The Provision of Information on Mobile Banking Using Local Ambassadors : Evidence on Adoption from Peru *

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Abstract

Using data from a randomized experiment in Peru, we study the influence of social networks on the adoption and usage of a newly launched electronic wallet (BIM) through information provision in poor peri-urban and rural communities. Treated groups in our study receive the information from a local ambassador, while control groups receive it from an external agent. Local ambassadors self-select from the population of students attending an elite university and benefiting from a merit-based scholarship targeted to the economically disadvantaged (Beca18). We find that treated network's members are twice more likely to attend information sessions, as well as twice more likely to sign up for the e-wallet than those in the control group. Our results are consistent with a mechanism in which the credibility of the provider of information matters for adoption.

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1 Introduction

It is well understood that lack of financial inclusion severely restricts the well-being and economic opportunities of the poor. In the Peruvian context, only 29% of adults had a bank account by 2014; and among the poorest 40%, this proportion was only 18%.[1] 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. [2] At about the same time, in February 2016, Pagos Digitales Peruanos (PDP), a company founded by the members of the Peruvian Banking Association (ASBANC) and more than 30 e-money users, launched BIM, an electronic wallet (EW) targeting the "financially excluded". Despite the simplicity involved in activating a BIM account, as well as the potential benefits associated to the usage of a mobile-money platform [3], its adoption has remained low. In the rural and peri-urban communities on which our study focuses, less than 1% of the interviewed households reported having a BIM account activated by June 2018 (that is, two years after BIM was launched).

Puzzled by the difficulties faced by BIM diffusion, particularly in rural and peri-urban communities in Peru, our study aims at evaluating whether the delivery of information regarding the new BIM by local ambassadors (role models) to their household's network members can significantly increase adoption and usage rates in such settings. For this purpose, in July and August 2018 we implemented a Randomized Control Trial which randomly assigned household networks to either receive a BIM information session from a local ambassador (treated group) or from an external agent (control group). Local ambassadors in our study self-selected from the population of students attending an elite university and benefiting from Beca18, a government program promoting social inclusion in higher education.

Beca18 provides scholarships to socioeconomically disadvantaged individuals from peri-urban and rural communities who just finished public high school and have obtained admission into an elite Peruvian university. We partnered with one of these universities and informed, in very general terms, Beca18 fellows in this institution about a pilot program related to financial inclusion in which they were expected to play an active role. Approximately 130 Beca18 fellows registered to participate. For all the registered students we carefully mapped their parents' network and half of them were randomly assigned to the treatment group.

From late September 2017 to late June 2018, Beca18 fellows in the treatment group

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

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

[3] See for example Suri and Jack (2016) for a detailed discussion of the long term benefits of WE adoption and usage in Kenya

received training related to soft skills, financial literacy, team work and the new BIM. After these training sessions, in late July 2018, they returned to their communities to perform as local academic ambassadors and provided BIM training and information sessions to randomly selected members of their parents' network. On the other hand, Beca18 fellows not selected for the treatment did not received any kind of training or information related to the new EW, and their parents' network members received information and training related to BIM from external agents who assumed the role of BIM-PDP technical field staff.

Our results indicate that treated networks members are twice as likely to attend the BIM sessions compared to non treated ones. They also show that BIM affiliation more than doubles if training and information related to BIM is provided by our academic ambassadors. These results are statistically significant and robust to the inclusion of additional covariates and the exclusion of the Beca18 fellow parents from the estimation sample. Interestingly, in the case of attendance, the treatment has a higher effect on individuals with lower levels of general trust in strangers; as well as among individuals who reside in communities with better financial infrastructure. Given that the cost of sending an external agent to a community is comparable to that of sending a Beca18 fellow, our results suggest that using community role models as academic ambassador represents a cost-effective way to transmit information into peri-urban and rural communities.

This paper closely relates to the recent literature on the transmission of knowledge and adoption of a new technology through a network in developing countries. In this sense, it is akin to the research of Munshi (2004), and Conley and Udry (2010).[4] Nevertheless, most of the works in this literature focus on the adoption of new crops or agricultural technologies; and there is still limited evidence related to the adoption of mobile banking technologies among the rural poor in developing countries. Also importantly, while in the last years a few studies have explored the adoption of mobile banking services in developing countries (see for example Dalton et al. (2018)); to the best of our knowledge ours is the first experimental field-based study to explore the adoption of a new EW at its initial launching stages and in a context with no previous exposure to mobile-money instruments. In this sense, we provide valuable lessons for scenarios in which mobile-money mechanisms are being introduced for the very first time among low income individuals.

Conceptually, our study design borrows from Banerjee et al. (2013), who study the transmission of information (about microfinance loans) within a network (neighborhood), and the relevance of specific households to the diffusion and adoption of the product/service. They

[4] Conley and Udry (2010) find that the effect of usage (and profitability) of new inputs in agriculture by neighbors influences the adoption of such inputs by a particular farmer.

show that specific community leaders (those with higher communication centrality) have a greater influence on the probability of households participating in the (microfinance) program. It is also influenced by the work of Goyal (2017), related to the importance of the "royal family" at influencing behaviour within a network. Inspired by these studies' insights, we use academic talented individuals from the network, who have been able to access an elite education institution and therefore potentially have or could have achieved a special network status, to promote the new BIM. Nevertheless, we must stress out that while we find that they perform better than externals agents at diffusing BIM information and encouraging its adoption, we are unable to state whether the diffusion effects observed through these role models are higher than the ones that would have been observed if other community members had been in charge of BIM diffusion instead.

While it is well known that the likely adoption rate of mobile-money instruments will depend on whether agents are used to other forms of payments (e.g. cash, credit, debit cards), usage benefits, and whether a large player uses it regularly (e.g. government cash-transfers), our study adds network-relationship considerations to the mobile-payment literature. Though the population size (network) already using the EW have been mentioned as a factor influencing possible new users (Sahut (2008)), the direct employment of community members (academic ambassadors) to diffuse information and promote adoption is a novelty within the literature. Such tasks are typically the purview of administrative staff of the involved NGO or financial institutions (Karlan and Valdivia (2011), Valdivia (2015)). We are not aware of another experimental study who uses local ambassadors for the diffusion of electronic wallets in peri-urban and rural poor communities in developing countries.

Theoretical models regarding the adoption of a new technology (Innovation Diffusion Theory – Rogers (1995) and Technology Acceptance Model – Davis (1989)) have been around for years, and suggest that factors like security, trust, perceived usefulness, and perceived ease of use need to be considered. Such factors have also being emphasized by theoretical approaches related to the adoption of electronic/mobile payments platforms (Jim Chen and Adams (2005) and Sahut (2008)). Our study confirms the relevance of the trust mechanism highlighted in these theoretical studies; as the estimated intervention effect related to BIM meetings attendance was higher for individuals with lower levels of trust in strangers.

The rest of the paper proceeds as follows. Section 2 explains in detail the institutional context and the functioning of the new BIM electronic wallet. Section 3 describes our experimental design and the data set. Section 4 develops a motivational model. Section 5 explains our empirical strategy. We report our results in Section 6. The final section concludes and sets policy recommendations.

2 Context

Given the Peruvian poor's lack of access to formal financial services, in 2015 the Peruvian government announced its Strategic Plan for Financial Inclusion, which points to electronic money platforms as key mechanisms for speeding up financial inclusion. In early 2016, PDP launched BIM: an electronic wallet targeted to those without access to financial services. PDP is a joint venture created in 2014 by the members of the Peruvian Banking Association-ASBANC and more than 30 e-money users

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 phone services and to deposit and withdraw money from/to the government-owned National Bank (Banco de la Nación, in Spanish).

Activating a BIM account required a basic cellphone (which more than 80% of the population owns) and the National Identification Document (DNI, for its name in spanish). 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).[5]

Operating BIM does not require going to a bank agency to access funds nor physically meet to transfer wealth (as cash transfers do). For small entrepreneurs, it can facilitate business transactions, such as paying for inputs and receiving payments. These features are also relevant for poor households as cash transfers play an important role smoothing consumption shocks.

