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

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ABSTRACT

How can we promote the adoption of mobile banking among the socially and economically disadvantaged? We compare the effectiveness of two strategies, seeded diffusion via incentivized 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 traditional marketing campaign at the regional level. 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. We additionally show that the seeded incentivized diffusion relies on features of the underlying community networks known to promote diffusion of information and trust. Our results emphasize the necessity of personalized approaches to promote technological products such a mobile banking among vulnerable populations.

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 of escaping poverty (Aghion and Bolton, 1997; Banerjee et al., 2013). Existing evidence confirms that access to banking can indeed reduce poverty (Burgess and Pande, 2005; Dupas and Robinson, 2013). Despite significant progress in recent years, only 71% of adults in the developing world possess a bank account (Demirgüç-Kunt et al., 2022).

Since women are widely recognized as key drivers of economic development (Duflo, 2012), access to banking can empower them by increasing control over household finances and enhancing their economic agency. Yet, a persistent gender gap in financial inclusion remains: in developing countries, women are 6 percentage points less likely than men to own a bank account and similar disparities exist in account usage even among account holders (Demirgüç-Kunt et al., 2022).[1] These gaps likely stem from gender-specific barriers, such as greater risk aversion, lower literacy, limited access to information, and

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[1] According to the World Bank, women with an account are 8–9 percentage points less likely than men to save formally in Sub-Saharan Africa and Latin America. Gender gaps are even more widespread in the use of accounts for cash management across developing economies.

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family roles that constrain autonomy.[2] Such persistent disparities not only reinforce existing gender inequalities – especially pronounced in developing contexts – but also impede broader economic development.

The narrowing of the gender gap in account ownership – from 9% in 2011 to 6% in 2021 – has been largely attributed to the rise of mobile banking (m-banking, henceforth; Demirgüç-Kunt et al. (2022)). M-banking is particularly promising in the developing world, where most people now live in areas with mobile phone coverage and own mobile devices, while the cost of usage continues to fall (see e.g. Aker and Mbiti, 2010; Fabregas et al., 2019). Since m-banking offers a unique opportunity to extend formal credit and savings to the "unbanked" and "underserved" populations, the benefits may especially significant for socially and economically disadvantaged groups, including women (World Bank, 2018). By bypassing some of the institutional constraints of traditional financial systems, m-banking may help mitigate problems of elite capture and gender-based exclusion from formal credit markets (La Porta et al., 2002; Sapienza, 2004). It may also help eliminate structural barriers that contribute to unequal access for certain subpopulations (Riquelme and Rios, 2010).

Yet despite these advantages, adoption rates of m-banking remain significantly lower than mobile phone penetration and the expectations it has generated (Donner and Tellez, 2008). Unlike messaging apps, m-banking faces a different set of challenges: lack of information, limited trust, low self-efficacy, restrictive social norms, and perceived social and financial risks (Donner and Tellez, 2008; Mobarak and Saldanha, 2022).[3] Moreover, the actual use of digital money in developing economies is still limited: only 57% of adults actively use it, compared to over 95% in high-income countries (Demirgüç-Kunt et al., 2022). This is a missed opportunity, as active use of digital money is closely linked to broader financial inclusion – such as access to credit and savings – and has been associated with the narrowing of gender gaps worldwide (Demirgüç-Kunt et al., 2022).

Promoting the adoption, diffusion, and effective use of m-banking among women should therefore be a development priority. It is essential not only for fostering inclusive economic growth but also for advancing gender equity. In addition, m-banking provides safe, affordable, and accessible tools for vulnerable populations to store, send, and receive money, making it a critical instrument for financial resilience.

In this paper, we compare the effectiveness of two promotion strategies, seeded diffusion via incentivized 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 poor women in rural areas.

To address these aims, we implemented a behavioral intervention involving female beneficiaries of the conditional cash transfer program *JUNTOS* in the Piura region of Peru. Prior to any intervention, we divided the sample geographically into five areas – two intervened and three non-intervened control areas – and conducted a baseline survey on a random sample of approximately 1000 women in the intervened areas and approximately 1000 in the control, all enrolled in *JUNTOS*. This survey collected information on socio-economic and demographic characteristics, as well as on social network structures. Although the intervention eventually unfolded in three phases, this sequence was not planned in advance but emerged in response to unforeseen developments during implementation.

Phase I *Seeded Diffusion via Incentivized Local Leaders*: In the two intervened areas, we implemented a behavioral intervention based on seeded diffusion. Specifically, we trained existing community leaders – known as *mother leaders*, who had been previously selected by *JUNTOS* beneficiaries to serve as intermediaries between local women and the program – to promote an m-banking application within their communities. This app allows users to manage bank accounts and transfer funds digitally. Training was delivered by a local firm, and we subsequently monitored how many community members each leader successfully enrolled in the system, incentivizing their performance. The three non-intervened areas received no intervention at this stage.

Phase II *Traditional Marketing Campaign*: After the initial seeded diffusion, the firm managing the m-banking application (app, hereafter) launched an indiscriminate traditional marketing campaign across the entire Piura region, including both the intervened and non-intervened areas. This campaign was not coordinated by the research team. We continued to track m-banking adoption during this phase in all five areas.

Phase III *Reinforcer of Seeded Diffusion*: To ensure that low adoption rates during the marketing campaign were not due to market saturation, once the campaign has finished, we relaunched the seeded diffusion in the same two intervened areas. Once again, mother leaders promoted the app within their communities. The control areas again remained without intervention.

In summary, the intervened areas were exposed to all three phases of the intervention in the order described above, whereas the non-intervened control areas were only exposed to the campaign. Throughout all stages, we tracked m-banking adoption using administrative data provided by the firm managing the app and compared outcomes between intervened and non-intervened areas. See Section 2 for further details of the intervention.

Our main findings show that take-up rates during the first stage of the study – when the seeded diffusion strategy was implemented – were substantially higher than during the subsequent traditional marketing campaign. When comparing adoption in the intervened and control areas during the marketing campaign, we find no statistically significant differences. However, once the campaign ended and the seeded diffusion was relaunched, adoption increased again by approximately 340% relative to both the traditional marketing campaign and the control areas. Although this difference is not statistically significant, the seeded diffusion strategy consistently outperformed the traditional marketing campaign. According to our data, the traditional marketing campaign was largely ineffective in promoting m-banking: adoption rates did not differ significantly between intervened and non-intervened areas during this phase.

These conclusions remain robust across a series of robustness checks (see Section 3 for details). Most importantly, because our inference relies on the assumption that omitted variable bias does not drive the estimated effects, we assess this possibility using the approach proposed by Oster (2019). This analysis rather suggests that our estimates may be conservative, implying that the actual effectiveness of our personalized promotion strategy using local leaders could be even greater than reported.

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

[2] See Section 1.2 of Demirgüç-Kunt et al. (2022) for a detailed analysis of the factors affecting low rates of account ownership and use among women and other disadvantaged groups.

[3] Brown et al. (2003) find that high levels of perceived risk have prevented people from adopting m-banking in South Africa in early 2000's.

success of the seeded diffusion can be attributed to the social processes taking place on the social network in the communities. More precisely, having friends in the intervened area (i.e., informed friends) are important determinants of adoption. We also find suggestive evidence that, in line with network theory, other network features promoting information flow and trust play a role (see Section 3.2 for details).

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) for reviews. While our findings align with this literature, 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.

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 to spread information, 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,[4] contrasting with significant adoption rates in our intervention 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.

We also contribute methodologically to the literature on field interventions affected by *treatment externalities*, a term used by Miguel and Kremer (2004). Such externalities are common in small-scale interventions, especially in settings where it is infeasible to sufficiently separate treatment and control areas—such as densely populated urban environments.[5] In these contexts, treated individuals are often directly or indirectly connected to those in control groups, resulting in spillovers that can attenuate estimated treatment effects and increase the risk of Type II errors. Programs may thus appear ineffective or too costly when their full impacts are underestimated, as shown in health (Miguel and Kremer, 2004) and labor market interventions (Heckman et al., 1999). Using social network data, we document evidence of such spillovers and show how they vary with network distance, corroborating that our estimated intervention effects are likely conservative. These findings offer insights for researchers and policymakers on how to detect, measure, and account for or potentially exploit such externalities in program evaluation.

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 (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 a broader financial inclusion initiative launched in February 2016 in Peru, which brought together commercial banks, telecom companies, and financial institutions. Central to this effort was the collaboration with *JUNTOS*,[6] the state-run conditional cash transfer program. As part of its strategy, *JUNTOS* promoted the use of BIM, a mobile wallet developed and managed by Pagos Digitales Perú (PDP)—a private consortium created by a wide range of financial and telecommunications entities with the goal of establishing a unified platform for mobile banking in the country.

JUNTOS is a conditional 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. 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*.

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

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

[5] Using the categorization proposed by Angelucci and Di Maro (2016), this would fall under the case of social externalities. For example, a young person who receives preventive sexual health information may share what she has learned with her friends. In doing so, the benefits of the intervention extend beyond the direct recipients, influencing others within their social network. See Rascón Ramírez (2025) for a full discussion.

[6] *JUNTOS* stands for *"Programa Nacional de Apoyo Directo a los más Pobres – JUNTOS"*. More details can be found on the webpages of Juntos: https://www.gob.pe/juntos.

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.[7]

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.[8]

2.2. Mother leaders

An important feature of *JUNTOS* is its nationwide network of collaborators. In particular, beneficiaries are organized around *madres líderes* (mother leaders; referred to throughout the paper as MLs or simply leaders), who serve as the main point of contact between beneficiaries and the program. These leaders volunteer their time to train beneficiaries on health and education-related topics, help disseminate the program's objectives, and encourage compliance with the co-responsibilities required by *JUNTOS*.[9] They also address doubts of program beneficiaries and incentivize 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.[10]

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, Fig. A.1 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 *caserí o* 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.[11] 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 is at least one BIM agent in close proximity to each *caserío*. Fig. A.2 of Appendix provides a map of the area under study, showing the spatial distribution of the randomly chosen participants in both the intervened and non-intervened areas.

