The role of information and trust in the demand for 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

[4]Universidad de Piura and CAM-UDEP

[5]Institutos de Estudios Peruanos

[5]Universidad del Pacífico

This version: October 19, 2019

Abstract

In this paper 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 peri-urban 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 led by agent external to the community. Our evidence suggests that lack of information impedes product adoption, which is itself limited by lack of trust towards the individual who passes the information.

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

*We are grateful to María Laura Alzua and Guillermo Cruces and participants at Africa Region Econometrics Society 2019, Peruvian Economic Association Meetings 2019, Chilean Economic Association Meetings 2019 and UDEP Economics Research Seminar for their helpful comments. We thank Jessica Salazar, at PDP, for her extraordinary support in providing us with the administrative adoption and usage data, and Rodrigo Chang and Paul Corcuera for their excellent research assistance as well as for their comments to 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 fraction of adults in the developing world do not hold bank accounts, impeding their ability to safely store cash and transfer money. High transaction costs, including fees, minimum balance requirements and travel time to a bank branch, are barriers to their financial inclusion (Bachas et al., 2018). Interventions to bank the unbanked have focused on reducing supply-side barriers, with mixed results (Dupas et al., 2018). In Kenya, mobile money technology has successfully reduced transaction costs, especially for those living in remote areas not well serviced by banks, and improved their well-being (Suri et al., 2012; Suri and Jack, 2016).

A new electronic wallet platform was introduced in 2016 in Peru as part of the national plan to speed up financial inclusion. Yet, two years later, in the rural and peri-urban areas on which our study focuses, less than 1 percent of interviewed households reported having an e-wallet.

To understand this puzzle, we focus our attention on demand-side factors, namely the role of information and trust. Indeed, the Peruvian e-wallet platform, BIM, already addresses the main other constraints faced by consumers: it operates from basic cellphones which more than 80% of the population owns; opening the account is free; and BIM neither charges for deposit nor transfers and features a small charge for cash-out operations (1% of total amounts).

In this paper, we experiment with a novel way to boost information acquisition on the e-wallet that exploits existing social ties between the promoter and community members. Social networks play an important role in influencing learning and diffusion of technology (Jackson, 2011; Munshi, 2004; Conley and Udry, 2010). Looking at participation to a microfinance loan program, Banerjee et al. (2013) find that the key to information diffusion is information passing from seed individuals (see also Cai et al. (2015). They show that, once information passing is accounted for, participation to the microfinance program by peers does not influence one's own decision to participate. To do so, they estimate a model of network diffusion of information and demand for microfinance services. Most often, researchers cannot observe whether a conversation over the product or technology to be promoted actually took place, and are thus unable to provide direct evidence that being a network member is key to information passing.

To fill this gap, we experiment with the social identity of the individual who is picked up to provide the information and explore how information acquisition and adoption of product are affected by it. We study a setting in which information passing on a new product takes place during a specific event designed for this purpose. Observed participation to the event provides us with a measure for the demand for information which we expect to depend on who the messenger is.

More specifically, we contrast two mechanisms to encourage participation to information and training workshops on the new mobile money platform in remote areas of Northern Peru. In the treatment group, the promoter leading the information and training workshop is 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 fellows as the local ambassadors. In the control group, a similar set of community members are invited to attend a similar workshop but led by an agent external to the community who was recruited for this task by the banks. Randomization is based on our sample of local ambassadors from whom we listed family network members. Treatment and control groups are comprised of family networks of local ambassadors. In the treatment group, local ambassadors return to their community of origin to lead a BIM training workshop. In the control group, external agents are used as an alternative approach to "treating" the community with information about the BIM.

We recruited the local ambassadors from the set of recipients of the Peru flagship scholarship program (Beca18). This program targets bright high school graduates living in disadvantaged peri-urban and rural communities who have obtained admission into an elite Peruvian university. To conduct this study, we partnered with one of these universities (Universidad de Piura or UDEP) to obtain permission to recruit and train Beca18 fellows on the e-wallet technology, as well as to conduct a baseline survey in April-June 2018. Parents of Beca18 agreed on having an information and training workshop on the BIM held at their home. We also partnered with Pagos Digitales Peruanos (PDP), a company founded by the members of the Peruvian Banking Association and more than 30 e-money users that launched BIM. PDP facilitated access to the external BIM promoters whose role was to deliver information to our control group. We also obtained access to PDP administrative data to measure take-up of BIM. We do not look at usage because just a few months after our experiment on the promotion of the BIM e-wallet to peri-urban and rural areas, PDP decided to switch to a platform for smartphones.

Using this research design, we test a number of hypotheses. Firstly, we expect invited participants to be more likely to attend the workshop led by the member of their network. Success in passing information crucially depends on the attendance of community members to the workshop. These individuals may 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. Because they are socially connected to the Beca18 fellow, invited participants may trust him or her to provide reliable information on the product. Higher trust may occur because they expect to continue to interact in the future with the fellow or the fellow's parents. As a result, if lack of interest to participating to the workshop is indeed driven by a trust failure, our treatment should be more successful at encouraging participation, with a higher impact on attendance for the distrustful.

Secondly, we expect the net effect of the treatment on take-up to be of an indeterminate sign, for two main reasons. First, the treatment may affect the composition of the pool of workshop participants, attracting those who are the most distrustful of outsiders, resulting in lower take-up among the treated.[1] Second, if participants believe network promoters to pass on more credible information than external agents, we can expect higher take-up among the treated. Overall take-up in the treatment group can then be expected to be higher than in the control group only if the latter effect offset the former one.

Thirdly, if information asymmetry on the consumer side is a barrier to adoption, information acquisition should increase take-up of the financial product. Though we do not have a pure control group that did not get any information, we can exploit the exogenous variation in workshop attendance due to treatment assignment to estimate the effect of information acquisition on take-up of the financial product. 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 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 product is a barrier to financial inclusion for the distrustful, a population that is typically more difficult to reach out to.

