and financial services prevents many individuals in the developing world from improving their production and employment prospects, and therefore their chances to exit poverty (Aghion and Bolton, 1997; Banerjee et al., 2013).

The existing evidence confirms that access to banking may indeed reduce poverty (Burgess and Pande, 2005; Dupas and Robinson, 2013). However, only slightly more than 50% of adults in developing countries report having a bank account, this fraction being considerably lower for women (World Bank, 2014). Since the vast majority of people in developing countries currently live in areas with mobile phone coverage and have access to mobile phones, and the costs of owning and using a mobile phone are steadily decreasing (see e.g. Aker and Mbiti 2010 or Fabregas et al. 2019), mobile banking (m-banking, henceforth) offers a unique opportunity to provide access to formal credit and saving opportunities to the "unbanked" population. Due to its wide accessibility, m-banking might additionally alleviate the concerns that traditional banking opportunities and formal credit might be susceptible to elite capture (La Porta et al., 2002; Sapienza, 2004). Consequently, the benefits from m-banking seem to be particularly dramatic for the socially and economically disadvantaged (World Bank, 2018).

Despite these considerations, the adoption rates of m-banking lag significantly behind the number of mobile phone users and the expectations generated (Donner and Tellez, 2008). The reason may be that the adoption of m-banking–unlike instant messaging services–faces different challenges such as lack of information, trust, self-efficacy beliefs, social norms, and certain social risks (Donner and Tellez, 2008; Mobarak and Saldanha, 2022).[1] Although women have been recognized as the driving force of economic development in many areas around the Globe (Duflo, 2012) and the positive impact of (m-)banking is particularly pronounced for women (Suri and Jack, 2016; Dupas and Robinson, 2013), m-banking adoption rates among women remain particularly low (Karjaluoto et al., 2010). Naturally, women may face different barriers ranging from higher aversion to risks, literacy issues, poorer access to information, and family roles. Nevertheless, the access to m-banking may provide women with more autonomy and control over household finances. Therefore, the existing gender gap in the access to banking services may not only deepen gender inequality that is particularly large in developing countries, but also limits the economic development and growth in these areas. As a result, the adoption, diffusion, and use of m-banking among women in the developing world should be a priority for economic development, as well as for the promotion of women rights. Moreover, m-banking provides safe and affordable options to vulnerable populations to store, send and receive money.

[1] Brown et al. (2003) find that high levels of perceived risk prevents people to take-up m-banking in South Africa.

In this paper, we compare the effectiveness of two promotion strategies, seeded diffusion via incentivised local leaders and a traditional marketing campaign, in spreading the adoption of m-banking among poor women in rural Peru. Network theory and experimental evidence advocate for the former approach (Banerjee et al., 2013, 2019; Beaman et al., 2021). However, if information is frictionless and the low adoption is solely due to lack of information, more widespread broadcasting might be more beneficial. In practice, both seeded diffusion strategies and traditional marketing campaigns are widely employed (Banerjee et al., 2024). When promoting mobile banking, participants require a certain level of trust in the technology and the institutions backing their money. Hence, both information frictions and lack of trust may explain the low adoption rates of certain technologies. Additionally, differing gender roles might introduce other frictions for women. Our study set-up allows us to analyze the effectiveness of these two promotion strategies in diffusing m-banking and other products that carry similar social and non-social risks among women.

To address these aims, we have designed a protocol exhibiting features of both a field study and natural experiment. Before the actual behavioral intervention, we conducted a baseline survey to a sample of women who where at that time beneficiaries of the conditional cash transfer program *JUNTOS* living in the geographical region of Piura, Peru. The survey consisted of a questionnaire that collected data on standard socio-economic and demographic characteristics and subjects' social networks. We then divided the sample into two treatment areas and three control areas. Sample sizes are approximately 1,000 women per treatment and control group. Consequently, we evaluate in three stages the impact of both the incentivised local leader intervention (seeded diffusion) and the traditional marketing campaign in the communities where our study took place. As part of the seeded diffusion strategy, we exploited the existence of local leaders (know as mother leaders) selected by *JUNTOS* beneficiaries. These leaders were trained by a local firm to promote the diffusion of a m-banking application (app, hereafter) in their communities. This app enables people to manipulate their banking accounts and transfer funds to other m-banking users. After the training sessions, we monitored how many community members were enrolled by the leaders. Once this first stage was completed, the firm managing the major Peruvian m-banking application launched a region-level marketing campaign. The authors had no control over its implementation and timing. The campaign was spread across the whole region of Piura. This campaign represents a natural experiment that happened after the first stage of the seeded diffusion strategy. Last, to make sure that potentially low adoptions during the campaign were not due to market saturation, we relaunched the seeded diffusion once the marketing campaign has finished. In all three stages, we monitored adoption rates in both treatment and control areas using administrative data.

Our main findings show that take-up rates during the first stage of our study are much higher than during the subsequent marketing campaign. When comparing control and treatment areas during the implementation of the traditional campaign, we find no statistical differences between them. However, as the campaign ends and our intervention is relaunched, adoption increases again by 50% compared to both the traditional campaign and the control group. Although these differences are not significant, the seeded diffusion strategy largely outperforms the traditional marketing campaign. According to our data, the traditional marketing campaign was ineffective in promoting m-banking: the difference in adoption rates between treatment and control areas is not statistically significant during the traditional marketing campaign.

Using the data from the baseline survey, we further analyze the determinants of adoption. As expected, the take-up probability is more pronounced for younger, richer, and more educated people, but the success of the seeded diffusion to a large extent can be attributed to the social processes taking place on the social network in the communities. More precisely, the network distance to local leaders and having many treated (i.e., informed) friends are major determinants of adoption. Last, centrality in the network is unrelated to adoption, but we find an important role of the clustering coefficient: women in more clustered neighborhoods are more likely to affiliate for m-banking. Therefore, the density of relationship plays a crucial role in the diffusion process of m-banking, which is complementary to that of network distances.

These results have important practical implications for policymakers, practitioners, and technology-based firms. Our findings underscore the pivotal role of personalized approaches in promoting technologies that involve inherent social and non-social risks, and require trust, such as m-banking, as well as new agricultural technologies or medical products. Leveraging underlying social networks proves to be a cost-effective and efficient strategy for technology diffusion and related products, surpassing impersonal promotion strategies. In the presence of local leaders chosen by their respective communities, such leveraging can be attained without the need to collect network data. Importantly, our results indicate that these strategies may be effective for women.

Our study contributes to the literature on diffusion and social networks, as well as to development economics research focused on the promoting new technologies among impoverished populations. Numerous studies highlight the crucial role of social networks, their structure, and information diffusion in promoting various technologies, products, and services. Some of these studies explore how social networks can be leveraged. Examples include Foster and Rosenzweig (1995); Conley and Udry (2010); Banerjee et al. (2013, 2019); Alatas et al. (2016), or Beaman et al. (2021); see Breza (2016) or Breza et al. (2019).

Two studies closely related to ours are Banerjee et al. (2024) and BenYishay and Mobarak (2019). In the former, the authors assess the effectiveness of seeded diffusion compared to a broader broadcasting campaign during the 2016 demonetization in India, reporting that widespread broadcasting is less effective than seeded diffusion. Their emphasis is different from ours, focusing on incentives for social learning and information aggregation. In contrast, our primary interest lies in the adoption of a product requiring both information diffusion and trust. Additionally, they explore a situation where inaction incurs costs, while our study operates in a context where the *status quo* carries no negative welfare consequences. As for BenYishay and Mobarak (2019), they examine the effectiveness of incentivizing various local leaders to promote the adoption of an agricultural technology in Malawi. Notably, control areas in both our study and BenYishay and

Mobarak (2019) exhibit minimal adoption,[2] contrasting with significant adoption rates in our treated areas with locally-selected leaders and BenYishay and Mobarak (2019)'s groups, where leaders share the group identity with the target population. Our study shares similarities with Banerjee et al. (2024) and BenYishay and Mobarak (2019), comparing the efficacy of seeded diffusion using incentivized local leaders who share identity with the target population versus widespread broadcasting to promote the adoption of an innovation. However, our focus differs as we concentrate on the adoption of a financial technology, targeting low-income women.