Within the targeted area, we divided the sample into two intervened areas (Monte Sullón and Catacaos) and three non-intervened control areas (La Legua, Simbila and Nuevo Catacaos). The first control area is naturally separated by a river. Simbila is located on the opposite side of the river, while Nuevo Catacaos directly borders the intervened areas. The proximity allows to measure possible spillovers from the intervened areas to this *caserío*. The selection was done so that there was approximately the same number of women beneficiaries of *JUNTOS* in the intervened and non-intervened areas. Fig. 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.[12]

In total, we interviewed 2,016 randomly selected individuals from the population of *JUNTOS* beneficiaries, with roughly half from intervened areas and half from non-intervened areas. The network contains data on 6,447 individuals and 7,568 relationships. Fig. A.3 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,

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

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

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

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

[11] 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.

[12] For non-randomized 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 estimates using such information. However, we estimate our effects using regression analysis with and without covariates, considering the distance to intervened mother leaders and subjects from intervened areas. Our main conclusions remain the same.

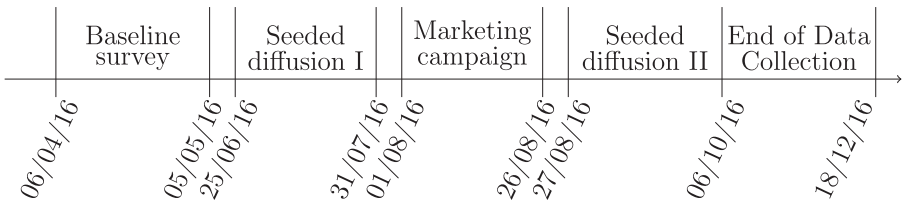


Fig. 1. Timeline of the study.

meaning that there is no other large community of people separated from the giant component. All but one interviewed individual named 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.

With the aim of encouraging the download and use of the BIM mobile banking application, we designed an intervention that leveraged the leaders of *JUNTOS* to promote the use of BIM among their beneficiaries and contrast it with a marketing campaign. The phasing described in the following section reflects the timing of the whole intervention that we evaluate.

2.4. Phases of the intervention

The study relies on the comparison between the intervened and non-intervened areas to assess the effects of our intervention. Because the allocation of the intervened areas was not random (i.e., we have 5 groups and the intervention was selected at the group-level), we carefully explore differences at baseline between control and intervened areas.

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 PDP. 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* in the intervened areas 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 Fig. A.3. 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 4.23 and 4.66 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*).[13] The intervention aimed to make each mother leader an ambassador of BIM, promoting its use among as many people as possible. They were encouraged 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 intervened *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, after Phase I concluded, *Pagos Digitales Perú* (PDP) launched a marketing campaign promoting the take-up and usage of the BIM app. The campaign has targeted indiscriminately the whole Piura region. This means that both our intervened and non-intervened areas were exposed to the campaign. 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.

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 Fig. A.4). 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 Fig. 1. They were once again provided with the same materials as in Phase I to collect information about the people they affiliated.

Before turning to the results, it is crucial to outline the types of data at our disposal. In addition to the information gathered during the survey and questionnaire phase discussed earlier, *Pagos Digitales Perú* (PDP) provided us with data – referred to as *administrative data* throughout this study – on app downloads in the study areas at the conclusion of each intervention phase. This includes data from both the pre-intervention period and the end of our data collection. These records indicate whether a phone number registered in a given area had downloaded the BIM app during a particular intervention phase. While we can estimate the overall adoption rates across the entire areas in each phase, individual-level linkage is possible only for those included in our survey sample. No additional administrative data were made available to us. Although PDP also shared transaction data, the short timeframe of our study prevented any meaningful analysis of usage patterns. Consequently, our analysis focuses on technology adoption – measured through downloads – rather than on transaction behavior.[14]

[13] One Peruvian sol is equivalent to USD $0.28 and British pound £0.21 (July, 2025) approximately.

[14] 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.

3. Results

This section discusses our findings using two types of data: survey and 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. Administrative data was used to know the actual downloads of our sample participants that took place in intervined and control areas. Since the administrative data only contains information on the number of app downloads, Section 3.1 analyzes the intervention estimates using survey data. Section 3.2 examines the mechanisms associated with the adoption of BIM using only the survey data.

3.1. Intervention estimates

As a first step, Table 1 reports the coefficients of a dummy that identifies the geographical areas that were intervened. Our dependent variable is defined as the new BIM affiliation rates observed before the interventions were launched and throughout the three phases of this study explained in Section 2.4. We use linear probability models (LPM) with covariates, clustering our standard errors at the ML level using the small-sample method for cluster-robust variance estimation suggested by Pustejovsky and Tipton (2018).[15] 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*, *Marketing Campaign*, and *Seed 2*, respectively. Also note that Pre-Intervention refers to the 2 months prior to the Seeded Intervention.

Table 1 shows that *Seed 1* was the most successful strategy for promoting the adoption of BIM. Although people living in intervened areas were initially less likely to be affiliated with BIM *prior to* our intervention (T-test, $p < 0.05$), column (3) reveals that during the implementation period of *Seed 1*, beneficiaries in these areas were 5.7 percentage points (pp.) more likely to affiliate to BIM. In contrast, neither the *Marketing Campaign* nor the *Seed 2* intervention shows significant coefficients for the intervention dummy. During the whole period, all three phases jointly increased affiliation rates by 7.9 pp. among individuals living in the intervened areas compared to control areas.

Was the Marketing Campaign simply ineffective or are we observing saturation effects? While saturation effects may occurred in our context, we note that the campaign was launched indiscriminately across the entire Piura region, as mentioned in Section 2.4. If the campaign had been effective, we would have observed increases in both intervention and control areas. However, as shown by the control group means reported in Table 1, adoption rates in control areas remained practically unchanged from the *Seed 1* phase. Although we cannot directly test for saturation effects due to the region-wide implementation, the absence of adoption increases in control areas suggests limited campaign effectiveness rather than saturation in the intervened areas alone. In addition, a saturation effect should have prevented the intervened areas from further adopting BIM during our Phase 3. In contrast, we observe in column (5) that, although the effect is not statistically significant, the take-up increased by an estimated 340% once we relaunched our main intervention. Below, we demonstrate that this effect is likely underestimated. This finding further contradicts the saturation argument as an explanation for the marketing ineffectiveness.

Table 1
Estimates of intervention coefficients.

Variables	(1) All phases	(2) Pre-intervention	(3) Seed 1	(4) Marketing campaign	(5) Seed 2
		T0	T1	T2	T3
Intervened (=1)	0.079***	−0.005**	0.057***	0.010	0.017
	[0.027]	[0.003]	[0.014]	[0.008]	[0.014]
Observations	2003	2003	2003	2003	2003
R-squared	0.056	0.021	0.046	0.011	0.013
Covariates	Yes	Yes	Yes	Yes	Yes
Control mean	0.019	0.009	0.004	0.001	0.005

Note: The dependent variables represent the new affiliation rates that occurred in each period. Column (1) shows the difference in take-up rates between the intervened and control areas without distinguishing the timing of adoption (i.e. from the pre-intervention period 6/4/16 until 6/10/16); column (2) considers take-up rates from 26/4/16 until 24/6/16; column (3) covers the period 25/6/16 until 31/7/16 when the first Seeded Intervention (*Seed 1*) was launched; column (4) examines the period from 1/8/16 until 26/8/2016 when the Marketing campaign was launched; and column (5) covers from 27/8/16 until 6/10/16 when the reinforcer *Seed 2* was launched while the Marketing campaign was still running. P-values of t-test using a SUR model with clustered standard errors: T1 vs. T0 ($p < 0.000$), T2 vs. T1 ($p = 0.001$), T3 vs. T2 (0.421) and T3 vs. T1 (0.014). Table A.2 in the Appendix shows the covariates used in these models; Table A.3 provides the estimates without covariates. Clustered standard errors at mother leader level in brackets using Pustejovsky and Tipton (2018). *** p < 0.01, ** p < 0.05, * p < 0.1.

A key limitation of our analysis is the possibility of endogeneity bias. To assess the robustness of our findings, we calculated the relative degree of selection on unobservables that would be required to nullify our main finding for *Seed 1*. Table 2 presents estimates of this relative degree, represented by δ, using the approach developed by Oster (2019). We find two key results: $|\delta| > 1$ and $\delta < 0$. The first result indicates that our findings are robust to potential omitted variable bias from unobservables, according to the benchmark suggested by Oster (2019). This means that unobserved confounders would need to be extraordinarily influential, in fact, 28 times more than the measured variables in our model, to account for the entire *Seed 1* intervention coefficient.

The second result implies that unobserved confounders would need to operate in the opposite direction from our observed controls to eliminate our findings. This suggests that any remaining omitted variable bias would actually work against the selection bias from observed confounders, potentially underestimating our intervention coefficients. This interpretation is further supported by the differences in intervention estimates between models with and without covariates (see Tables 1 and A.3).

In sum, the combination of the large magnitude ($|\delta| = 28$) and opposite direction ($\delta < 0$) provides strong evidence that unobserved confounders are unlikely to nullify our main findings for *Seed 1*. Although our results for *Seed 2* are not significant, the estimate of this effect in Table 2 in fact suggest that the estimated effect in Table 1 is also underestimated. Last, these results show that the estimated intervention coefficient, when considering all phases together, is also largely underestimated, probably driven by both seeded interventions during which the MLs encouraged JUNTOS beneficiaries to affiliate with BIM m-banking.

Using the remaining 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 intervened group increased the BIM adoption within the whole population living in the intervened communities by 1.50 pp, compared to only 0.20 pp in the control areas; this difference is statistically significant at a 1% (*Chi-square test*, $p < 0.000$).

[15] In Table A.4, we also present wild cluster bootstrapped p-values and confidence intervals (CI) of our intervention coefficients using the approach by Cameron et al. (2008), the small-sample for cluster-robust correction of Pustejovsky and Tipton (2018) and the combined estimation of p-values and CI using both approaches. We also present in Fig. A.6 the distribution of wild bootstrapped intervention estimates and their confidence intervals. Because Cameron et al. (2008) approach does not allow to estimate standard errors, we have used Pustejovsky and Tipton (2018)'s approach for all estimates shown in tables to facilitate statistical inference using t-tests.

Table 2
Relative degree of selection in unobservables needed to nullify the intervention coefficients (δ).

Intervention status		δ
All phases	All	−77.4
Pre-intervention	T0	1.8
Seeded intervention (Seed 1)	T1	−27.8
Marketing campaign	T2	−0.9
Reinforcer of seeded intervention (Seed 2)	T3	−1.2

Note: Deltas (δ) were calculated using an $R_{max} = 1.3\tilde{R}$, where $\tilde{R}$ is the R^2 from our models with covariates in Table 1, following Oster (2019).