We find that 35% of invited participants attended the workshop in the control group and 70% of them did so in the treatment group. Being invited to attend a workshop led by a Beca18 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. This evidence suggests that using local ambassadors to pass information is much more effective than the alternative approach that consists of sending external agents. The treatment effect is even higher on

[1] We can expect the treatment effect on take-up among the most distrustful to be lower because of their lower priors on the usefulness of the technology.

those who are more distrustful by an additional 16-17 percentage points.[2] We do not have a design to identify a causal effect on participation to the workshop according to the level of distrust. The effect may be driven by a correlate to being distrustful. We checked 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 the information (Guiso et al. (2008); Calcagno and Monticone (2015); Patacchini and Rainone (2017)). Once they attend the workshop, the subjects have an opportunity to update their beliefs about the product which could, in turn, affect their decision to sign up on the platform (i.e., take-up the product). We find a positive and significant LATE with a magnitude of the order of 10 percentage points. This evidence suggests that lack of information impedes the adoption of the new product. Finally, we find a 3 percentage point increase in take-up, which though small in absolute terms represents a doubling of the adoption rate obtained for the control group. This holds even though the network treatment attracted more distrustful people. We indeed find that the latter are less likely to adopt as a result of the treatment than trustful network members.

Our paper is close to 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. They find the former to be more effective than the later. 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 villagers on whether at least one information and training session were held by communicators, they show evidence that the extent to which information is passed depends in part on the identity of the communicator. In a companion paper, Beaman et al. (2018) select seeds to maximize diffusion of the technology based on the predictions of various diffusion models. They find that more conversations about the technology occurred with selected seeds in treated villages than with counterfactual shadow seeds, i.e., individuals 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 as they can be trusted to pass on credible information, corroborating the results from these three papers.[3]

[2] The trust question is as follows: *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 either 4 or 5.

[3] These papers also investigate adoption diffusion, while we do not.

Our contribution is to offer a novel research protocol specifically designed to focus on the role of the identity of the promoter in passing information. Two particular features of the design are important in that respect. First, in our setting, passing of information takes place during a specific event designed for this purpose, allowing us to record participation to the workshop and use it to measure information passing. Second, because randomization is based on the sample of local ambassadors from whom we listed family network members, we can control the identities of potential receivers (i.e., individual the promoter attempted to reach out to). 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, as we focus on a financial product for which many of the common supply-side barriers have been removed, our study provides novel evidence that lack of information and lack of general trust are obstacles to financial inclusion. Second, our study suggests that, in order to effectively reach out with information and training on a new product, the identity of the promoter is crucial. 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. Beca18 fellows 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 the aspects of Beca18 fellows identity that makes them effective at passing the information, though we have suggestive evidence it is related to being trusted to provide reliable information on the product.

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 Peru, only 29% of adults held a bank account in 2014; among the poorest 40%, this proportion was only 18%.[4] In response to this situation, the Peruvian government announced the National Plan for Financial Inclusion in 2015, which set special emphasis on the development of mobile-money platforms as mechanisms to speed up financial inclusion.[5] 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 to speed up financial inclusion.

BIM is an electronic wallet operating from a cellphone that 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 and withdraw money to/from 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. One had to dial the number *838#, enter ones DNI, 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 the total amount).

Since the BIM account immediately connects its holder with a financial institution,[6] 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 usage 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 emphasis of BIM has been on major urban areas, where 60% of the adult population still does not have a bank account. BIM had been promoted through TV, radio spots, newspapers, and social media (Facebook and YouTube). By

[4] http://www.bancomundial.org/es/news/press-release/2015/06/11/peru-familias-peruanas-avanzan-hacia\-la-inclusion-financiera

[5] https://mef.gob.pe/contenidos/archivos-descarga/ENIF.pdf

[6] Banco de la Nación manages the funds.

August 2016, close to 100,000 accounts had been activated. PDP, however, faces challenges to expand BIM adoption to peri-urban neighborhoods, geographically distant small urban communities and rural districts.

Given this context, we identified Beca18 fellows as local ambassadors to promote the new product. Together with PDP, we decided to assess whether they could successfully reach out to these peri-urban and rural communities. Beca18 is Peru flagship scholarship program for higher education. 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 disadvantage households, most of them located in peri-urban and rural communities, who have achieved high academic standards in high school as measured by Peruvian high school GPA, and have been admitted to an eligible educational institution.[7][8] The Beca18 grant includes tuition, school supplies, local transportation costs, a laptop (or similar equipment), administrative costs to obtain a title, and possibly travel and accommodation to 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.

3 Motivational framework

Since the recent literature stresses out the role of information passing from known and trusted sources, we chose to study the effectiveness of an information transmission strategy in which Beca18 fellows act as messengers. We argue that the information passing through Beca18 fellowsis likely to be more trusted than that 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

[7] Its literal translation is *Scholarship18*.

[8] 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.

much lower (Bachas et al. (2018); Suri et al. (2012)). A critical feature of this product is that it relies on network externalities, see e.g. Sahut (2008): consumer adoption of the product 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 product. A typical response is to offer financial information and education. But, the evidence on the effectiveness of these programs is mixed (Miller (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 (Valente, 2012; Kim et al., 2015; Maclean et al., 2019). In the finance literature, general lack of trust is 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 confirm 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

To motivate our empirical investigation, this section builds on the previous discussion of the determinants of the demand for financial products. We are interested in two related barriers to adoption: (1) lack of information on the product 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 is provided, agents may fail to update their beliefs on the product 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 towards unsophisticated applicants.

We consider a setting where consumers cannot perfectly observe the quality of the e-wallet before using it. There are two types of agents who 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 to introduce the e-wallet. Prior to attending it, they know the identity of the promoter (Beca18 or external agent). 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 on how credible the information about the product is perceived.

We now explicitly lay out the hypotheses on how Beca18 fellows may influence the decision of their household network members to attend the BIM information and training workshops as well as to adopt the newly launched Peruvian electronic wallet.

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 may provide Beca18 fellows with an incentive to truthfully reveal the quality of the technology. Indeed, once community members will start using it, 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 reputation and can be blamed in the future if they misled their parents' friends into adopting the technology, the information they provide will be credible and trusted. In contrast, external agents may 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 will be perceived as biased. External agents may thus be less credible than the local ambassadors.

Hypothesis 2: *Distrustful people are more likely to attend the information and training workshop that is 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 can expect that the treatment affects the composition of the pool of workshop participants, attracting those who are the most distrustful of outsiders. If the most distrustful hold lower beliefs on the value of the product, they may be less likely to sign up for the product, decreasing take-up among the treated. Suppose that there were no change in the composition of the pool of participants to the workshop (*Hypothesis 1* rejected). Then, we could 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 passed on 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 information provision, we can expect the treatment to result in an increase in take-up. Overall, take-up in the treatment group can then be expected to be higher than in the control group only if the latter (positive) effect offset the former (negative) one.