Since the BIM account immediately connects its holder with a financial institution (the bank that will manage the funds), 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 doesn't have a bank account. BIM had been promoted through TV, radio spots, newspapers, and social media (Facebook and YouTube). By August 2016, close to 100,000 accounts had been activated. PDP, however, faces challenges to expand BIM adoption in peri-urban neighborhoods, geographically distant small urban communities

[5]Until December 2018, BIM only charged a fee for cash-out operations (1% of the total amount).

and rural districts. PDP is sufficiently aware of the difficulties related to take-up in such contexts, mainly due to trust issues and resistance to change .

In this context, we consider the use of Beca18 fellows as a cost-effective way to reach these peri-urban communities. Beca18 is one of the most well-known and popular educational government programs in the country. 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 in per-urban and rural communities) who have achieved high academic standards in high school (measured by Peruvian high school GPA), and have been admitted to an eligible educational institution.[6][7] Arguably Beca18 fellows could be seen as role models in their communities and their opinion highly valued.

Before applying to Beca18 scholarships, candidates must been admitted into an eligible institution. By the time of our intervention, these institutions were free to set their entry requirements and Beca18 admission quota. 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. Candidates must submit an admission letter with the rest of their application to the Ministry of Education. The Ministry publishes the final list of fellows by late May. To keep their scholarship, fellows must maintain a college GPA of 10.5 on a 20-point scale.

3 Experimental design

Our information dissemination approach is straightforward: we propose to implement a BIM diffusion strategy in which Beca18 fellows act as messengers. The recent findings in the microfinance literature support the logic of our intervention (see Banerjee et al. (2013)). We argue that Beca18 fellows' opinion/information is likely to be more trusted than that provided by community outsiders. Consequently, a BIM diffusion intervention in which Beca18 fellows are the main messengers is expected to have a stronger effect on attendance and adoption than if performed by external agents.

To implement our RCT, in late August 2017 we invited Beca18 fellows at an elite university in Northern Peru to be part of a campaign supporting the diffusion of financial services in their neighborhoods / communities, with no mention at this point of the BIM or the spe-

[6] Its literal translation is *Scholarship18*

[7] Households are classified as poor or extreme poor by the Household targeting system run by the Ministry of Social Inclusion.

cific role they might play in its diffusion.[8] To encourage participation, we indicated that this activity will count for extracurricular academic credits. Approximately 130 Beca18 fellows registered to participate.

For each Beca18 fellow (in both treatment and control groups), we mapped their household (parents) network within their neighborhood/community. Beca18 fellows had to ask their parents about 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 and invited them to participate in BIM training and information diffusion sessions.

We therefore have one network group per Beca18 fellow. Half of these groups were randomly allocated to treatment; that is they received information and training about the BIM from a Beca18 beneficiary; while the other half received information and training from external agents that played the role of BIM-PDP field staff. These "network groups" are our randomized units. In other words, we randomly assigned half of the Beca18 participants to our treatment group and half to our control group.[9]

In order to minimize contamination effects, such as information transmission about the program from the selected Beca18 fellows to the not-selected ones; information related to BIM was provided in the last two months of their training (May-June 2018), just before they have to travel to their communities to have the BIM presentation sessions. Moreover, they signed confidentiality agreements, committing not to mention details of the intervention to individuals outside the treatment branch. To avoid geographical spillovers, we include in our analysis only neighborhoods/communities that are relatively distant from each other.[10].

We must emphasize that the role of our academic ambassadors, Beca18 fellows in the treatment group, was only to diffuse information and provide training about the BIM. We did not required them in any way to force any network member to adopt BIM. Our academic ambassadors just provided clear 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.

It is possible that Beca18 fellows fail to achieve the expected results not because they are not relevant role models in their neighbour/community network; but because the external agents in the treatment group are considerably more experienced at information diffusion

[8] We mentioned that the project was related to financial inclusion in a general and abstract way, without mention to specifics. Only the students who accepted to participate and were assigned to the treatment group were informed about the BIM and the role they are expected to play.

[9] We indicated that there was a limited number of spots available and that a lottery system was going to be employed.

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

and training related to financial services. To alleviate this concern, our local ambassadors were carefully trained. Their sessions incorporated practical cases and simulations to enhance their capabilities as diffusers of financial information. The training of Beca18 fellows in the treatment group took place from September to October 2017, and from May to June 2018.

Lastly, it is important to mention two critical issues that could affect the external validity of our study. First, we only work with Beca18 recipients 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.

3.1 Data Collection: Baseline Survey

Our baseline survey took place from April 21st until June 3rd, 2018. We work with 58 Beca18 fellows in the control group, and 60 fellows in the treatment one. [11] Our final working database consists of 1131 observations in total.[12]

Table 1 presents the baseline summary statistics for a key set of variables in our sample, containing 609 individuals in the treatment group and 522 individuals in the control one. For economic characterization and financial knowledge, among the variables included we have head employment, household expenditures (food and transport), ownership of a cellphone, usage and knowledge of a BIM account, and "Household Trust". The variables "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 they don't). Likewise, the variable "Head BIM (Account)" indicates whether or not the household head reports having a BIM account (1 if it has, 0 otherwise). The variable Food and Transport Expenditures captures the average monthly amount (In Peruvian Soles) spent on each of these items.

We also analyze the household level of trust. "Household trust" is a binary variable built from the trust level reported by the household head and, in its absence (or lack of informa-

[11] We were not able to collect baseline information for the network of 5 Beca18 fellows in the control group and for 4 Beca18 fellows in the treatment group. These students either did not provide their network information, or explicitly asked the research team to be excluded from the study. An additional network had to be dropped from the control sample as there was serious evidence that this person was not poor and therefore ineligible for the Beca18 program. We also added networks from our initial pilot sample.

[12] Interviewed households were told the the UDEP was implementing the survey to obtain information about the general socioeconomic conditions in the area. There was no mention of the electronic wallet (EW) or of the Beca18 program.

tion), the trust level reported by the spouse.[13] The information comes from the questions: *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 answers range from 1 to 3, we claim the household has a relatively high level of trust and the variable takes the value of 1 (it is 0 otherwise).

We also analyze 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.

As we can observe, the 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 (the average is 0.06%). Similarly, less than 2.4% of the household heads knew about the BIM system by the time of the interview. 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.

In Table 1 we also perform a raw mean difference comparison among treatment and control units. We clustered the standard errors in this Table by the student (Beca18 ambassador) contact list; that is, by the student household network. As we can observe, for none of the variables analyzed in Table 1 we find a statistically significant difference between the treatment and control groups We take this as clear evidence that our randomization process was successful at achieving balance among treatment and control units.

3.1.1 Invitations and BIM Presentations Session

During the southern hemisphere winter break, Beca18 fellows in the treatment group invited their parents' network members included in the baseline survey to attend meetings regarding the use of BIM. Network members of control group students were invited by an external individual assuming the role of a BIM-PDP agent to attend the same type of meeting.[14] The meeting protocols were exactly the same in both groups, the only difference was the messenger. These meetings/training sessions took place from late July to late August 2018 at the Beca18 fellow dwelling (see Table 2 for a detailed timeline).[15]

[13] We find 12 observations where the was no information for either the head of the house or the spouse.

[14] They were contacted by phone and invited to the meeting. Reminder phone calls were also performed. The external agent also asked the Beca18 control household to remind network members about the training session.

[15] Each presenter was paid their transfer cost to reach a community and an stipend to provide refreshments to participants during the day of the presentation.

External presenters were told they had to provide information and training about the new BIM electronic wallet; and none of them, but one, knew they were part of an experiment.[16]

Still, we can't discard the possibility that Beca18 students in the control group linked their involvement in the initial UDEP call to the BIM presentation sessions that were later delivered to their household network. However, it is unclear how this knowledge, at that time, would have affected attendance and BIM affiliation.

A roster of attendants was kept in each meeting. Each attendant had to confirm his/her cell phone number collected in the baseline. If the number had changed, they needed to write his/her new one. They also had to sign the attendance rooster to confirm they actually attended the meeting. These records are used to generate the "attendance" variable.