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 assets), more likely to have heard about m-banking and own a mobile phone; see Table A.2 in the Appendix for more details. Based on column (1) in Table A.2, older participants are less likely to affiliate with respect to our reference category. Participants with secondary or higher education are 2.8 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 domestic 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 2.4 pp. more likely to affiliate with BIM than those who have not heard about m-banking before.

(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. This indicates that the impact of our "incentivized local leaders" intervention extended beyond the immediate social network of our leaders (see also Fig. A.9).[16] 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 examine the role of network distance and other network characteristics more systematically, Tables A.5–A.12 in Appendix report a series of regressions that explore how network distances, the intervention status of friends, and standard network measures correlate with participants' affiliation decisions.[17] Since we explore several network measures that are highly correlated, each model variation uses one single variable. All regressions employ the small-sample cluster-robust correction developed by Pustejovsky and Tipton (2018). Our main conclusions are based on regressions that interact the intervention dummy with terciles of the network variable of interest.

We present results both with and without multiple hypothesis testing correction following Benjamini and Hochberg (1995), with our conclusions based on the corrected specifications. Because network variables contain substantially more missing values than the covariates in Table 1, we also present tables without the intervention-network interaction to demonstrate how the estimated coefficients change when the estimation sample is reduced due to missing observations. Overall, we conclude that the loss of observations when including different network characteristics barely changes the estimated intervention coefficients when they are compared with those shown in Table 1 (see Tables A.6 and A.8).

Table A.10 shows that estimated intervention effects are lower for participants who are closest to control group members (1st tercile). This suggests that proximity to non-intervened individuals may dilute intervention effectiveness *vis-à-vis* the control area, possibly through social influence or peer effects that work against the intervention. Moreover, the effectiveness of the intervention is attenuated among participants with the lowest proportion of intervened friends (1st tercile). This result suggests that that peer intervention density enhances intervention effectiveness, consistent with positive spillover effects and social reinforcement mechanisms. Fig. A.7 shows marginal effects of predicted affiliation rates. These results tentatively suggest that greater distance from control participants (Fig. A.7(b)) may be associated with higher adoption rates, while having more friends from the intervened area appears linked to increased affiliation (Fig. A.7(c)).

Finally, we examine how individual centrality and local embeddedness, measured by the clustering coefficient, influence affiliation with BIM in Table A.12 in Appendix. After applying multiple hypothesis testing corrections, the interactions with the intervention dummy do not reach conventional significance levels. Nevertheless, the marginal effects of the predicted affiliation rate, presented in Fig. A.8, indicate that, higher levels of connectivity, betweenness, and clustering correspond to greater affiliation rates.

However, as shown in Fig. A.7(b), the precision of our estimates decreases as the value of these network variables increases, warranting cautious interpretation of these patterns. Although not statistically significant, the observed direction aligns with the interpretation that m-banking adoption requires both exposure to information and certain levels of trust. Beyond proximity to intervened leaders and having more informed friends, higher adoption is associated with increased exposure to information and a higher probability of being targeted by a leader. This is reflected in higher local and global centrality. Simultaneously, more cohesive network neighborhoods, as indicated by a higher clustering coefficient, foster trust and cooperative environments (Coleman, 1988; Putnam, 2000). These are necessary ingredients for convincing people to adopt a product that requires trust. Both explanations conform to traditional hypotheses in network theory (Coleman, 1988; Putnam, 2000; Vega-Redondo, 2007; Jackson et al., 2008).[18]

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 intervened individuals

[16] See Fig. A.5 for the geographical distribution of the take-up rate in the intervened areas.

[17] Since sampled network data might generate certain biases in network measures and the estimates (see, e.g., Hsieh et al., 2024), our regression analysis in Tables A.5–A.12 in the Appendix employs 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. This assumes that the bias is evenly distributed across the distribution of the network measure.

[18] It has been observed that diffusion and take-up are positively correlated with connectivity and centrality (e.g., Banerjee et al., 2013; Alatas et al., 2016). Regarding the clustering coefficient, although few theoretical papers acknowledge its role in network diffusion (e.g., Campbell, 2013; Ruiz-Palazuelos et al., 2023), Centola (2010) provides rare empirical evidence but cannot separate the effect of clustering from that of distance. We provide suggestive correlational evidence, demonstrating the clustering coefficient's impact beyond network distances.

support the interpretation that adoption of m-banking requires trust in the technology. In addition, it may increase 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 approached by a ML.

4. Conclusions

This study explores the comparative impact of two distinct strategies for promoting mobile banking technology: one leveraging local leaders within social networks and the other relying on traditional marketing campaigns. Our findings reveal that empowering and incentivizing community leaders yields significantly better outcomes compared to conventional, impersonal marketing efforts, which demonstrated minimal effectiveness in our research context. Moreover, we uncover that a substantial portion of the success in our seeded diffusion approach can be attributed to the dynamics within the underlying social networks. Importantly, our findings contribute to the existing literature by demonstrating that the effectiveness of seeded diffusion extends to women, who often encounter more barriers to adopting traditional banking services and technologies in developing countries.

However, our study has several limitations that warrant careful consideration. The non-random assignment of control and intervention areas means that our causal interpretations rely on the assumption that omitted variable bias does not influence our intervention effects.[19] Although our robustness analysis suggests this is not the case, the non-random assignment still requires caution in interpreting our results causally.

The proximity of our intervened and control areas raises the possibility of contamination issues. If information and adoption decisions spill over into our control areas, the reported statistics might underestimate the true effects, as suggested by our robustness tests. In numerous regressions, we meticulously controlled for distances between participants based on various factors, and the results are robust to these controls. These regressions indeed show that some *treatment externalities* (Miguel and Kremer, 2004), primarily observed in intervened areas, indeed exist, and our work demonstrates that they can be measured by network data.

While our study focuses on mobile banking adoption, 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. Within our sample, individuals with higher socioeconomic status and education levels are inclined to adopt with the intent of using the app, rather than merely satisfying the community leaders. However, our inability to assess both the quantitative impact of our intervention on usage and the longevity of its effects remains a critical consideration for policymaking.

Lastly, there are natural concerns regarding the external validity of our results. We implemented our design in specific areas in northern Peru, where the program *JUNTOS* has been operating for quite some time, with extensive infrastructure and local leadership. The specificity of our banking application to this region further complicates the extrapolation of our results to other contexts or products. Thus, we refrain from making too general claims regarding the extendability of our design and results.

Despite these limitations, our study, along with existing literature, suggests broader applicability of our conclusions to products requiring a foundation of trust—akin to mobile banking's inherent need for trust with features like "having money in the cell phone". This trust aligns with social network dynamics, underscoring the pivotal role of social interactions in the diffusion process.

CRediT authorship contribution statement

Pablo Brañas-Garza: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Data curation, Conceptualization. **Jaromír Kovářík:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Ericka G. Rascón Ramírez:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization.

Appendix

See Figs. A.1–A.9 and Tables A.1–A.12.

[19] See Table A.1 for the differences in observables across the intervened and control areas.

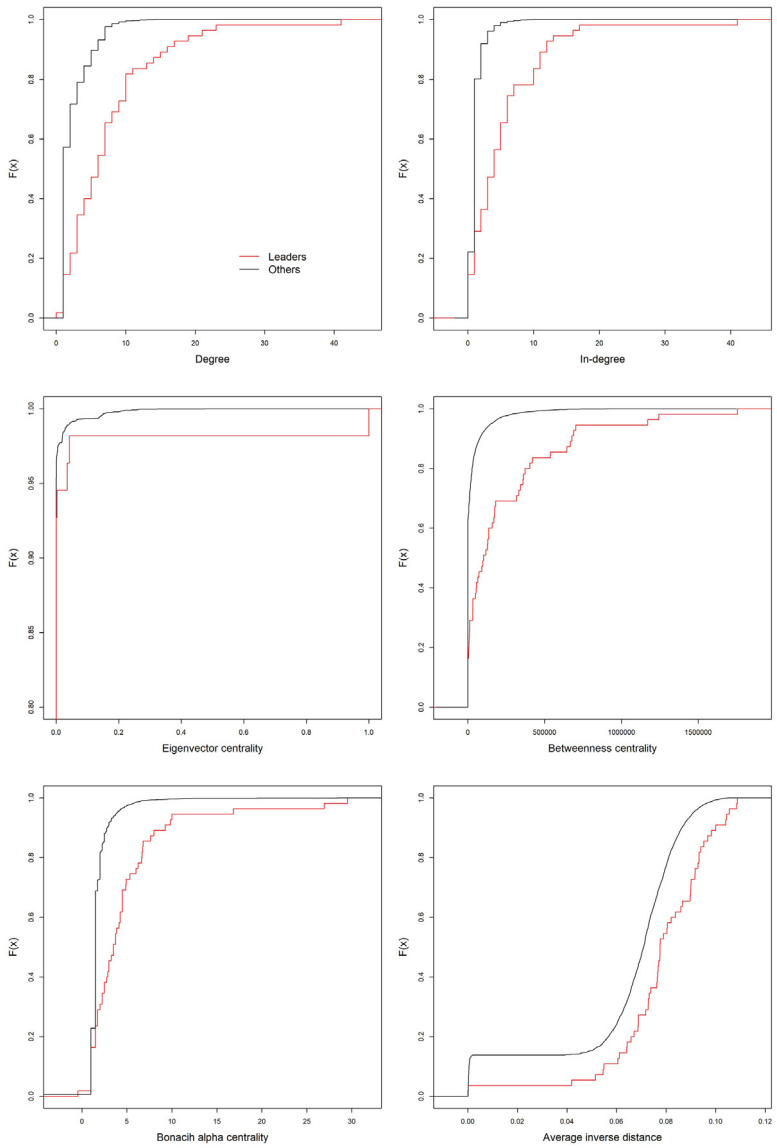


Fig. A.1. Cumulative distributions of various centrality measures, disaggregated for leaders (red) and other subjects (black), show that leaders are more central compared to non-leaders, regardless of the centrality measure considered.