While our findings align with existing literature, we contribute in two key ways. First, despite the acknowledged importance of women in development, the gender dimension in technology adoption has received limited attention, with Beaman and Dillon (2018) as an exception. Second, we underscore the complementary role of the clustering coefficient in enhancing diffusion processes. Although few theoretical papers acknowledge the role of clustering in network diffusion (e.g., Campbell, 2013; Ruiz-Palazuelos et al., 2023), Centola (2010) and our study provide rare empirical evidence. While Centola (2010) establishes causality from network structure to adoption, he cannot separate the effect of clustering from that of distance. We rather provide correlational evidence, demonstrating the clustering coefficient's impact beyond network distances. We hypothesize that, for products like m-banking, requiring trust and entailing risks, transitive triples and non-redundant paths in denser neighborhoods facilitate information flow, aligning with the notion that denser neighborhoods foster trust and cooperative environments (Coleman, 1988; Putnam, 2000).

The remainder of this paper is structured as follows. The next section introduces the study design. Section 3 presents the results and Section 4 concludes. The Appendix contains more detailed and additional information regarding the study design and the results.

2 Study design

2.1 Background

Although Peru has been considered a suitable target for the inclusion of microfinance programs, it exhibits the lowest rates of financial inclusion in Latin America with only 57% of adults having a bank account (World Bank, 2014; Demirgüç-Kunt et al., 2022). This exclusion affects mainly the most vulnerable groups such as women and poor populations, who would particularly benefit from technological innovations such as m-banking (World Bank, 2018).

This study was part of an initiative starting in February 2016, seeking to promote financial inclusion in Peru. The initiative was carried out in cooperation with several commercial banks and other financial entities, telecom corporations, and–most importantly for us–the state-run program *JUNTOS*. The *Programa Nacional de Apoyo Directo a los más Pobres – JUNTOS* (*JUNTOS*, throughout the paper) is a Peruvian conditional

[2] Banerjee et al. (2024) lack a pure control group to contrast with the treatment groups.

cash transfer program which is part of the national initiative of the Peruvian government to eradicate poverty by promoting social policies, social inclusion, and local development. The program was founded in 2005 and its objectives, financing sources, and structure are regulated by law.[3] An important part of the policy of *JUNTOS* is to provide incentives to access health services, nutrition, and education through active participation and surveillance of community leaders. The beneficiaries of *JUNTOS* are selected at the household level (rather than the region or community level), seeking to particularly target people under the poverty line. Since *JUNTOS* promotes human capital investment through larger access to health services and education for children, women are commonly targeted by its policies due to their key role in child development. The targeted women typically live in low-security areas with little access to formal banking. As a result, the promotion of m-banking is one of the priorities of *JUNTOS*. More precisely, *JUNTOS* promotes the mobile-phone application BIM (digital wallet) developed and managed by *Pagos Digitales Perú* (PDP), a private firm founded by a large number of financial institutions, telecommunication firms, and other entities with the objective to create and promote the unified platform BIM for m-banking in Peru. BIM is relatively simple, secure, and cheap. It works on both feature and smart phones (an important attribute at the time of our study and given the economic situation of the targeted population), and it provides more privacy to social program beneficiaries compared to standard means of money manipulation. BIM does not require users to have a bank account. To create a BIM account, users need to introduce their ID number. If they want to receive a money transfer, they do not need an account. And to deposit cash in their digital wallet, they can do it by visiting one of the correspondent BIM agents.[4]

By using BIM, individuals can avoid carrying cash and visiting a bank in person. Moreover, they can manage their banking accounts and transfer funds. Currently, many banks and local stores in Peru accept payments through BIM in Peru. However, 77% of transactions in Peru were still conducted in cash during our interventions.[5]

2.2 Mother Leaders

An important feature of *JUNTOS* is that they have developed a network of collaborators throughout the whole country. In particular, the beneficiaries are organized around *madres líderes* (mother leaders in English; MLs or leaders, throughout the paper) who serve as the conduit of interactions between the beneficiaries and *JUNTOS*. These leaders voluntarily contribute to train program beneficiaries on health- and education-related matters, disseminate the objectives of the program, and motivate beneficiaries to comply with their co-responsibilities as JUNTOS beneficiaries.[6] They also address doubts of

[3] More details can be found on the webpages of Juntos: `https://www.gob.pe/juntos`.

[4] For more information about how BIM operates, visit `https://www.bbvaresearch.com/wp-content/uploads/2016/03/DEO_Mar16_Cap3.pdf`.

[5] See further details about BIM and cash usage in `https://mibim.pe/tu-billetera-movil/que-es-bim/`.

[6] As with other conditional cash transfer programs, *JUNTOS* encourages a co-responsibility between the beneficiary and the government where monthly payments are conditional on the compliance of regular

program beneficiaries and incentivise them to be involved in entrepreneurial initiatives. MLs also guide beneficiaries about how to withdraw their cash transfer from the bank, as well as inform them when their deposits are ready to be withdrawn. When deposits are suspended, MLs also inform beneficiaries about the reasons why this may have happened.[7]

MLs are, on average, 37 years old with a minimum level of education ranging from complete primary to secondary school. They primarily devote their time to domestic chores but have some previous leadership experience (Pereyra Zaplana, 2015). In our study, the sample of MLs show similar characteristics (i.e., they are, on average, 38.6 years old where 24% has primary education, 67% secondary and 9.5% higher education). The maximum time they can exercise as MLs is two years. According to a qualitative analysis described by Pereyra Zaplana (2015), some of the main attributes of MLs are good communication skills, cooperation, proactivity, sociability, responsibility, and motivation.

Because of the multiple responsibilities of MLs and because they serve as the intermediary between the local representative of the social program and the beneficiaries, these local leaders are suitable for disseminating information about banking-related matters, and therefore being seeds of the diffusion process. In addition, Figure A1 in the Appendix shows that the leaders are more central in the community networks under study, both locally and globally, regardless of the centrality measure used. Therefore, their centrality in the networks, the nature of their responsibilities, and the high level of trust beneficiaries have in them provide these leaders with access to many people who trust their advice, making them suitable seeds of diffusion for our intervention.

2.3 Intervention and Data Collection

The intervention took place in Catacaos in the proximity of Piura, the capital of the Piura province in the north-west of Peru. The Catacaos district has a population of 72,863 inhabitants, the fourth largest population in the Piura province (INEI, 2009). The Peruvian National Institute of Statistics and Informatics (INEI for its acronym in Spanish) estimated that in 2013, approximately 47% of the population in Catacaos lived below the poverty line, significantly higher than the average 35% in the Piura region. During the implementation of this study, Catacaos comprised 6,301 beneficiaries of *JUNTOS*, distributed in around 30 *caseríos*. In Peru, a *caserío* refers to a concentrated population of between 151 and 1,000 inhabitants, living permanently in partially dispersed locations, having at least one functioning educational center and a multi-purpose community center.[8] For our intervention, we selected the *caseríos* Catacaos, Monte Sullón, La Legua, Nuevo Catacaos, and Simbilá for the following reasons. In these areas, over 50% of the households are beneficiaries of *JUNTOS*, indicating that these five *caseríos* are particularly deprived. However, compared to other areas, there is a large ownership of mobile phones in these *caseríos*, which is a technological requirement for affiliation with BIM. Additionally, there

health check-ups and schooling attendance of children and adolescents who are enrolled in the program.

[7] For more information on the responsibilities of MLs, see Pereyra Zaplana (2015).

[8] For more information on the definition of *caserío* visit `https://www2.congreso.gob.pe/sicr/cendocbib/con4_uibd.nsf/19D5492DF8BC558105257B810061BC79/$FILE/requisitos_categorizacion_ccpp_a_caserio.pdf`

is at least one BIM agent in close proximity to each *caserío*. Figure A2 of Appendix provides a map of the area under study, showing the spatial distribution of treated and control participants.

