Lima SCHOOL OF ECONOMICS

WORKING PAPER - 006

Local ambassadors promote mobile banking in Northern Peru

Marcos Agurto
Habiba Djebbari
Sudipta Sarangi
Brenda Silupú
Carolina Trivelli
Javier Torres

January 2020

Local ambassadors promote mobile banking in Northern Peru.*

M. Agurto,[1] H. Djebbari,[2] S. Sarangi,[3] B. Silupú,[4] C. Trivelli,[5] J. Torres[6] ,

[1]Universidad de Piura and Lima School of Economics

[2]Aix-Marseille Univ., CNRS, EHESS, Central Marseille, IRD, AMSE, Marseille, France

[3]Department of Economics, Virginia Tech and Lima School of Economics

[4]Universidad de Piura and CAM-UDEP

[5]Institutos de Estudios Peruanos

[5]Universidad del Pacífico

This version: January 6, 2020

Abstract

We experiment with a novel way to boost information acquisition that exploits existing social ties between the promoter of a new financial technology and community members. We offer information and training workshops on a new mobile-money platform in periurban and rural areas in Peru. In the treatment group, workshops are led by promoters who are personally known to the invited participants. In the control group, comparable individuals are invited to attend similar workshops, but the workshops are led by agents external to the community. Our findings suggest that lack of information impedes product adoption, which is itself limited by lack of trust in the individual who provides the information.

JEL Classification: D91, G23, I22, I31, O33
Keywords: Financial inclusion, social networks, information transmission, trust.

*For their helpful comments, we are grateful to María Laura Alzua, Guillermo Cruces, and participants at the Africa Region Econometrics Society 2019 meetings, the Peruvian Economic Association 2019 meetings, the Chilean Economic Association 2019 meetings, and the UDEP Economics Research Seminar. We thank Jessica Salazar at PDP for her extraordinary support in providing us with administrative adoption and use data, and Rodrigo Chang and Paul Corcuera for their excellent research assistance as well as for their comments on earlier drafts of this document. This work was supported by the Partnership for Economic Policy PIERI Award No. 12942. IRB approval obtained from PEP Ethical Committee on 2017-08-08. Experiment registered under No. 0002479 on the AEA RCT registry.
Corresponding author: Marcos Agurto, marcos.agurto@udep.edu.pe, +51 73 284500 ext. 3134.

1 Introduction

A large proportion of adults in the developing world do not own bank accounts, making it difficult for them to store cash and transfer money safely. Mobile money platforms can considerably reduce supply-side barriers, including fees, minimum-balance requirements, and indirect costs (Suri et al. (2012); Bachas et al. (2018)). On the demand side, however, consumers may fail to fully understand these new financial services, hindering early-stage adoption. How information is provided may thus be critical to improved financial inclusion.

Our objective is to test whether social ties are more effective in transmitting information and fostering the adoption of a new product than external agents. Social networks play an important role in the diffusion of technology (Foster and Rosenzweig (1995); Munshi (2004); Conley and Udry (2010); Jackson (2011). Banerjee et al. (2013) and Cai et al. (2015) assess alternative models through which networks impact choices and find evidence that direct communication between the initially informed and their network members is key. Network positions of messengers are also found to influence information transmission (see also Beaman et al. (2018); Banerjee et al. (2019)). This literature assumes that senders do not have strategic motives when communicating information.[1] In this paper, we provide new insights into the role of networks as trustworthy sources of information. We consider a setting in which social proximity reassures people that the information provided is reliable whereas outsiders may be perceived to hold strategic motives and therefore provide less informative messages than friends.

We design a novel experimental research protocol that isolates the effect of the social identity of the messenger on information acquisition and adoption of a new financial service. Our study is set in Peru, where a nation-wide digital money platform, Billetera Movil or BiM, was launched in 2016. Part of the national plan for financial inclusion, it however failed to reach remote periurban and rural populations.[2] In 2018, we offered information and training workshops about BiM to these populations under two contrast mechanisms intended to encourage participation. In the treatment group, the promoter leading the workshop was an academically successful young college student personally known to the invited participants as the son/daughter of a friend, neighbor, or relative. We refer to these students as the local ambassadors. In the control group, a similar set of community members were invited to attend a workshop led by an agent from outside the community. The family network members of our local ambassadors were listed, and the network groups randomly assigned to treatment or control. As a result, treatment and control groups are composed of the family networks of local ambassadors.

[1] Following the seminal work by Crawford and Sobel (1982), a theoretical literature investigates endogenous network formation in the presence of strategic communication (Hagenbach and Koessler (2010); Galeotti et al. (2013)).

[2] Two years after the launch of BiM, in the rural and periurban areas on which our study focuses, barely 1% of respondents held a BiM account.

We recruited local ambassadors from recipients of the Peruvian Beca18 scholarship, a flagship program for higher education. The scholarships are targeted at bright high school graduates living in disadvantaged periurban and rural communities and who obtain admission to an elite Peruvian university. We worked in partnership with one of these universities to recruit and train Beca18 scholarship holders in e-wallet technology, as well as to conduct a baseline survey in April-June 2018. Parents of Beca18 participants agreed to host an information and training workshop on BiM in their homes. We also partnered with Pagos Digitales Peruanos (PDP), the company that launched BiM. PDP supported us in the training of the external BiM promoters delivering information to our control group. Access to PDP administrative data enabled us to measure take-up and use of BiM. Use is expected to be low, as PDP decided to switch to a smartphone platform only a few months after the start of our study, which offered training on the platform designed for basic cellphones.

Using this research design, we test a number of hypotheses. First, we expect invited participants to be more willing to attend workshops led by a member of their network. One key benefit from attending is learning about the new financial service, and social proximity to the information provider may foster a belief that reliable information can be gathered during the workshop. Local ambassadors may be more trusted to provide reliable information than external agents. Higher trust could occur because community members expect to continue to interact with the fellow or the fellow's parents in the future. As a result, if lack of interest in participating in the workshop were, indeed, partly driven by a trust failure, our network-promotion treatment would be more successful at encouraging participation, with a higher impact on attendance on the most distrustful.

Secondly, we expect the net effect of the treatment on take-up to be of an indeterminate sign because of two countervailing forces. On the one hand, the treatment may affect the composition of the pool of workshop participants, attracting those who are the most distrustful of people, resulting in lower take-up among the treated. On the other hand, if participants believe that network promoters provide more credible information than would external agents, we expect higher take-up among the treated. Overall take-up in the treatment group would be higher than in the control group only if the latter effect offsets the former.

Thirdly, if information asymmetry on the consumer side were a barrier to adoption, information acquisition would increase take-up of the financial service. Though we do not have a pure control group (which received no information), we exploit the exogenous variation in workshop attendance due to treatment assignment to estimate the effect of information acquisition on take-up of the financial service. If lack of information were a barrier to financial inclusion, we would expect a positive local average treatment effect (LATE) of information on take-up that is identified for those who respond to the network-promotion treatment by changing their decision to participate to the workshop. We expect this parameter to inform us on the extent to which unfamiliarity with the financial service is a barrier to financial inclusion for the distrustful, a population typically more difficult to reach out to.

We find that 35% of invited participants attend the workshop in the control group and 70% of them do so in the treatment group. Being invited to attend a workshop led by a local ambassador thus doubles the likelihood that information is delivered compared to a counterfactual state in which the workshop is led by an outsider to the community. Using local ambassadors to pass on information is significantly more effective than sending external agents. The treatment effect is higher by an additional 16-17 percentage points for those who are distrustful of people [3] Our design does not allow us to identify the causal treatment effect on participation in the workshop according to the level of distrust. The effect may be driven by a correlate to being distrustful. We check the robustness of our result by including interaction effects along potential confounders. The differential effect related to trust remains. This evidence suggests that the acquisition of information is limited by lack of trust towards the individual picked to pass on the information (Guiso, Sapienza and Zingales (2008); Calcagno and Monticone (2015); Patacchini and Rainone (2017)).

We find a 3 percentage-point increase in take-up as a result of the network-promotion treatment. The effect is statistically significant and, though small in absolute terms, represents a doubling of the adoption rate obtained for the control group. This finding holds even though the network-promotion treatment attracts more distrustful people. We indeed find that distrustful participants are less likely to adopt as a result of the treatment than trustful network members. Finally, our network-promotion treatment may affect adoption as it encourages more people to acquire information. Both treatment and control groups are invited to attend the workshops during which information is provided, but treatment group members are more likely to do so. Once they attend the workshops, the subjects could update their beliefs about the product which should affect their decision to sign up on the

[3] The trust question was as follows: *Which of the following options more accurately reflects your thoughts on the following statement: People only have the best of intentions? 1: Always, 2: Most of the times, 3: Sometimes, 4: Rarely, 5: Never.* Individuals were considered distrustful if they answered either 4 or 5.

platform (i.e., take-up the service). We find a positive and significant effect of attending the workshop on adoption, with a magnitude of the order of 10 percentage points. This evidence suggests that lack of information impedes the adoption of the new service.

Our paper closely follows the research of Cole et al. (2013), BenYishay and Mobarak (2018) and Beaman et al. (2018). Cole et al. randomize whether information on a rainfall insurance product is provided to households by a trusted local agent or a trained enumerator and find the former to be more effective. BenYishay and Mobarak (2018) investigate the extent to which social networks can be used to identify a credible source of information about agricultural technology. Using self-reported data from participants in information and training sessions, they show evidence that the extent to which communicators pass on information depends in part on the identity of the communicator. In a companion paper, Beaman et al. (2018) select "seeds individuals" to maximize diffusion of the technology based on the predictions of various diffusion models. They find that more conversations about the technology occur with selected seeds in treated villages than with counterfactual shadow seeds, i.e., those who would have been chosen as seed given their network position in control villages. We also find that social ties can be more effective promoters, corroborating the results from these three papers.

Our contribution is to offer a novel research protocol specifically designed to focus on the role of the social identity of the promoter in transmitting information. Two particular features of the design are important in that respect. First, in our setting, information transmission takes place during a specific event designed for this purpose, allowing us to record participation to the workshop and use attendance to measure the extent to which information is transmitted. Second, because randomization is based on the sample of local ambassadors from whom we listed family network members, we are able to control the characteristics of the potential receivers (i.e., the individuals that promoters attempt to reach). As such, our design allows us to attribute the difference in participation and adoption exclusively to the identity of the messenger.

We draw two main policy lessons from this study. First, our study offers novel evidence that lack of information and lack of general trust are important obstacles to financial inclusion. Second, our study suggests that, in order to effectively provide information and training on a new product, the identity of the promoter is crucial. The evidence may be especially relevant when reaching out with information to rural and periurban communities. In the case of Peru, there are about 50,000 Beca18 young fellows located over all the country who can be mobilized to reach out to members of disadvantaged communities and trigger behavioral change.

One important remark is in order. Our local ambassadors differ from regular promotion agents on a number of dimensions. Among other, they are socially connected with the subject pool and are academically successful young fellows. Based on our research design, we cannot precisely pin down which aspects of Beca18 fellows' identity makes them effective at passing on information, though our evidence suggests it is related to being trusted to provide reliable information on the financial service.

The rest of the paper proceeds as follows. In Section 2, we explain in detail the institutional context and provide details on the new BiM electronic wallet. In section 3, we motivate and formalize the hypotheses to test. In section 4, we describe the experimental design, empirical strategy and data. We report and discuss our findings in Section 5 and conclude in Section 6.