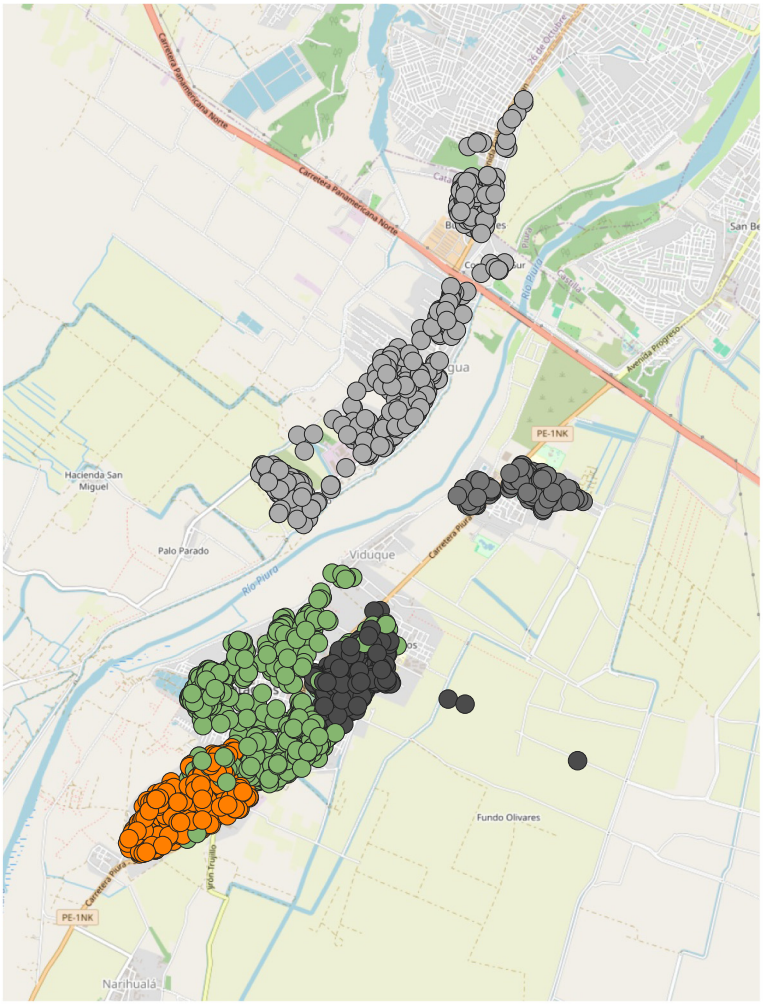


Fig. A.2. Geolocations of interviewed participants. Monte Sullón (orange) and Catacaos (green) are intervened areas and La Legua (light gray), Simbila and Nuevo Catacaos (dark gray) control.

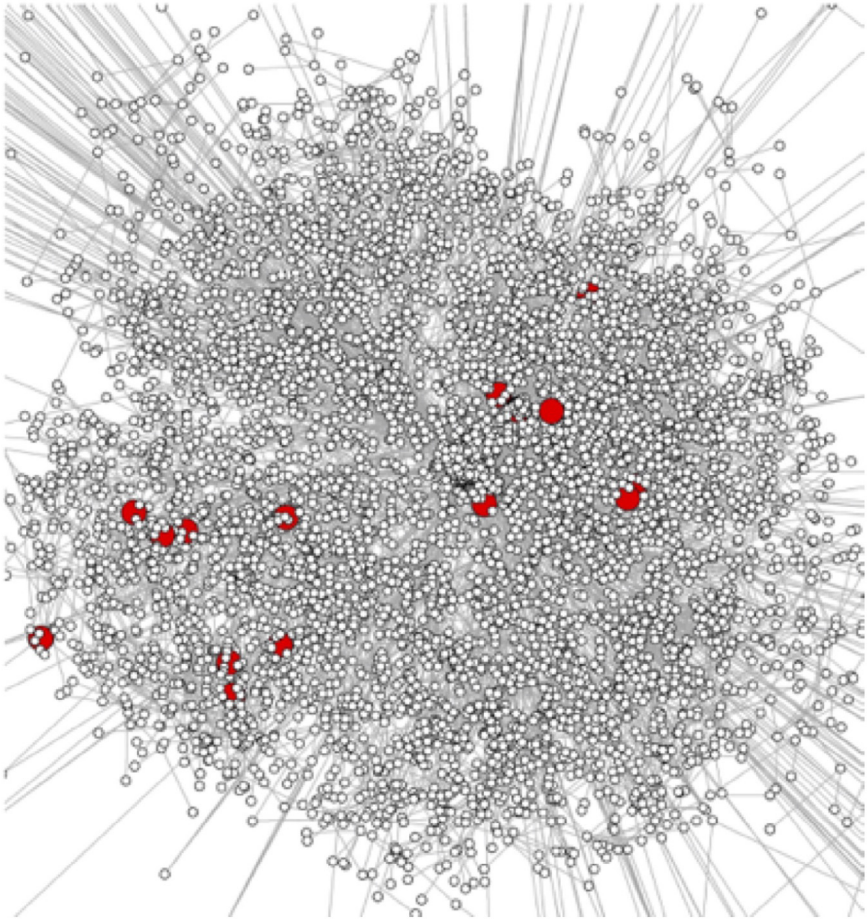


Fig. A.3. The elicited network of surveyed and named individuals. In red, the mother leaders are identified.



Fig. A.4. Illustration of the marketing campaign.

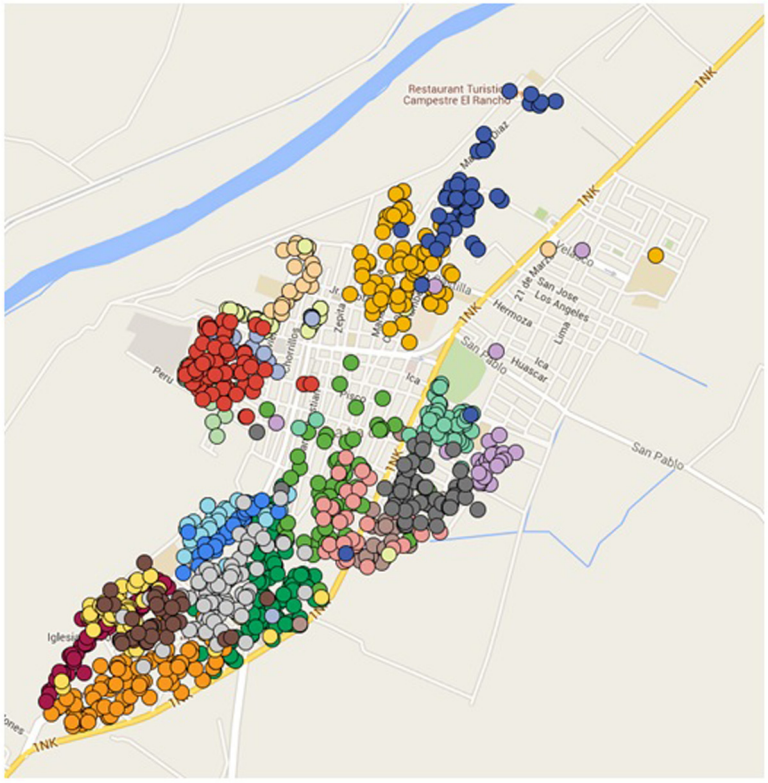


Fig. A.5. Geographical distribution of take-ups in the intervened areas.

Table A.1
Comparison of the sample descriptive statistics between control and intervened participants prior to the intervention.

Variables	T-C Difference	Control Mean	Observations
Socio-demographics			
Age 19–25	0.0101	0.079	1983
Age 26–40	−0.100***	0.601	1983
Age 41–55	0.066**	0.278	1983
Age 56-more	0.024*	0.043	1983
Sec/high school	−0.033	0.554	1983
Household size	0.165	5.278	1983
Housewife w/business	0.029	0.207	1983
Employee	−0.018	0.191	1983
No. earners at home	0.114**	1.408	1983
Living with partner	0.091***	0.335	1983
Married	−0.129***	0.510	1983
Separated	−0.001	0.101	1983
Mobile	−0.063	0.480	1983
Radio	−0.106***	0.606	1983
Tv	−0.083***	0.851	1983
Iron	−0.096***	0.354	1983
Gas cooker	−0.129***	0.720	1983
Fridge	−0.108***	0.386	1983
Landline	0.021***	0.016	1983
Assets	−0.564***	3.415	1983
No. rooms	0.073	2.933	1983
Potable water	−0.062*	0.857	1983
Affiliation, m-Banking, financial education and contact w/mother leader (ML)			
BIM affiliation pre-intervention	−0.007**	0.009	1983
Know about m-banking	−0.049	0.454	1983
Know about BIM	−0.032	0.317	1983
Any course in financial edu	−0.115***	0.803	1983
Meet weekly w/ML	0.096*	0.118	1983
Meet every 15 days w/ML	0.141***	0.174	1983
Meet monthly w/ML	−0.213***	0.575	1983
Meet every 2 mths. or more w/ML	−0.025	0.132	1983
Network characteristics			
Distance to intervened mother leader (index 0-1)	−0.053**	0.170	1983
Distance to control (index 0-1)	0.233***	0.043	1834
Proportion of intervened friends	0.690***	0.165	1934
Centrality	−0.127	1.466	1983
Betweenness	9173.698*	39,871.186	1983
Clustering	0.010*	0.016	1983
Degree	0.561**	3.185	1983

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

Table A.2
Intervention estimates using covariates.