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

We do not have a pure control group that did not get 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 product. 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 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 product 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 of the randomized control trial (RCT) we conducted in Northern Peru. Our outcomes of interest are participation to an information and training workshop on BIM and take-up of the EW. Our experimental units are community members belonging 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 at an elite university in Northern Peru[9] to be part of a campaign promoting financial inclusion in their neighborhoods/communities. To encourage participation, we indicated that this activity will count for extracurricular academic credits. Approximately 130 out of 500 Beca18 fellows registered to participate.

We mapped Beca18 family network in the neighborhood/community where they reside. To do so, in early September 2018, Beca18 fellows ask their parents (father and mother) 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 in terms of interaction intensity and trust. We selected 8 to 10 members from this set to construct family network groups.[10] These are the community members who were invited to participate to information and training workshops on the BIM.

We observe one family network group per Beca18 fellow. These family network groups are our randomized units. Half of these groups were randomly allocated to treatment, i.e., they received information and training about the BIM from a Beca18 beneficiary; while the other half received information and training from external agents hired by PDP. With this design, we control the identity of those who receive the 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 to BIM workshop and adoption explained by 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 expect to

[9]Universidad de Piura (UDEP).

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

be informed and trained on the BIM by the son/daughter of a friend, relative or neighbor; control family network expect an external agent working for the banks.

The BIM workshops took place during the southern hemisphere winter break (July-August 2018), a convenient time for the college students to head back home. Beca18 parents agreed to host these workshops at their home. In the treatment group, the son/daughter of the host invited his/her family network to participate to an information and training session on the 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 performed. The external agent also asked the Beca18 parents to remind network members about the training session. All promoters received a per diem to pay for travel cost to the community and a stipend to pay for refreshments for all participants of the workshop.

A roster of attendants was kept at each meeting. Each attendant had to confirm his/her cell phone number collected in the baseline. They also had to sign the attendance roster to confirm they actually attended the meeting. These records are used to generate the variable describing participation to the BIM workshop.

Support to this experimental design was provided by PDP who offered us access to agents they hired for the promotion of the BIM as well as administrative data on the activation 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

Given this experimental protocol, only half of the Beca18 participants to our study had a trip back home paid for and the opportunity to lead a workshop on the BIM. We made it transparent to all that there was a limited number of resources available and that a lottery system was 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 want to share the contents of the workshop with control Beca18 fellows, especially that they all attend the same university. To minimize this potential bias, the information related to BIM was provided in the last two months of training (May-June 2018),[11] just before the local ambassadors had to travel to their communities to lead the BIM workshop. Moreover, Beca18 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 linked their involvement in the initial general training on financial inclusion to the BIM workshop sessions that were later delivered to their household network at their parents' place. If this were the case, family network members may believe that the external agents were recommended by their Beca18 as a trusted source of information. We would then underestimate the effects of the treatment. Note that external agents were not told they were visiting a Beca18 family.[12] Still, we cannot discard the possibility that control family networks did associate the BIM workshop with the involvement of the son/daughter of their host to a study on financial inclusion.

In addition to minimizing contamination bias, we design the experiment to avoid geographical spillovers. To do so, we include in our analysis only neighborhoods/communities that are relatively distant from each other.[13]. Figures 1 and 2 shows the geographical dispersion of the communities. Treatment networks are depicted in blue while control ones are in red. Our intervention mainly covers the northern regions of Tumbes, Piura, Cajamarca, Amazonas, Lambayeque and La Libertad.

We must emphasize that the role of our academic ambassadors, Beca18 fellows in the treatment group, was 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 BIM. Our academic ambassadors were trained to provide information about the BIM benefits as well as its implied risks and how to mitigate them. This objective was clearly explained to them during the training sessions.

Another concern is that Beca18 fellows fail to achieve the expected results not because they are not credible sources of information for their family network group 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, our local

[11] 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.

[12] 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.

[13] Our partner university provided us with the precise geographic location of the communities of the Beca18 fellows who agree to participate

ambassadors were carefully trained. Their sessions incorporated 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 one for Beca18. It 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. Secondly, we only study the BIM adoption decisions of network members of the Beca18 household, which may not be representative of a typical network in the community. Given these considerations, our conclusions cannot straightforwardly be extended to every community with a Beca18 fellow, neither to all networks within these communities.

4.2 Data

Our baseline survey took place from April 21st to June 3rd, 2018. We work with 58 Beca18 fellows in the control group, and 60 fellows in the treatment one.[14] Our final working sample consists of 1131 observations in total. Interviewed households were told the UDEP was implementing the survey to obtain information about the general socioeconomic conditions in the area. There was no mention of a future campaign to promote the electronic wallet or of the Beca18 program.

In Table 2, we present baseline summary statistics for a key set of variables for our sample, which is comprised of 609 individuals in the treatment group and 522 individuals in the control one. The two outcomes of interest are participation to information and training workshop and signing-up to activate the e-wallet platform. Participation is based on attendance at the workshop and e-wallet take-up is measured three months after the workshops took place (December 2018) on the basis of administrative data shared by PDP. We do not look at e-wallet usage for transfers and payments because BIM was no longer supported on basic cellphones starting February 2019 (an announcement made in January 2019).

We collected data on head employment, household expenditures (food and transport), ownership of a cellphone, usage and knowledge of a BIM account, among others. The variables

[14] 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 as it became clear that the Beca18 fellow did not belong to the program. Finally, we include networks from our initial pilot sample.

"Head BIM (Knowledge)" and "Spouse BIM (Knowledge)" are binary variables that indicate whether or not the head or spouse knows about the new BIM product (1 they know, 0 otherwise). Likewise, the variable "Head BIM (Account)" indicates whether or not the household head reports having a BIM account (1 if it has, 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 gather data on the household level of trust. "Household trust" is a binary variable built from the trust level as reported by the household head, or, if absent, by the spouse.[15] The trust question is as follows: *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*. "Household trust" takes value 1 if individuals responded 1, 2 or 3, and 0 otherwise.

Households head's average age is 47 years, and the majority of heads are male (80%). Almost none of the heads reported 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 household heads knew about the BIM system by the time of the interview. Even fewer spouses did. In terms of education, close to 40% of the household heads completed secondary school, while 25% of the spouses interviewed achieved this level of education. In terms of access to formal banking services, 27% of the heads reported 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 difference 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). 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 promotion campaigns. People

[15]We find 12 observations where there was no information for either the head or the spouse.

may self-select into these groups and thus differ across observed and unobserved characteristics that could also explain their demand for information. A difference between these groups based on observational data may not be exclusively attributed to differences in the identity of the promoters is 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.