2 Context

In 2014 only 29% of Peruvian adults held a bank account; among the poorest 40%, this proportion was only 18% (See World Bank (2015)). In response to these significant low levels of access among the poor to formal financial services, in 2015 the Peruvian government announced the National Plan for Financial Inclusion. The plan emphasized the development of mobile-money platforms as mechanisms to speed up financial inclusion (see MEF (2015)). At about the same time, in early 2016, Pagos Digitales Peruanos (PDP), a company founded by the members of the Peruvian Banking Association and more than 30 e-money users, launched BiM, an electronic wallet designed to foster financial inclusion.

BiM operates from a cellphone and allows individuals to deposit and get cash (with the help of a BiM agent in the community or through a registered ATM), as well as to transfer money to other BiM account holders. BiM also allows individuals to pay for phone services and to deposit into and withdraw money from accounts in the government-owned National Bank (Banco de la Nación).

Activating a BiM account required a basic cellphone (which more than 80% of the population owns) and a National Identification Document (NDI). One had to dial the number ∗838#, enter ones NDI, select the bank that will manage the account, and choose a four-digit secret code (required for transactions). Until December 2018, BiM only charged a fee for cash-out operations (1% of total).

Because BiM immediately connects its holders to a financial institution, its adoption potentially constitutes the first step towards financial inclusion, opening the door to other banking services such as savings accounts and small credits. BiM creates an individual financial record that can provide banks with the information required to facilitate such services. The Peruvian government also considered using the BiM platform to deliver cash transfers associated with social programs, in order to expand coverage and reduce operating costs.

According to PDP, the initial diffusion of BiM was in major urban areas, where 60% of the adult population still does not have a bank account. BiM was promoted through TV, radio spots, newspapers, and social media . By August 2016, close to 100,000 accounts had been activated. PDP, however, faced challenges in expanding BiM adoption to periurban neighborhoods, geographically distant small urban communities, and rural districts.

Given this context, we identified Beca18 fellows as local ambassadors to promote the new service. Together with PDP, we decided to assess whether they could successfully reach out to these periurban and rural communities. Beca18 is Peru flagship scholarship program for higher education.[4] The program was created at the end of 2011 and is managed by the Ministry of Education. It provides full scholarships for post-secondary education to high school graduates living in socioeconomically disadvantaged households, most of them located in periurban and rural communities, who have achieved high academic standards in high school (measured by Peruvian high school GPA) and have been admitted to an eligible educational institution.[5] The Beca18 grant includes tuition, school supplies, local transportation costs, a laptop (or similar equipment), administrative costs to obtain a degree, and possibly travel to and accommodation at the university. Recipients of the scholarship are selected by the Ministry of Education among all applicants in a given year. To keep their scholarship, fellows must maintain a college GPA of 10.5 on a 20-point scale.

[4]Its literal translation is *Scholarship18*.

[5]Households are classified as poor or extreme poor by the Ministry of Social Inclusion based on a household poverty score. This system is used to target social benefits to the poor.

3 Motivational framework

We stress the role of information transmitted by known and trusted sources. We set up our main hypotheses regarding the effectiveness of an information-transmission strategy in which Beca18 fellows act as messengers. We argue that the information passing via Beca18 fellows is more likely to be trusted than information provided by community outsiders. Consequently, a BiM information intervention in which Beca18 fellows are the main messengers is expected to have a stronger effect on information acquisition and adoption of the e-wallet than if performed by external agents.

3.1 Adoption of an electronic wallet

High transaction costs may explain the low take-up of financial products (Burgess and Pande, 2005). Digital money platforms typically charge lower fees than the banks. Indirect transaction costs in the form of travel distance and foregone activities are also potentially much lower (Bachas et al., 2018; Suri et al., 2012). A critical feature of e-money services is that they rely on network externalities, see e.g. Sahut (2008). Consumer adoption of the service depends on the local density of small businesses that accept e-wallet payments and offer a cash-out option, as well as the local density of ATMs.

On the demand side, information asymmetries may hinder adoption, especially at the earlier stages of diffusion. Consumers may fail to fully understand the new service. A typical response is to offer financial information and education (Miller et al., 2014). The perceived quality of information is likely to affect whether agents update their beliefs on the product. Information quality may depend on the contents of the information/training that is offered, as well as the channel of delivery (e.g., through mass media, in a classroom setting or at a community meeting). It could also depend on the identity of the messenger.

Networks interventions are widely used in public health to pass on health information and diffuse best practices (Kim et al., 2015; Valente, 2012; Maclean et al., 2019). In the finance literature, general lack of trust has been found to affect stock market investments (Guiso et al., 2008). Calcagno and Monticone (2015) find that investors with low level of financial literacy are less likely to consult an expert and invest in risky assets. Looking at take-up of financial services among young American adults, Patacchini and Rainone (2017) find that adoption is correlated within social networks. This set of papers rely on non-experimental approaches to identify these effects. Importantly, they provide suggestive evidence that a trust-based mechanism is what drives their result: when facing a risk, individuals place greater value on information coming from people they trust. Recent experimental evidence confirms the role of social network in sustaining trust and facilitating financial inclusion. These include studies on the demand for insurance (Cole et al., 2013; Cai et al., 2015) and loans (Karlan et al., 2009) in developing countries.

3.2 Main hypotheses

Building on the previous discussion of the determinants of the demand for financial services, we focus are interested in two related barriers to adoption: (1) lack of information on the service being offered, (2) lack of trust in the quality of the information provided. The two issues are related in the sense that, even if information and training were provided, agents may fail to update their beliefs on the service if they perceive that the information is not credible. There is some evidence that such distrust is grounded. For instance, Anagol et al. (2017) find that life insurance agents in India provide misleading information to uninformed consumers. In Mexico, Giné et al. (2014) find that credit and savings officers do not voluntary disclose information on avoidable fees and commissions, especially in the case of unsophisticated applicants.

We consider a setting in which consumers cannot perfectly observe the quality of the e-wallet before using it. Two types of agents provide information to consumers: external agents or academically successful members of the community (Beca18 fellows). In both cases, consumers are invited to attend a presentation at which the e-wallet is introduced. Prior to attending it, they know the identity of the promoter. Consumers decide whether to attend or not the presentation and, after hearing about the new technology, whether to adopt it or not. Decision to adopt depends upon how credible they perceive information about the service to be.

We now explicitly lay out the hypotheses regarding the influence of Beca18 fellows on the decisions of their household network members to attend information and training workshops and to adopt the newly launched BiM.

Hypothesis 1: *Invited participants are more likely to attend the workshop led by the member of their network than the one led by an external agent.*

Future and repeated interactions with their own community would provide Beca18 fellows with an incentive to truthfully reveal the quality of the technology. Indeed, once community members start using the platform, the quality of the technology will be revealed. Both the Beca18 messengers and community members know that there will be ex post revelation. If Beca18 fellows care about their reputations and about the possibility of being blamed for misleading their parents' friends into adopting the technology, the information they provide would be credible and trustworthy. In contrast, external agents would be perceived by community members as having an interest in over-stating the quality of the technology. If community members think external agents are paid according to performance - measured by the number of new e-wallet subscriptions they obtained, the information provided would be perceived as biased. External agents would thus be less credible than the local ambassadors.

Hypothesis 2: *Distrustful people are more likely to attend the information and training workshop led by a local ambassador than one led by an external agent.*

Suppose consumers face different time costs and hold different beliefs about the reliability of the information they may get from the Beca18 fellow or the external agent. In particular, we can expect more trusting people to be less likely to question the credibility of the information coming from external agents, resulting in a differential effect of the treatment according to the capacity of the receiver to trust.

Hypothesis 3: *Adoption of e-wallet may be higher or lower in the group led by a local ambassador compared to the group led by an external agent. The net effect of the treatment on adoption is of an indeterminate sign.*

If ***Hypothesis 1*** is correct, we could expect that the network-promotion treatment to affect the composition of the pool of workshop participants, and Beca18 to attract relatively more those who are the most distrustful of outsiders. If the most distrustful belief less in the value of the product, they would be less likely to sign up for it, decreasing take-up among the treated. Conversely, if there were no change in the composition of the pool of participants to the workshop (*Hypothesis 1* rejected), we would expect an increase in take-up as a result of the treatment. Indeed, interests of the sender and the receivers of the information should be closer in the treatment group (Beca18) than in the control group (external agent). As a result, the information transmitted regarding the quality of the product should be more precise in the treatment group than in the control group. If, in addition, the quality of the technology is higher than what it was perceived prior to holding the workshop, we would expect the treatment to result in an increase in take-up. Overall, take-up in the treatment group could then be expected to be higher than in the control group only if the latter (positive) effect offsets the former (negative) one.

Hypothesis 4: *Information acquisition should increase take-up of the financial service.*

We do not have a pure control group that does not receive any information. To test this hypothesis, we exploit the exogenous variation in workshop attendance due to treatment assignment to estimate the effect of information acquisition on take-up of the financial service. If lack of information is a barrier to financial inclusion, we expect a positive local average treatment effect (LATE) of information on take-up that is identified for those who respond to the network-promotion treatment by changing their decision to participate to the workshop. We expect this parameter to inform us on the extent to which unfamiliarity with the financial service is a barrier to financial inclusion for the distrustful, a population that is typically more difficult to reach out to.

4 Experimental design, empirical strategy and data

4.1 Experimental design

This section presents the design and implementation of our experiment. Our outcomes of interest are participation in an information and training workshop on BiM, and take-up (adoption) of the mobile banking service. Our experimental units are community members who belong to Beca18 family networks. A timeline of activities is presented in Table 1.

4.1.1 Treatment definition, random assignment and main activities

To implement our RCT, in late August 2017, we invited Beca18 fellows from an elite university in Northern Peru, Universidad de Piura, to be part of a campaign to promote financial inclusion in their neighborhoods/communities. To encourage participation, we indicated that this activity would count for extracurricular academic credits. Close to 130 of approximately 500 Beca18 fellows registered to participate.

We identified the members of the Beca18 family network groups in the neighborhood/community where they reside. To do so, in early September 2018, Beca18 fellows asked their parents to list the names and contact information of the community members with whom they interact the most. They also had to ask their parents to rank their connections with these individuals in terms of interaction intensity and trust. We selected eight to ten members from this set to construct family network groups, and they became the community members who were invited to participate in BiM information and training workshops.[6]

We observe one family network group per Beca18 fellow. These family network groups are our randomization units. Half of these groups were randomly allocated to treatment (i.e., they received information and training about BiM from their Beca18 fellow); the other half received information and training from external agents hired by PDP. With this design, we control the identity of the recipients of information and training, ensuring that they are, on average, similar prior to treatment. Our random assignment guarantees comparability among treatment and control groups, ruling out differences in participation in BiM workshop and adoption attributable to factors specific to the individuals receiving the information. The only difference between treated and control family network groups is the identity of the individual selected to promote BiM: treated family network groups expected to be informed and trained on BiM by the son/daughter of a friend, relative or neighbor; control family networks expected a PDP external agent.