Variables	(1) All phases	(2) Pre-intervention	(3) Seed 1	(4) Marketing campaign	(5) Seed 2
		T0	T1	T2	T3
Intervened (=1)	0.079***	−0.005**	0.057***	0.010	0.017
	[0.027]	[0.003]	[0.014]	[0.008]	[0.014]
Age 26–40	−0.047**	−0.016	−0.016	−0.001	−0.015
	[0.019]	[0.009]	[0.012]	[0.007]	[0.012]
Age 41–55	−0.022	−0.016	−0.004	0.003	−0.006
	[0.027]	[0.010]	[0.019]	[0.011]	[0.016]
Age 56 or more	−0.084***	−0.020*	−0.048***	−0.003	−0.013
	[0.027]	[0.010]	[0.016]	[0.006]	[0.016]
Sec/High school	0.028***	0.001	0.020**	0.002	0.005
	[0.010]	[0.002]	[0.009]	[0.002]	[0.006]
Household size	−0.002	−0.000	−0.000	−0.002	−0.000
	[0.004]	[0.001]	[0.002]	[0.002]	[0.002]
Housewife w/ business	0.003	0.002	0.003	0.001	−0.003
	[0.014]	[0.005]	[0.009]	[0.004]	[0.005]
Employee	−0.008	0.006	−0.016	0.004	−0.002
	[0.018]	[0.006]	[0.012]	[0.005]	[0.008]
HH members work	0.006	0.001	0.001	0.001	0.002
	[0.010]	[0.002]	[0.008]	[0.001]	[0.003]
Living w/partner	−0.020	−0.012	−0.013	0.008	−0.003
	[0.024]	[0.009]	[0.021]	[0.006]	[0.008]
Married	−0.001	−0.009	−0.001	0.008*	0.001
	[0.019]	[0.008]	[0.017]	[0.004]	[0.008]
Separated	−0.001	−0.010	0.003	0.005	0.002
	[0.025]	[0.010]	[0.026]	[0.005]	[0.008]
Assets	0.014***	0.002**	0.010***	0.000	0.002
	[0.004]	[0.001]	[0.004]	[0.000]	[0.001]
# of bedrooms	0.003	0.002*	0.001	−0.001	0.001
	[0.004]	[0.001]	[0.003]	[0.001]	[0.001]
Potable water	0.006	−0.008*	0.003	0.004	0.007
	[0.013]	[0.004]	[0.009]	[0.005]	[0.009]
Knowing about m-banking	0.024*	0.005	0.011	0.001	0.007
	[0.013]	[0.004]	[0.007]	[0.003]	[0.007]
Knowing about BIM	−0.007	0.004	−0.001	−0.005*	−0.005
	[0.018]	[0.006]	[0.013]	[0.003]	[0.005]
Any financial education	0.014	−0.004	0.001	0.007	0.010
	[0.018]	[0.004]	[0.012]	[0.006]	[0.006]
Meet every 15 days w/ML	−0.004	−0.002	0.002	−0.009	0.005
	[0.018]	[0.004]	[0.016]	[0.008]	[0.009]
Meet monthly w/ML	−0.013	0.004	−0.017	−0.002	0.003
	[0.017]	[0.005]	[0.014]	[0.005]	[0.008]
Meet every 2 mths. or more w/ML	−0.008	0.000	−0.011	−0.005	0.008
	[0.018]	[0.006]	[0.017]	[0.010]	[0.009]
Observations	2003	2003	2003	2003	2003
R-squared	0.056	0.021	0.046	0.011	0.013
Covariates	Yes	Yes	Yes	Yes	Yes
Control mean	0.0194	0.00860	0.00430	0.00110	0.00540

Robust standard errors in brackets.
*** p < 0.01, ** p < 0.05, * p < 0.10.

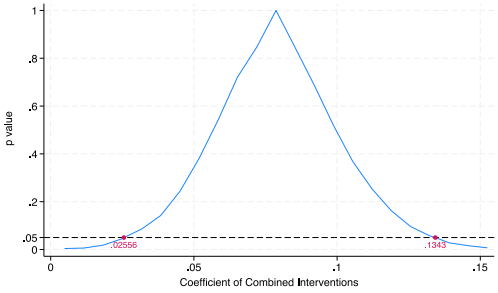
Table A.3
Estimates of intervention coefficients without covariates.

Variables	(1) All phases	(2) Pre-intervention	(3) Seed 1	(4) Marketing campaign	(5) Seed 2
		T0	T1	T2	T3
Intervened (=1)	0.070***	−0.007**	0.054***	0.008	0.014
	[0.026]	[0.003]	[0.014]	[0.007]	[0.012]
Observations	2003	2003	2003	2003	2003
R-squared	0.022	0.002	0.023	0.003	0.004
Covariates	No	No	No	No	No
Control mean	0.019	0.009	0.004	0.001	0.005

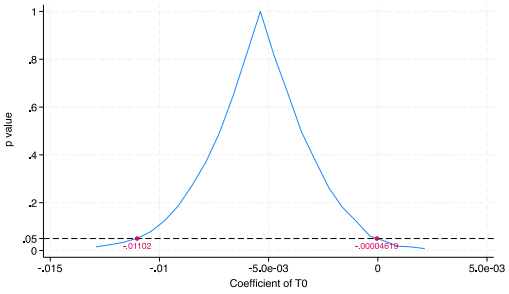
Note: The dependent variables represent the new affiliation rates that occurred in each period. Column (1) shows the difference in take-up rates between the intervened and control areas without distinguishing the timing of adoption (i.e. from the pre-intervention period 6/4/16 until 6/10/16); column (2) considers take-up rates from 26/4/16 until 24/6/16; column (3) covers the period 25/6/16 until 31/7/16 when the first Seeded Intervention (*Seed 1*) was launched; column (4) examines the period from 1/8/16 until 26/8/2016 when the Marketing campaign was launched; and column (5) covers from 27/8/16 until 6/10/16 when the reinforcer *Seed 2* was launched while the Marketing campaign was still running. Clustered standard errors at mother leader level in brackets using Pustejovsky and Tipton (2018). *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.4
Intervention estimates: P-values and confidence intervals.

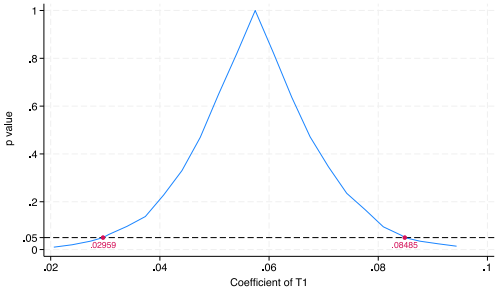
Intervention status		Implementation date		Intervention effects	p− value	Confidence Intervals	
		Start	End			Min	Max
Wild cluster bootstrap: Cameron et al. (2008)							
All combined phases	All	6/4/16	6/10/16	0.079	0.001	0.028	0.133
Pre-interventions	T0	6/4/16	24/6/16	−0.005	0.042	−0.011	0.000
Seeded Int. I (Seed 1)	T1	25/6/16	31/7/16	0.057	0.000	0.027	0.086
Marketing campaign	T2	1/8/16	26/8/16	0.010	0.149	−0.002	0.025
Reinforcer of seeded Int. (Seed 2)	T3	27/8/16	6/10/16	0.017	0.270	−0.007	0.043
Small-sample corrected cluster-robust variance estimator: Pustejovsky and Tipton (2018)							
All combined phases	All	6/4/16	6/10/16	0.079	0.009	0.022	0.136
Pre-interventions	T0	6/4/16	24/6/16	−0.005	0.055	−0.011	0.000
Seeded Int. I (Seed 1)	T1	25/6/16	31/7/16	0.057	0.000	0.029	0.086
Marketing campaign	T2	1/8/16	26/8/16	0.010	0.200	−0.006	0.026
Reinforcer of seeded Int. (Seed 2)	T3	27/8/16	6/10/16	0.017	0.247	−0.012	0.045
Wild cluster bootstrap: Cameron et al. (2008) & Small-sample Corrected Cluster-robust Variance Estimator: Pustejovsky and Tipton (2018)							
All combined phases	All	6/4/16	6/10/16	0.079	0.003	0.026	0.134
Pre-interventions	T0	6/4/16	24/6/16	−0.005	0.048	−0.011	0.000
Seeded Int. I (Seed 1)	T1	25/6/16	31/7/16	0.057	0.000	0.030	0.085
Marketing campaign	T2	1/8/16	26/8/16	0.010	0.152	−0.002	0.024
Reinforcer of seeded Int. (Seed 2)	T3	27/8/16	6/10/16	0.017	0.252	−0.007	0.042



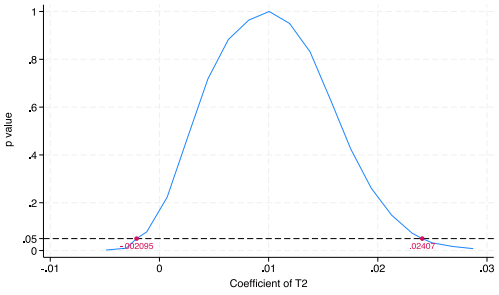
(a) All Combined Phases



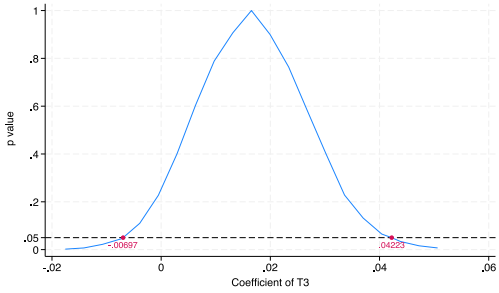
(b) Pre-Interventions



(c) Seeded Intervention I (Seed 1)



(d) Marketing Campaign



(e) Reinforcer of Seeded Int. (Seed 2)

Fig. A.6. Distributions of wild bootstrapped intervention estimates and their confidence intervals by phase.

Table A.5
Estimates of Intervention Coefficients using Network Distance to Intervened Mother Leader, Control and Intervened Friends.

Variables	(1) All estimation sample	(2) All phases	(3) Pre-intervention	(4) Seed 1	(5) Marketing campaign	(6) Seed 2
			T0	T1	T2	T3
Distance to intervened mother leader						
Intervened	0.077***	0.064**	−0.007**	0.048***	0.012	0.010
	(0.027)	(0.028)	(0.003)	(0.013)	(0.009)	(0.013)
Distance to ML (1st)		0.030**	0.003	0.020*	−0.005	0.012*
		(0.014)	(0.003)	(0.011)	(0.004)	(0.006)
Observations	1983	1983	1983	1983	1983	1983
R-squared	0.055	0.058	0.021	0.047	0.012	0.014
Distance to control						
Intervened	0.080***	0.058**	−0.006	0.040***	0.010	0.015
	(0.027)	(0.026)	(0.005)	(0.012)	(0.008)	(0.014)
Distance to control (1st)		−0.029**	−0.002	−0.024***	0.001	−0.004
		(0.012)	(0.005)	(0.009)	(0.002)	(0.007)
Observations	1834	1834	1834	1834	1834	1834
R-squared	0.063	0.064	0.022	0.050	0.013	0.014
Proportion of intervened friends						
Intervened	0.076***	0.056**	−0.004	0.042***	0.009	0.010
	(0.026)	(0.023)	(0.003)	(0.012)	(0.007)	(0.011)
Prop. of intervened friends (1st)		−0.030**	0.002	−0.022**	−0.000	−0.009
		(0.012)	(0.004)	(0.009)	(0.001)	(0.008)
Observations	1934	1934	1934	1934	1934	1934
R-squared	0.058	0.060	0.021	0.046	0.014	0.013

Note: Table A.2 shows the covariates used in the models displayed in this table. Clustered standard errors at mother leader level in brackets using Pustejovsky and Tipton (2018). *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.6
Estimates of intervention coefficients using network distance to intervened mother leader, control and intervened friends considering false discovery rate (Benjamini and Hochberg, 1995).