There are two differences that may be worth discussing. First, household heads 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 almost 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.[16] We will control for these differences in some of our specifications. [17]

4.3 Empirical strategy

To study the impact of our intervention on BIM workshop attendance and BIM adoption, we simply compare outcomes of individuals in treated networks to those in control ones. Given random assignment of the treatment, control group networks constitute a counterfactual for what treated group networks would have experienced had they not been treated.[18] We estimate the following model:

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

where the outcome variable Y_{in} represents either attendance at the BIM workshop, which is 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 the receiving the information through the local ambassador, 0 if

[16] Only 7 household heads overall reported having a BIM account; and it happened that 6 of them are in the treatment group. These individuals represent a very small proportion of the total sample, we consider that it is a matter of pure random luck.

[17] We have 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 Faculty. We did not find systematic differences among fellows in the treated and control groups. These results can be provided under request

[18] Note that the benchmark control state is one where community members get information from an external agents. This represents the business-as-usual information transmission mechanism.

the information was supposed to be passed 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).[19]

To explore heterogenous effects in relation to the level of distrust, we consider the following model:

$$Y_{in} = \alpha_2 + \beta_2 Treated_{in} + \delta Distrustful_{in} + \delta' Treated_{in} x Distrustful_{in} + X'_{in}\gamma_2 + \epsilon_{in}. \quad (2)$$

According to *Hypothesis 1*, we expect to obtain a positive estimate for β_1 when looking at workshop attendance. This effect should be higher for the most distrustful according to *Hypothesis 2*, which implies δ' positive and indicates that lack of trust is an impediment to BIM take-up. *Hypothesis 3* implies that, when looking at BIM take-up as the outcome, the sign of β_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, 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 product for those whose decision to attend the workshop is affected by the treatment (i.e. compliers). The main equation is as follows:

$$Y_{in} = \lambda_0 + \lambda_1 Attend_{in} + X'_{in}\gamma_3 + \mu_{in}, \quad (3)$$

and we instrument $Attend_{in}$ by $Treated_{in}$. According to *Hypothesis 4*, we expect 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 to the BIM workshop and take-up BIM, 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:

$$Y_n = \alpha_4 + \beta_4 Treated_n + \epsilon_n \quad (4)$$

[19] We also estimate a probabilistic model. The marginal effects would show the impact of the intervention on the likelihood of either attending the meeting or activating a BIM account.

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 suggests that the heterogenous 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 who passes it. In this regard, the social identity of the messenger is an important factor influencing the reach of the e-wallet promotion campaign, particular among low trust individuals.

5.1 Information passing

The results in Table 3 confirm that our treatment had a significant effect on workshop attendance. Column one shows that while 35% of the network members attended the meeting in the control group, the number goes up to 70% for members in the treated group. That is, the treatment doubles the likelihood of receiving the message. A similar result is observed when we add "Head Employment" as a control variable in column two. The analysis at the aggregate network level in column three points out that close to four more people attend the BIM presentation session if it is given by a local academic ambassadors instead of an external agent. Excluding the Beca18 fellow parents from the estimations (last columns in the table) does not alter our results. In the motivational framework in Section 3 we argued that the interests of the sender and network members are expected to be more aligned in the treatment than in the control group. As such, we also argue that the driver of the effect on attendance is the draw/trust a valued member of the community can have within his/her own network.

We advocate the importance of this finding for managers of e-money operators in particular and policy makers in general, as it highlights a secure mechanism for the diffusion of new financial technologies or social programs, particularly in distant rural contexts. Indeed, introducing new information through a local ambassador ensures a larger reach within the invited audience.

5.2 E-wallet adoption and usage

Table 4 presents the estimations results for the intervention effect on affiliation (BIM account activation or take-up). In the specifications corresponding to this table, we also add pre-treatment BIM affiliation as a control variable [20]. The constant's coefficient in column 1 reveals that the affiliation rate in the control group was just about 4%. With the treatment, BIM uptake increases by about 4 percentage points. That is, the adoption rate more than doubles. 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 product or service in the past. Still, the overall take up rate doesn't go above 8%; which suggest that there are critical barriers to affiliation other than lack of knowledge or distrust in the new technology. Identifying and addressing such barriers should be the focus of future research.

As before, the last two columns exclude the Beca18 fellow parents from our estimation sample. Though the affiliation rate for the control group remains virtually the same, the estimated impact of the intervention drops by approximately 1.5 percentage points (to about 2.5%); taking the overall affiliation rate to 6%. Though the reduction in sample size didn't lead to 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 analyzes the overall intervention treatment effect on BIM usage. The estimations show a minimal 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 would gather a larger crowd and significantly incentivize people to activate an account; the effect on usage - at least in the short run- appears to be almost null.

[20] In other words, we estimate an ANCOVA model, as it allows us to increase our estimation power.

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 lead to a up-take well above the national averages.

It is also relevant to highlight that the usage of an electronic wallet is also critically influenced by, and to a degree conditional on, the economic infrastructure in place (i.e. the opportunities a person has on making commercial transactions with BIM) and the external transactions/services that are linked to a BIM account, such as government conditional cash transfers or the possibility of paying for government related services. The lack of the appropriate infrastructure or external transactions/services associated to BIM hinders the use of the electronic wallet. PDP states that there were unexpected delays in the implementation of the BIM functionality in financial agents platforms, particularly in rural areas. It also mentions that in many cases in which the platform was operative, agents did not receive the necessary training by the financial operators involved in the initiative [21].

Our motivational framework also argues that if the quality regarding the new technology surpasses the assumed quality prior attendance, network members in the treatment group would be more likely to adopt. If there is no updating because the information provided is in line with the prior, then we would not find any difference in take-up between treatment and control. Our results seem to close to this interpretation. Though the attendance effect is sizeable, the impact on affiliation is markedly smaller, and the difference between usage - for control and treatment groups - is virtual non-existent.

5.3 Lack of information as a barrier to adoption

Policy makers and managers of financial organizations and NGOs, as PDP in our study context, 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. While self-selection into attendance poses an empirical challenge in terms of estimating such effects; our intervention provides us with an advantageous framework to deal with this empirical issue. In our study, assignment to treatment was random (decided by a lottery), and henceforth exogenous to individuals pre-treatment characteristics. Moreover, in Section 5.1

[21] During our training sessions, Beca18 fellows were required to withdraw cash from an agent affiliated with the Peruvian National Bank. In several instances, these agents were not aware that their platforms allowed them to perform BIM transactions and our local ambassadors had to instruct them "*insitu*" how to perform them.

we showed that treatment assignment is strongly related to attendance. We can then use treatment assignment as an instrument for attending a BIM presentation session.[22] It is also important to mention that the content of the training sessions was designed with the support of PDP and that local ambassadors and external agents provided attendants with the same information content and material (the protocol given to the ambassadors and externals to organize and deliver their BIM information sessions was identical).