The BiM workshops took place during the southern hemisphere winter break (July-August 2018), a convenient time for college students to head back home. Beca18 parents agreed to host these workshops at their homes. In the treatment group, the son/daughter of the host invited his/her family network to participate in an information and training session on BiM. In the control group, Beca18 family network groups were invited by a PDP agent. In both experimental groups, family network members were contacted by phone. Reminder phone calls were also made, and the external agents asked Beca18 parents to remind network members about the training session. All promoters received a per diem to pay for travel costs to the community and a stipend to pay for refreshments for all participants in the workshop.

A roster of attendance was kept at each meeting. Each participant had to confirm the cellphone number that had been collected in the baseline and to sign an attendance roster to confirm their actual presence. These records are used to generate the variable that described participation in the BiM workshop.

[6]See Appendix 7.1 for a description of the selection process.

We closely collaborated for this study with PDP, who advised and supported us for the training of the promoters and facilitated access to the administrative data on the activation and usage of BiM by our study participants. We also had support from the Universidad de Piura (UDEP) to enroll Beca18 college students in our study and access their information.

4.1.2 Potential concerns with the research design

Given this experimental protocol, only half of the Beca18 fellows who initially registered for our study received payment for a trip back home and the opportunity to lead a workshop on the BiM. We made it transparent to all that resources were limited and that a lottery system would be employed to select those who would play an active role in the campaign to promote financial inclusion in their communities.

Another concern is contamination bias. Treated Beca18 fellows may have wanted to share the contents of the workshop with control Beca18 fellows, especially given that they all attended the same university. To minimize this potential bias, the information related to BiM was provided in the last two months of the academic year, just before the local ambassadors were to travel to their communities to lead BiM workshops.[7] Moreover, Beca18 students signed a confidentiality agreement, committing not to mention details of the intervention to individuals outside the treatment branch.

A related concern is that Beca18 students in the control group would link their involvement in the initial intervention selection stages to the BiM workshop sessions that were later delivered to their household network at their parents' homes. If this were to have been the case, family network members might have believed that the external agents were recommended by their Beca18 contacts as a trusted source of information, causing an underestimation of the effects of treatment. External agents were not told they were visiting a Beca18 family.[8] Still, we could not discard the possibility that control family networks did associate the BiM workshop with the involvement of the son/daughter of their host.

In addition to minimizing contamination bias, we designed the experiment to avoid geographical spillovers. To do so, we include in our analysis only neighborhoods / communities that are relatively distant from each other.[9] Figure 1 shows the geographical dispersion of

[7] General training of Beca18 fellows on financial inclusion took place from September to October 2017, and specific training on the BiM from May to June 2018.

[8] Only one external agent, who works at the Center for Small Business Support at UDEP knew about the link to Beca18 fellows. He was carefully instructed not to discuss it with the other external agents.

[9] Our partner university provided us with the precise geographic location of the communities of the Beca18 fellows who agreed

these communities. Treatment networks are depicted in blue while control networks are in red. Our study mainly covers the Northern regions of Tumbes, Piura, Cajamarca, Amazonas, Lambayeque, and La Libertad.

We must emphasize that the role of the local ambassadors, Beca18 fellows in the treatment group, is only to pass on information and provide training about the BiM. We did not require that they get their family network members to sign up for the BiM. The local ambassadors were trained to provide information about BiM benefits as well as implied risks and how to mitigate them. This objective was clearly explained to them during when they were trained on the BiM.

Another concern is that Beca18 fellows would fail to achieve the expected results not because they are not credible sources of information but because the external agents in the treatment group are considerably more experienced at information transmission and training related to financial services. To alleviate this concern, the local ambassadors were carefully trained. Their sessions incorporated leadership skills, financial literacy lectures and practical cases and simulations to enhance their capabilities as promoters of financial information. The e-wallet training for the external agents was the same as the training for Beca18 and included theory, presentation skills, and practice with the BiM.

Lastly, it is important to mention two critical issues that could affect the external validity of our study. First, we only work with Beca18 fellows who volunteered to participate, which may differ from those who did not volunteer. Secondly, we only study the BiM adoption decisions of network members of the Beca18 household, which may not be representative of the community. Given these considerations, our conclusions cannot straightforwardly be extended to every community with a Beca18 fellow, neither to all members of these communities.

4.2 Data

The main outcomes of interest in our study are participation in an BiM information and training workshop as well as adoption and usage of the e-wallet. Participation was based on attendance at a workshop, and e-wallet take-up and usage was measured three months later (i.e., in December 2018) on the basis of administrative data shared by PDP. We do not look beyond this time frame for adoption and usage because BiM was no longer supported on basic

to participate.

cellphones, which are prevalent in our study areas, starting February 2019 (an announcement made in January 2019).[10]

Our baseline survey took place from April 21-June 3, 2018. In our final sample we work with 58 Beca18 fellows in the control group and 60 fellows in the treatment group.[11] Our final working sample consists of 1,131 observations. Interviewed households were told that UDEP was implementing the survey to obtain information about general socioeconomic conditions in the area. There was no mention of the Beca18 program or of a future campaign to promote the electronic wallet.

In Table 2, we present baseline summary statistics for a key set of variables for our sample, which is composed of 609 individuals in the treatment group and 522 individuals in the control group. We collected data on employment of the head of household, household expenditures (food and transport), ownership of a cellphone, and use and knowledge of a BiM account, among others. The variables "Head BiM (Knowledge)" and "Spouse BiM (Knowledge)" are binary variables that indicate whether or not the head of household or spouse knows about the new BiM service (1 if they know, 0 otherwise). Likewise, the variable "Head BiM (Account)" indicates whether or not the head of household reports holding a BiM account (1 if holds, 0 otherwise). Food and transport expenditures represent average monthly amounts (in Peruvian soles) spent on each of these items. We also have information on the head's and spouse's education level, the number of rooms and restrooms in the household, and the material of the household's walls. The education level is categorized using binary variables, indicating whether the head (and spouse) have completed primary and secondary education. The variable "Wall Material" takes the value of 1 if house's walls are made of brick or concrete, and 0 otherwise.

We also gathered data on households' level of trust. "Household trust" is a binary variable built from the trust level as reported by the head of household or, if absent, by the spouse.[12] The trust question is as follows: *Which of these options more accurately reflects your thoughts on the following statement: People only have the best of intentions? 1: Always, 2: Most of*

[10]PDP discontinued its Unstructured Supplementary Service Data platform in February 2009. This platform allowed BIM to be accessible from any type of phones, even basic ones. Starting in February 2019 BiM was only accessible through Messenger or a Google App, which require access to a smartphone and internet

[11]We were not able to collect baseline information for the network of 5 Beca18 fellows in the control group and for 4 Beca18 fellows in the treatment group. These students either did not provide their network information, or explicitly asked the research team to be excluded from the study. An additional network had to be dropped from the control sample when it became clear that the student did to satisfy the Beca18 eligibility criteria.

[12]We found twelve observations in which there was no information for either the head of household or the spouse.

the times, 3: Sometimes, 4: Rarely, 5: Never. "Household trust" takes value 1 if individuals responded 1, 2 or 3, and 0 otherwise.

The average age of the heads of households is 47, and the majority (80%) are men. Almost none of the heads of households report having a BiM account (less than 1%), according to self-reported data as well as the PDP administrative source. Similarly, less than 2.4% of the heads of households know about the BiM system at the time of the interview. Even fewer spouses do. In terms of education, close to 40% of the heads of households completed secondary school, while 25% of the spouses achieved this level of education. In terms of access to formal banking services, 27% of the heads report owning a bank account. Just about 60% of households state that that they trust others.

In Table 2, we also show that individuals in the two experimental groups are comparable prior to treatment on the basis of the observed variables we selected. We estimate mean differences between treatment and control units, clustering standard errors by Beca18 family network group. We find no statistically significant difference between the treatment and control groups except for two variables (more below).

There are two differences that may be worth discussing. First, head of households in the control group are more likely to have an occupation (the question is: *Does the head of the household has a job?* 1: Yes 0: No.). The coefficient of the *treatment* indicator is 0.06 and it is statistically significant at the 10% level. Note that the control group (baseline) probability of employment is at 78%, so the relative difference is not so large. Second, there is a statistically significant difference (at a 10% level) on the initial BiM adoption but it is driven by very few observations.[13] We will control for these differences in our specifications, where relevant.[14]

4.3 Empirical strategy

Recall that our first objective is to compare those who acquire information from someone they personally know and trust, to those who acquire it from external agents as is typically the case in these promotional campaigns. People may self-select into these groups and thus differ across observed and unobserved characteristics that could also explain their demand

[13]Only seven household heads overall report having a BiM account; six of these are in the treatment group. These individuals represent a very small proportion of the total sample, so these differences may have occurred by chance.

[14]We also compared some observable characteristics of Beca18 fellows in the treatment and control groups, such as gender, pre-treatment GPA, pre-treatment number of credits taken, and area of study. We find no systematic differences among fellows in the treated and control groups. These results are available upon request.

for information. In addition, difference between these groups based on observational data may not be exclusively attributed to differences in the identity of the promoters but also to differences in the identity of the receivers. Our experimental design allows us to abstract from the latter and identify the causal effect of the identity of the promoter on information acquisition and adoption of the new technology.

To study the impact of our intervention on BiM workshop attendance and BiM adoption (***Hypotheses 1 and 3***), we simply compare outcomes of individuals in the treatment group to those in control group. Given random assignment of the treatment, control group networks constitute a counterfactual for what treated group networks would have experienced had they not been offer the information from a local ambassador.[15] We estimate the following model:

$$Y_{in} = \alpha_1 + \beta_1 Treated_{in} + X_{in}^{'}\gamma_1 + \epsilon_{in}, \tag{1}$$

where the outcome variable Y_{in} represents either attendance at the BiM workshop (a dummy equal to 1 if individual i in network n attended the workshop and 0 otherwise) or take-up of BiM (again a dummy equal to 1 if individual i in network n activated a BiM account and 0 otherwise). $Treated_{in}$ is a binary variable equal to 1 if individual i in network n was randomly assigned to receive the information through the local ambassador or 0 if the information was transmitted by an external agent. $X_{in}^{'}$ is a set of pre-treatment control variables, and the error term ϵ_{in} is assumed to be correlated among individuals that belong to the same network (i.e., we estimate clustered standards errors at the network level in all our linear model specifications).[16]

To explore heterogeneous effects in relation to the level of distrust (*Hypothesis 2*), we consider the following model:

$$Y_{in} = \alpha_2 + \beta_2 Treated_{in} + \delta Distrustful_{in} + \delta' Treated_{in} x Distrustful_{in} + X_{in}^{'}\gamma_2 + \epsilon_{in}. \tag{2}$$

According to ***Hypothesis 1***, we expect to obtain a positive estimate for β_1 in equation (1) when looking at workshop attendance. This effect should be higher for the most distrustful according to ***Hypothesis 2***, which implies a positive δ' in equation (2). ***Hypothesis 3***

[15]Note that the benchmark control state is one in which community members receive information from an external agent. This represents the business-as-usual information-transmission mechanism.

[16]We also estimated a probabilistic model. The marginal effects are the estimated impacts of the network-promotion treatment on the likelihood of BiM workshop participation and on BiM account activation.

implies that, when looking at BiM take-up as the outcome, the sign of β_1 in equation (1) is indeterminate, as the treatment also changes the mix of individuals attending the workshop.