Cell phone numbers were sent to PDP officials in order to verify if individuals had activated a BIM account and monitor their usage. PDP provided us with adoption and usage rate updates starting the first week of September 2018. Our estimates are based on data given until the end of that year.

4 Motivational Model

This sections outlines a motivational model to highlight how Beca18 fellows might influence the decision of their household network members to attend an information session, adopt, and use an electronic wallet.

Consider a recently developed productivity improving technology. The technology needs to be adopted by members of a community/network in order to have an effect on the performance of the members and on overall output. Two types of agents may provide the information to the communities: external agents and academically successful members of the community (Beca18 fellows). Both of them invite the community for a presentation session to introduce the new technology. Each member of the community decides whether to attend or not the presentation and, after hearing about the new technology, whether to adopt it or not. Receivers cannot perfectly observe the quality of the technology before using it. We want to understand how credible Beca18 fellows and external agents are at providing information. Decision to adopt depends on how the information about the quality of the product is perceived.

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

[16] One external agent that works at the Center for Small Business Support at our partner university knew about the experiment taking place, but he was carefully instructed not to mention anything of this to the rest of the external agents.

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 get bonus when they sign up for the mobile account, the information provided will be perceived as biased. External agents may thus be less credible than Beca18 ambassadors.

We expect that, in the treatment group, interests of the sender (Beca18 fellow) and the receivers of the information to be much closer/aligned than in the control group. We also expect the information passed on the quality of the product to 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 treatment group receivers to be more likely to adopt the technology than control group receivers. 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, even though we could expect the treated units to be more likely to attend the information session than the control units.

Besides providing us with predictions on the effect of treatment, this discussion also highlights trust as a key mechanism through which the effects are generated. In particular, we can expect more trusty 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.

5 Empirical specifications

To study the impact of our intervention on meeting attendance and BIM affiliation/adoption, we simply compare individuals in treated networks to those in control ones. First, we estimate a simple difference in means model:

$$Y_{in} = \alpha + \beta_1 Treated_{in} + X_{in}^{'} \beta_2 + \epsilon_{in} \tag{1}$$

Where the outcome variable Y represents: "Attendance$_{in}$" a dummy equal to 1 if individual i in netework n attended the meeting, or, "AffiliationBIM$_{in}$" a dummy equal to 1 if the individual i in network n activated a BIM account. "$Treated_{in}$" is a binary variable equal to 1 if the individual belongs to a treated network. X'_{in} is a set of possible control variables and the error term ϵ_{in} is assumed to be correlated among individuals that belong to the same network (hence, we estimate clustered standards errors at the network level in all our linear model specifications).

Furthermore, we also estimate a difference in means models using the aggregated information set at the network level. That is, we collapse the outcomes variables by student network. The outcomes variables hence become continuous and represent the number of people attending an information session, or the number of people affiliating to BIM:

$$Y_n = \alpha + \beta_1 Treated_n + \epsilon_n \tag{2}$$

where Y is the network outcome ("Attendance$_n$" and "AffiliationBIM$_n$").

Also, given that we have baseline information for whether the household reported having a BIM account or not before the intervention; as a robustness check we estimate a difference in differences model for BIM affiliation by comparing individuals in treated households to those in control ones in two periods; pre and post intervention.

Finally, using random treatment assignment as an instrumental variable for BIM meeting attendance, we estimate the effect of attending a BIM training and information session on BIM affiliation. This estimation provides us with a local average treatment effect (LATE); that is, the effect for those whose attendance behaviour is affected by the instrument (i.e. compliers).

6 Results

Tables 3 and 4 present our main results for the short-term treatment effects on BIM meeting attendance and BIM account activation three months after our intervention (that is, up to November 2018).[17] The first three columns in both tables include the Beca18 fellow household parents (if selected) in the sample. The last three exclude them as a robustness check. Out of those, the first two columns present OLS estimations with and without controls (e.g., whether the head of the household was employed or whether the head was affiliated

[17] On January 2019, PDP started sending text messages to BIM users announcing the cancellation of its platform for analog cellphones. The cancellation occurred on February 1st. From that date onward, the usage of BIM is restricted to smartphones and BIM can only be accessed trough either Messenger or a free App available at Google Store. This decision markedly affected individuals in peri-urban and distant rural communities, where access to smartphones and internet data is limited, particularly among the poor. In order for our study not to be affected by this decision and context, we stop our analysis at the end 2018. However, our results also hold if we use data for January 2019.

to the electronic wallet even before the information session). The lats specification collapses the information at the network level. Overall, we find positive and statistically significant intervention effects on attendance and BIM affiliation.

6.1 Attendance

Table 3 shows that our treatment had a significant effect on 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 attendance. A similar result is observed when we add "Head Employment" as a control variable. The analysis at the aggregate network level 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 (last columns in the table) does not alter our results. Our motivational framework argues 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 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 policy makers and managers of e-money operators, as it highlights a secure mechanism for the diffusion of social programs or new technologies, particularly in distant rural contexts. Indeed, introducing new information through a local ambassador ensures a larger reach within the invited audience.

6.2 Affiliation and Usage

Table 4 presents estimations results for the intervention effect on affiliation (BIM account activation). In the specifications corresponding to this table, we also add pre-treatment BIM affiliation as a control variable [18]. 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 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.

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

As before, the last three 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 made it lose its statistical significance. Still, the relative effect remains sizable compared to the base case. Moreover, the aggregation at the network 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.

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 [19].

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 -

[19] 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.

for control and treatment groups - is virtual non-existent.

6.3 The Effect of Attending a BIM Training Session on Adoption: Instrumental Variable Approach

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. 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 6.1 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.[20] 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[21]. We find that the affiliation rate increases by 12 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 claim that our BIM sessions have 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

[20] 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.

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

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 trough 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 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.

7 Robustness Check: Difference-in-Differences Estimation

To take advantage of our baseline survey, increase our sample size and tests the robustness of our findings, Table 7 estimates the impact of the intervention on affiliation rates using a difference in differences approach. Specifically, we use the baseline survey as a pre-treatment period for both control and treated network members. Provided that the groups share a common trend, the interaction coefficient should give us an unbiased estimation of the additional effect of receiving the information from a Beca18 fellow. We focus on affiliation as it is an outcome for which we find robust statistical significance, and it conforms rationale behind the difference in differences approach.[22]

Our results indicate that while receiving the information from an external agent would lead 2% to 3% of the population to register; receiving it from a Beca18 fellow would generate a 6% to 9% registration rate. The additional effect is substantial and highly significant. The results are in line with our previous findings (a 4 to 6 percentage point treatment effect), and set our argument that information that comes from a valued network member would be given more consideration than information that comes from outsiders. Given that our sample has basically double, the estimated effects are not affected by the exclusion of the Beca18 own household from the sample. We hence argue that the lost of significance in previous estimations were due to a smaller sample size.

[22]Attendance to the information session can only be compared across groups in post-treatment period.

8 Heterogeneous effect

This section explores an array of heterogeneous treatment effects on attendance and affiliation, as functions of context relevant social and demographic characteristics. Tables 8 and 9 use the self-reported household (head) distrust in society (recovered from the baseline survey) to test if our treatment intensity 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). Specifically, we estimate models for both attendance and affiliation and focus on the interaction between household distrust and the treatment variable. As we discussed previously in the 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*. For the estimations in this sections, if the answers are either 4 or 5, we claim that the individual is distrustful and the indicator variable takes the value of 1 (it is 0 otherwise).

For the attendance model, 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 1% level. Nonetheless, the interaction coefficient between our distrust indicator and the treatment dummy is positively estimated at 0.17 and is statistically significant at the 10% level. This clearly indicates that, in terms of attendance, people who exhibit more distrust in society were impacted more by the treatment than people with a relatively higher trust level.This finding is in line with our motivational framework. Due to future repeated with the Beca18 fellow, an invitation by her would be assumed to be more likely to provide useful information and hence draw more people to attend.