Table 6 presents the two-stage least square estimation for the effect of BIM meeting attendance on BIM affiliation[23]. We find that the affiliation rate increases by 11 percentage points if a member of the Beca18 household network attended our BIM training sessions. The exclusion of the Beca18 fellow parents from the estimation sample reduces the magnitude of the effect (to a 6 percentage points affiliation increase) and its significance, but it is still 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 estimates capture a LATE effect. This is, the attendance effect for those individuals whose behaviour is affected by the instrument (compliers). For this to be the case, the monotonicity or no-defiers assumption must hold. There should not be individuals within the Beca18 household network who will attend the meeting when an external hold it, but won't attend it when a local ambassador is in charge. Given our study context, we estimate that such cases will 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 given by a Beca18 fellow could only affect affiliation through the increased likelihood of attendance to such session. This is not guaranteed by the random nature of our instrument; as there may exist other channels through which the instrument can affect BIM adoption. For instance, local ambassadors can talk directly to members of their household network about the new electronic wallet (BIM), even if they did not attend the sessions. While we can not completely rule out this possibility, it is relevant to point out that our intervention took place during the academic winter break, which lasts only for 3 weeks, as opposed to the 3 months students have in their summer break. This timing minimizes Beca18 fellows exposure to those who did not attend the sessions. Informational externalities caused by BIM session attendants

[22]We have also compared the observable characteristics of people attending the information session for the treatment vs control group. For the majority of variables, we find no discernible differences.

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

providing, those who did not attended, information about the new electronic wallet, can also be present and even be more common in the treatment group. Note, however, that these two issues, if any, will likely introduce a downward bias in our estimated effects.

5.4 Heterogeneous effects in relation to individual trust

In the motivational section in this paper, one of our main hypothesis is that distrustful people is expected to attend in higher proportions the BIM information and training workshop that is led by a local ambassador than one led by an external agent. In this section we empirically assess this hypothesis by introducing an interaction term between our treatment and a distrust indicator.

Table 7 uses the self-reported household (head) distrust in society (recovered from the baseline survey) to test if our treatment intensity on attendance depends on how trusting an individual is (that is, we use the trust reported by her household head as a proxy for the individual own trust). As we discussed previously in Section 3, the trust information comes from the 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, 6: Household head is missing.* For the estimations in this sections, if the answer is 5, we claim that the individual is distrustful and the indicator variable takes the value of 1 (it is 0 otherwise).

For the attendance regressions in Table 7, our hypothesis is clearly confirmed; as we find that distrustful people are more reluctant to attend the BIM information sessions. The distrust coefficient value is -0.13, and it is statistically significant at the 5% level. Nonetheless, the interaction coefficient between our distrust indicator and the treatment dummy is positively estimated at 0.18 and is statistically significant at the 10% level. This clearly indicates that, in terms of message dissemination, people who exhibit more distrust in society were impacted more by our treatment than people with a relatively higher levels of trust level.[24]

While in the motivation section we clearly hypothesized that in terms of attendance more distrustful people will be more affected by the treatment, we did not state any hypothesis related to whether the adoption or take-up decision of such individuals will be more or less

[24] As stated in the motivation section, future and repeated interactions with their own community may provide Beca18 fellows with an incentive to truthfully reveal the quality of the technology. Indeed, once community members will start using it, the quality of the technology will be revealed. Both the Beca18 messengers and community members know that there will be ex post revelation. If Beca18fellows care about their reputation and can be blamed in the future if they misled their parents' friends into adopting the technology, the information they provide will be credible and trusted.

affected by the treatment. The difficulty here lies o the fact that our treatment does not only affects the identity of the messenger, but as the results in Table 7 suggest, also the trust composition of the group attending the BIM workshop. Henceforth, it is unclear how any empirical evidence related to trust heterogeneity related to the adoption decision should be interpreted in this context. Nevertheless, in Table 8 we present the readers with results for the affiliation or take-up regressions that include an interaction term between the treatment variable and our distrust indicator. As we can observe, the distrust coefficient is relatively small and not statistically significant; while the coefficient for the interaction effect is negative and statistically significant at the 5 percent level. In other words, in terms of adoption, the effect seems to be higher for individuals with higher levels of trust.

5.5 Other sources of heterogeneity and robustness checks

Our estimated effects in the previous section may be purely driven by the attendance and, later on, 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. We find that on average, and as expected, relatives are more likely to attend the information sessions; however, they are not more likely to affiliate. More importantly, there is no evidence of heterogeneous effects related to relatives for neither workshop attendance nor BIM affiliation. The interaction effect is relatively small, not robustly significant and negative in both cases. That means that, if any, relatives would be less affected by the intervention. Lastly, the treatment coefficients associated with attendance and affiliation in Tables 9 and 10 remain comparable to those estimated 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. We expect such benefits and familiarity to depend on the degree of financial development in the community. Accordingly, in Tables 11 and 12. we use the presence of at least one ATM from the government-run National Bank (Banco de la Nación) in the community as an indicator of financial development and interact the constructed binary variable with our treatment indicator to check for such differential effects.

In terms of attendance, we find that people from financially developed contexts (communities with better financial infrastructure) are more impacted by the treatment. Regarding affiliation, some of our regressions show a direct positive effect of financial development on affiliation. That is, network members are more likely to activate an account if their community has an ATM. However, in this case we do not find evidence of heterogeneous treatment effects related to financial development.

In Table 11, specifically in columns four and eight, we add in the attendance regressions the distrust indicator and its interaction with the treatment variable. As we can observe, the interaction between financial development and treatment still has a positive sign and remains statistically significant. The distrust indicator also remains statistically significant and has the same sign and size as in our estimations in Table 7. The coefficient for the interaction term between the distrust and treatment indicators has the same sign and is relatively close in size to that estimated in Table 7; however, it lacks statistical significance. Access to a higher level of financial infrastructure and the economic and social interactions that arise from such exposure are likely related to the individuals' general levels of trust/distrust. Such connection across general distrust and financial development may explain the lower coefficient we obtain for the interaction term among distrust and the treatment indicator in this case.

It is important to highlight that while people with access to better financial infrastructure may have more interest in learning about a financial technological innovation or are more familiar working with financial technologies; our results do not allow us to rule out the possible effect of other variables that could also be related with financial infrastructure and attendance; such as ease of transportation, higher urban density or overall local economic activity.