Finally, using random treatment assignment as an instrumental variable for BiM workshop attendance (***Hypothesis 4***), we estimate the effect of attending a BiM training and information session on BiM take-up. This model provides us with a local average treatment effect (LATE) of information acquisition on take-up of the service for those whose decision to attend the workshop is affected by the treatment (i.e. compliers). The main equation is as follows:

$$Y_{in} = \lambda_0 + \lambda_1 Attend_{in} + X_{in}^{'}\gamma_3 + \mu_{in}, \tag{3}$$

and we instrument $Attend_{in}$ by $Treated_{in}$. According to ***Hypothesis 4***, we expected a positive estimate for λ_1, indicating that information acquisition is a barrier to BiM take-up.

In addition to looking at the individual likelihood to participate in the BiM workshop and BiM take-up, we aggregate these data at the network level and estimate the effect of the treatment on the number of individuals attending the workshop and the number of individuals signing-up for BiM within each family network group. The model is as follows:

$$Y_n = \alpha_4 + \beta_4 Treated_n + \epsilon_n \tag{4}$$

where Y_n is the network outcome, $Treated_n$ is the treatment dummy (with variation across networks n, and $epsilon_n$ is the error term defined at the network level.

5 Results

In this section, we present our empirical findings and discuss them in the light of the hypotheses laid out in Section 3. We also check the robustness of our main findings. We report the treatment effects on workshop participation and e-wallet take-up, as well as how these effects differ according to the level of trust of the individual. We also report the LATE estimate for the effect of workshop participation on e-wallet take-up.

We find positive effects for both workshop attendance and take-up, and for the first one we also find a differential effect related to trust, as predicted by our stated hypotheses. We also find a positive LATE effect for workshop participation on take-up. Our robustness checks suggest that the heterogeneous results related to individual trust do not reflect other mechanisms.

Overall our evidence suggests that lack of information impedes product adoption; but also that the acquisition of information is limited by lack of trust towards the individual in charge of transmitting the information. In this regard, the social identity of the messenger is an important factor influencing the reach of the e-wallet promotional campaign, particular among low trust individuals.

5.1 Transmission of information

In Table 3, we present our estimated treatment effects on BiM workshop attendance. Column 1 shows that while 35% of the network members attended the meeting in the control group, the proportion attending is twice as large (70%) in the treated group, a statistically significant difference. Local ambassadors are much more successful at reaching out to their network members than external agents are. Treatment group members are twice more likely to acquire the information on BiM than control group members. This finding is robust to the inclusion of "Head Employment" as a control variable in column 2. The analysis at the aggregate network level in column 3 points out that close to four more people attend BiM presentation session if it is given by a local ambassador instead of an external agent. Excluding the Beca18 fellow parents from the estimations (last columns in the table) does not change the results. These findings are in line with ***Hypothesis 1***. They are consistent with the idea that interests of the sender and network members are more aligned in the treatment than in the control group, and that the effect on information acquisition is related to the draw/trust a valued member of the community can have within his/her own network.

The social identity of the messenger does matter: in our context, local ambassadors ensure a larger reach within the invited audience. In terms of policy implications, our finding highlights a secure mechanism for the diffusion of new financial technologies in particular and other programs for which an information failure is identified. This information delivery mechanism may be particularly relevant for populations residing in distant rural contexts.

5.2 BiM adoption and usage

Table 4 presents the estimated treatment effect on BiM take-up (BiM account activation), following the specification laid out in Equation (1). In all the specifications, we include pre-treatment BiM affiliation as a control variable. According to column 1, take-up rate in the control group is just about 4%. With the treatment, BiM uptake increases by about 4 percentage points, a statistically significant difference. Receiving the information and training form a local ambassador rather than an external agent leads to a doubling of the adoption rate. This is an effect of sizable magnitude considering the limited reach PDP has in these areas/communities and the lack of exposure of these individuals to any similar e-money service or service in the past. Still, the overall take up rate remains low, which suggest that there are critical barriers to adoption other than lack of knowledge on the new technology. Identifying and addressing such barriers should be the focus of future research.

As in the previous table, the last two columns exclude the Beca18 fellow parents from our estimation sample. Though the take-up rate for the control group remains virtually the same, the estimated impact of the intervention drops by approximately 1.5 percentage points, taking the overall take-up rate to 6%. Though the reduction in sample size does not result in an increase in the standard errors, the reduction in the size of the coefficient affected its statistical significance (the coefficient in column 4 is statistically significant only at the 10% level). Still, the relative effect remains sizable compared to the base case. Moreover, the aggregation at the network level presents a comparable and significant coefficient.

Table 5 shows the estimated treatment effect on BiM usage. We find a small effect close to one percentage point, which is only statistically significant in columns one to three. Though the provision of information by an academic ambassador helps gathering a larger crowd and significantly encourages people to activate an account, the effect on usage - in the short run - appears to be almost null. In addition to discontinuing the platform for basic cellphones, PDP experienced delays in the implementation of BiM functionality in rural areas. In many cases in which the platform was operative, bank agents did not receive the necessary training by operators involved in the initiative [17]. Nevertheless, it is important to mention that at the national level, by July 2019, only 5% of adults had activated a BiM account; and out of them, just 3% percent were regular users. Relative to these figures, the results obtained by our intervention are significant and will increase adoption above the national averages.

[17] As part of the information and training workshops, Beca18 fellows had to demonstrate cash withdrawal by involving an agent affiliated with the Peruvian National Bank. In several instances, these agents were not aware of the existence of a platform that allows them to perform BiM transactions and our local ambassadors had to instruct them on how to perform them.

Overall, though the attendance effect is sizeable, the impact on take-up is markedly smaller, and the difference in usage between treatment and control groups is virtually non-existent. A small impact on take-up is consistent with the fact that the treatment affects the composition of the groups attending BiM workshops, attracting more distrustful people whose propensity to adopt may be lower in the absence of the treatment. As for usage, the lack of a well-developed local network of agents as well as PDP decision to switch to a platform for smartphones may explain the lack of use despite activation.

5.3 Lack of information as a barrier to adoption

Policy makers and managers of financial organizations and NGOs, such as PDP in the context of our study, are also interested in estimating the effectiveness of training and information programs on the adoption of new technologies or financial services, particularly in rural settings. According to our ***Hypothesis 4***, information acquisition should result in an increased take-up. As explained in Section 4.3, we use treatment assignment as an instrument for attending a BiM workshop so as to identify the effect of workshop attendance on BiM take-up.

Table 6 presents the two-stage least square estimation for the effect of BiM workshop attendance on BiM affiliation.[18] We find that the affiliation rate increases by eleven percentage points if a member of the Beca18 household network attended the BiM training sessions. The exclusion of the Beca18 fellows' parents from the estimation sample reduces both the magnitude of the effect (to a six-percentage- point increase in affiliation) and its significance, but it remains significant at the 10% level. Hence, we can conclude that our BiM training sessions had a positive and marked effect on the affiliation rate.

Note that our identification strategy reveals a LATE effect — that is, the effect for individuals whose choice to attend is affected by the instrument (compliers). For the identification to be sound, the monotonicity or no-defiers assumption must hold. There should be no individuals within the Beca18 household network who would attend the workshop led by an external agent but would not attend if a local ambassador were in charge. Given our study context, we estimate that such cases would be extremely rare.

The validity of the estimates in this section depends on whether the exclusion restriction holds. That is, receiving the invitation to an information session led by a Beca18 fellow

[18]as in Table 4, we also control for the pre-treatment outcome in the IV regressions

should only affect affiliation through the increased likelihood of attendance. This is not guaranteed by the random nature of our instrument because other channels through which the instrument could affect BiM adoption may exist. For instance, local ambassadors could have talked directly to members of their household network about the new electronic wallet (BiM), even if those members did not attend the sessions. While we cannot completely rule out this possibility, our intervention took place during the academic winter break, which lasts for only three weeks, as opposed to the three-month summer break. This timing minimizes Beca18 fellows' exposure to those who did not attend the sessions. Informational externalities caused by BiM session attendees providing information about the electronic wallet to those who did not attend may also have existed and may have been more common in the treatment group. This last two issues, however, to the extent they occurred, would likely introduce a downward bias in our estimated effects.

5.4 Heterogeneous effects in relation to trust

In the motivational section in this paper, one of our main hypothesis states that distrustful people are expected to attend BiM information and training workshops in higher proportions if they are led by a local ambassador rather than by an external agent (***Hypothesis 2***). In this section we empirically assess this hypothesis by introducing an interaction term between our treatment variable and a distrust indicator from self-reports expressed by heads of household during the baseline survey. Based on Equation (2), we test whether the treatment effect on attendance depends on how trusting an individual is.[19]

From the results laid out in Table 7, our hypothesis is clearly confirmed. As expected from ***Hypothesis 2***, the interaction term coefficient between the distrust indicator and the treatment dummy is positive. Attendance is 18 percentage-points higher for the distrustful as a result of the treatment. This effect is statistically significant at the 10% level. This clearly indicates that, in terms of message dissemination, social ties have a higher leverage on information acquisition for those who exhibit more distrust in people than for those with relatively higher levels of trust. We also find that distrustful people are more reluctant to attend BiM workshops. There is a negative relationship between distrust and BiM workshop attendance.

[19] Recall from Section 4.2 that the trust information comes from the question: *Which of the following options reflects more accurately your thoughts on the following statement: People only have the best intentions? 1: Always, 2: Most of times, 3: Sometimes, 4: Few times, 5: Never, 6: Household head is missing.* For the estimates in this section, we claim that the individual is distrustful if the answer to this question is 5, the indicator variable takes the value of 1 (it is 0 otherwise).

While we hypothesized that the attendance of more distrustful people would be more affected by the treatment, we did not state any hypothesis related to whether the adoption or take-up decision of such individuals would be more or less affected by the treatment. The difficulty here lays in the fact that our treatment does not affect solely the identity of the messenger. Rather, as the results in Table 7 suggest, the treatment also affects composition of the group attending BiM workshops, attracting the most distrustful. Consequently, it is unclear how the treatment would interact with levels of trust in people. Nevertheless, in Table 8 we present the results of the affiliation or take-up regressions that include an interaction term between the treatment variable and the distrust indicator. The estimated coefficient for the interaction variable is negative and statistically significant at the 5% level. The relationship between distrust and take-up is weak. More importantly, the relatively small average impact displayed in Table 4 hides a heterogeneity in relation to trust. The treatment effect on take-up is positive and of the order of 4-6 percentage-points for individuals with low levels of trust, and not significantly different from zero for those with high levels of trust.

5.5 Other Sources of Heterogeneity and Robustness Checks

Our estimated effects may be driven purely by the attendance and, later, by the affiliation of close relatives within the Beca18 household network. To rule out this possibility, in Tables 9 and 10 we interact our treatment variable with an indicator of whether the person is a Beca18 relative. There is no evidence of heterogeneous effects related to being a relative for workshop attendance nor BiM affiliation. The interaction effect is relatively small, not robustly significant, and negative in both cases. There is also only a weak relationship between workshop attendance/BiM affiliation and being a relative. Lastly, the main effect on attendance and affiliation in Tables 9 and 10 remain comparable to those presented in Tables 3 and 4.

Attendance and affiliation can also be influenced by the benefits an individual expects to derive from the new BiM and/or her familiarity with or previous exposure to other financial products, with possible increasing returns to being informed by a local ambassador in places in relation to the degree of exposure. We anticipate that exposure to other financial products would depend upon the degree of financial development in the community. While people with access to better financial infrastructure may have more interest in learning about a financial technological innovation or may be more familiar working with financial technologies, we cannot rule out the possible effect of other variables that may also be related to financial infrastructure (ease of transportation, higher urban density, or overall local economic activity, for example).