Table 9 presents our results for affiliation. As we can observe, neither the distrust coefficient nor the interactions effects for affiliation are large or robustly significant. The treatment doesn't seem to have a heterogeneous effect on distrustful individuals when it comes to the adoption decision, at least in the short term.

It is possible that our effects are purely driven by the attendance and, later on, affiliation of relatives within the Beca18 student household network, To rule out this possibility, in the estimations that correspond to tables 10 and 11 we interact our treatment variable with an indicator of whether the person is a relative of our academic ambassador. We find that, on average, relatives are more likely to attend the information sessions but not more likely to affiliate. More importantly, the treatment does not have a heterogenous effect on relatives for neither attendance or affiliation. The interaction effect is 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 remain comparable with the ones estimated in Tables 3 and 4.[23]

Tables 12 and 13 explore whether the treatment effect is a function of the degree of financial development observed in the individual's community. We use the presence of at least one ATM from the government-run National Bank (Banco de la Nacion) in the community, as an indicator of higher financial development. We interact the constructed binary variable with our treatment to check for 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. Moreover, the presence of financial infrastructure explains more than a third of the overall effect on attendance. The interpretation of such results is straightforward. We argue that people who have better financial infrastructure in their community may have more interest in learning about a financial related technological innovation, as they may expect to derive more benefits from the new product or service. Particularly, if the person who is making the invitation is a member of their network.

Regarding affiliation, note that 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 find evidence of heterogenous treatment effects related to our financial development indicator.

While we have argued that people who have a a higher level of financial infrastructure in their community may have more interest in learning about a financial technological innovation (attendance); our results do not allow us to rule out the possible effect of other variables that could be related with financial infrastructure and attendance; such as ease of transportation, higher urban density or overall local economic activity.

9 Cost Effectiveness

An intervention that employs Beca18 fellows to disseminate information and promote the adoption of the new BIM in peri-urban and distant rural communities is more cost-effective that a strategy that relies on external agents for the same purpose.

The employment of Beca18 fellows as academic ambassadors required a payment of the bus trip to their communities (which varied depending on its geographical location), a lump

[23]Tables 15 to 22 in the appendix presents further interactions with trust in the banking system, closeness to the Beca18 student, and the person's age and education. In general, for all of them we find no heterogeneous effect of treatment on either attendance or affiliation.

sum payment of 60 soles (close to US$ 19), an a stipend of 20 soles (or US$ 6.25) to provide some refreshments to meeting participants. External agents were also paid their bus travel costs to each visited community, were given a stipend of 20 soles to provide refreshments to meeting participants, and received a similar payment as Beca18 fellows for each training session provided.

Given, the better performance Beca18 fellows had regarding attendance (double the presentation sessions crowd) and affiliation (more than double the affiliation rate), their employment as a cost-effective way to transmit information regarding a new technology or, even, new government programs is conclusive.

10 Conclusions

This paper studies the short term impact of a randomized intervention promoting the adoption of a recently launched electronic wallet (BIM) in distant peri-urban and rural communities in Peru, with no previous exposure to e-money instruments. The intervention was implemented in July-August 2018 and the outcomes recovered by the end of November.

In the treatment group, academically successful young members (Beca18 fellows) of these poor peri-urban and rural communities delivered information and training to their household networks. In the control group the information was delivered by external agents playing the role of representatives of the electronic wallet company. Our findings indicate Beca18 fellows are able to congregate a significantly higher proportion of participants in the electronic wallet (BIM) diffusion meetings. Treated network's members were two times more like to attend the information sessions (70% vs 35%). Additionally, the treated group network members show statistically significant higher affiliation rates, even after excluding the Beca18 fellow parents. The difference is between two to three times higher. Still, even with these significant differences, the adoption of the electronic wallet remained low for both groups. In neither group did the adoption rate went above 10% on average. The adoption rate observed in the treatment group is however higher that the current national average, which by July 2019 was about 5%.

We also explore heterogeneous treatment effects related to network members distrust, degree of kinship and presence of financial infrastructure at the community level. We found statistically significant evidence for heterogeneous effects related to attendance. Distrusting people is less likely to abstain from attending if a Beca18 member is in charge of the training session, and a higher development of financial infrastructure in a person's community is related to a higher attendance rates. We do not find similar heterogeneous impacts for affiliation. We also able to rule out that our main effects related to attendance and affiliation are primarily explained by the behaviour of close relatives.

Given that the cost of sending an external agent to a community is comparable to that of sending a Beca18 fellow; we argue that our results suggest that using a community role model as an academic ambassador represents a cost-effective way to transmit information on the benefits of new technologies to peri-urban and rural communities. Moreover, local ambassadors could help in the process of information diffusion and implementation of government social programs.

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Table 1: Network members characteristics Treated vs Controls

	Mean		Mean Test				
	Treated	Control	Difference	P_value	N	Mean	SD
Head Cellphone	0.84	0.87	-0.03	0.28	1,131	0.857	0.350
Head Employment	0.78	0.84	-0.06	0.12	1,131	0.811	0.392
Household's Trust	0.60	0.55	0.05	0.36	1,117	0.573	0.495
Head BIM (Knowledge)	0.03	0.02	0.01	0.62	1,131	0.0239	0.153
Transport Expenditure	74.09	96.03	-21.94	0.16	1,131	84.22	144.7
Food Expenditure	476.35	475.48	0.87	0.98	1,131	475.9	306.6
Head BIM (Account)	0.01	0.00	0.01	0.10	1,060	0.00660	0.0810
Spouse BIM (Knowledge)	0.02	0.01	0.01	0.17	841	0.0178	0.132
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	0.01	0.72	1,131	0.398	0.490
Spouse has Primary School	0.36	0.31	0.05	0.31	1,131	0.337	0.473
Spouse has Secondary School	0.25	0.25	0.00	0.99	1,131	0.251	0.434
House Total Number of Rooms	3.28	3.14	0.15	0.36	1,130	3.214	1.870
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	47.56	46.86	0.69	0.53	1,131	47.24	12.83
Number of Obs.	609	522					
Networks:	60	58					

Note: As it is standard ***,** and * indicate statistical significance at the 1, 5 and 10 percent level. Standard errors clustered at the network level are presented in brackets. "Head primary" and "Spouse primary" are binary variables that take the value 1 if the person has only primary studies. Similarly, "Head secondary" and "Spouse secondary" are binary variables that take the value 1 if the person has only secondary studies. The variable "Wall Material" takes the value 1 when the house's wall is made of brick or concrete, and 0 otherwise. The network of the head and the spouse consist of the people with whom they interact the most. They can include friends, neighbours and relatives but they must not include people who live in the same house. The variable "Head Trust" was built from the following question: *Which of the following options reflect more accurately your thoughts on the following statement*: People only have the best intentions? The possible answers were 1: Always, 2: Most of times, 3:Sometimes, 4: Few times, 5:Never. If the answers range from 1 to 3, we claim the household head has a high level of trust and the variable takes a value of 1 (is 0 otherwise). The variable "Wall Material" takes the value 1 when the house's wall is made of brick or concrete, 0 otherwise.