The level of financial development in a given community may be related to the level of trust individuals have in the banking system, and once we control for such trust, our distrust effects in Table 7 may not longer be relevant. To test for this 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 13 and 14 we explore the effect of trust in financial institutions on workshop attendance and BIM adoption. 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 benefits from attendance; the treatment effect is increasing in this type of trust. In columns four and eight in this Table we also add the general distrust indicator and its interaction with the treatment variable to the attendance regressions. Note that the estimated coefficients for the general level of distrust and its interaction term with treatment remain similar in sign and size to those in Table 7 as well as statistically significant. In other words, our general distrust related results in the previous section are not likely driven by trust in financial institutions.

It is also possible that our results are mainly driven by individuals with a higher level of social interactions with the Beca18 household. As an additional robustness check, in Tables 15 and 16 we include a measure of such connectedness: the number of weekly hours the Beca18 household spends with a specific network member, as well as its interaction term with the treatment indicator. As we can observe, 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 related to distrust in people obtained in 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 remain negative in sign but it is not statistically significant.

Individual distrust can also be potentially correlated with education and age. Henceforth. as a final robustness check, we test for heterogenous effects related to these two variables. In Tables 17 and 18 we explore heterogenous effects related to education on workshop attendance and BIM take-up respectively; while in Tables 19 and 20 we do the same for age. Table 17 shows that there is no evidence of either direct or heterogenous effects of education on attendance. Table 18 provides some weak evidence suggesting that higher educated people is 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 in column six. With respect to age, neither Tables 19 or 20 present any consistent evidence on direct or heterogenous effects on workshop attendance or BIM affiliation. In this regard, we conclude that it is unlikely that the heterogenous results related to distrust obtained in the previous section in this paper are just capturing differentiated effects related to the individual's age or education.

6 Conclusions

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

We report results from a field experiment conducted in remote areas of Northern Peru for which we contrast two mechanisms to encourage participation to information and training workshops. In the treatment group, the workshop is 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 expect 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 are invited to attend a workshop delivering the same services but led by an agent external to the community who was recruited for this task by the banks.

We find that participation to 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 ones. Though the take-up remains low, it is two to three times larger in the network promotion treatment. Importantly, we find evidence that participation to an information and training workshop leads to an increase of 10 percentage point in take-up at these early stages of adoption. All in all, our findings point to the lack of familiarity with e-wallet product together with general distrust issue as a barriers for the take-up of the new financial product.

One remark is in order. We find little effect on actual use of the e-wallet on financial transactions. This is easily explained by the fact than not long after starting their promotion of this e-wallet, the banks decided to discontinue the product and to switch to a much expansive device (smartphone) as a platform for a new e-wallet application. In this sense, part of the distrust in the initial technology was well justified.

More generally, we provide evidence that it is not sufficient to expand the supply of financial products and that banks need to directly address the trust issue. Our work shows that a promotion campaign involving community members is a cost-effective way to reach out to 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 is likely to be 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 effectively promote an existing product 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. 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.

Dupas, P., Karlan, D., Robinson, J., and Ubfal, D. (2018). Banking the unbanked? evidence from three countries. *American Economic Journal: Applied Economics*, 10(2):257–97.

Giné, X., Martinez, C., and Mazer, R. (2014). Financial disclure 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.

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.

Miller, Margaret J.; Reichelstein, J. E. S. P. C. H. Z. B. H. (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. and Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*, 354(6317):1288–1292.

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.

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	0.03	0.02	0.01	0.62	1,131	0.0239	0.153
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	476.02	475.86	0.16	1.00	1,131	475.9	306.9
Household Trust	0.60	0.55	0.05	0.34	1,117	0.572	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	0.03	0.68	1,131	0.426	0.495
Number of Restrooms	0.98	0.96	0.02	0.85	1,130	0.970	0.639
Head Age	47.59	46.91	0.69	0.54	1,131	47.28	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	

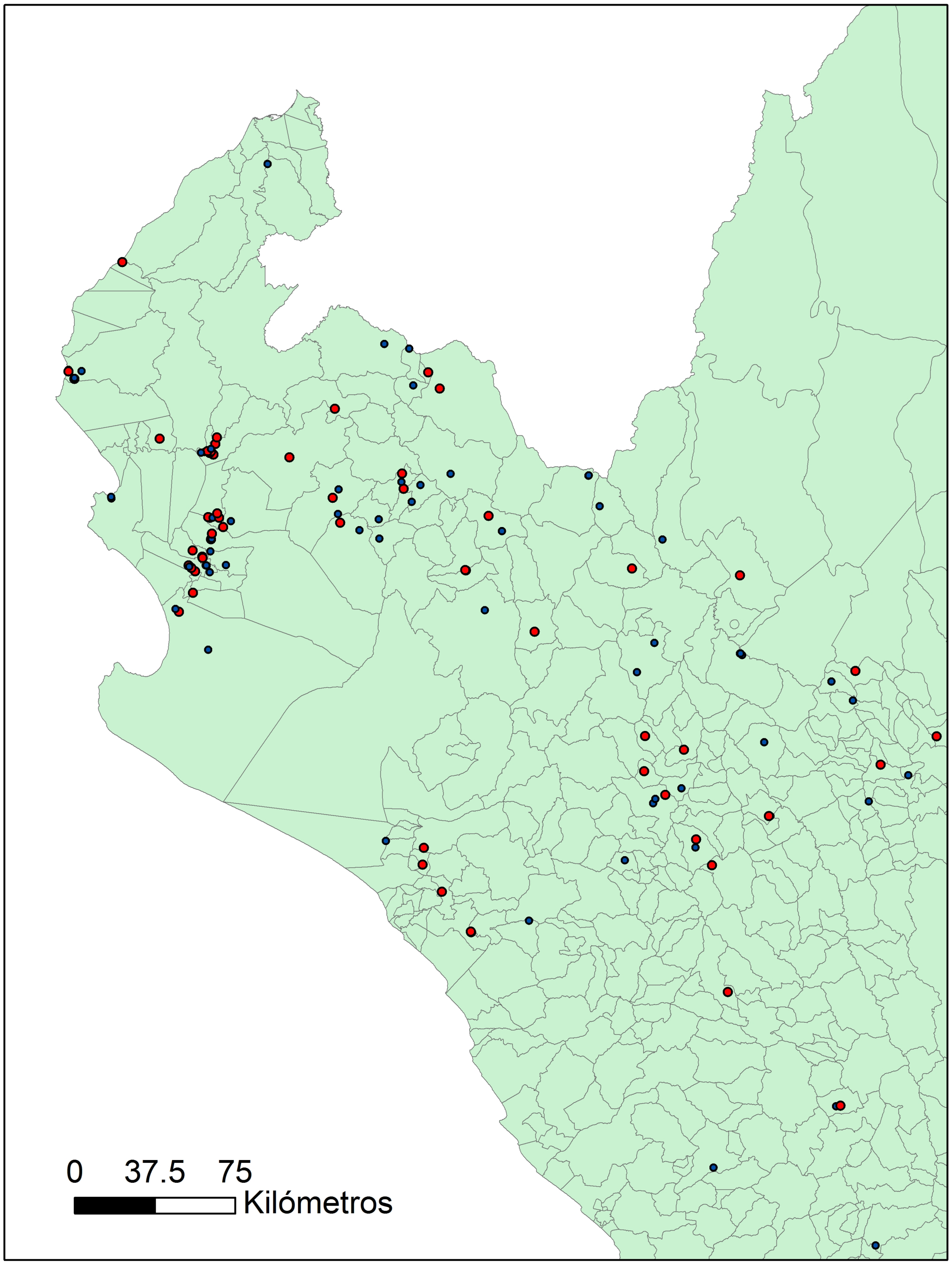
Notes: Distrust is based on the following question "Which of the following options reflect more accurately your thoughts on the following statement: People only have the best of intentions? 1: Always, 2: Most of the times, 3: Sometimes, 4: Rarely, 5: Never". Individuals are considered distrustful if 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)	(2)	(3)	(4)
	Affiliation: OLS	Affiliation: OLS	Affiliation: OLS	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 we had a total of 128 Beca18 fellows who volunteer for the project. 65 were randomly allocated to the control group and the rest to the treatment one. As mentioned previously, We first asked them to report their household network members with the support of their parents. We asked for up to 15 network members in the household head network as well as in the spouse network. For each individual reported we asked for a series of characteristics, which include the person cellphone number. Tables 1 and 2 compares the characteristics of these individuals for the treatment and control groups. From these reported network members, and taking into account our budget restrictions, we decided to collect baseline information for 8 to 10 of them. These are also the individuals who were invited to the training/information-diffusion sessions.