Variables	(1) All estimation sample	(2) All phases	(3) Pre-intervention	(4) Seed 1	(5) Marketing campaign	(6) Seed 2
			T0	T1	T2	T3
Distance to intervened mother leader						
Intervened	0.077***	0.064*	−0.007**	0.048**	0.012	0.010
	(0.027)	(0.028)	(0.003)	(0.013)	(0.009)	(0.013)
Distance to ML (1st)		0.030	0.003	0.020	−0.005	0.012
		(0.014)	(0.003)	(0.011)	(0.004)	(0.006)
Observations	1983	1983	1983	1983	1983	1983
R-squared	0.055	0.058	0.021	0.047	0.012	0.014
Distance to control						
Intervened	0.080***	0.058**	−0.006	0.040**	0.010	0.015
	(0.027)	(0.026)	(0.005)	(0.012)	(0.008)	(0.014)
Distance to control (1st)		−0.029**	−0.002	−0.024**	0.001	−0.004
		(0.012)	(0.005)	(0.009)	(0.002)	(0.007)
Observations	1834	1834	1834	1834	1834	1834
R-squared	0.063	0.064	0.022	0.050	0.013	0.014
Proportion of intervened friends						
Intervened	0.076***	0.056**	−0.004	0.042**	0.009	0.010
	(0.026)	(0.023)	(0.003)	(0.012)	(0.007)	(0.011)
Prop. of Intervened friends (1st)		−0.030**	0.002	−0.022**	−0.000	−0.009
		(0.012)	(0.004)	(0.009)	(0.001)	(0.008)
Observations	1934	1934	1934	1934	1934	1934
R-squared	0.058	0.060	0.021	0.046	0.014	0.013

Note: Table A.2 shows the covariates used in the models displayed in this table. Clustered standard errors at mother leader level in brackets using Pustejovsky and Tipton (2018). *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.7
Estimates of intervention coefficients using network variables.

Variables	(1) All estimation sample	(2) All phases	(3) Pre-intervention	(4) Seed 1	(5) Marketing campaign	(6) Seed 2
			T0	T1	T2	T3
Centrality						
Intervened	0.077***	0.077***	−0.005**	0.057***	0.010	0.015
	(0.027)	(0.027)	(0.003)	(0.014)	(0.008)	(0.013)
Centrality (1st)		−0.003	−0.001	−0.002	−0.001	0.002
		(0.009)	(0.003)	(0.007)	(0.003)	(0.004)
Observations	1983	1983	1983	1983	1983	1983
R-squared	0.055	0.055	0.021	0.044	0.011	0.012
Betweenness						
Intervened	0.077***	0.077***	−0.005**	0.057***	0.010	0.015
	(0.027)	(0.027)	(0.003)	(0.014)	(0.008)	(0.013)
Betweenness (1st)		0.005	0.002	−0.000	0.004	−0.001
		(0.009)	(0.004)	(0.006)	(0.003)	(0.004)
Observations	1983	1983	1983	1983	1983	1983
R-squared	0.055	0.055	0.021	0.044	0.012	0.012
Clustering						
Intervened	0.077***	0.076***	−0.005**	0.056***	0.011	0.015
	(0.027)	(0.027)	(0.003)	(0.014)	(0.008)	(0.013)
Clustering (1st)		−0.017	0.001	−0.017	0.008	−0.009
		(0.018)	(0.005)	(0.014)	(0.006)	(0.008)
Observations	1983	1983	1983	1983	1983	1983
R-squared	0.055	0.055	0.021	0.045	0.012	0.013
Degree						
Intervened	0.077***	0.078***	−0.005**	0.057***	0.010	0.015
	(0.027)	(0.027)	(0.003)	(0.014)	(0.008)	(0.013)
Degree (1st)		0.010	0.002	0.008	0.003	−0.002
		(0.011)	(0.003)	(0.009)	(0.003)	(0.003)
Observations	1983	1983	1983	1983	1983	1983
R-squared	0.055	0.055	0.021	0.045	0.011	0.012

Note: Table A.2 shows the covariates used in the models displayed in this table. Clustered standard errors at mother leader level in brackets using Pustejovsky and Tipton (2018). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.8
Intervention estimates using survey data with network variables considering false discovery rate (Benjamini and Hochberg, 1995).

Variables	(1) All estimation sample	(2) All phases	(3) Pre-intervention	(4) Seed 1	(5) Marketing campaign	(6) Seed 2
			T0	T1	T2	T3
Centrality						
Intervened	0.077***	0.077**	−0.005*	0.057***	0.010	0.015
	(0.027)	(0.027)	(0.003)	(0.014)	(0.008)	(0.013)
Centrality (1st)		−0.003	−0.001	−0.002	−0.001	0.002
		(0.009)	(0.003)	(0.007)	(0.003)	(0.004)
Observations	1983	1983	1983	1983	1983	1983
R-squared	0.055	0.055	0.021	0.044	0.011	0.012
Betweenness						
Intervened	0.077***	0.077**	−0.005*	0.057***	0.010	0.015
	(0.027)	(0.027)	(0.003)	(0.014)	(0.008)	(0.013)
Betweenness (1st)		0.005	0.002	−0.000	0.004	−0.001
		(0.009)	(0.004)	(0.006)	(0.003)	(0.004)
Observations	1983	1983	1983	1983	1983	1983
R-squared	0.055	0.055	0.021	0.044	0.012	0.012

(*continued on next page*)

Table A.8 (*continued*).

Variables	(1) All estimation sample	(2) All phases	(3) Pre-intervention	(4) Seed 1	(5) Marketing campaign	(6) Seed 2
			T0	T1	T2	T3
Clustering						
Intervened	0.077***	0.076**	−0.005*	0.056***	0.011	0.015
	(0.027)	(0.027)	(0.003)	(0.014)	(0.008)	(0.013)
Clustering (1st)		−0.017	0.001	−0.017	0.008	−0.009
		(0.018)	(0.005)	(0.014)	(0.006)	(0.008)
Observations	1983	1983	1983	1983	1983	1983
R-squared	0.055	0.055	0.021	0.045	0.012	0.013
Degree						
Intervened	0.077***	0.078**	−0.005*	0.057***	0.010	0.015
	(0.027)	(0.027)	(0.003)	(0.014)	(0.008)	(0.013)
Degree (1st)		0.010	0.002	0.008	0.003	−0.002
		(0.011)	(0.003)	(0.009)	(0.003)	(0.003)
Observations	1983	1983	1983	1983	1983	1983
R-squared	0.055	0.055	0.021	0.045	0.011	0.012

Note: Table A.2 shows the covariates used in the models displayed in this table. Clustered standard errors at mother leader level in brackets using Pustejovsky and Tipton (2018). *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.9
Estimates of intervention coefficients using network distance to mother intervened leader, control and intervened friends. *Interactions with network variables.*

Variables	(1) All phases	(2) Pre-intervention	(3) Seed 1	(4) Marketing campaign	(5) Seed 2
		T0	T1	T2	T3
Distance to intervened mother leader					
Intervened	0.060**	−0.007***	0.040***	0.013	0.014
	(0.029)	(0.003)	(0.013)	(0.010)	(0.013)
Distance to ML (1st)	0.019	0.001	−0.005	−0.001	0.024*
	(0.014)	(0.009)	(0.005)	(0.002)	(0.013)
Intervened*Dist. to ML (1st)	0.015	0.002	0.034**	−0.005	−0.016
	(0.023)	(0.010)	(0.015)	(0.005)	(0.014)
Observations	1983	1983	1983	1983	1983
R-squared	0.058	0.021	0.048	0.012	0.015
Distance to control					
Intervened	0.078***	−0.006	0.064***	0.008	0.013
	(0.029)	(0.009)	(0.015)	(0.006)	(0.016)
Distance to control (1st)	−0.008	−0.002	−0.000	−0.001	−0.005
	(0.016)	(0.010)	(0.006)	(0.001)	(0.010)
Intervened*Dist. to control (1st)	−0.042*	0.000	−0.048***	0.003	0.004
	(0.024)	(0.010)	(0.017)	(0.005)	(0.015)
Observations	1834	1834	1834	1834	1834
R-squared	0.065	0.022	0.052	0.013	0.014
Proportion of intervened friends					
Intervened	0.077***	−0.002	0.058***	0.008	0.012
	(0.028)	(0.005)	(0.016)	(0.006)	(0.016)
Prop. of intervened friends (1st)	−0.008	0.004	−0.005	−0.001	−0.007
	(0.010)	(0.007)	(0.005)	(0.001)	(0.007)
Intervened*Prop. of int. friends (1st)	−0.053**	−0.007	−0.043***	0.002	−0.005
	(0.022)	(0.007)	(0.016)	(0.003)	(0.018)
Observations	1934	1934	1934	1934	1934
R-squared	0.062	0.022	0.048	0.014	0.013

Note: Table A.2 shows the covariates used in the models displayed in this table. Clustered standard errors at mother leader level in brackets using Pustejovsky and Tipton (2018). *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.10
Estimates of intervention coefficients using network distance to intervened mother leader, control and intervened friends considering false discovery rate (Benjamini and Hochberg, 1995).
Interactions with network variables.