Table 2: Timeline

Date	Activities
2016	BIM was launched
2017: August	UDEP invited Beca18 students
2017: October	Training sessions of Beca18
2018: April-June	Baseline survey
2018: July-August	Meetings/training sessions (treatment)
2018: November	End of treatment

Table 3: Attendance

				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
	Attendance: OLS		Attendance: Network†	Attendance: OLS	Attendance: Network†
Treatment	0.355***	0.351***	3.946***	0.395***	3.942***
	(0.0404)	(0.0412)	(0.402)	(0.0419)	(0.392)
Head Employment		-0.0568			
		(0.0373)			
Constant	0.347***	0.395***	3.045***	0.287***	2.276***
	(0.0283)	(0.0442)	(0.251)	(0.0290)	(0.234)
N	1131	1131	118	1024	118
R^2	0.136	0.138	0.510	0.164	0.523
F	77.14	41.32	96.53	88.51	101.2
Region FE	Yes	Yes	Yes	Yes	Yes
Mean: Treated	0.69		6.93	0.67	6.14
Mean: Control	0.35		6.93	0.29	2.35

Notes: The dependent variable is an indicator of whether the individual attended the presentation. 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 4: BIM Affiliation

				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
	Affiliation: OLS		Affiliation: Network‡	Affiliation: OLS	Affiliation: Network‡
Treatment	0.0380***	0.0373***	0.413***	0.0234*	0.249**
	(0.0135)	(0.0134)	(0.135)	(0.0131)	(0.122)
Head Employment		-0.0101			
		(0.0162)			
Constant	0.0313***	0.0399**	0.346***	0.0307***	0.312***
	(0.00934)	(0.0165)	(0.0986)	(0.00858)	(0.0847)
N	1131	1131	118	1024	118
R^2	0.122	0.122	0.225	0.154	0.214
F	31.62	21.07	9.368	31.62	4.175
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 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

	(1)	(2)	(3)	(4)	(5)
				Excluding Beca18 family	
	Usage: OLS		Usage: Network†	Usage: OLS	Usage: Network†
Treatment	0.0129*	0.0141*	0.133*	0.00976	0.0915
	(0.00703)	(0.00716)	(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)	(0.00444)	(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	6.691	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	0.107***	0.107***	0.106***	0.0593*	0.0591*
	(0.0402)	(0.0403)	(0.0407)	(0.0333)	(0.0335)
Head of Household's Sex		0.0147	0.0159		0.0124
		(0.0191)	(0.0200)		(0.0187)
Head Employment			-0.00697		
			(0.0173)		
Constant	-0.00371	-0.0157	-0.0104	0.0288	0.0189
	(0.0414)	(0.0415)	(0.0421)	(0.0414)	(0.0409)
	Dependent variable: Attendance, Instrumental variable: Treatment				
	First Stage				
Treatment	0.355***	0.355***	0.351***	0.394***	0.395***
	(0.0402)	(0.0403)	(0.0409)	(0.0417)	(0.0417)
Household Head Sex		-0.0503	-0.0404		-0.0435
		(0.0371)	(0.0375)		(0.0375)
Head Employment			-0.0514		
			(0.0378)		
Constant	0.409***	0.449***	0.484***	0.354***	0.389***
	(0.0539)	(0.0651)	(0.0737)	(0.0587)	(0.0707)
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: Difference in differences: BIM Affiliation

			Excluding Beca18 family	
	(1)	(2)	(3)	(4)
	BIM Afiliacion	BIM Afiliacion	BIM Afiliacion	BIM Afiliacion
Period	0.0287***	0.0287***	0.0279***	0.0279***
	(0.00946)	(0.00946)	(0.00937)	(0.00937)
Treatment	-0.000641	-0.000349	-0.000757	-0.000522
	(0.00586)	(0.00591)	(0.00638)	(0.00641)
Period × Treatment	0.0402***	0.0402***	0.0403***	0.0403***
	(0.0140)	(0.0140)	(0.0141)	(0.0140)
Head Employment		0.00435		0.00437
		(0.00877)		(0.00922)
Constant	0.00830**	0.00461	0.00917**	0.00549
	(0.00388)	(0.00761)	(0.00429)	(0.00800)
N	2262	2262	2155	2155
R^2	0.0341	0.0342	0.0329	0.0330
F	19.39	15.09	18.54	14.51
Region FE	Yes	Yes	Yes	Yes

Notes: Period is an indicator of whether the observations are not part of the baseline survey. 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%.

Table 8: BIM Attendance & Distrust

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	
	Attendance: OLS	Attendance: OLS	Probit	Attendance: OLS	Attendance: OLS	Probit
Treatment	0.336***	0.332***	0.309***	0.376***	0.373***	0.338***
	(0.0410)	(0.0416)	(0.0335)	(0.0420)	(0.0424)	(0.0324)
Distrust	-0.134***	-0.139***	-0.134**	-0.133***	-0.139***	-0.150**
	(0.0481)	(0.0468)	(0.0563)	(0.0481)	(0.0465)	(0.0650)
Distrust × Treatment	0.179**	0.171*	0.176*	0.172*	0.165*	0.189*
	(0.0881)	(0.0882)	(0.0990)	(0.0914)	(0.0916)	(0.102)
Head Employment		-0.0597			-0.0588	
		(0.0372)			(0.0386)	
Constant	0.427***	0.477***		0.374***	0.424***	
	(0.0535)	(0.0670)		(0.0585)	(0.0734)	
N	1131	1131	1115	1024	1024	1014
R^2	0.140	0.143		0.168	0.170	
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Distrust is an indicator of whether the individual doesn't think that other people have good intentions. 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%.

Table 9: BIM Affiliation: Distrust

				Excluding Beca18 family		
	(1) Affiliation: OLS	(2) Affiliation: OLS	(3) Probit	(4) Affiliation: OLS	(5) Affiliation: OLS	Probit
Treatment	0.0446***	0.0443***	0.0470***	0.0306**	0.0306**	0.0316**
	(0.0149)	(0.0147)	(0.0170)	(0.0145)	(0.0146)	(0.0161)
Distrust	0.0183	0.0180	0.0245	0.0238	0.0240	0.0281
	(0.0266)	(0.0266)	(0.0334)	(0.0278)	(0.0279)	(0.0295)
Distrust × Treatment	-0.0629	-0.0635	-0.0688	-0.0703*	-0.0701*	-0.0831
	(0.0382)	(0.0383)	(0.0515)	(0.0365)	(0.0364)	(0.0545)
Head Employment		-0.00403			0.00119	
		(0.0168)			(0.0157)	
Constant	0.0461	0.0495		0.0562	0.0552	
	(0.0403)	(0.0396)		(0.0436)	(0.0428)	
N	1131	1131	1062	1024	1024	966
R^2	0.0251	0.0251		0.0287	0.0288	
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Distrust is an indicator of whether the individual doesn't think that other people have good intentions. 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%.

Table 10: BIM Attendance & Referred Person being a Relative

				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
Treatment	0.351***	0.344***	0.347***	0.392***	0.379***
	(0.0412)	(0.0419)	(0.0457)	(0.0424)	(0.0430)
Relative		0.0696*	0.0762		0.123***
		(0.0364)	(0.0681)		(0.0376)
Constant	0.459***	0.451***	0.450***	0.404***	0.387***
	(0.0675)	(0.0679)	(0.0684)	(0.0740)	(0.0759)
N	1131	1131	1131	1024	1024
R^2	0.139	0.142	0.142	0.166	0.178
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 Affiliation & Referred Person being a Relative

				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0383***	0.0381***	0.0517***	0.0239*	0.0324**
	(0.0138)	(0.0144)	(0.0148)	(0.0139)	(0.0154)
Relative		0.00173	0.0357		0.0369
		(0.0187)	(0.0289)		(0.0301)
Relative × Treatment			-0.0557		-0.0373
			(0.0371)		(0.0376)
Constant	0.0496	0.0494	0.0421	0.0564	0.0491
	(0.0406)	(0.0399)	(0.0380)	(0.0440)	(0.0412)
N	1131	1131	1131	1024	1024
R^2	0.0231	0.0231	0.0256	0.0262	0.0283
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 12: BIM Attendance & BN ATM

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.351***	0.349***	0.278***	0.392***	0.389***	0.315***
	(0.0412)	(0.0414)	(0.0567)	(0.0424)	(0.0427)	(0.0574)
BNATM		0.0317	-0.0554		0.0323	-0.0590
		(0.0397)	(0.0580)		(0.0410)	(0.0596)
BNATM × Treatment			0.159**			0.166**
			(0.0789)			(0.0817)
Constant	0.458***	0.443***	0.489***	0.403***	0.387***	0.434***
	(0.0675)	(0.0662)	(0.0730)	(0.0740)	(0.0727)	(0.0793)
N	1131	1131	1131	1024	1024	1024
R^2	0.138	0.139	0.145	0.166	0.167	0.173
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	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%.