Within the targeted area, we divided the sample into two treatment areas (Monte Sullón and Catacaos) and three control areas (La Legua, Simbila and Nuevo Catacaos). The first two control areas are naturally separated by a river from La Legua and Simbila. Nuevo Catacaos borders directly with the treated areas and it thus enables to measure possible spillovers from the treatment to this *caserío*. The selection was done so that there was approximately the same number of women in the treated and non-treated areas.

Figure 1 displays the different stages of our field study and their chronological distribution. In April and May 2016, we collected a baseline survey in the five areas under scrutiny. The survey was administered to a randomly selected sample of women who where beneficiaries of the social program *JUNTOS*. The survey consisted of a questionnaire that collected sociodemographic characteristics, as well as mobile usage and financial information. The survey also collected social network data, including 5 names of friends who were also beneficiaries of *JUNTOS* and 2 non-beneficiaries friends. These data also contain information on how much people have interacted with such friends. Additionally, we asked each individual to name a person they consider suitable for diffusing gossip, a person they believe can mobilize others, and provide their self-perceived centrality. The network data is particularly relevant in our study because it enables to analyze the role of social contacts in the diffusion of m-banking in the communities.[9]

In total, we have interviewed 2,015 individuals. The network contains data on 6,447 individuals and 7,568 relationships. Figure A3 in the Appendix visualizes the elicited network. Since most network members did not participate in our study, the number of reciprocal links is below 1%. The network contains a giant component, comprising 5,559 (86.2%) individuals. Therefore, 86.2% of people in our network can access each other either directly or indirectly through network connections. The second largest component only includes 24 individuals, meaning that there is no other large community of people separated from the giant component. All but one interviewed individual name someone. Hence, our network contains only one isolated individual, but other socially isolated people may appear in our adoption data if they downloaded the app but were not named by any surveyed individual. Both the interviewed and non-interviewed individuals have on average 2.35 links to others. Even though most network members are well connected, the fact that most people in the areas were not interviewed naturally increases the distances and lowers considerably the clustering in our network; compared to typical social networks of the type and size analyzed here. The average and maximal distances in the giant component are, respectively, 14.7 and 39. The average clustering coefficient is 0.047, much lower than in a typical social network of this size and connectivity. The network contains 55 leaders (out of a total 83 in the area), out of which 21 were interviewed.

[9]For non-randomised field experiments, network data can be also useful to control for the potential contamination between experimental arms. Because in our data we observe very low take-up rates of control subjects, we do not re-weight our final treatment effects using such information. However, we estimate our effects using regression analysis with and without covariates, considering the distance to mother leaders and to treated subjects. Our main conclusions remain the same.

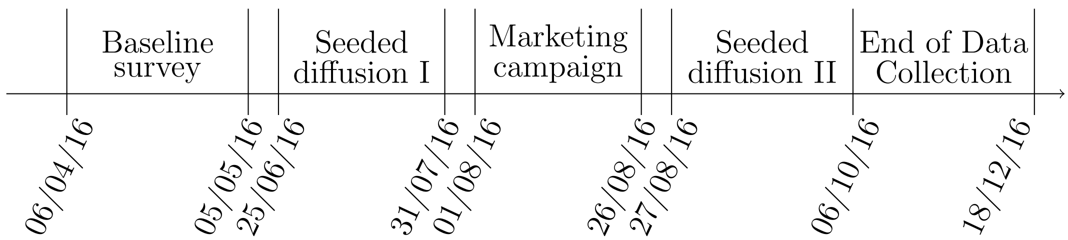

Figure 1: Timeline of the study.

In June 2016, an impact evaluation was undertaken by the authors to assess the effectiveness of an intervention that aim to stimulate the download and use of the m-banking application BIM in close coordination with *JUNTOS*. The intervention consisted of several phases, each with distinct objectives. The first objective was to increase the proportion of program beneficiaries that download the app and the second to increase its use among the beneficiaries of *JUNTOS*. Since we only manage to track transaction data during the intervention, this short period was not enough to observe changes in the use of the mobile app. Thus, we primarily focus on the adoption of the technology rather than the number of transactions conducted by the women who took part in this study.[10]

The study relies on the comparison between control and treatment groups to assess the effects of our intervention. Because the allocation of the treatment was not random (i.e., we have 5 groups and treatment was selected at the group-level), we carefully explore differences at baseline between control and treatment areas. In our regression analysis, we control for those observed variables where we found significant differences. To be able to isolate the effectiveness of the intervention, we spaced out data collection before, during, and after the intervention designed by the authors and the traditional marketing campaign run by BIM. Our study comprises three phases, each lasting for about one month:

Phase I – Seeded Intervention. Between June and July 2016, the authors randomly selected 21 mother leaders of *JUNTOS* to train them on how to download and use the BIM app and to explain the social and economic benefits of the app. The leaders were also instructed on how to affiliate other people. The leaders are a key aspect of our intervention due to the trust that the beneficiaries of *JUNTOS* have in them. This trust is also reflected in the position they have as key players in their social network, see Figure A3. Out of the 21 leaders invited to participate, 18 arrived to the training.

All trained mother leaders received a monetary reward for participating (15 *soles* in cash or 16.5 *soles* in their BIM account, equivalent to 4 and 4.4 dollars respectively). They were informed that they could receive additional monetary rewards for (i) every person they encourage to affiliate to BIM (2 *soles*) and (ii) every affiliated person that use the app (1 *sol*).[11] The intervention aimed to make each mother leader an ambassador of BIM, promoting its use among as many people as possible. They were encouraged

[10] Additionally, there were important privacy issues regarding the use of the application that did not allow the authors to continue tracking this information after the intervention ended.

[11] One Peruvian sol is equivalent to USD $0.27 and British pound £0.21 (July, 2024) approximately.

to view this opportunity as a temporary yet profitable business that would provide real monetary value and help them in their daily lives. All the instructed leaders belonged to the two treated *caseríos* Catacaos and Monte Sullón; none belonged to any control area. Each leader received a registration notebook in which they were instructed to collect names and phone numbers of all individuals they affiliated. This information allowed us to track all app downloads right after the training of the mother leaders until the end of the third phase of this study.

Phase II – Traditional Marketing Campaign. In August 2016, *Pagos Digitales Perú* (PDP) launched a marketing campaign promoting the take-up and use of the BIM app. The authors had neither control over the timing of this campaign nor knowledge that this intervention was about to take place during the intervention involving mother leaders. Hence, this phase was completely exogenous to the authors and to the original design of Phase I. The marketing campaign had three components of outdoor advertisement to promote the use of BIM. The first component entailed the use of local *mototaxis* hired by PDP which displayed informative messages about BIM (see Figure A4). The second was delivered through advertising banners and panels about BIM. PDP hired the Peruvian outdoor-advertisement firm Global Impact Outdoor to rollout these two marketing strategies. The third component involved the use of radio spots, bought by PDP, in two stations: Radio Nova FM and Radio Antena 10 FM. The trained leaders were informed that they would receive no monetary rewards for affiliating others during Phase II. Importantly, they were not informed about the existence of the third phase.

Phase III – Reinforcer of Seeded Intervention. In this phase, the trained leaders were recontacted and informed that they could once again earn monetary rewards for affiliating other members of their community and for their use of BIM during a specified period, as shown in the timeline in Figure 1. They were once again provided with the same materials as in Phase I to collect information about the people they affiliated.

3 Results

This section discusses our findings using two types of data: a sample of *JUNTOS* beneficiaries (survey data) and the public in general (administrative data). The former includes a random sample of females who were beneficiaries of *JUNTOS* at the time of data collection; the latter considers all females and males aged between 15 and 65 years living in the areas under study. Both data sources collected data of population living in treatment and control areas. Since the administrative data only contains information on the number of app downloads, Section 3.1 analyzes the overall treatment effects using survey and administrative data. Section 3.2 examines the mechanisms associated with the adoption of BIM using only the survey data.