Accordingly, in Tables 11 and 12, we include an indicator for the presence of at least one ATM from the government-run National Bank (Banco de la Nación) in the community as a proxy for financial development and interact the constructed binary variable with our treatment indicator to check for differential treatment effects. In terms of attendance, we find that people from financially developed contexts (communities with better financial infrastructure) are more affected by the treatment, with a 16 percentage-point higher effect at a 5% significance level (column 3 of Table 11). This represents 45% of the average treatment effect (reported in column 1 of Table 11). Regarding affiliation, however, we do not find evidence of heterogeneous treatment effects related to financial development (see Table 12).

Access to a higher level of financial infrastructure and the economic and social interactions that arise from such exposure are likely related to individuals' general levels of trust/distrust. In Table 11 in which we show the effects on workshop attendance, we also include the distrust indicator and its interaction with the treatment variable, saturating the models (column 4 and column 8). As can be observed, the interaction between financial development and treatment remains positive and statistically significant. The distrust indicator also remains statistically significant and has the same sign and size as in our estimates in Table 7. More importantly, the coefficient of the interaction term between distrust and treatment has the same sign and is of slightly smaller magnitude compared to the one shown in Table 7; moreover, it lacks statistical significance. The correlation between general distrust and financial development may explain the loss in precision we obtain for the interaction term between distrust and the treatment indicator in the saturated model (column 4 and column 8).

The level of financial development in a given community may be related to the level of trust individuals have in the banking system, and the distrust effects and differential treatment effects found in Table 7 may cease to be relevant once trust in banks is accounted for. To test such a possibility, we construct a trust in banks indicator, which takes the value of 1 if the individual reports the maximum possible level of trust in these institutions and 0 otherwise. In Tables 13 and 14 we explore the effect of the treatment on workshop attendance and BiM adoption in relation to the trust held in financial institutions . The results in Table 13 suggest that, while people with higher trust in banks are less likely to attend the workshops, probably because they are already financially included and expect little benefit from attendance, the treatment effect is increasing in this type of trust. In columns four and eight in Table 13, we include the general distrust indicator and its interaction with the treatment variable to the attendance regressions (saturated models). Note that the estimated coefficients for the general level of distrust and its interaction term with the treatment variable remain similar in sign and size to those in Table 7 and are also statistically significant. In other words, the general distrust-related results reported in the previous section are not likely driven by trust in financial institutions.

It is also possible that our results are driven mainly by individuals with a higher level of social interactions with the Beca18 household. As an additional robustness check, Tables 15 and 16 include a measure of such connectedness: the number of weekly hours the Beca18 household spends with a specific network member, as well as the interaction term of this variable with the treatment indicator. As can be observed, the results show that proximity/closeness to the presenter's household does not have an impact on either attendance or adoption: both the level variable and its interaction term with the treatment indicator lack statistically significance. Moreover, the main findings regarding distrust (Tables 7 and 8) remain generally unchanged: in terms of message dissemination, the treatment has a significant, larger effect for distrustful people. Note that, in the case of BiM affiliation, the interaction term among the treatment and distrust indicators remains negative but is not statistically significant.

Individual distrust can also be potentially correlated with education and age. As a final robustness check, therefore, we test for heterogeneous effects related to these two variables. In Tables 17 and 18 we show the heterogeneous effects related to education on workshop attendance and BiM take-up, respectively. We do the same for age in Tables 19 and 20. Table 17 shows that there is no evidence of either direct or heterogeneous effects of education on attendance. Table 18 provides some weak evidence suggesting that more highly educated people are more likely to adopt BiM and that the treatment effect is higher for less educated people; however, the interaction term among education and the treatment variable is only statistically significant at the 10% level in column 6. With respect to age, neither Tables 19 or 20 present any consistent evidence on direct or heterogeneous effects on workshop attendance or BiM affiliation. In this regard, we conclude that it is unlikely that the heterogeneous results related to distrust capture solely differentiated effects related to individuals' age or education.

6 Conclusions

Lack of familiarity with the e-wallet is one factor limiting its adoption. The technology has the potential to foster financial inclusion, especially for those living in remote periurban and rural areas. Yet take-up is typically an issue with financial products. Thus, to reach out to the unbanked, a successful promotional campaign needs to gain their trust.

We report results from a field experiment conducted in remote areas of Northern Peru that contrasts two mechanisms to encourage participation in information and training workshops. In the treatment group, the workshop was led by an academically successful young person who grew up in the community (Beca18 scholarship recipient) and who is personally known to the invited participants as the son/daughter of a friend, neighbor or relative. We expected that invited participants to trust this fellow, who is a member of their network, to effectively communicate with them about the product quality. In the control group, a similar set of community members were invited to attend a workshop focused on the same services but led by a PDP agent external to the community.

We find that participation in e-wallet workshops doubles when invited participants expect to be informed and trained by a network member (70% vs 35%). This effect is even larger among the most distrustful participants. Though take-up remains low, it is two to three times larger in the network-promotion treatment. Importantly, we find evidence that participation in an information and training workshop leads to an increase of ten percentage points in take-up at the early stages of adoption. All in all, our findings are that barriers for take-up of the new financial service include lack of familiarity with the service and general distrust issues.

We find little effect on actual use of the e-wallet for financial transactions. This is easily explained by the fact that, not long after starting our promotion campaign of this e-wallet, PDP decided to discontinue the platform that allowed BIM to be accessible from basic cell-phones, and switched to a much expansive device (smartphones) as a platform to operate the e-wallet through a downloadable application available in Google Apps. In this sense, part of the distrust in the initial technology seems justified.

More generally, we provide evidence, first, that it is not sufficient to expand the supply of financial products and, second, that banks need to address the trust issue directly. Our work shows that a promotional campaign involving community members is a cost-effective way to reach even the most reluctant individuals and foster early stages of adoption of a new product. It would be interesting to test whether tighter regulation for consumer protection could be as effective in fostering trust and speeding up financial inclusion. More generally, trust in the information source is an important and typically overlooked factor for the adoption of other types of products and behavior (e.g., vaccination), though it remains unclear how to motivate community members to promote an existing product effectively when the majority of the community is against its use.

References

Anagol, S., Cole, S., and Sarkar, S. (2017). Understanding the advice of commissions-motivated agents: Evidence from the Indian life insurance market. *The Review of Economics and Statistics*, 99(1):1–15.

Bachas, P., Gertler, P., Higgins, S., and Seira, E. (2018). Digital financial services go a long way: Transaction costs and financial inclusion. *AEA Papers and Proceedings*, 108:444–48.

Banerjee, A., Chandrasekhar, A. G., Duflo, E., and Jackson, M. O. (2019). Using Gossips to Spread Information: Theory and Evidence from Two Randomized Controlled Trials. *The Review of Economic Studies*.

Banerjee, A. V., Chandrasekhar, A., Duflo, E., and Jackson, M. O. (2013). The diffusion of microfinance. *Science*, 341:1236498.

Beaman, L., BenYishay, A., Magruder, J., and Mobarak, A. M. (2018). Can network theory-based targeting increase technology adoption? Working Paper 24912, National Bureau of Economic Research.

BenYishay, A. and Mobarak, A. M. (2018). Social Learning and Incentives for Experimentation and Communication. *The Review of Economic Studies*, 86(3):976–1009.

Burgess, R. and Pande, R. (2005). Do rural banks matter? evidence from the Indian social banking experiment. *American Economic Review*, 95(3):780–795.

Cai, J., De Janvry, A., and Sadoulet, E. (2015). Social networks and the decision to insure. *American Economic Journal: Applied Economics*, 7(2):81–108.

Calcagno, R. and Monticone, C. (2015). Financial literacy and the demand for financial advice. *Journal of Banking & Finance*, 50:363 – 380.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., and Vickery, J. (2013). Barriers to household risk management: Evidence from india. *American Economic Journal: Applied Economics*, 5(1):104–35.

Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *American Economic Review*, 100(1):35–69.

Crawford, V. P. and Sobel, J. (1982). Strategic information transmission. *Econometrica*, 50(6):1431–1451.

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

Galeotti, A., Ghiglino, C., and Squintani, F. (2013). Strategic information transmission networks. *Journal of Economic Theory*, 148(5):1751–1769.

Giné, X., Martinez, C., and Mazer, R. (2014). Financial disclosure in Mexico: evidence from an audit study. Policy Research Working Paper 6902, World Bank.

Guiso, L., Sapienza, P., and Zingales, L. (2008). Trusting the stock market. *The Journal of Finance*, 63(6):2557–2600.

Hagenbach, J. and Koessler, F. (2010). Strategic Communication Networks. *The Review of Economic Studies*, 77(3):1072–1099.

Jackson, M. O. (2011). An overview of social networks and economic applications. volume 1 of *Handbook of Social Economics*, pages 511 – 585. North-Holland.

Karlan, D., Mobius, M., Rosenblat, T., and Szeidl, A. (2009). Trust and Social Collateral. *The Quarterly Journal of Economics*, 124(3):1307–1361.

Kim, D. A., Hwong, A. R., Stafford, D., Hughes, D. A., O'Malley, A. J., Fowler, J. H., and Christakis, N. A. (2015). Social network targeting to maximise population behaviour change: a cluster randomised controlled trial. *The Lancet*, 386(9989):145 – 153.

Maclean, J. C., Buckell, J., and Marti, J. (2019). Information source and cigarettes: Experimental evidence on the messenger effect. Working Paper 25632, National Bureau of Economic Research.

MEF (2015). Estrategia nacional de inclusión financiera. Technical report, Ministerio de Economía y Finanzas.

Miller, M., Reichelstein, J., Salas, C., and Zia, B. (2014). Can you help someone become financially capable? a meta-analysis of the literature. (6745).

Munshi, K. (2004). Social learning in a heterogeneous population: technology diffusion in the Indian green revolution. *Journal of Development Economics*, 73(1):185–213.

Patacchini, E. and Rainone, E. (2017). Social ties and the demand for financial services. *Journal of Financial Services Research*, 52(1):35–88.

Sahut, J.-M. (2008). The adoption and diffusion of electronic wallets. *International Journal of Economics and Management Engineering*, 2(5).

Suri, T., Jack, W., and Stoker, T. M. (2012). Documenting the birth of a financial economy. *Proceedings of the National Academy of Sciences*, 109(26):10257–10262.

Valente, T. W. (2012). Network interventions. *Science*, 337(6090):49–53.

World Bank (2015). Familias peruanas avanzan hacia la inclusión financiera. Press release, World Bank.