Table 13: BIM Affiliation & BN ATM

				Excluding Beca18 family	
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0383***	0.0358**	0.0425***	0.0239*	0.0281*
	(0.0138)	(0.0138)	(0.0159)	(0.0139)	(0.0163)
BNATM		0.0320**	0.0402		0.0337
		(0.0154)	(0.0247)		(0.0240)
BNATM × Treatment			-0.0151		-0.0141
			(0.0295)		(0.0295)
Constant	0.0496	0.0347	0.0303	0.0564	0.0401
	(0.0406)	(0.0365)	(0.0339)	(0.0440)	(0.0364)
N	1131	1131	1131	1024	1024
R^2	0.0231	0.0273	0.0275	0.0262	0.0295
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 1: Map 1

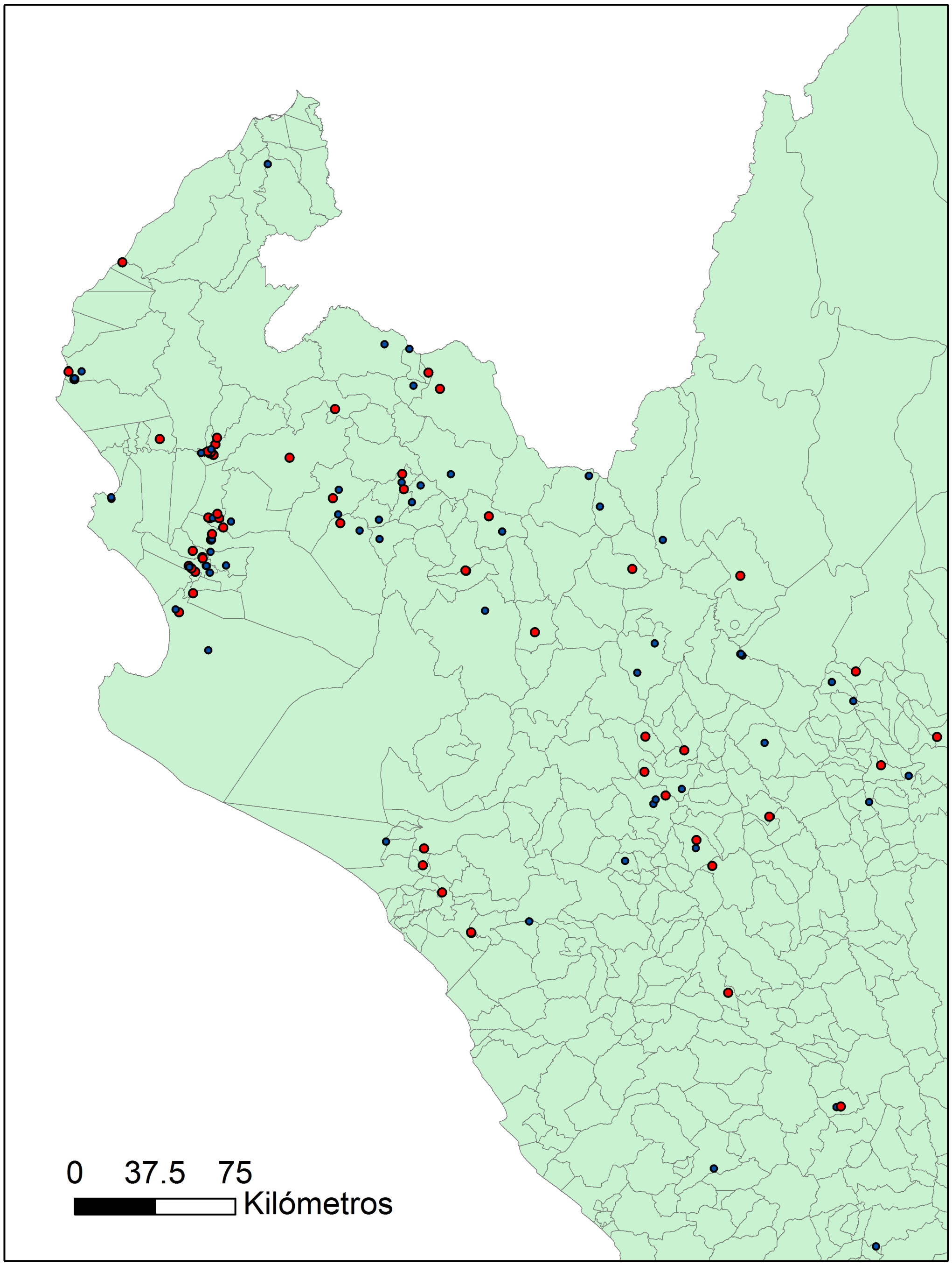
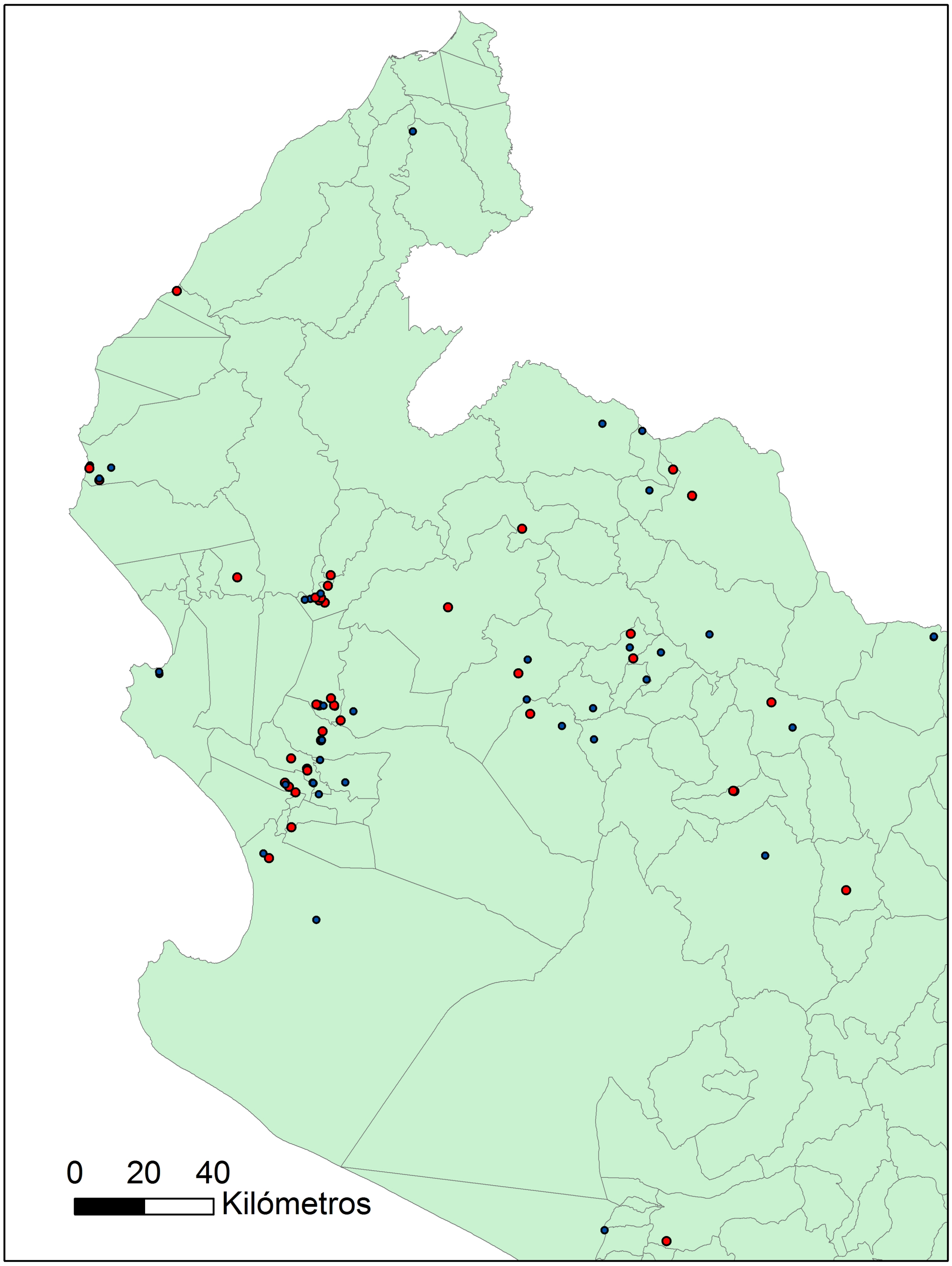


Figure 2: Map 2



11 Appendix

11.1 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.