3.1 Treatment effects

As a first step, Table 1 reports the treatment effects on the accumulated BIM affiliation rates using our sample of *JUNTOS* beneficiaries before our interventions and throughout the three phases of this study. We use linear probability models (LPM) without covariates, clustering our standard errors at the ML level. Our dependent variable is whether the respondent was affiliated to BIM or not at the end of a particular phase. To simplify the labels of tables and figures, we rename our three phases "Seeded intervention", "Traditional Marketing Campaign," and "Reinforcer of Seeded Intervention" as *Seed 1*, *Campaign*, and *Seed 2*, respectively. Table 1 shows that *Seed 1* is the most successful strategy promoting the adoption of BIM, followed by *Seed 2*. Table 1 shows that, although people in our sample were less likely to be affiliated with BIM before our intervention ($p < 0.05$), all phases of the intervention resulted in higher affiliation rates in the treated areas compared to the control areas. During the whole study, all three phases jointly increased affiliation rates by 7.1 percentage points (pp) among our survey respondents in the treated areas, while the intervention *Seed 1* alone increased the adoption by 5pp. The marketing campaign and the reinforcer of our seeded intervention increased the take-ups further by 0.8 and 1.4 percentage points, respectively. Next, we compare more formally the differences between the intervention phases.

Table 1: Treatment Effects using Survey Data without any covariates.

Variables	(1) All Phases	(2) Pre-Intervention	(3) T0 + Seed 1	(4) T1 + Campaign	(5) T2 + Seed 2
		T0	T1	T2	T3
Treatment	0.071***	-0.007**	0.049***	0.057***	0.071***
	[0.026]	[0.003]	[0.014]	[0.016]	[0.026]
Constant	0.023***	0.009***	0.013***	0.014***	0.019***
	[0.005]	[0.003]	[0.004]	[0.004]	[0.005]
Observations	2,015	2,015	2,015	2,015	2,015

Note: Dependent variables are the *Accumulated Affiliation Rates* at the end of phase specified in the column name. Column (1) shows the difference in take-up rates between the treatment and control areas without distinguishing the moment of adoption (i.e. the pre-treatment until two months after the last intervention); column (2) compares take-up rates at the end of the pre-intervention; column (3) compares the accumulated take-up rates during the pre-intervention and *Seed 1*; columns (4) compares the accumulated take-up rate considering the additional effect of the *Campaign*; column (5) considers the additional effect of *Seed 2*, the reinforcer of the *Seed 1* intervention. Clustered standard errors at mother leader level in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Figure 2 reports the estimated differences in treatment effects between subsequent phases. To estimate these differences, we used covariates in our regressions to account for the statistical unbalances between control and treatment units, as shown in Table

A1 in the Appendix. Our LPM are estimated using a seemingly unrelated regression (SUR) to account for the correlation of error terms across models. The significant levels shown in Figure 2 correspond to hypothesis tests comparing, respectively, *Seed 1* vs *Pre-Intervention* (T1 vs T0), *Campaign* vs *Seed 1* (T2 vs T1), *Seed 2* vs *Campaign* (T3 vs T2) and *Seed 1* vs *Seed 2* (T3 vs T1).

Our results corroborate that the treatment effect is largely driven by our "Seeded intervention," during which the MLs encouraged JUNTOS beneficiaries to affiliate to the BIM m-banking. Table A2 in the Appendix reports the full regression details behind the estimates in Figure 2, particularly illustrating the robustness of our findings to controlling for a large variety of confounding factors.

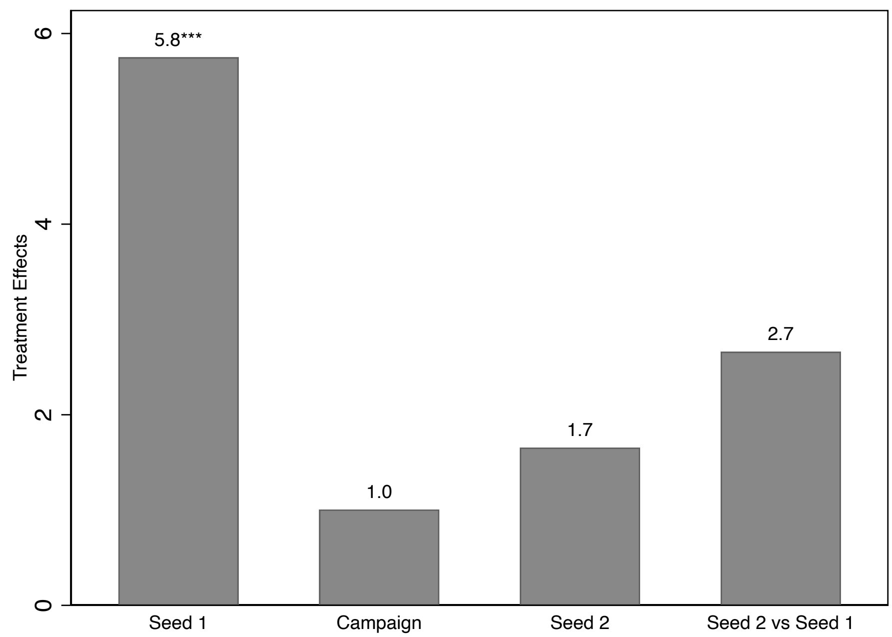

Figure 2: Treatment Effects of the different phases or our study (%): "Seeded intervention" (Seed 1), "Traditional Marketing Campaign" (Campaign) and "Reinforcer of Seeded Intervention" (Seed 2). The different treatment effects are estimated using a SUR with covariates (see Table A2 in the Appendix for further regression details); *** p<0.01, ** p<0.05, * p<0.1.

Using administrative data of the entire adult male and female population living in the same areas (rather than only the surveyed *JUNTOS* beneficiaries), we find that the treatment group increased the BIM adoption within the whole population living in the treatment communities by 1.50 pp, compared to only 0.20 pp in the control areas; this difference is statistically significant at a 1% ($p < 0.0001$).

The marketing campaign was less effective than both interventions, *Seed 1* and *Seed 2*. As shown in Figure 2, the *Campaign* achieved an additional percentage point of affiliations in treatment areas. When comparing the additional affiliations between the *Campaign* and *Seed 1* (T2 vs T1 in Figure 2), the take-up increases corresponds to around 17.5% (=1/5.7) of the overall effect observed under *Seed 1*, but the increase is not significantly different. When comparing the new adoption rates between the *Campaign* and *Seed 2*, we observe that the proportion of people adopting the technology corresponds to an additional 1.5 percentage points under *Seed 2*; again, we do not find significant difference between the *Campaign* and *Seed 2* (T3 vs T2). However, this increase represents 50% of the take-up during the campaign. That is, the low adoption rates during the marketing campaign are not explained by saturation of the market and support the claim that marketing campaigns might be essentially ineffective promoting m-banking.

3.2 Mechanisms behind the diffusion

Using our baseline survey data, we analyze the factors associated with the increase in the number of affiliations to BIM. We first analyze both the socio-demographic characteristics associated with the adoption of m-banking. Then, we extend our analysis by exploring the role of the underlying networks.

(1) Socio-demographic characteristics associated with BIM affiliation. We find that individuals affiliated with BIM tend to share five common features: they are younger, more educated, wealthier (measured by ownership of domestic appliances), and more likely to have heard about m-banking and own a mobile phone; see Table A2 in the Appendix for more details. Moreover, older participants are less likely to affiliate with respect to our reference category. Based on column (2) in Table A2, participants with secondary or higher education are 2.1 pp more likely to affiliate with BIM than those having no education or primary school. The percentage of women in our sample with either secondary or higher education are 70.6% and 52.5% among the affiliated and non-affiliated, respectively. The majority of women reported having at home at least one of the following appliances: a TV, an iron, a kitchen of gas, or a fridge (99.2% and 94.2% of affiliated and non-affiliated women respectively). Mobile phone ownership was much lower: 74% and 43% of affiliated and non-affiliated, respectively. Sharing of mobile phones among family members was not uncommon in the area during our study. Last, those women having some prior knowledge about m-banking are 1.6 pp more likely to affiliate with BIM than those who have not heard about m-banking before. Similar coefficients are observed for the rest of phases.