Table 1: Timeline

Date	Activities
2016	BiM was launched
2017: August	Recruitment of Beca18 students at UDEP
2017: September	Mapping of Beca18 family networks
2017: October	Training sessions of Beca18 at UDEP
2018: April-June	Baseline survey in the communities
2018: July-August	BiM workshops in the communities (treatment)
2018: December	Endline data collection (administrative)

Table 2: Network members characteristics Treated vs Controls

	Mean		Mean Test				
	Treated	Control	Difference	Pvalue	N	Mean	SD
Head Cellphone	0.84	0.87	-0.03	0.25	1,131	0.856	0.351
Head Employment	0.78	0.84	-0.06	0.11	1,131	0.810	0.393
Head BIM: Knowledge	0.02	0.02	0.00	0.73	1,131	0.0230	0.150
Head BIM: Account	0.01	0.00	0.01	0.10	1,060	0.006	0.081
Head has Primary School	0.38	0.35	0.02	0.61	1,131	0.368	0.482
Head has Secondary School	0.40	0.39	0.02	0.68	1,131	0.397	0.489
Spouse BIM: Knowledge	0.02	0.01	0.01	0.17	841	0.0178	0.132
Spouse has Primary School	0.36	0.31	0.04	0.33	1,131	0.336	0.473
Spouse has Secondary School	0.25	0.25	0.00	0.96	1,131	0.252	0.434
Transport Expenditure	74.01	96.03	-22.02	0.16	1,131	84.17	144.7
Food Expenditure	475.36	475.86	-0.50	0.99	1,131	475.6	306.8
Household Trust	0.59	0.55	0.05	0.36	1,117	0.571	0.495
Number of Rooms	3.28	3.14	0.14	0.38	1,130	3.217	1.869
Wall Material	0.44	0.41	0.02	0.70	1,131	0.425	0.495
Number of Restrooms	0.98	0.96	0.01	0.86	1,130	0.969	0.638
Head Age	47.59	46.91	0.68	0.54	1,131	47.27	12.85
Household Head Gender (Male)	0.80	0.80	0.00	0.91	1,131	0.803	0.398
Household owning a bank account	0.25	0.29	-0.04	0.32	1,131	0.271	0.444
No. of obs.	609	522					
No. of networks	60	58					

Note: *Network* identifies the network members of the head and the spouse. *Household Trust* is based on the following question: "Which of the following options reflect more accurately your thoughts on the following statement: People only have the best intentions? 1: Always, 2: Most of times, 3: Sometimes, 4: Few times, 5: Never." If the answer ranges from 1 to 3, the variable takes value of 1, and 0 otherwise. *Wall Material* takes the value 1 when the house's wall is made of brick or concrete, and 0 otherwise.

Table 3: Participation to the workshop

				Excluding Beca18 parents	
	(1)	(2)	(3)	(4)	(5)
	Attendance: OLS		Attendance: Network^{+}	Attendance: OLS	Attendance: Network^{+}
Treatment	0.358***	0.354***	3.971***	0.397***	3.967***
	(0.0403)	(0.0410)	(0.400)	(0.0417)	(0.390)
Head Employment		-0.0554			
		(0.0369)			
Constant	0.348***	0.395***	3.049***	0.287***	2.280***
	(0.0283)	(0.0440)	(0.251)	(0.0289)	(0.234)
N	1131	1131	118	1024	118
R^2	0.139	0.141	0.517	0.167	0.530
F	78.84	42.08	98.51	90.56	103.4
Region FE	Yes	Yes	Yes	Yes	Yes
Mean: Treated	0.70		6.93	0.67	6.14
Mean: Control	0.35		3.1	0.29	2.35

Notes: ***,** and * indicate statistical significance at the 1, 5 and 10 percent level. Standard errors clustered at the network level are presented under parenthesis. The dependent variable is an indicator of whether the invited participant attended the training workshop. All regressions include region fixed effects and are clustered at the student family network level. In Col. 4 and 5, sample size is reduced as we restrict the analysis by excluding Beca18 parents.
$^{+}$ Col. 3 and 5: the outcome variable is the number of invited participants who attended the workshop.

Table 4: BIM Affiliation

				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
	Affiliation: OLS		Affiliation: Network†	Affiliation: OLS	Affiliation: Network†
Treatment	0.0385***	0.0379***	0.420***	0.0239*	0.257**
	(0.0136)	(0.0135)	(0.136)	(0.0132)	(0.123)
Head Employment		-0.00834			
		(0.0164)			
Constant	0.0319***	0.0390**	0.351***	0.0314***	0.316***
	(0.00940)	(0.0166)	(0.0995)	(0.00866)	(0.0858)
N	1131	1131	118	1024	118
R^2	0.122	0.122	0.236	0.153	0.223
F	31.59	21.05	9.541	31.54	4.334
Region FE	Yes	Yes	Yes	Yes	
Mean: Treated	0.077		0.77	0.06	0.57
Mean: Control	0.036		0.33	0.036	0.3

Notes: The dependent variable is an indicator of whether the individual is affiliated to BIM. All regressions are controlled by geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

† We collapse the outcomes variables by student network. The outcomes variables become continuous, and represents the attendance or take up ratio per student network.

Columns 1,2 and 4 are controlled by the number of previous affiliations to BIM (before treatment).

Table 5: BIM Usage

				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
	Usage: OLS		Usage: Network‡	Usage: OLS	Usage: Network‡
Treatment	0.0129*	0.0141*	0.133*	0.00976	0.0915
	(0.00703)	(0.00717)	(0.0691)	(0.00745)	(0.0652)
Head Employment		0.0182***			
		(0.00498)			
Constant	0.00634	-0.00908**	0.0584	0.00644	0.0544
	(0.00385)	(0.00445)	(0.0361)	(0.00427)	(0.0359)
N	1131	1131	118	1024	118
R^2	0.00711	0.0110	0.0646	0.00932	0.0698
F	3.347	6.695	3.705	1.718	1.974
Region FE	Yes	Yes	Yes	Yes	Yes
Mean: Treated	.018		0.18	.014	0.13
Mean: Control	.007		0.07	.008	0.07

Notes: The dependent variable is an indicator of whether the individual uses BIM. All regressions are controlled by geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

‡ We collapse the outcomes variables by student network. The outcomes variables become continuous, and represents the attendance or take up ratio per student network.

Table 6: 2SLS - BIM Affiliation

	Dependent Variable: BIM Affiliation				
				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
	Second Stage				
Attendance	0.108***	0.108***	0.107***	0.0602*	0.0601*
	(0.0401)	(0.0402)	(0.0407)	(0.0333)	(0.0334)
Head of Household's Sex		0.0155	0.0165		0.0133
		(0.0191)	(0.0200)		(0.0186)
Head Employment			-0.00544		
			(0.0174)		
Constant	-0.00407	-0.0168	-0.0127	0.0284	0.0177
	(0.0414)	(0.0416)	(0.0422)	(0.0414)	(0.0409)
	Dependent variable: Attendance, Instrumental variable: Treatment				
	First Stage				
Treatment	0.358***	0.357***	0.354***	0.397***	0.397***
	(0.0401)	(0.0401)	(0.0408)	(0.0415)	(0.0415)
Household Head Sex		-0.0498	-0.0400		-0.0432
		(0.0370)	(0.0374)		(0.0373)
Head Employment			-0.0500		
			(0.0376)		
Constant	0.408***	0.448***	0.481***	0.353***	0.388***
	(0.0539)	(0.0650)	(0.0734)	(0.0587)	(0.0705)
N	1131	1131	1131	1024	1024
Region FE	Yes	Yes	Yes	Yes	Yes

Notes: All regressions are controlled by geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.
All columns are controlled by the number of previous affiliations to BIM (before treatment).

Table 7: BIM Attendance & Distrust

			Excluding Beca18 family	
	(1)	(2)	(3)	(4)
	Attendance: OLS	Attendance: OLS	Attendance: OLS	Attendance: OLS
Treatment	0.313***	0.310***	0.357***	0.355***
	(0.0460)	(0.0467)	(0.0482)	(0.0486)
Distrust	-0.136**	-0.140**	-0.139**	-0.145***
	(0.0549)	(0.0544)	(0.0547)	(0.0537)
Distrust × Treatment	0.184*	0.177*	0.186*	0.179*
	(0.0950)	(0.0953)	(0.0971)	(0.0977)
Head Employment		-0.0606		-0.0652
		(0.0405)		(0.0435)
Constant	0.468***	0.519***	0.414***	0.469***
	(0.0605)	(0.0722)	(0.0642)	(0.0784)
N	829	829	746	746
R^2	0.139	0.142	0.166	0.169
Region FE	Yes	Yes	Yes	

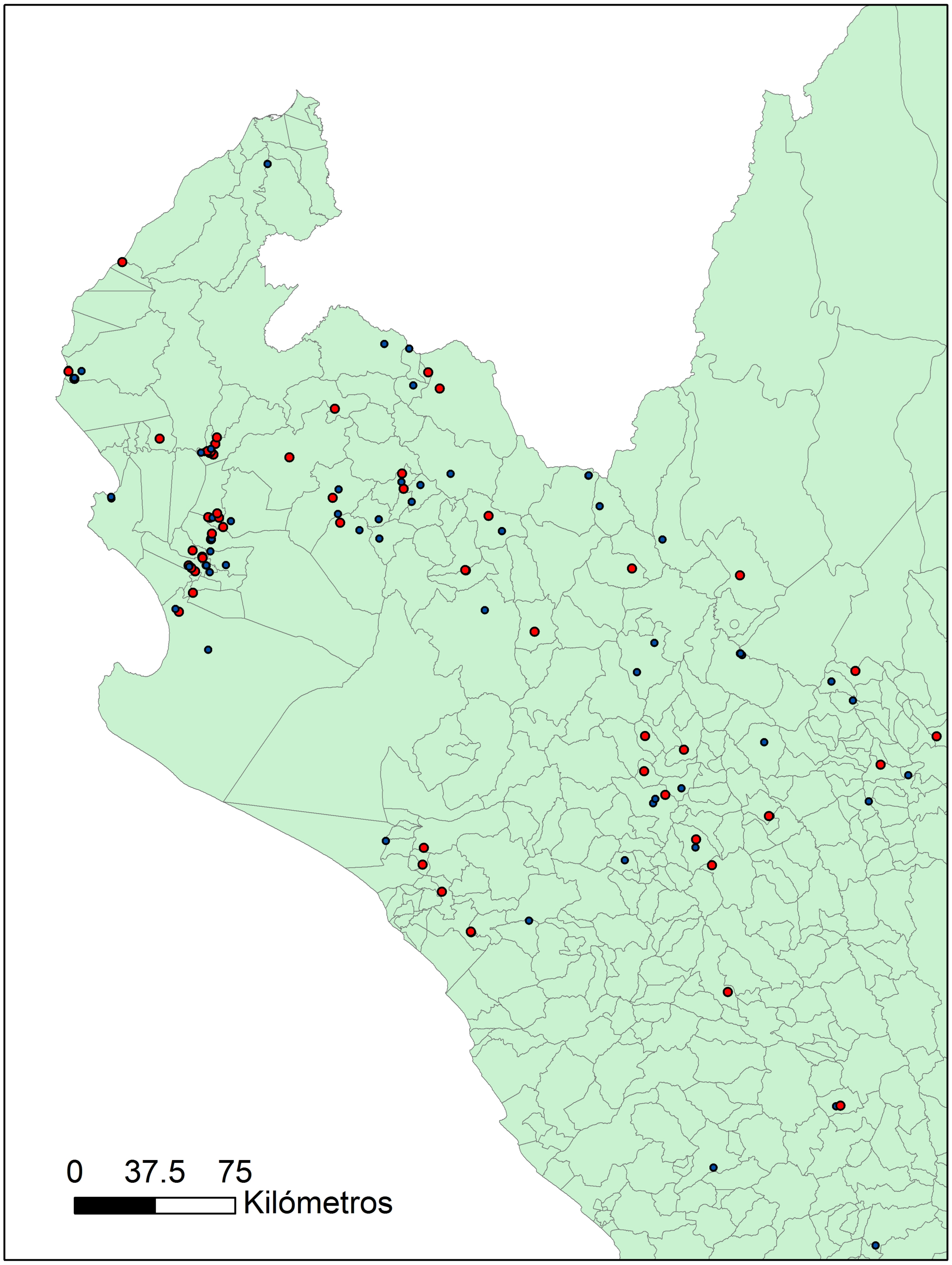
Notes: Distrust is based on the following question "Which of the following options reflect more accurately your thoughts on the following statement: People only have the best of intentions? 1: Always, 2: Most of the times, 3: Sometimes, 4: Rarely, 5: Never". Individuals are considered distrustful if they answer 5. All regressions are controlled by geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%. We lost observations by including the Distrust variable because it includes missing values.