Figure 3: Histogram in Education Level. Attendance vs No Attendance.

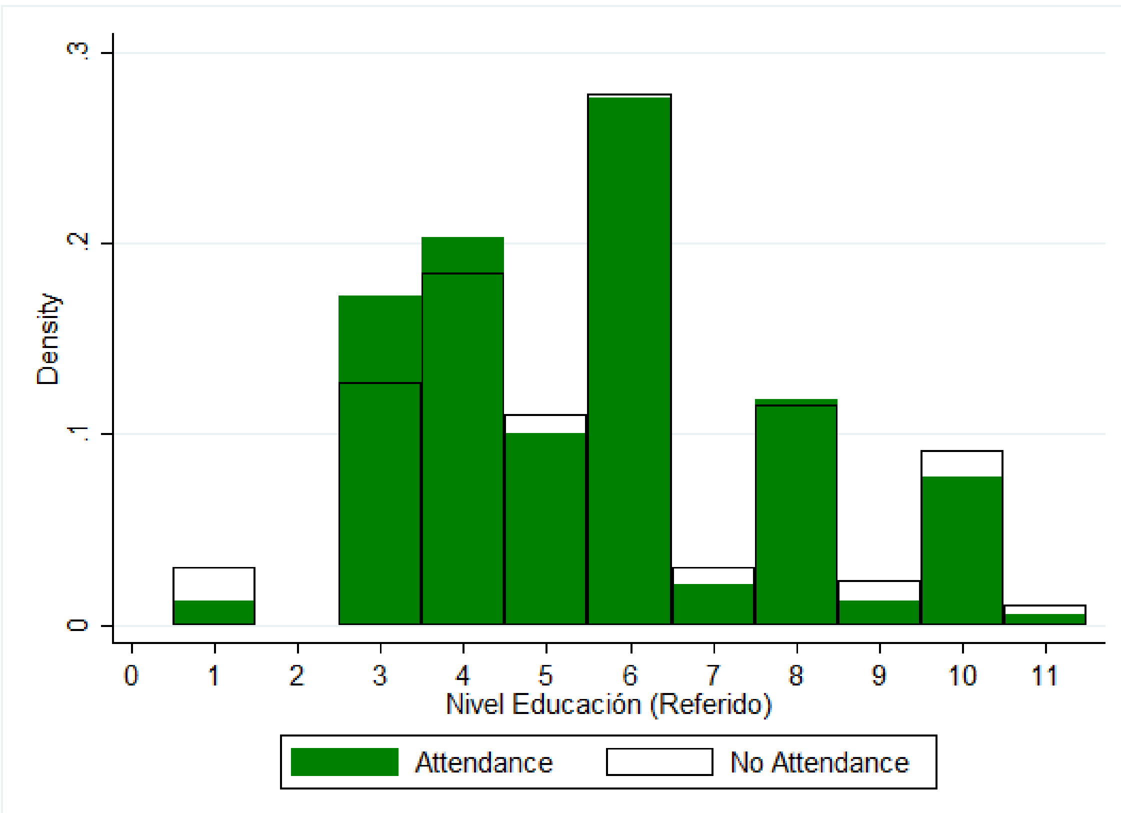


Figure 4: Histogram in Age. Attendance vs No Attendance.

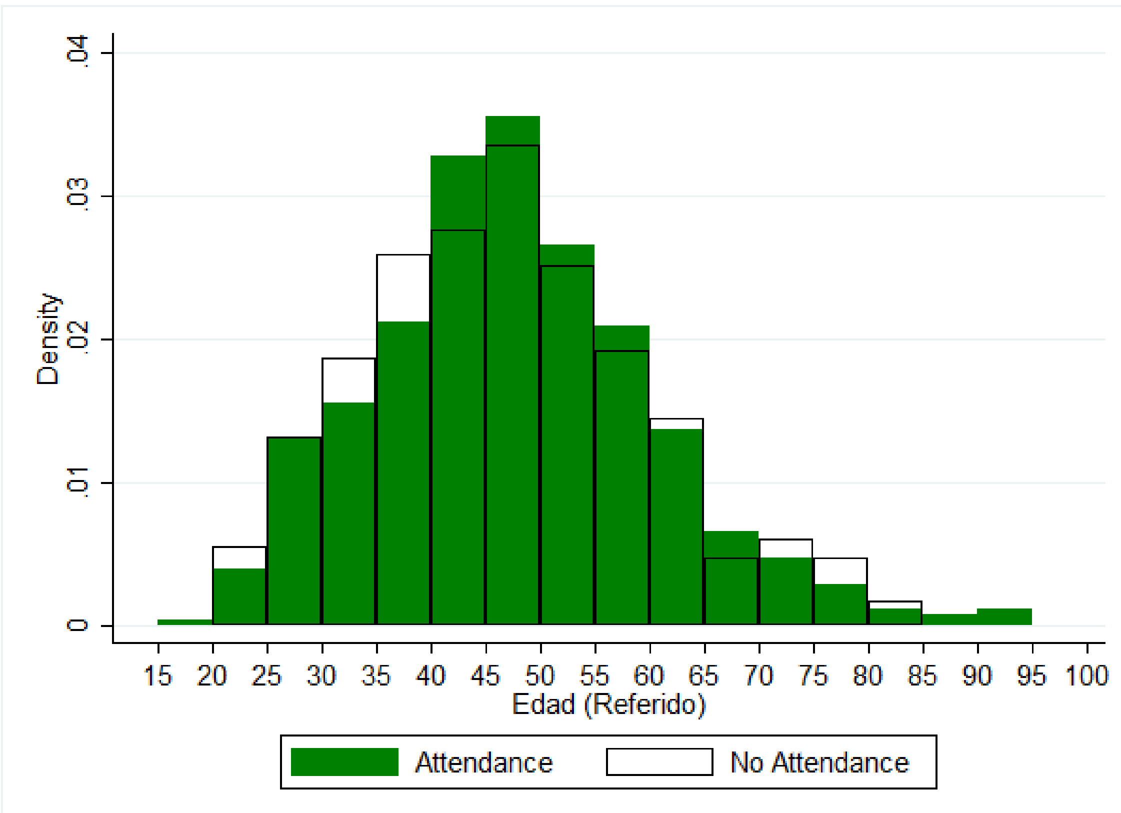


Table 14: BIM Attendance/Affiliation & Distrust with Account Interaction

	Attendance			Affiliation		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.372***	0.355***	0.361***	0.0468***	0.0527***	0.0490***
	(0.0440)	(0.0441)	(0.0452)	(0.0165)	(0.0178)	(0.0180)
Distrust		-0.135***	-0.112*		0.0167	-0.00399
		(0.0479)	(0.0665)		(0.0264)	(0.0279)
Distrust × Treatment		0.166*	0.112		-0.0624	-0.0262
		(0.0897)	(0.113)		(0.0382)	(0.0451)
BankAccount	0.0229	0.0261	0.0352	0.0261	0.0258	0.0176
	(0.0406)	(0.0411)	(0.0458)	(0.0295)	(0.0295)	(0.0270)
BankAccount × Treatment	-0.0847	-0.0875	-0.109	-0.0303	-0.0303	-0.0159
	(0.0605)	(0.0607)	(0.0672)	(0.0377)	(0.0377)	(0.0378)
BankAccount × Distrust			-0.0718			0.0646
			(0.123)			(0.0640)
BankAccount × Distrust × Treatment			0.209			-0.132*
			(0.209)			(0.0789)
Constant	0.449***	0.465***	0.464***	0.0427	0.0428	0.0447
	(0.0680)	(0.0672)	(0.0685)	(0.0353)	(0.0347)	(0.0364)
N	1131	1131	1131	1131	1131	1131
R^2	0.140	0.144	0.145	0.0243	0.0263	0.0278
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Distrust is an indicator of whether the individual doesn't think that other people have good intentions. BankAccount is an indicator of whether the head has a bank account. 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 15: BIM Attendance & Trust in Banks