(2) Network characteristics associated with BIM affiliation. First, we observe that over 80% of BIM affiliates come from outside the leaders' direct social-network neighborhood. That is, the impact of "incentivized local leaders" intervention reached beyond the immediate social network of our leaders (see Figure A6). Nevertheless, being close to a trained leader is a key determinant of adoption. The average distance to a leader of participants belonging to the giant component of the network who took up m-banking is 4.37 steps, compared to 5.05 for the non-affiliated. This difference is significant using both t-test and non-parametric Wilcoxon rank-sum test ($p = 0.016$ and 0.008, respectively).

To analyze the role of distances more systematically, Table A3 reports a series of regressions reflecting how network distances and the adoption behavior of one's friends correlate with participants affiliation decision.[12] Since we explore several network measures that are highly correlated, each model variation uses one single variable. Figure A6 shows the take-up and the network distance. Focusing on column (4) in the table that reflects the *Seed 1* intervention, we corroborate the key role of being located close to a ML in the network. Even after controlling for the socio-demographics discussed above, people belonging to the first tercile of the distance to a ML are 3.6 percentage points more likely to affiliate in the treated areas, compared to those in the second and third terciles. We also observe that having shorter distance to an individual in treated communities increases the changes of being affiliated, while the contrary occurs with the network distance to an individual from a control area. The estimates further reveal that distances to a ML and other treated individuals explain an important share of the treatment effect of our *Seed 1* intervention; the inclusion of these variables in our regression models lowers considerably the estimated treatment effect and its significance level.[13]

Last, we analyze how individual centrality and local embeddedness affect the affiliation with BIM in Table A4 in the Appendix. We observe that neither local nor global centrality plays any role. In contrast, the effect of all the interventions is partially boosted in network communities with high levels of local clustering. The coefficient of the interaction between the lowest tercile of clustering and the treatment dummy in column (2) in Table A4 is -0.058 and significant at 5%. This latter finding is in line with the hypotheses that m-banking requires certain levels of trust, on the one hand, and the commonly accepted idea that denser neighborhoods generate trust and cooperative environments (Coleman, 1988; Putnam, 2000). Although we do not find any significant impact in any other regression with clustering in Table A4, Hsieh et al. (2024) suggest that the effect of the clustering coefficient on economic outcomes is likely to be considerably biased downwards with our network elicitation procedure and our sampling rate.[14]

All these findings corroborate that the adoption of technologies may be more successful if interventions consider the social network of potential users. The particular impact of being close to a ML and other treated individuals and belonging to dense local neighborhoods support the interpretation that adoption of m-banking requires trust in the technology. In addition, it may increases the self-perception of users about their own ability to use such technology. Data collected by a phone interview by the authors suggest that the self-perception about how to use mobile technologies improved for those participants who were assigned to the intervention and were treated by the ML.

[12]Since sampled network data might generate certain biases in network measures and the estimates (Hsieh et al., 2024), in our regression analysis we use as regressors dummy variables identifying the first tercile of the distribution of the corresponding network measure to mitigate such biases rather than the direct network measure, see Tables A4 and A3 in the Appendix. This assumes that the bias is evenly distributed across the distribution of the network measure.

[13]Related to this point, the fraction of treated friends affect take-up positively, whereas the fraction of affiliated friends has no effect.

[14]In fact, the same seems to happen for economic effects of network distances; see Hsieh et al. (2018).

4 Conclusions

This study underscores a crucial recommendation: the training and incentivization of community leaders prove to be significantly more effective than traditional impersonal marketing campaigns, which were found to be essentially ineffective in our study. The evidence presented here, as well as in other studies, indicates that these conclusions are applicable more broadly to products that demand a certain level of trust, akin to the inherent trust required for mobile banking with features like "having money in the cell phone". This characteristic of mobile banking aligns with the identified associations of clustering, distance to the mother leader, and distance to treated friends with the likelihood of affiliation with BIM.

Importantly, our findings contribute to existing literature by demonstrating that these recommendations extend to women, who often encounter more barriers to the adoption of novel technologies in developing countries.

Two primary limitations of our study should be acknowledged. Firstly, the proximity of treated and control areas raises the possibility of contamination issues. Nevertheless, if information and adoption decisions spill over into our control areas, the reported statistics would underestimate the true estimates. Moreover, in numerous regressions, we meticulously control for distances between participants based on whether they were community leaders, whether they were treated or not, and whether they were affiliated or not and the results are robust to these control.

Secondly, our study concentrates on m-banking adoption, yet an intriguing avenue for exploration would be the analysis of app usage. Unfortunately, due to privacy constraints, access to data on subjects' app usage during or after the study was not granted. Nonetheless, several findings strongly indicate that the results concerning adoption would likely extend to usage. We replicate key findings from the literature on the diffusion of innovations and products in the developing world, and within our sample, individuals with higher socio-economic status and education levels are inclined to adopt with the intent of using the app, rather than merely satisfying the MLs. This confidence in the generalizability of our results to usage is tempered by our inability to assess both the quantitative impact of our intervention on usage and the longevity of its effects: two pertinent issues for policymaking.

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5 Appendix

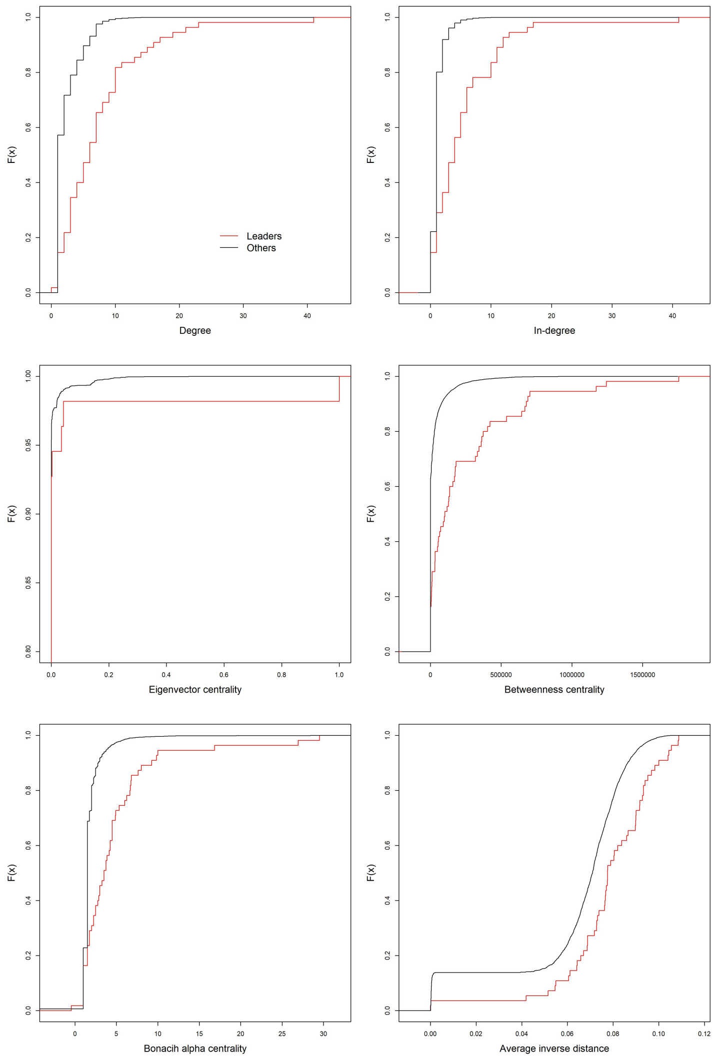

Figure A1: Cumulative distributions of various centrality measures, disaggregated for leaders (red) and other subjects (black), show that leaders are more central compared to non-leaders, regardless of the centrality measure considered.