Table 8: BIM Affiliation: Distrust

			Excluding Beca18 family	
	(1) Affiliation: OLS	(2) Affiliation: OLS	(3) Affiliation: OLS	(4) Affiliation: OLS
Treatment	0.0620***	0.0620***	0.0402**	0.0403**
	(0.0156)	(0.0155)	(0.0173)	(0.0173)
Distrust	0.0264	0.0263	0.0286	0.0289
	(0.0258)	(0.0258)	(0.0276)	(0.0276)
Distrust × Treatment	-0.0788**	-0.0790**	-0.0791**	-0.0789**
	(0.0377)	(0.0379)	(0.0370)	(0.0369)
Head Employment		-0.00102		0.00251
		(0.0194)		(0.0185)
Constant	0.0478	0.0487	0.0617	0.0596
	(0.0452)	(0.0442)	(0.0495)	(0.0482)
N	829	829	746	746
R^2	0.0398	0.0398	0.0446	0.0446
Region FE	Yes	Yes	Yes	Yes

Notes: Distrust is based on the following question "Which of the following options reflect more accurately your thoughts on the following statement: People only have the best of intentions? 1: Always, 2: Most of the times, 3: Sometimes, 4: Rarely, 5: Never". Individuals are considered distrustful if they answer 5 All regressions are controlled by geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%. We lost observations by including the Distrust variable because it includes missing values.

Figure 1: Map 1



(a)

Note: Treatment networks are depicted in blue while control ones in red

7 Appendix

7.1 Selection of Individuals to be included in the baseline (data)

Originally, 131 Beca18 fellows volunteered for the project. There were three pairs of siblings, so the effective number of volunteers was 128. Sixty-five were randomly allocated to the control group and the rest to the Treatment group. We asked them to report their household network members with the support of their parents. We asked for up to fifteen members in the network of the head of head of household and fifteen in the spouse's network. For each individual reported we asked for a series of characteristics, which included cellphone number. Tables 1 and 2 compare the characteristics of these individuals in the treatment and control groups. From these network members, and taking into account our budget restrictions, we collected baseline information for eight to ten. These are also the individuals who were invited to training/information-diffusion sessions.

We therefore randomly selected fourteen individuals per self-reported network and provided their information to the field team in charge of the baseline, so they could locate 8-10 individuals and interview them. To select fourteen individuals per network we used the following protocol:

1. First, we identified those individuals for whom a cell phone number had been reported, dropping those for whom cell phone was not reported (a cell phone was necessary to activate a BiM account).

2. We then identified those individuals whose names were repeated in the head of household and spouse of head of household network, and randomly keep one observation.

3. We then identified individuals who belonged to the same household and randomly kept one of them in the sample.

4. We then counted the effective number of individuals reported by the head of household and the spouse of the head of household. This was the effective list of household network members.

5. If the effective household network list included fourteen or fewer members, then all of them were included.

6. If the effective list included more than fourteen members, then one of the following two cases applied:

(a) If the effective number of individuals listed by each head of household and spouse of head of household was higher than seven, we randomly selected seven individuals from each list.

(b) If, for only one respondent, the number of listed individuals was lower than seven, we kept all the members and randomly selected a number of individuals from the other respondent's network to reach fourteen observations.

Table 9: BIM Attendance & Referred Person being a Relative

				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
Treatment	0.354***	0.347***	0.347***	0.394***	0.393***
	(0.0410)	(0.0416)	(0.0457)	(0.0422)	(0.0477)
Relative		0.0715*	0.0708		0.149**
		(0.0362)	(0.0674)		(0.0688)
Relative × Treatment			0.00117		-0.0412
			(0.0794)		(0.0816)
Constant	0.456***	0.447***	0.448***	0.401***	0.378***
	(0.0673)	(0.0677)	(0.0681)	(0.0738)	(0.0761)
N	1131	1131	1131	1024	1024
R^2	0.141	0.145	0.145	0.169	0.181
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes

Notes: All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

Table 10: BIM Affiliation & Referred Person being a Relative

				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0389***	0.0389***	0.0522***	0.0246*	0.0331**
	(0.0138)	(0.0145)	(0.0149)	(0.0140)	(0.0154)
Relative		0.000813	0.0340		0.0351
		(0.0187)	(0.0286)		(0.0299)
Relative × Treatment			-0.0548		-0.0365
			(0.0369)		(0.0375)
Constant	0.0480	0.0479	0.0408	0.0546	0.0477
	(0.0407)	(0.0400)	(0.0381)	(0.0441)	(0.0413)
N	1131	1131	1131	1024	1024
R^2	0.0249	0.0249	0.0272	0.0282	0.0301
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes

Notes: All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

Table 11: BIM Attendance & BN ATM

					Excluding Beca18 family			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.354***	0.351***	0.280***	0.228***	0.394***	0.392***	0.317***	0.265***
	(0.0410)	(0.0413)	(0.0563)	(0.0618)	(0.0422)	(0.0424)	(0.0569)	(0.0650)
BNATM		0.0327	-0.0548	-0.0802		0.0334	-0.0584	-0.0871
		(0.0392)	(0.0580)	(0.0642)		(0.0405)	(0.0596)	(0.0640)
BNATM × Treatment			0.160**	0.206**			0.167**	0.225**
			(0.0782)	(0.0852)			(0.0809)	(0.0878)
Distrust				-0.117*				-0.119**
				(0.0611)				(0.0563)
Distrust × Treatment				0.127				0.126
				(0.0952)				(0.0950)
Constant	0.456***	0.441***	0.487***	0.561***	0.401***	0.385***	0.432***	0.513***
	(0.0673)	(0.0659)	(0.0726)	(0.0837)	(0.0738)	(0.0723)	(0.0789)	(0.0916)
N	1131	1131	1131	829	1024	1024	1024	746
R^2	0.141	0.142	0.148	0.152	0.169	0.170	0.176	0.181
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: BNATM is an indicator of whether there is a "Banco de la Nacion" ATM close to the individual. All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%. We lost observations by including the Distrust variable because it includes missing values.

Table 12: BIM Affiliation & BN ATM

				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0389***	0.0361**	0.0408**	0.0246*	0.0262
	(0.0138)	(0.0138)	(0.0159)	(0.0140)	(0.0164)
BNATM		0.0351**	0.0409		0.0344
		(0.0154)	(0.0247)		(0.0241)
BNATM × Treatment			-0.0105		-0.00901
			(0.0295)		(0.0297)
Constant	0.0480	0.0315	0.0285	0.0546	0.0381
	(0.0407)	(0.0365)	(0.0340)	(0.0441)	(0.0365)
N	1131	1131	1131	1024	1024
R^2	0.0249	0.0299	0.0300	0.0282	0.0322
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes

Notes: BNATM is an indicator of whether there is a "Banco de la Nacion" ATM close to the individual. All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

Figure 2: Histogram in Education Level. Attendance vs No Attendance.

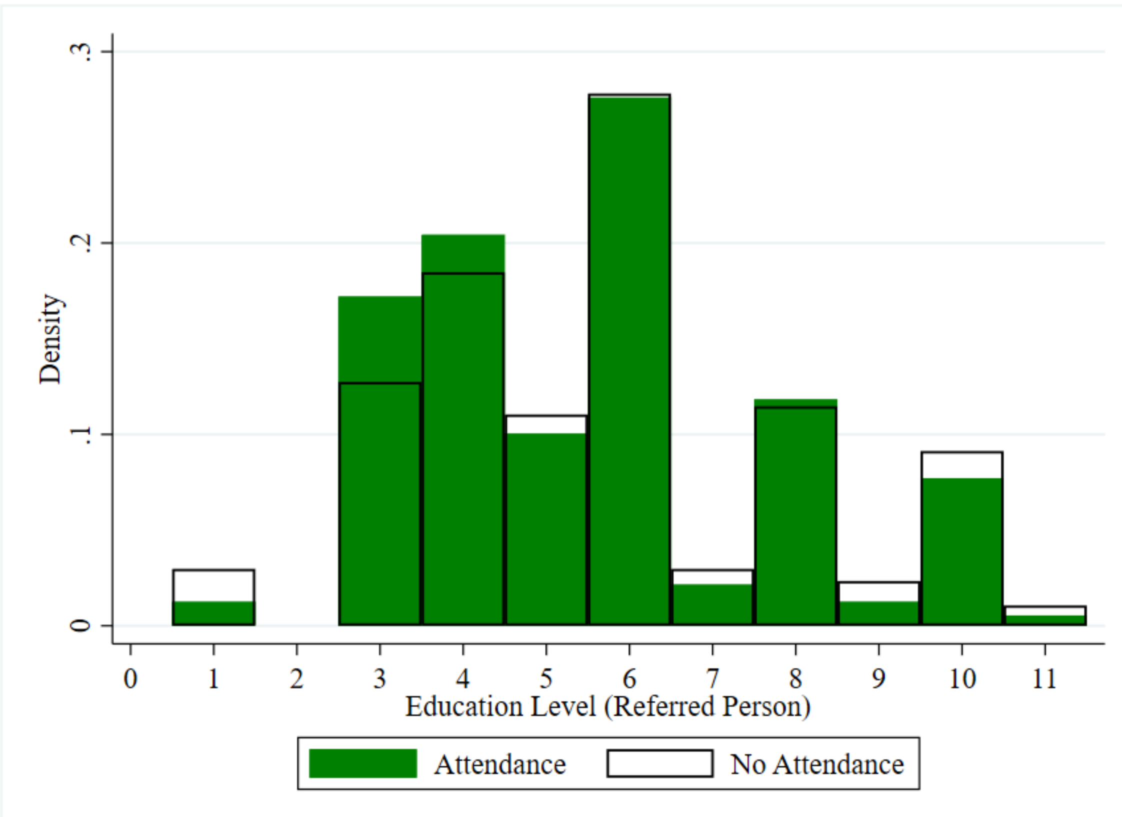


Figure 3: Histogram in Age. Attendance vs No Attendance.