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.351***	0.354***	0.279***	0.392***	0.393***	0.333***
	(0.0412)	(0.0416)	(0.0845)	(0.0424)	(0.0426)	(0.0871)
BankTrust		-0.00556	-0.0166		-0.00247	-0.0112
		(0.00872)	(0.0141)		(0.00872)	(0.0135)
BankTrust × Treatment			0.0195			0.0154
			(0.0172)			(0.0175)
Constant	0.458***	0.485***	0.523***	0.403***	0.415***	0.445***
	(0.0675)	(0.0800)	(0.0946)	(0.0740)	(0.0835)	(0.0959)
N	1131	1131	1131	1024	1024	1024
R^2	0.138	0.139	0.140	0.166	0.166	0.167
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: BankTrust is an indicator of whether the individual trust in banks. 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 & Trust in Banks

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0383***	0.0408***	0.0305	0.0239*	0.0263*	0.0158
	(0.0138)	(0.0133)	(0.0381)	(0.0139)	(0.0136)	(0.0375)
BankTrust		-0.00479	-0.00629		-0.00460	-0.00613
		(0.00446)	(0.00591)		(0.00433)	(0.00577)
BankTrust × Treatment			0.00266			0.00271
			(0.00842)			(0.00818)
Constant	0.0496	0.0730	0.0782	0.0564	0.0788	0.0841
	(0.0406)	(0.0503)	(0.0548)	(0.0440)	(0.0537)	(0.0577)
N	1131	1131	1131	1024	1024	1024
R^2	0.0231	0.0244	0.0245	0.0262	0.0275	0.0276
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: BankTrust is an indicator of whether the individual trust in banks. 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 & Time Spent

				Excluding Beca18 family			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.356***	0.332***	0.332***	0.336***	0.373***	0.332***	0.336***
	(0.0512)	(0.0416)	(0.0459)	(0.0502)	(0.0424)	(0.0459)	(0.0502)
Time	0.00288		0.00250	0.00301		0.00250	0.00301
	(0.00370)		(0.00236)	(0.00371)		(0.00236)	(0.00371)
Time × Treatment	-0.000563			-0.000747			-0.000747
	(0.00459)			(0.00461)			(0.00461)
Distrust		-0.139***	-0.167***	-0.168***	-0.139***	-0.167***	-0.168***
		(0.0468)	(0.0509)	(0.0505)	(0.0465)	(0.0509)	(0.0505)
Distrust × Treatment		0.171*	0.204**	0.205**	0.165*	0.204**	0.205**
		(0.0882)	(0.0937)	(0.0933)	(0.0916)	(0.0937)	(0.0933)
Constant	0.370***	0.477***	0.398***	0.395***	0.424***	0.398***	0.395***
	(0.0805)	(0.0670)	(0.0843)	(0.0807)	(0.0734)	(0.0843)	(0.0807)
N	786	1131	786	786	1024	786	786
R^2	0.148	0.143	0.153	0.153	0.170	0.153	0.153
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 18: BIM Affiliation & Time Spent

				Excluding Beca18 family			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.0213	0.0443***	0.0254	0.0229	0.0306**	0.0254	0.0229
	(0.0207)	(0.0147)	(0.0183)	(0.0208)	(0.0146)	(0.0183)	(0.0208)
Time	-0.000770		-0.000460	-0.000770		-0.000460	-0.000770
	(0.00125)		(0.000761)	(0.00127)		(0.000761)	(0.00127)
Time × Treatment	0.000343			0.000458			0.000458
	(0.00151)			(0.00154)			(0.00154)
Distrust		0.0180	-0.0136	-0.0135	0.0240	-0.0136	-0.0135
		(0.0266)	(0.0169)	(0.0170)	(0.0279)	(0.0169)	(0.0170)
Distrust × Treatment		-0.0635	-0.0349	-0.0355	-0.0701*	-0.0349	-0.0355
		(0.0383)	(0.0326)	(0.0333)	(0.0364)	(0.0326)	(0.0333)
Constant	0.0662	0.0495	0.0689	0.0711	0.0552	0.0689	0.0711
	(0.0535)	(0.0396)	(0.0505)	(0.0527)	(0.0428)	(0.0505)	(0.0527)
N	786	1131	786	786	1024	786	786
R^2	0.0229	0.0251	0.0250	0.0251	0.0288	0.0250	0.0251
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 19: BIM Attendance & Referred Person's Education

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.351***	0.339***	0.376***	0.392***	0.377***	0.435***
	(0.0412)	(0.0415)	(0.0808)	(0.0424)	(0.0435)	(0.0846)
Education Level		-0.00309	0.000240		-0.00318	0.00194
		(0.00757)	(0.0111)		(0.00794)	(0.0117)
Education Level × Treatment			-0.00658			-0.0102
			(0.0140)			(0.0149)
Constant	0.458***	0.468***	0.449***	0.403***	0.404***	0.376***
	(0.0675)	(0.0692)	(0.0792)	(0.0740)	(0.0760)	(0.0864)
N	1131	1028	1028	1024	934	934
R^2	0.138	0.133	0.133	0.166	0.158	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 20: BIM Affiliation & Referred Person's Education

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0383***	0.0361**	0.0811**	0.0239*	0.0214	0.0913**
	(0.0138)	(0.0142)	(0.0394)	(0.0139)	(0.0140)	(0.0401)
Education Level		0.00402	0.00807**		0.00227	0.00849**
		(0.00358)	(0.00404)		(0.00362)	(0.00426)
Education Level × Treatment			-0.00801			-0.0124*
			(0.00672)			(0.00668)
Constant	0.0496	0.0287	0.00606	0.0564	0.0449	0.0104
	(0.0406)	(0.0401)	(0.0393)	(0.0440)	(0.0430)	(0.0426)
N	1131	1028	1028	1024	934	934
R^2	0.0231	0.0249	0.0262	0.0262	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 21: BIM Attendance & Referred Person's Age

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.351^{***}	0.341^{***}	0.555^{***}	0.392^{***}	0.380^{***}	0.549^{***}
	(0.0412)	(0.0415)	(0.120)	(0.0424)	(0.0433)	(0.124)
Age		-0.000365	0.00220		-0.00164	0.000412
		(0.00133)	(0.00180)		(0.00136)	(0.00178)
Age × Treatment			-0.00462^{*}			-0.00368
			(0.00249)			(0.00262)
Constant	0.458^{***}	0.474^{***}	0.360^{***}	0.403^{***}	0.474^{***}	0.383^{***}
	(0.0675)	(0.0940)	(0.102)	(0.0740)	(0.0960)	(0.102)
N	1131	1028	1028	1024	934	934
R^2	0.138	0.133	0.136	0.166	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 22: BIM Affiliation & Referred Person's Age

				Excluding Beca18 family		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0383***	0.0343**	0.0166	0.0239*	0.0200	0.0218
	(0.0138)	(0.0146)	(0.0447)	(0.0139)	(0.0145)	(0.0420)
Age		0.000262	0.0000494		0.000474	0.000495
		(0.000439)	(0.000551)		(0.000440)	(0.000429)
Age × Treatment			0.000383			-0.0000383
			(0.000851)			(0.000841)
Constant	0.0496	0.0311	0.0406	0.0564	0.0299	0.0289
	(0.0406)	(0.0483)	(0.0532)	(0.0440)	(0.0503)	(0.0517)
N	1131	1028	1028	1024	934	934
R^2	0.0231	0.0238	0.0239	0.0262	0.0292	0.0292
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%.