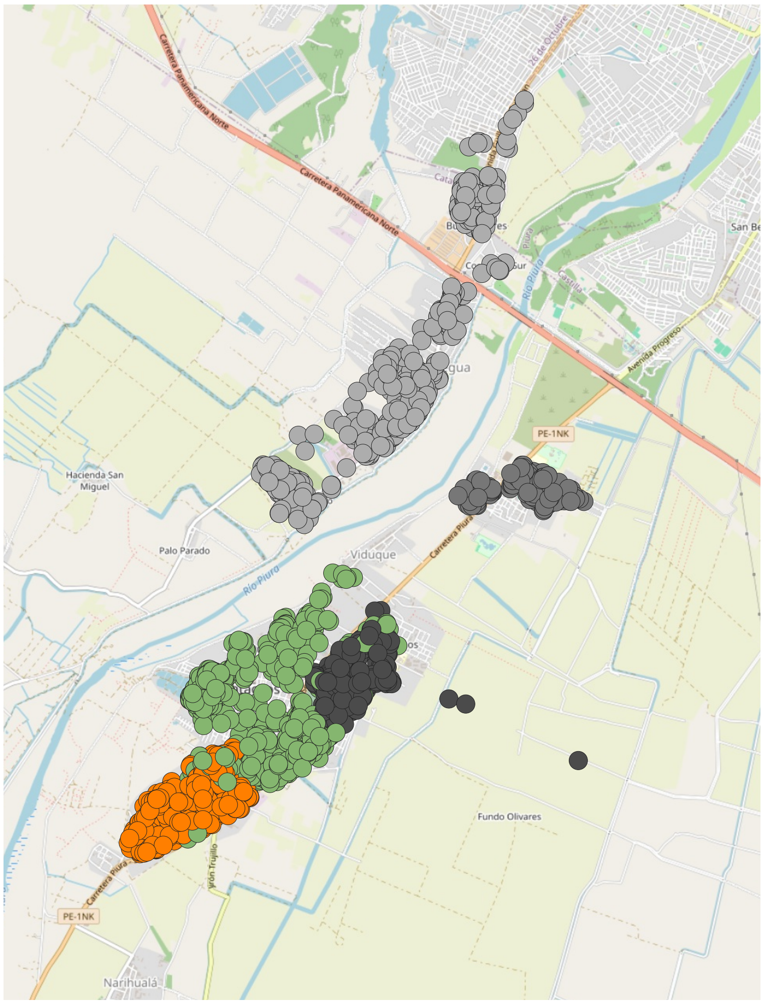

Figure A2: Geolocations of interviewed participants. Monte Sullón (orange) and Catacaos (green) are treatment areas and La Legua (light gray), Simbila and Nuevo Catacaos (dark gray) control.

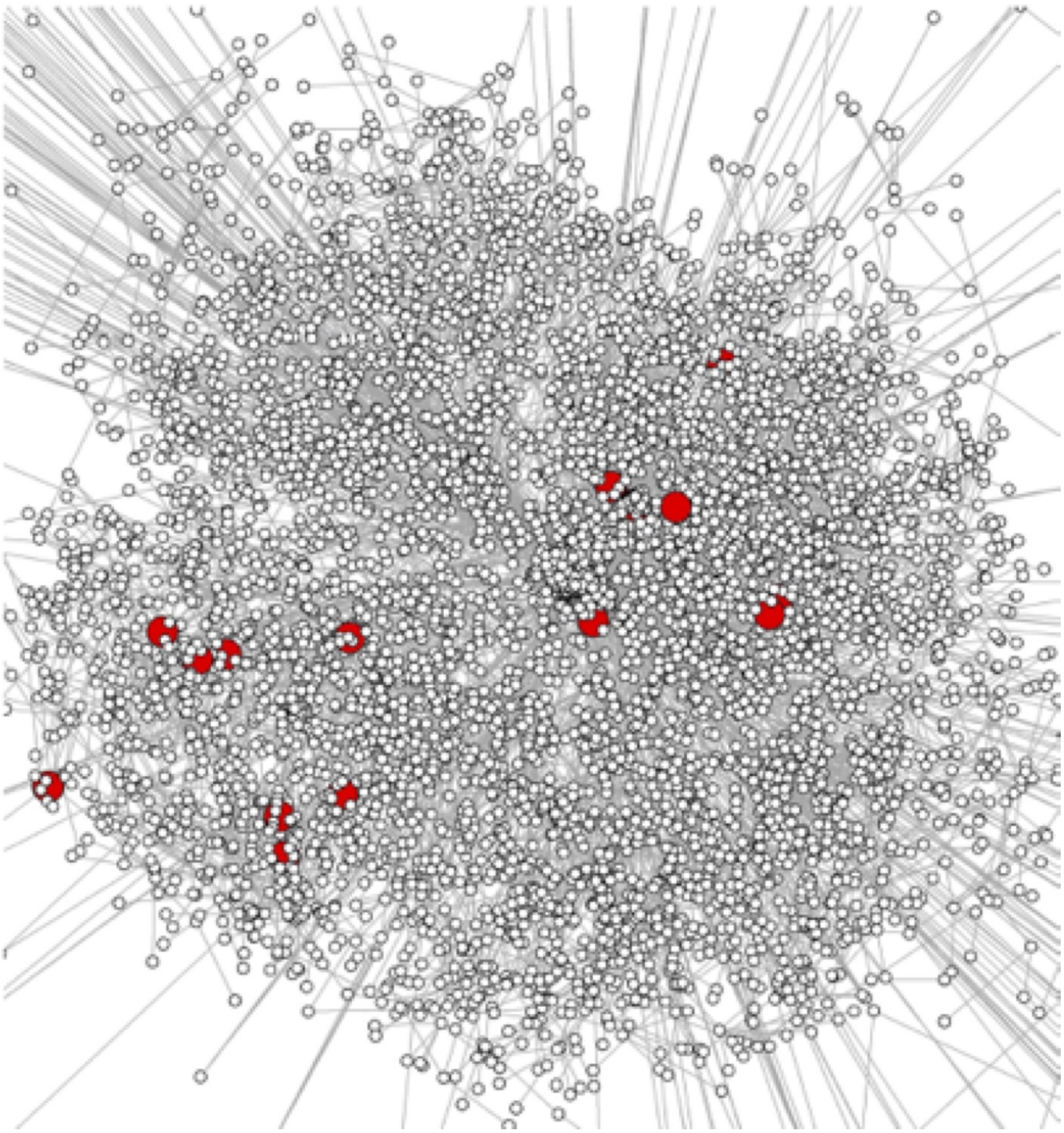

Figure A3: The elicited network of surveyed and named individuals. In red, the mother leaders are identified.

Figure A4: Illustration of the marketing campaign.

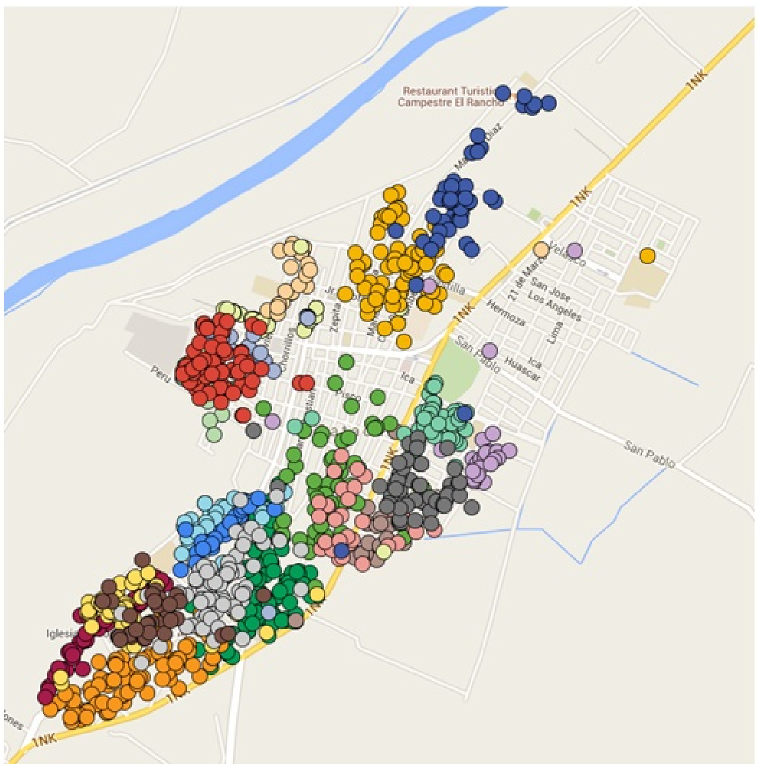

Figure A5: Geographical distribution of take-ups in the treated areas.