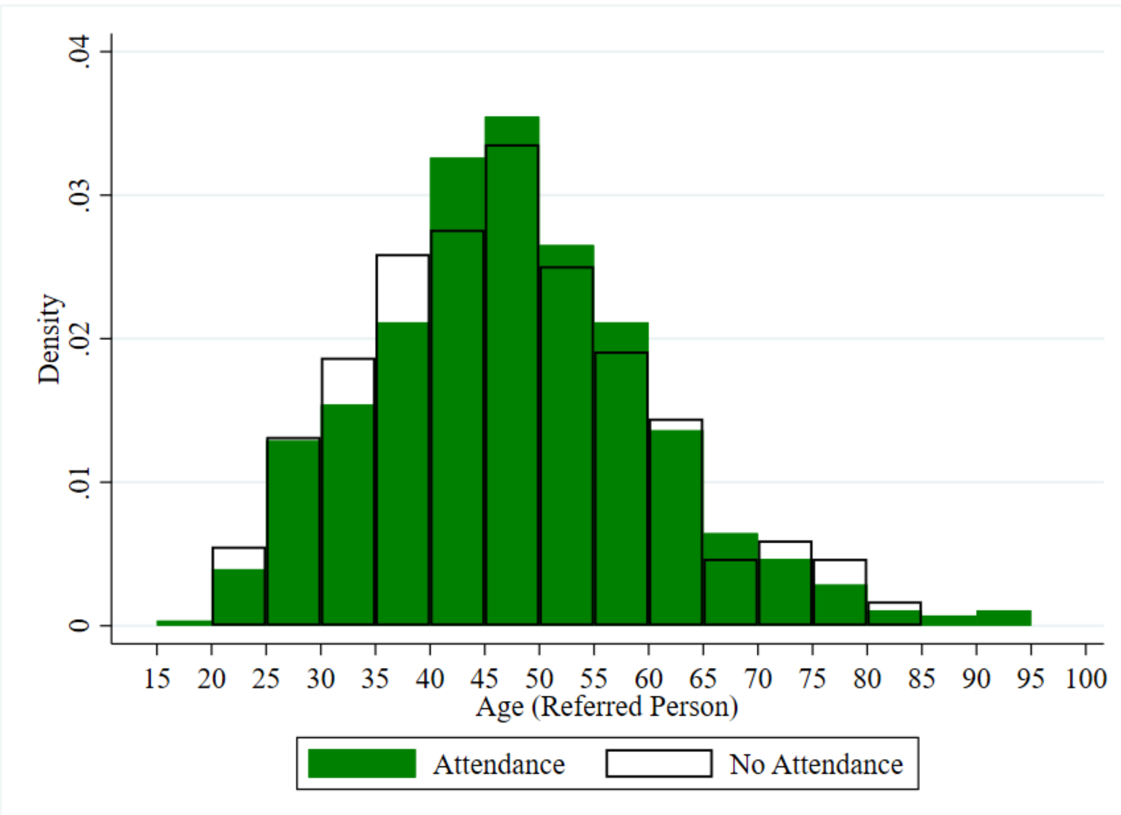


Table 13: BIM Attendance & Trust in Banks

					Excluding Beca18 family			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.354***	0.323***	0.316***	0.270***	0.394***	0.369***	0.363***	0.330***
	(0.0410)	(0.0513)	(0.0518)	(0.0598)	(0.0422)	(0.0531)	(0.0536)	(0.0620)
BankTrust		-0.213*	-0.405***	-0.338***		-0.151	-0.316***	-0.291***
		(0.116)	(0.0438)	(0.0726)		(0.115)	(0.0637)	(0.0632)
BankTrust × Treatment			0.386*	0.685***			0.326	0.689***
			(0.197)	(0.104)			(0.204)	(0.100)
distrust				-0.133**				-0.122*
				(0.0607)				(0.0645)
Distrust × Treatment				0.243**				0.248**
				(0.121)				(0.123)
Constant	0.456***	0.479***	0.487***	0.502***	0.401***	0.445***	0.453***	0.473***
	(0.0673)	(0.0953)	(0.0948)	(0.0991)	(0.0738)	(0.0864)	(0.0856)	(0.0894)
N	1131	683	683	529	1024	622	622	480
R^2	0.141	0.123	0.126	0.137	0.169	0.157	0.159	0.176
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: BankTrust is based on the following question "Do you trust banks? 1: Very low , 2: Low, 3: Medium, 4: High, 5: Very high, 6: Missing". Individuals are considered trustful if they answer 5. All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%. We lost observations by including the distrust variable because it includes missing values.

Table 14: BIM Affiliation & Trust in Banks

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0389***	0.0370*	0.0374*	0.0246*	0.0254	0.0255
	(0.0138)	(0.0193)	(0.0196)	(0.0140)	(0.0193)	(0.0197)
BankTrust		-0.0535***	-0.0416*		-0.0494***	-0.0452*
		(0.0146)	(0.0247)		(0.0150)	(0.0271)
BankTrust × Treatment		-0.0240			-0.00846	
			(0.0308)			(0.0333)
Constant	0.0480	0.0962	0.0956	0.0546	0.123	0.123
	(0.0407)	(0.0790)	(0.0796)	(0.0441)	(0.0852)	(0.0858)
N	1131	683	683	1024	622	622
R^2	0.0249	0.0335	0.0335	0.0282	0.0451	0.0451
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: BankTrust is based on the following question "Do you trust banks? 1: Very low , 2: Low, 3: Medium, 4: High, 5: Very high, 6: Missing". Individuals are considered trustful if they answer 5. All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%. We lost observations by including the Distrust variable because it includes missing values.

Table 15: BIM Attendance & Time Spent

				Excluding Beca18 family			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.361***	0.310***	0.309***	0.315***	0.355***	0.309***	0.315***
	(0.0507)	(0.0467)	(0.0524)	(0.0603)	(0.0486)	(0.0524)	(0.0603)
Time	0.00273		0.00236	0.00330		0.00236	0.00330
	(0.00385)		(0.00285)	(0.00556)		(0.00285)	(0.00556)
Time × Treatment	-0.000698			-0.00126			-0.00126
	(0.00472)			(0.00630)			(0.00630)
Distrust		-0.140**	-0.174***	-0.175***	-0.145***	-0.174***	-0.175***
		(0.0544)	(0.0621)	(0.0609)	(0.0537)	(0.0621)	(0.0609)
Distrust × Treatment		0.177*	0.222**	0.224**	0.179*	0.222**	0.224**
		(0.0953)	(0.102)	(0.102)	(0.0977)	(0.102)	(0.102)
Constant	0.367***	0.519***	0.441***	0.434***	0.469***	0.441***	0.434***
	(0.0797)	(0.0722)	(0.0917)	(0.0861)	(0.0784)	(0.0917)	(0.0861)
N	785	829	579	579	746	579	579
R^2	0.148	0.142	0.148	0.148	0.169	0.148	0.148
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Time represents the number of weekly hours spent with the individual. All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

Table 16: BIM Affiliation & Time Spent

				Excluding Beca18 family			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.0217	0.0620***	0.0405*	0.0324	0.0403**	0.0405*	0.0324
	(0.0206)	(0.0155)	(0.0216)	(0.0262)	(0.0173)	(0.0216)	(0.0262)
Time	-0.000739		-0.000718	-0.00194		-0.000718	-0.00194
	(0.00133)		(0.000916)	(0.00141)		(0.000916)	(0.00141)
Time × Treatment	0.000359			0.00163			0.00163
	(0.00158)			(0.00177)			(0.00177)
Distrust		0.0263	-0.00554	-0.00396	0.0289	-0.00554	-0.00396
		(0.0258)	(0.0135)	(0.0141)	(0.0276)	(0.0135)	(0.0141)
Distrust × Treatment		-0.0790**	-0.0458	-0.0488	-0.0789**	-0.0458	-0.0488
		(0.0379)	(0.0324)	(0.0331)	(0.0369)	(0.0324)	(0.0331)
Constant	0.0643	0.0487	0.0793	0.0876	0.0596	0.0793	0.0876
	(0.0537)	(0.0442)	(0.0574)	(0.0616)	(0.0482)	(0.0574)	(0.0616)
N	785	829	579	579	746	579	579
R^2	0.0248	0.0398	0.0434	0.0444	0.0446	0.0434	0.0444
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Time represents the number of weekly hours spent with the individual. All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

Table 17: BIM Attendance & Referred Person's Education

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.354***	0.340***	0.374***	0.394***	0.378***	0.434***
	(0.0410)	(0.0414)	(0.0814)	(0.0422)	(0.0434)	(0.0850)
Education Level		-0.00354	-0.000433		-0.00361	0.00135
		(0.00763)	(0.0113)		(0.00799)	(0.0118)
Education Level × Treatment			-0.00614			-0.00988
			(0.0141)			(0.0150)
Constant	0.456***	0.469***	0.452***	0.401***	0.405***	0.378***
	(0.0673)	(0.0693)	(0.0796)	(0.0738)	(0.0761)	(0.0866)
N	1131	1029	1029	1024	935	935
R^2	0.141	0.133	0.134	0.169	0.159	0.159
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

Table 18: BIM Affiliation & Referred Person's Education

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0389***	0.0360**	0.0807**	0.0246*	0.0213	0.0909**
	(0.0138)	(0.0142)	(0.0393)	(0.0140)	(0.0140)	(0.0400)
Education Level		0.00405	0.00808**		0.00229	0.00849**
		(0.00358)	(0.00404)		(0.00361)	(0.00426)
Education Level × Treatment			-0.00797			-0.0124*
			(0.00671)			(0.00667)
Constant	0.0480	0.0288	0.00621	0.0546	0.0449	0.0105
	(0.0407)	(0.0401)	(0.0393)	(0.0441)	(0.0430)	(0.0426)
N	1131	1029	1029	1024	935	935
R^2	0.0249	0.0249	0.0262	0.0282	0.0289	0.0326
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

Table 19: BIM Attendance & Referred Person's Age

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.354***	0.342***	0.550***	0.394***	0.381***	0.545***
	(0.0410)	(0.0414)	(0.120)	(0.0422)	(0.0432)	(0.124)
Age		-0.000388	0.00211		-0.00165	0.000338
		(0.00133)	(0.00180)		(0.00136)	(0.00177)
Age × Treatment			-0.00450*			-0.00357
			(0.00250)			(0.00262)
Constant	0.456***	0.475***	0.363***	0.401***	0.474***	0.386***
	(0.0673)	(0.0941)	(0.102)	(0.0738)	(0.0960)	(0.102)
N	1131	1029	1029	1024	935	935
R^2	0.141	0.133	0.136	0.169	0.160	0.162
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

Table 20: BIM Affiliation & Referred Person's Age

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0389***	0.0341**	0.0167	0.0246*	0.0199	0.0219
	(0.0138)	(0.0146)	(0.0447)	(0.0140)	(0.0145)	(0.0420)
Age		0.000258	0.0000489		0.000470	0.000495
		(0.000439)	(0.000551)		(0.000439)	(0.000429)
Age × Treatment			0.000376			-0.0000443
			(0.000851)			(0.000840)
Constant	0.0480	0.0315	0.0408	0.0546	0.0302	0.0291
	(0.0407)	(0.0483)	(0.0532)	(0.0441)	(0.0503)	(0.0517)
N	1131	1029	1029	1024	935	935
R^2	0.0249	0.0238	0.0239	0.0282	0.0291	0.0291
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All regressions are controlled by head employment, geographic region fixed effects and clustered at the student network level. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

Table 21

Database: Encuesta de Hogares 2017_ WIDE

	Observations
Raw data	1239
Pilot database	-28
Survey test	-16
Duplicates in Head House name	-1
Duplicates in DNI	-24
Mismatch with workshop data	-31
Duplicates cellphone number	-1
Student who asked to not be part of the study	-7
Total	1131