We therefore randomly selected 14 individuals per self-reported network and provided their information to the field team in charge of the baseline, so they could located 8-10 individuals and interview them. To select 14 individuals per network we used the following protocol:

1. First we identify those individuals for whom a cell phone has been reported. We drop those for which a cell phone is not reported (as a cell phone is necessary to activate a BIM account).

2. We then identify those individuals whose names are repeated in the head and spouse network, and randomly keep one observation.

3. We then identify individuals who belong to the same household and randomly keep one of them in the sample.

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

5. If the effective household network list is 14 or less, then all of them are included.

6. If the effective list includes more than 14 individuals then one of the following two cases apply:

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

(b) If for only one parent the number of listed individuals is lower than seven, we keep all of them and randomly select a number of individuals from the other parent's network to reach 14 observations.

Table 9: BIM Attendance & Referred Person being a Relative

				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
Treatment	0.354***	0.347***	0.349***	0.394***	0.395***
	(0.0410)	(0.0417)	(0.0458)	(0.0422)	(0.0477)
Relative		0.0699*	0.0753		0.154**
		(0.0369)	(0.0680)		(0.0693)
Relative × Treatment			-0.00900		-0.0515
			(0.0807)		(0.0828)
Constant	0.456***	0.448***	0.447***	0.401***	0.377***
	(0.0673)	(0.0677)	(0.0682)	(0.0738)	(0.0761)
N	1131	1131	1131	1024	1024
R^2	0.141	0.144	0.144	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***	0.0525***	0.0246*	0.0334**
	(0.0138)	(0.0145)	(0.0149)	(0.0140)	(0.0154)
Relative		0.000626	0.0347		0.0358
		(0.0189)	(0.0291)		(0.0304)
Relative × Treatment			-0.0561		-0.0378
			(0.0373)		(0.0380)
Constant	0.0480	0.0479	0.0406	0.0546	0.0475
	(0.0407)	(0.0400)	(0.0381)	(0.0441)	(0.0412)
N	1131	1131	1131	1024	1024
R^2	0.0249	0.0249	0.0273	0.0282	0.0302
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.

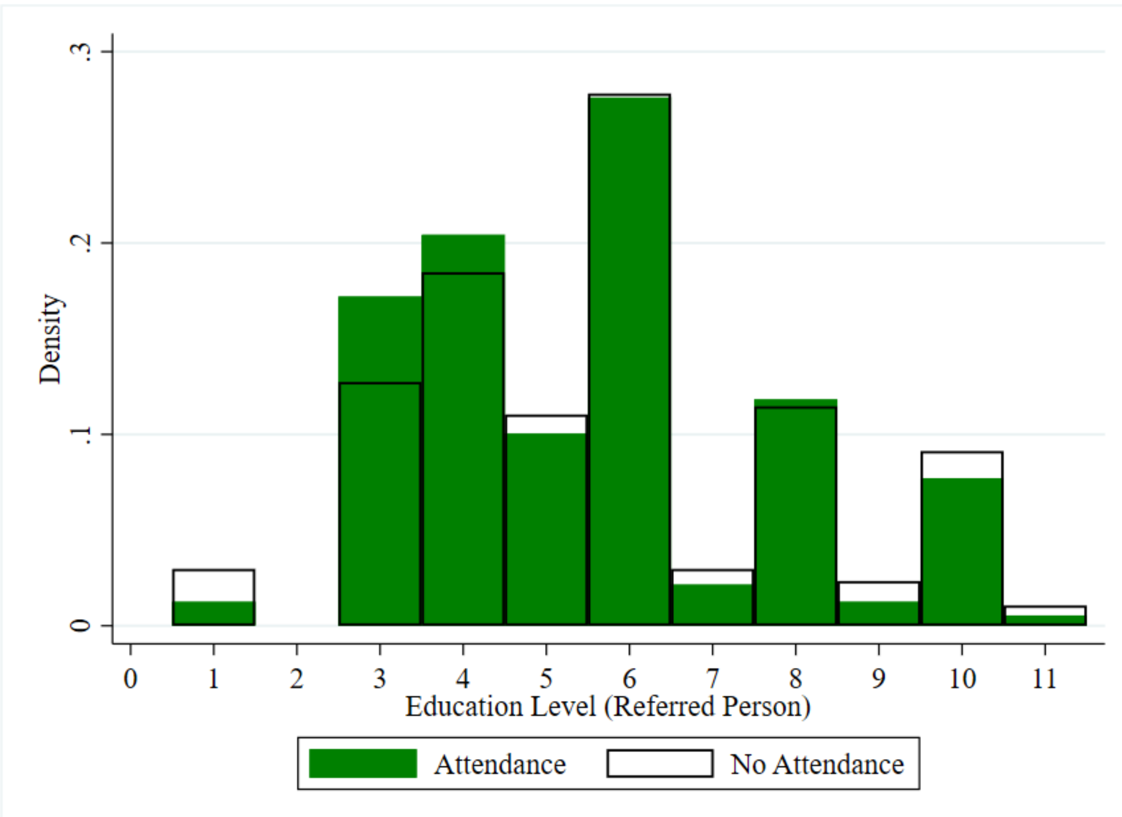


Figure 3: Histogram in Age. Attendance vs No Attendance.