Table A1: Comparison of the sample descriptive statistics between control and treatment participants prior to the intervention.

Variables	T-C difference	Control mean	Observations
Socio-demographics			
age 19-25	0.0101	0.079	1,983
age 26-40	-0.100***	0.601	1,983
age 41-55	0.066**	0.278	1,983
age 56-more	0.024*	0.043	1,983
sec/high school	-0.033	0.554	1,983
household size	0.165	5.278	1,983
housewife w/business	0.029	0.207	1,983
employee	-0.018	0.191	1,983
no. earners at home	0.114**	1.408	1,983
living with partner	0.091***	0.335	1,983
married	-0.129***	0.510	1,983
separated	-0.001	0.101	1,983
mobile	-0.063	0.480	1,983
radio	-0.106***	0.606	1,983
tv	-0.083***	0.851	1,983
iron	-0.096***	0.354	1,983
gas cooker	-0.129***	0.720	1,983
fridge	-0.108***	0.386	1,983
landline	0.021***	0.016	1,983
assets	-0.564***	3.415	1,983
no rooms	0.073	2.933	1,983
potable water	-0.062*	0.857	1,983
Affiliation, m-Banking, financial education and Contact w/mother leader (ML)			
BIM affiliation pre-intervention	-0.007**	0.009	1,983
know about m-banking	-0.049	0.454	1,983
know about BIM	-0.032	0.317	1,983
any course in financial edu	-0.115***	0.803	1,983
meet weekly w/ML	0.096*	0.118	1,983
meet every 15 days w/ML	0.141***	0.174	1,983
meet monthly w/ML	-0.213***	0.575	1,983
meet every 2 mths. or more w/ML	-0.025	0.132	1,983
Network characteristics			
centrality	-0.127	1.466	1,983
betweenness	9,173.698*	39,871.186	1,983
clustering	0.010*	0.016	1,983
degree	0.561**	3.185	1,983
distance to mother leader (index 0-1)	-0.053**	0.170	1,983
distance to 2nd mother leader (index 0-1)	-0.168***	0.511	1,665
distance to treated (index 0-1)	-0.280***	0.315	1,684
distance to control (index 0-1)	0.233***	0.043	1,834
distance to affiliated (index 0-1)	-0.110***	0.353	1,689
Proportion of treated friends	0.690***	0.165	1,934
Proportion of affiliated friends	0.029***	0.005	1,303

Note: T-C refers to the difference between control and treatment participants. Clustered standard errors at mother leader level. *** p<0.01, ** p<0.05, * p<0.1

Table A2: LPM: Treatment effects using covariates in a SUR.

Variables	(1) T0 Pre-Intervention	(2) T1 T0 + Seed 1	(3) T2 T1 + Campaign	(4) T3 T2 + Seed 2
treated	-0.005**	0.051***	0.061***	0.077***
	(0.003)	(0.013)	(0.016)	(0.026)
age 26-40	-0.016*	-0.034**	-0.035**	-0.050***
	(0.010)	(0.014)	(0.016)	(0.019)
age 41-55	-0.016	-0.020	-0.017	-0.026
	(0.010)	(0.021)	(0.022)	(0.026)
age 56 or more	-0.020**	-0.069***	-0.072***	-0.086***
	(0.010)	(0.017)	(0.018)	(0.028)
sec/high school	0.002	0.021**	0.023**	0.027***
	(0.002)	(0.009)	(0.009)	(0.010)
household size	-0.000	-0.000	-0.002	-0.002
	(0.001)	(0.002)	(0.002)	(0.004)
housewife with business	0.003	0.004	0.005	0.003
	(0.005)	(0.011)	(0.012)	(0.014)
employee	0.006	-0.009	-0.005	-0.006
	(0.006)	(0.013)	(0.015)	(0.018)
hh mem. work	0.001	0.003	0.004	0.007
	(0.002)	(0.008)	(0.008)	(0.009)
living w/partner	-0.012	-0.024	-0.016	-0.018
	(0.009)	(0.023)	(0.022)	(0.024)
married	-0.009	-0.009	-0.001	-0.001
	(0.008)	(0.018)	(0.018)	(0.019)
separated	-0.010	-0.011	-0.006	-0.005
	(0.010)	(0.026)	(0.025)	(0.023)
assets	0.002***	0.012***	0.012***	0.014***
	(0.001)	(0.003)	(0.004)	(0.004)
# of bedrooms	0.002**	0.002	0.001	0.003
	(0.001)	(0.003)	(0.003)	(0.004)
potable water	-0.009*	-0.007	-0.002	0.004
	(0.004)	(0.009)	(0.009)	(0.013)
knowing about mbanking	0.005	0.016**	0.017**	0.025*
	(0.004)	(0.008)	(0.008)	(0.014)
knowing about BIM	0.004	0.002	-0.004	-0.008
	(0.006)	(0.014)	(0.015)	(0.018)
any financial education	-0.005	-0.004	0.003	0.012
	(0.004)	(0.013)	(0.015)	(0.017)
every 15 d. meet w/ml	-0.002	-0.002	-0.011	-0.006
	(0.003)	(0.017)	(0.017)	(0.018)
mthly meet w/ml	0.004	-0.014	-0.016	-0.013
	(0.005)	(0.015)	(0.015)	(0.016)
every 2m meet w/ml	0.000	-0.012	-0.017	-0.012
	(0.006)	(0.016)	(0.018)	(0.018)
Constant	0.020	0.006	0.002	-0.011
	(0.016)	(0.032)	(0.033)	(0.040)
Observations	1,982	1,982	1,982	1,982