Variables	(1) All phases	(2) Pre-intervention	(3) Seed 1	(4) Marketing campaign	(5) Seed 2
		T0	T1	T2	T3
Distance to intervened mother leader					
Intervened	0.060*	−0.007**	0.040**	0.013	0.014
	(0.029)	(0.003)	(0.013)	(0.010)	(0.013)
Distance to ML (1st)	0.019	0.001	−0.005	−0.001	0.024
	(0.014)	(0.009)	(0.005)	(0.002)	(0.013)
Intervened*Dist. to ML (1st)	0.015	0.002	0.034	−0.005	−0.016
	(0.023)	(0.010)	(0.015)	(0.005)	(0.014)
Observations	1983	1983	1983	1983	1983
R-squared	0.058	0.021	0.048	0.012	0.015
Distance to control					
Intervened	0.078**	−0.006	0.064**	0.008	0.013
	(0.029)	(0.009)	(0.015)	(0.006)	(0.016)
Distance to control (1st)	−0.008	−0.002	−0.000	−0.001	−0.005
	(0.016)	(0.010)	(0.006)	(0.001)	(0.010)
Intervened*Dist. to control (1st)	−0.042*	0.000	−0.048**	0.003	0.004
	(0.024)	(0.010)	(0.017)	(0.005)	(0.015)
Observations	1834	1834	1834	1834	1834
R-squared	0.065	0.022	0.052	0.013	0.014
Proportion of intervened friends					
Intervened	0.077**	−0.002	0.058**	0.008	0.012
	(0.028)	(0.005)	(0.016)	(0.006)	(0.016)
Prop. of intervened friends (1st)	−0.008	0.004	−0.005	−0.001	−0.007
	(0.010)	(0.007)	(0.005)	(0.001)	(0.007)
Intervened*Prop. of int. friends (1st)	−0.053**	−0.007	−0.043**	0.002	−0.005
	(0.022)	(0.007)	(0.016)	(0.003)	(0.018)
Observations	1934	1934	1934	1934	1934
R-squared	0.062	0.022	0.048	0.014	0.013

Note: Table A.2 shows the covariates used in the models displayed in this table. Clustered standard errors at mother leader level in brackets using Pustejovsky and Tipton (2018). *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.11
Estimates of intervened coefficients using network variables.
Interactions with network variables.

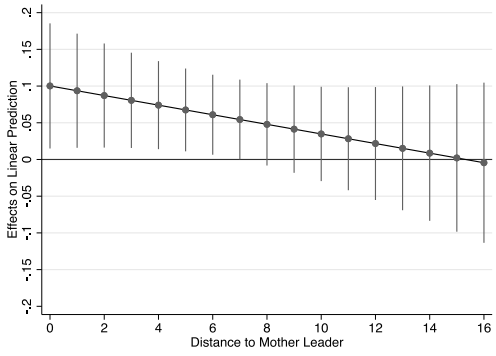
Variables	(1) All phases	(2) Pre-intervention	(3) Seed 1	(4) Marketing campaign	(5) Seed 2
		T0	T1	T2	T3
Centrality					
Intervened	0.075**	−0.010**	0.058***	0.013	0.013
	(0.030)	(0.005)	(0.016)	(0.011)	(0.014)
Centrality (1st)	−0.004	−0.005	−0.001	0.002	−0.000
	(0.006)	(0.006)	(0.004)	(0.002)	(0.004)
Intervened*Centrality (1st)	0.004	0.007	−0.002	−0.006	0.004
	(0.018)	(0.007)	(0.014)	(0.006)	(0.009)
Observations	1983	1983	1983	1983	1983
R-squared	0.055	0.022	0.044	0.011	0.012
Betweenness					
Intervened	0.083***	−0.002	0.061***	0.007	0.018
	(0.026)	(0.004)	(0.014)	(0.007)	(0.013)
Betweenness (1st)	0.014*	0.007	0.006*	−0.002	0.002
	(0.008)	(0.007)	(0.004)	(0.002)	(0.004)
Intervened*Betweenness (1st)	−0.017	−0.009	−0.012	0.010*	−0.006
	(0.017)	(0.008)	(0.012)	(0.006)	(0.008)
Observations	1983	1983	1983	1983	1983
R-squared	0.055	0.022	0.045	0.013	0.012

(*continued on next page*)

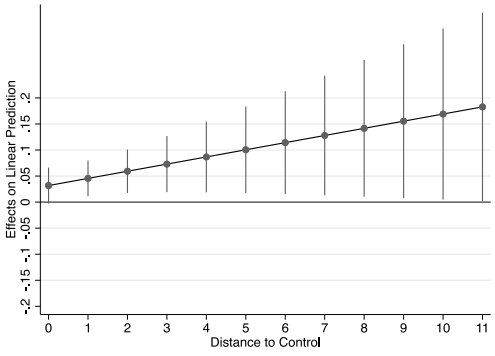
Table A.11 (*continued*).

Variables	(1) All phases	(2) Pre-intervention	(3) Seed 1	(4) Marketing campaign	(5) Seed 2
		T0	T1	T2	T3
Clustering					
Intervened	0.116***	−0.009	0.087***	0.002	0.036*
	(0.034)	(0.011)	(0.023)	(0.002)	(0.020)
Clustering (1st)	0.012	−0.002	0.006	0.002	0.006*
	(0.014)	(0.013)	(0.004)	(0.002)	(0.004)
Intervened*Clustering (1st)	−0.046	0.004	−0.036	0.010	−0.024*
	(0.029)	(0.013)	(0.022)	(0.008)	(0.013)
Observations	1983	1983	1983	1983	1983
R-squared	0.057	0.021	0.046	0.013	0.014
Degree					
Intervened	0.074***	−0.001	0.053***	0.006	0.016
	(0.025)	(0.004)	(0.013)	(0.006)	(0.013)
Degree (1st)	0.006	0.006	0.003	−0.002	−0.001
	(0.008)	(0.005)	(0.003)	(0.002)	(0.004)
Intervened*Degree (1st)	0.008	−0.009	0.010	0.010	−0.002
	(0.020)	(0.006)	(0.016)	(0.006)	(0.005)
Observations	1983	1983	1983	1983	1983
R-squared	0.055	0.022	0.045	0.012	0.012

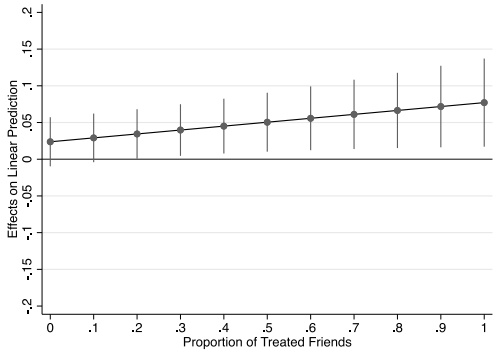
Note: Table A.2 shows the covariates used in the models displayed in this table. Clustered standard errors at mother leader level in brackets using Pustejovsky and Tipton (2018). *** p < 0.01, ** p < 0.05, * p < 0.1.



(a) Distance to Mother Leader



(b) Distance to Control



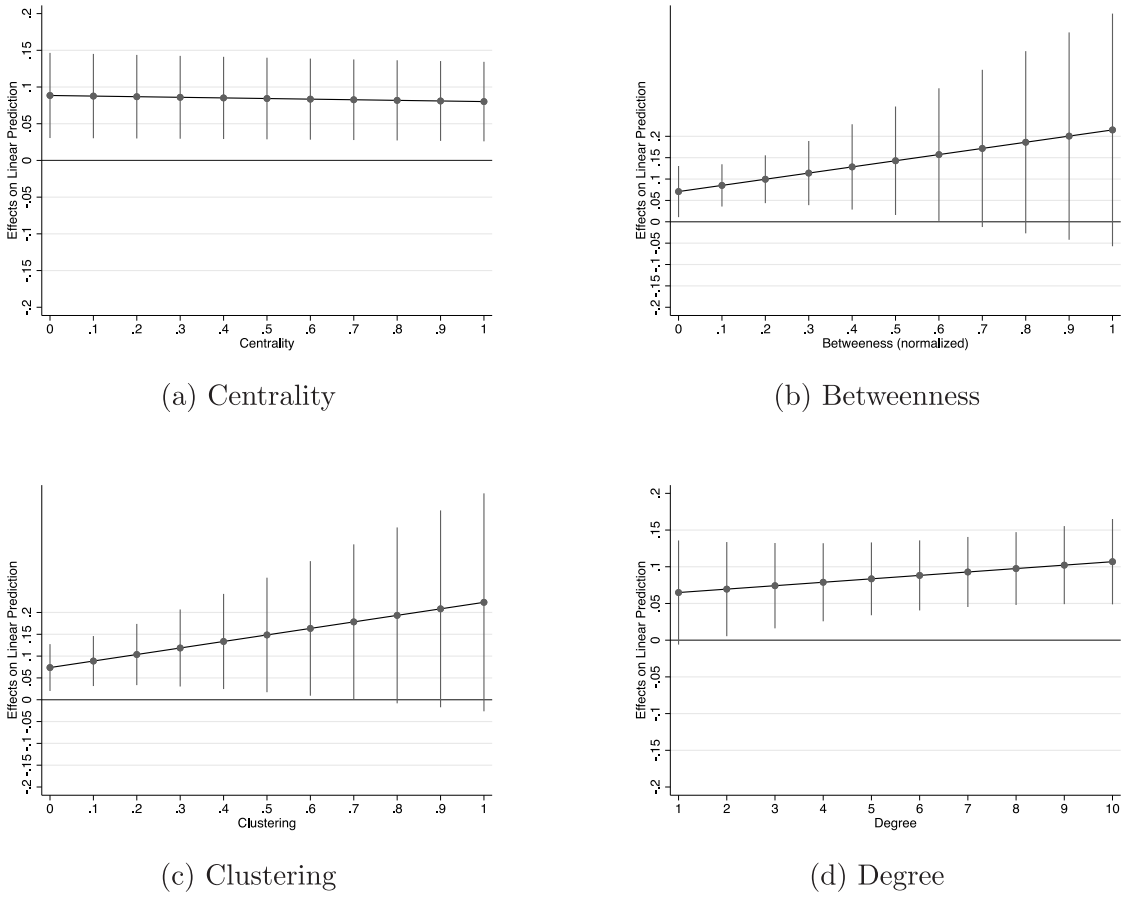
(c) Proportion of Intervened Friends

Fig. A.7. Marginal effects of linear predictions for network distance to mother leader, control and proportion of intervened friends.

Table A.12
Estimates of intervention coefficients using network variables considering false discovery rate (Benjamini and Hochberg, 1995). *Interactions with network variables*.