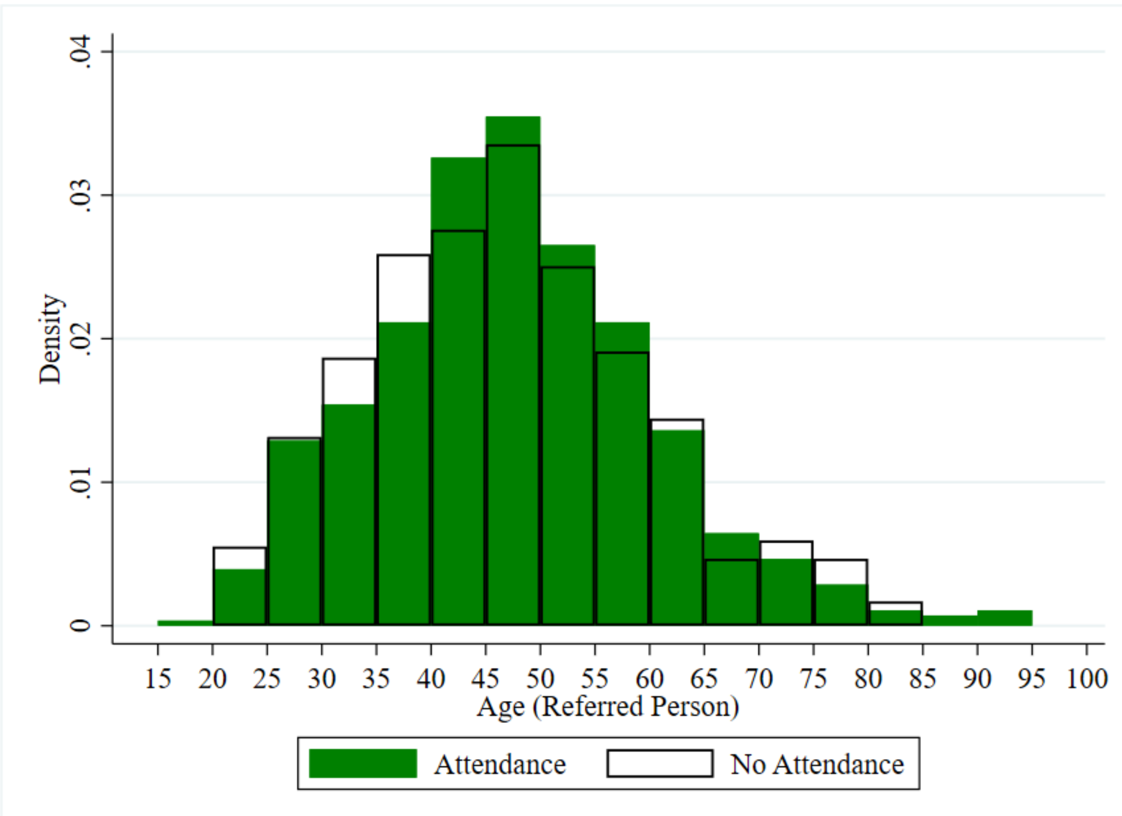


Table 13: BIM Attendance & Trust in Banks

					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	0.359***	0.310***	0.309***	0.312***	0.355***	0.309***	0.312***
	(0.0510)	(0.0467)	(0.0526)	(0.0606)	(0.0486)	(0.0526)	(0.0606)
Time	0.00290		0.00247	0.00283		0.00247	0.00283
	(0.00369)		(0.00281)	(0.00523)		(0.00281)	(0.00523)
Time × Treatment	-0.000704			-0.000491			-0.000491
	(0.00458)			(0.00603)			(0.00603)
Distrust		-0.140**	-0.175***	-0.176***	-0.145***	-0.175***	-0.176***
		(0.0544)	(0.0613)	(0.0604)	(0.0537)	(0.0613)	(0.0604)
Distrust × Treatment		0.177*	0.228**	0.228**	0.179*	0.228**	0.228**
		(0.0953)	(0.100)	(0.1000)	(0.0977)	(0.100)	(0.1000)
Constant	0.367***	0.519***	0.442***	0.439***	0.469***	0.442***	0.439***
	(0.0802)	(0.0722)	(0.0917)	(0.0865)	(0.0784)	(0.0917)	(0.0865)
N	786	829	579	579	746	579	579
R^2	0.149	0.142	0.151	0.151	0.169	0.151	0.151
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	0.0197	0.0620***	0.0370*	0.0294	0.0403**	0.0370*	0.0294
	(0.0207)	(0.0155)	(0.0215)	(0.0262)	(0.0173)	(0.0215)	(0.0262)
Time	-0.000782		-0.000807	-0.00189		-0.000807	-0.00189
	(0.00125)		(0.000889)	(0.00131)		(0.000889)	(0.00131)
Time × Treatment	0.000302			0.00147			0.00147
	(0.00152)			(0.00169)			(0.00169)
Distrust		0.0263	-0.00572	-0.00479	0.0289	-0.00572	-0.00479
		(0.0258)	(0.0130)	(0.0134)	(0.0276)	(0.0130)	(0.0134)
Distrust × Treatment		-0.0790**	-0.0434	-0.0455	-0.0789**	-0.0434	-0.0455
		(0.0379)	(0.0313)	(0.0317)	(0.0369)	(0.0313)	(0.0317)
Constant	0.0663	0.0487	0.0823	0.0900	0.0596	0.0823	0.0900
	(0.0534)	(0.0442)	(0.0571)	(0.0611)	(0.0482)	(0.0571)	(0.0611)
N	786	829	579	579	746	579	579
R^2	0.0255	0.0398	0.0446	0.0454	0.0446	0.0446	0.0454
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 $\times$ 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 $\times$ 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