Clustered standard errors at mother leader level; *** p<0.01, ** p<0.05, * p<0.1

Table A3: LPM: Treatment effects, Distance to Network and Friends' Affiliation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Phases		T1 T0 + Seed 1		T2 T1 + Campaign		T3 T2 + Seed 2	
treated	0.065**	0.062**	0.041***	0.033**	0.054***	0.046**	0.064**	0.060**
	(0.028)	(0.029)	(0.013)	(0.013)	(0.017)	(0.017)	(0.027)	(0.028)
distance to ML (1st)	0.026*	0.016	0.023**	-0.003	0.018	-0.005	0.030**	0.019
	(0.014)	(0.014)	(0.011)	(0.010)	(0.011)	(0.010)	(0.014)	(0.013)
treated*dist. to ML (1st)		0.014		0.036**		0.032*		0.015
		(0.022)		(0.017)		(0.017)		(0.022)
Observations	1,983	1,983	1,983	1,983	1,983	1,983	1,983	1,983
R-squared	0.057	0.057	0.046	0.047	0.047	0.048	0.058	0.058
treated	0.056**	0.025	0.037***	0.013	0.042***	0.013	0.053**	0.020
	(0.022)	(0.024)	(0.013)	(0.015)	(0.014)	(0.014)	(0.020)	(0.018)
distance to treated (1st)	0.031*	0.002	0.025**	0.002	0.030**	0.003	0.037**	0.007
	(0.018)	(0.016)	(0.011)	(0.011)	(0.012)	(0.011)	(0.017)	(0.016)
treated*dist. to treated (1st)		0.059		0.046**		0.054**		0.061*
		(0.035)		(0.021)		(0.022)		(0.032)
Observations	1,684	1,684	1,684	1,684	1,684	1,684	1,684	1,684
R-squared	0.065	0.067	0.051	0.052	0.057	0.059	0.066	0.068
treated	0.061**	0.081***	0.033**	0.057***	0.043***	0.065***	0.058**	0.078***
	(0.027)	(0.029)	(0.012)	(0.016)	(0.015)	(0.018)	(0.026)	(0.028)
distance to control (1st)	-0.024*	-0.004	-0.026**	-0.002	-0.025**	-0.003	-0.029**	-0.008
	(0.013)	(0.016)	(0.010)	(0.011)	(0.010)	(0.011)	(0.012)	(0.016)
treated*dist. to control (1st)		-0.039		-0.048**		-0.045**		-0.042*
		(0.027)		(0.019)		(0.019)		(0.023)
Observations	1,834	1,834	1,834	1,834	1,834	1,834	1,834	1,834
R-squared	0.064	0.065	0.049	0.051	0.054	0.056	0.064	0.065
treated	0.072***	0.052**	0.052***	0.045***	0.061***	0.055***	0.073***	0.058***
	(0.024)	(0.020)	(0.013)	(0.014)	(0.015)	(0.016)	(0.023)	(0.020)
distance to affiliated (1st)	0.031*	-0.003	0.015	0.003	0.014	0.003	0.028*	0.002
	(0.017)	(0.013)	(0.010)	(0.012)	(0.011)	(0.012)	(0.017)	(0.014)
treated*dist. to affiliated (1st)		0.056*		0.020		0.017		0.043
		(0.030)		(0.020)		(0.021)		(0.029)
Observations	1,689	1,689	1,689	1,689	1,689	1,689	1,689	1,689
R-squared	0.066	0.069	0.049	0.050	0.055	0.055	0.066	0.068
treated	0.053**	0.074**	0.037***	0.057***	0.046***	0.065***	0.056**	0.077***
	(0.023)	(0.028)	(0.013)	(0.016)	(0.015)	(0.018)	(0.023)	(0.028)
prop. of treated friends (1st)	-0.033***	-0.011	-0.021**	-0.000	-0.021**	-0.001	-0.030**	-0.008
	(0.011)	(0.010)	(0.010)	(0.008)	(0.010)	(0.008)	(0.012)	(0.010)
treated*prop. of t. friends (1st)		-0.055**		-0.050***		-0.048***		-0.053**
		(0.024)		(0.017)		(0.017)		(0.022)
Observations	1,934	1,934	1,934	1,934	1,934	1,934	1,934	1,934
R-squared	0.061	0.062	0.045	0.047	0.050	0.052	0.060	0.062
treated	0.065**	0.142***	0.046***	0.075**	0.053***	0.075***	0.068***	0.128***
	(0.024)	(0.036)	(0.013)	(0.028)	(0.015)	(0.027)	(0.024)	(0.035)
prop. of affiliated friends (1st)	-0.066***	0.003	-0.028	-0.002	-0.021	-0.001	-0.052**	0.002
	(0.021)	(0.018)	(0.023)	(0.014)	(0.024)	(0.014)	(0.022)	(0.018)
treated*prop. of aff. friends (1st)		-0.080**		-0.030		-0.023		-0.063*
		(0.032)		(0.030)		(0.031)		(0.031)
Observations	1,303	1,303	1,303	1,303	1,303	1,303	1,303	1,303
R-squared	0.071	0.072	0.055	0.056	0.057	0.057	0.069	0.070

All regressions control for covariates. *1st* refers to first tercile of the distribution of the corresponding network variable. Clustered standard errors at mother leader level; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: LPM: Treatment effects and Network characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		T1		T2		T3	
Variables	Phases		T0 + Seed 1		T1 + Campaign		T2 + Seed 2	
treated	0.076***	0.074**	0.051***	0.048***	0.061***	0.062***	0.077***	0.075**
	(0.027)	(0.030)	(0.013)	(0.016)	(0.016)	(0.020)	(0.026)	(0.030)
centrality (1st)	-0.002	-0.004	-0.003	-0.006	-0.004	-0.004	-0.003	-0.004
	(0.010)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)	(0.006)
treated*centrality (1st)		0.005		0.005		-0.000		0.004
		(0.020)		(0.015)		(0.016)		(0.018)
R-squared	0.055	0.055	0.043	0.043	0.046	0.046	0.055	0.055
treated	0.077***	0.082***	0.051***	0.058***	0.062***	0.065***	0.077***	0.083***
	(0.027)	(0.026)	(0.013)	(0.014)	(0.016)	(0.016)	(0.027)	(0.026)
betweenness (1st)	0.005	0.014	0.002	0.013	0.006	0.012	0.005	0.014*
	(0.009)	(0.009)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)
treated*betweenness (1st)		-0.017		-0.021		-0.011		-0.017
		(0.017)		(0.014)		(0.017)		(0.017)
R-squared	0.055	0.055	0.043	0.044	0.046	0.046	0.055	0.055
treated	0.075***	0.126***	0.050***	0.078***	0.061***	0.080***	0.076***	0.116***
	(0.027)	(0.034)	(0.013)	(0.024)	(0.017)	(0.024)	(0.027)	(0.033)
clustering (1st)	-0.022	0.015	-0.016	0.004	-0.008	0.006	-0.017	0.012
	(0.018)	(0.014)	(0.015)	(0.012)	(0.017)	(0.012)	(0.018)	(0.014)
treated*clustering (1st)		-0.058**		-0.032		-0.022		-0.046
		(0.028)		(0.024)		(0.027)		(0.028)
R-squared	0.056	0.057	0.044	0.045	0.046	0.046	0.055	0.057
treated	0.077***	0.072***	0.052***	0.052***	0.063***	0.058***	0.078***	0.074***
	(0.027)	(0.025)	(0.013)	(0.013)	(0.016)	(0.015)	(0.027)	(0.025)
degree (1st)	0.010	0.004	0.010	0.009	0.013	0.007	0.010	0.006
	(0.012)	(0.008)	(0.009)	(0.007)	(0.010)	(0.007)	(0.011)	(0.008)
treated*degree (1st)		0.012		0.001		0.011		0.008
		(0.022)		(0.017)		(0.019)		(0.020)
R-squared	0.055	0.056	0.044	0.044	0.046	0.047	0.055	0.055

All regressions control for covariates and the number of observations is 1,983. *1st* refers to first tercile of the distribution of the corresponding network variable. Clustered standard errors at mother leader level; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

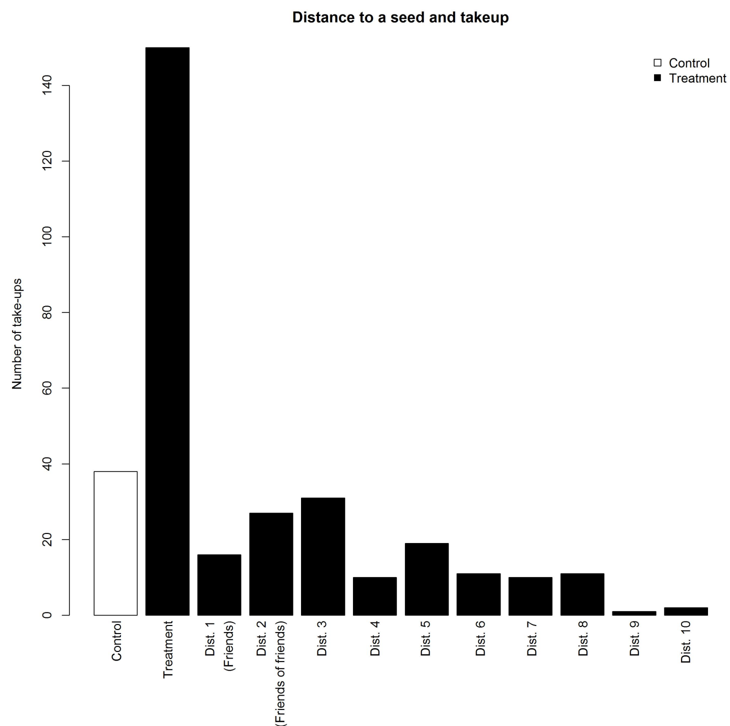

Figure A6: Take-up and Network Distance