Variables	(1) All phases	(2) Pre-intervention	(3) Seed 1	(4) Marketing campaign	(5) Seed 2
		T0	T1	T2	T3
Centrality					
Intervened	0.075**	−0.010*	0.058**	0.013	0.013
	(0.030)	(0.005)	(0.016)	(0.011)	(0.014)
Centrality (1st)	−0.004	−0.005	−0.001	0.002	−0.000
	(0.006)	(0.006)	(0.004)	(0.002)	(0.004)
Intervened*Centrality (1st)	0.004	0.007	−0.002	−0.006	0.004
	(0.018)	(0.007)	(0.014)	(0.006)	(0.009)
Observations	1983	1983	1983	1983	1983
R-squared	0.055	0.022	0.044	0.011	0.012
Betweenness					
Intervened	0.083**	−0.002	0.061***	0.007	0.018
	(0.026)	(0.004)	(0.014)	(0.007)	(0.013)
Betweenness (1st)	0.014	0.007	0.006	−0.002	0.002
	(0.008)	(0.007)	(0.004)	(0.002)	(0.004)
Intervened*Betweenness (1st)	−0.017	−0.009	−0.012	0.010	−0.006
	(0.017)	(0.008)	(0.012)	(0.006)	(0.008)
Observations	1983	1983	1983	1983	1983
R-squared	0.055	0.022	0.045	0.013	0.012
Clustering					
Intervened	0.116**	−0.009	0.087**	0.002	0.036
	(0.034)	(0.011)	(0.023)	(0.002)	(0.020)
Clustering (1st)	0.012	−0.002	0.006	0.002	0.006
	(0.014)	(0.013)	(0.004)	(0.002)	(0.004)
Intervened*Clustering (1st)	−0.046	0.004	−0.036	0.010	−0.024
	(0.029)	(0.013)	(0.022)	(0.008)	(0.013)
Observations	1983	1983	1983	1983	1983
R-squared	0.057	0.021	0.046	0.013	0.014
Degree					
Intervened	0.074**	−0.001	0.053**	0.006	0.016
	(0.025)	(0.004)	(0.013)	(0.006)	(0.013)
Degree (1st)	0.006	0.006	0.003	−0.002	−0.001
	(0.008)	(0.005)	(0.003)	(0.002)	(0.004)
Intervened*Degree (1st)	0.008	−0.009	0.010	0.010	−0.002
	(0.020)	(0.006)	(0.016)	(0.006)	(0.005)
Observations	1983	1983	1983	1983	1983
R-squared	0.055	0.022	0.045	0.012	0.012

Note: Table A.2 shows the covariates used in the models displayed in this table. Clustered standard errors at mother leader level in brackets using Pustejovsky and Tipton (2018). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.



(a) Centrality (b) Betweenness

(c) Clustering (d) Degree

Fig. A.8. Marginal effects of linear predictions for centrality, betweenness, clustering and degree.

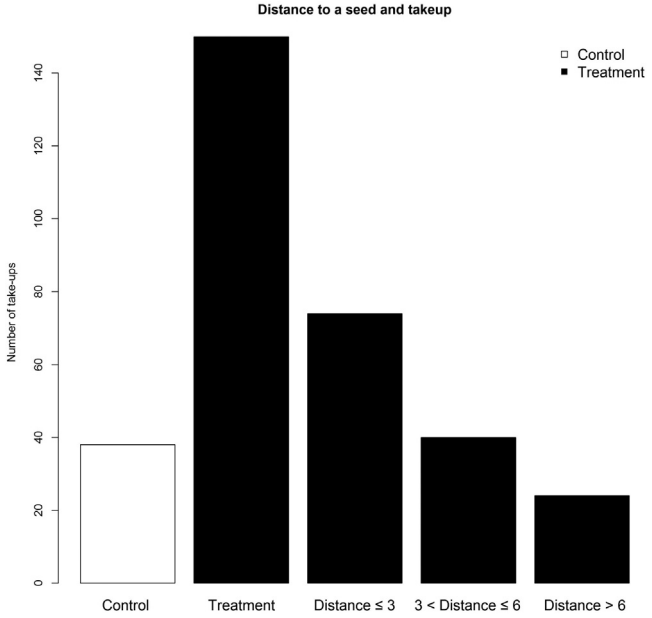


Fig. A.9. Take-up and network distance.

Data availability

Replication files are available at: https://doi.org/10.5281/zenodo.16884765.

References

Aghion, P., Bolton, P., 1997. A theory of trickle-down growth and development. Rev. Econ. Stud. 64 (2), 151–172.

Aker, J.C., Mbiti, I.M., 2010. Mobile phones and economic development in Africa. J. Econ. Perspect. 24 (3), 207–232.

Alatas, V., Banerjee, A., Chandrasekhar, A.G., Hanna, R., Olken, B.A., 2016. Network structure and the aggregation of information: Theory and evidence from Indonesia. Am. Econ. Rev. 106 (7), 1663–1704.

Angelucci, M., Di Maro, V., 2016. Programme evaluation and Spillover effects. J. Dev. Eff. 8 (1), 22–43.

Banerjee, A., Breza, E., Chandrasekhar, A.G., Golub, B., 2024. When less is more: Experimental evidence on information delivery during India's demonetization. Rev. Econ. Stud. 91 (4), 1884–1922.

Banerjee, A., Chandrasekhar, A.G., Duflo, E., Jackson, M.O., 2013. The diffusion of microfinance. Sci. 341 (6144), 1236498.

Banerjee, A., Chandrasekhar, A.G., Duflo, E., Jackson, M.O., 2019. Using gossips to spread information: Theory and evidence from two randomized controlled trials. Rev. Econ. Stud. 86 (6), 2453–2490.

Beaman, L., BenYishay, A., Magruder, J., Mobarak, A.M., 2021. Can network theory-based targeting increase technology adoption? Am. Econ. Rev. 111 (6), 1918–1943.

Beaman, L., Dillon, A., 2018. Diffusion of agricultural information within social networks: Evidence on gender inequalities from Mali. J. Dev. Econ. 133, 147–161.

Benjamini, Y., Hochberg, Y., 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. J. R. Stat. Soc. Ser. B Stat. Methodol. 57 (1), 289–300.

BenYishay, A., Mobarak, A.M., 2019. Social learning and incentives for experimentation and communication. Rev. Econ. Stud. 86 (3), 976–1009.

Breza, E., 2016. Field experiments, social networks, and development. In: The Oxford Handbook of the Economics of Networks. Vol. 4, Oxford University Press Oxford, pp. 412–439.

Breza, E., Chandrasekhar, A., Golub, B., Parvathaneni, A., 2019. Networks in economic development. Oxf. Rev. Econ. Policy 35 (4), 678–721.

Brown, I., Cajee, Z., Davies, D., Stroebel, S., 2003. Cell phone banking: predictors of adoption in South Africa—an exploratory study. Int. J. Inf. Manage. 23 (5), 381–394.

Burgess, R., Pande, R., 2005. Do rural banks matter? Evidence from the Indian social banking experiment. Am. Econ. Rev. 95 (3), 780–795.

Cameron, A.C., Gelbach, J.B., Miller, D.L., 2008. Bootstrap-based improvements for inference with clustered errors. Rev. Econ. Stat. 90 (3), 414–427.

Campbell, A., 2013. Word-of-mouth communication and percolation in social networks. Am. Econ. Rev. 103 (6), 2466–2498.

Centola, D., 2010. The spread of behavior in an online social network experiment. Sci. 329 (5996), 1194–1197.

Coleman, J.S., 1988. Social capital in the creation of human capital. Am. J. Sociol. 94, S95–S120.

Conley, T.G., Udry, C.R., 2010. Learning about a new technology: Pineapple in Ghana. Am. Econ. Rev. 100 (1), 35–69.

Demirgüç-Kunt, A., Leora, K., Dorothe, S., Ansar, S., 2022. The global findex database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19.

Donner, J., Tellez, C.A., 2008. Mobile banking and economic development: Linking adoption, impact, and use. Asian J. Commun. 18 (4), 318–332.

Duflo, E., 2012. Women empowerment and economic development. J. Econ. Lit. 50 (4), 1051–1079.

Dupas, P., Robinson, J., 2013. Savings constraints and microenterprise development: Evidence from a field experiment in Kenya. Am. Econ. J.: Appl. Econ. 5 (1), 163–192.

Fabregas, R., Kremer, M., Schilbach, F., 2019. Realizing the potential of digital development: The case of agricultural advice. Sci. 366 (6471), eaay3038.

Foster, A.D., Rosenzweig, M.R., 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. J. Political Econ. 103 (6), 1176–1209.

Heckman, J.J., LaLonde, R.J., Smith, J.A., 1999. The economics and econometrics of active labor market programs. In: Handbook of Labor Economics. Vol. 3, Elsevier, pp. 1865–2097.

Hsieh, C.-S., Hsu, Y.-C., Ko, S.I., Kovářík, J., Logan, T.D., 2024. Non-Representative sampled networks: Estimation of network structural properties by weighting. J. Econometrics 240 (1), 105689.

INEI, 2009. Estimaciones y Proyecciones de Población Total, Por Años Calendario y Edades Simples, 1950–2050. Report OI.N/223, Instituto Nacional de Estadísticas e Informática.

Jackson, M.O., et al., 2008. Social and Economic Networks, vol. 3, Princeton university press Princeton.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., 2002. Government ownership of banks. J. Financ. 57 (1), 265–301.

Miguel, E., Kremer, M., 2004. Worms: Identifying impacts on education and health in the presence of treatment externalities. Econometrica 72 (1), 159–217.

Mobarak, A.M., Saldanha, N.A., 2022. Remove barriers to technology adoption for people in poverty. Nat. Hum. Behav. 6 (4), 480–482.

Oster, E., 2019. Unobservable selection and coefficient stability: Theory and evidence. J. Bus. Econom. Statist. 37 (2), 187–204.

Pereyra Zaplana, R., 2015. Evaluación del rol de las madres líderes del programa JUNTOS.

Pustejovsky, J.E., Tipton, E., 2018. Small-sample methods for cluster-robust variance estimation and hypothesis testing in fixed effects models. J. Bus. Econom. Statist. 36 (4), 672–683.

Putnam, R.D., 2000. Bowling alone: America's declining social capital. In: Culture and Politics. Springer, pp. 223–234.

Rascón Ramírez, E.G., 2025. Randomized controlled trials. In: Liebe, U. (Ed.), Handbook of Quantitative Methods in Sociology. Edward Elgar.

Riquelme, H.E., Rios, R.E., 2010. The moderating effect of gender in the adoption of mobile banking. Int. J. Bank Mark. (5), 328–341.

Ruiz-Palazuelos, S., Espinosa, M.P., Kovářík, J., 2023. The weakness of common job contacts. Eur. Econ. Rev. 160, 104594.

Sapienza, P., 2004. The effects of government ownership on bank lending. J. Financ. Econ. 72 (2), 357–384.

Vega-Redondo, F., 2007. Complex Social Networks, vol. 44, Cambridge University Press.

World Bank, 2018. Global Financial Development Report 2017/18: Bankers Without Borders. World Bank.