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Follow the Leader: Community-based Health Insurance in West Africa*

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Abstract

In this study, we analyze the role of social networks in health insurance adoption in rural Guinea-Bissau. Using detailed social network data, and exploiting the mobilization of local female leaders to promote the insurance scheme, we find that, following the promoters' intervention, households' probability of take-up increased by 22 percentage points. Looking at effects along social networks, we find that households well connected to insurance promoters are more likely to adopt if promoters adopt as well. Lastly, our results show that distribution of insurance promotional material by the promoters has a positive effect in households' adoption and payment of health insurance.

JEL Classification: O12, I13, D83 Keywords: Health Insurance, Social Networks, Africa.

1 Introduction

Life in developing countries is risky. Households' well-being is highly susceptible to negative events, ranging from idiosyncratic shocks (unemployment or illness), to covariate shocks (weather events or political instability), that can push households below the poverty line.[1] Illness is among the most common income shocks, triggering not only out-of-pocket health expenditures but also forgone income due to workdays lost. [2] To cope with these losses, households often rely on informal risk-sharing arrangements. However, these risk-coping strategies provide only incomplete coverage, leaving households unable to completely smooth consumption. In this

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[1] See World Development Report 2014: Risk and Opportunity Managing Risk for Development (2014).

[2] See Krishna (2007).

setting health insurance has emerged as a promising avenue, allowing households to efficiently pool resources and manage income risk and vulnerability.

In this paper we examine the role of social networks in households' health insurance take-up decisions. In particular, we consider how mobilization of female community leaders as health insurance promoters influence households' adoption decisions. We take the case of a voluntary community-health insurance in one village in Guinea-Bissau and explore a seven-year panel of insurance take-up, combined with detailed network data and a mobilization intervention.

For our intervention, the health insurance provider recruited female village leaders as health insurance promoters. The promoters received a short training on the benefits and responsibilities associated with the community-health insurance, and in addition were given a promotional calendar to distribute outside of their household. The richness of our data allows us to first explore adoption decisions along the network over time, second test how promoters influence households' adoption decisions after the intervention, and third observe direct diffusion of promotional material and how it contributes to adoption decisions.

Our results show that households' adoption decisions tend to follow their peer-leaders' decisions, even before the intervention. After the promoters' intervention, we observe a sharp increase in adoption in the village. This represents a 22 percentage point increase in the probability of households being registered for health insurance. Testing for the role of social networks after the intervention, we show that being connected to the insurance promoters does not influence health insurance behavior, unless the health promoter herself is registered in the program. These results are especially large among households who are relatively highly connected to health adopting promoters. In particular, we find that households are 9.6 percentage points more likely to adopt if adopting promoters make up 10 percent of their social network. This represents a 43 percent increase. In addition, we also observe a modest increase in the number of individuals registered per household, suggesting that the main contribution of promoters is to attract new households into the program. However, we do not find strong evidence of health promoters' adoption rate influencing households' rate of fees paid. Lastly, we analyze how promoters' calendar dissemination influenced households' adoption decisions. We find that receiving the calendar increases the likelihood of households both adopting and paying for insurance on time.

This paper contributes to the literature on demand for microinsurance in developing countries. A number of studies have investigated the adoption of microinsurance, and one overarching conclusion from this literature is that - despite its potential - uptake, and renewal rates of microinsurance remain puzzlingly low (Eling, Pradhan, and Schmit, 2014). The literature has investigated a number of channels that could potentially increase take-up. As expected, adoption responds to changes in price. However, price alone cannot account for low adoption rates. Even when prices are heavily subsidized (Cole et al., 2013; Karlan et al., 2014), or the insurance is offered for free (Thornton et al., 2010) take-up rates remain below 50%. Lack of understanding of the insurance scheme is often also mentioned as an important deterrent to take up (Cole et al., 2013; Giné, Townsend, and Vickery, 2008). However, evidence of the impact of education interventions on insurance take-up has been somewhat disappointing. Studies by Cole et al. (2013) focusing on agricultural insurance in India, and Schultz, Metcalfe, and Gray (2013) on a health insurance scheme in Ghana, found no impact of financial-literacy training on insurance demand. The literature also points to the importance of trust in adoption decisions (Cai et al., 2014; Liu and Myers, 2016). Trust in insurance has been shown to increase following an insurance payout either to the individual himself, or in their social networks (Cole, Stein, and Tobacman, 2014; Karlan et al., 2014). Finally, distrust in insurance can also be mitigated by peer influence. For example, Cole et al. (2013) in India finds evidence that insurance take up increases when endorsed by trusted authorities.

Second, and more generally, we contribute to the literature on the role of social networks in financial decisions. The importance of peer influence has been documented in retirement savings decisions (Duflo and Saez, 2003), microfinance loans (Banerjee et al., 2013) and insurance (Cole, Stein, and Tobacman, 2014; Cai, Janvry, and Sadoulet, 2015; Chemin, 2018; Liu, Sun, and Zhao, 2014). In the context of rainfall insurance, Giné, Townsend, and Vickery (2008) provides early evidence on the importance of social networks in insurance decisions. Similar to our setting, the insurance was first targeted at opinion leaders, who helped publicize the insurance scheme. The authors find that insurance participation is higher among members of local groups and associations. The study by Cai, Janvry, and Sadoulet (2015) supports these findings. The authors experimentally offered weather insurance to farmers at information sessions. Results show that farmers whose peers attended the information sessions were better informed about the insurance and also more likely to purchase it. In the health context, Chemin (2018) finds that take-up is higher when the health insurance is presented to a pre-existing informal group, but take-up does not increase when information is presented by community leaders. In a health insurance scheme China, Liu, Sun, and Zhao (2014) find that rural households adopt health insurance when more households in the village adopt as well, which is consistent with information transmission through the network.

Lastly, we add to the growing literature on the role of 'promoters' or 'opinion leaders' in technology diffusion. BenYishay and Mobarak (2019) experimentally vary the entry points of agricultural innovations in Malawi and their subsequent effects through social networks. The authors show that the social identity of the promoter influences peers' knowledge and take-up decisions. In a study that targets opinion leaders to market improved cookstoves in Bangladesh, Miller and Mobarak (2014) document how opinion leaders' adoption decisions strongly influence their peers. Consistent with these results, Banerjee et al. (2013) for microfinance in India, and Kim et al. (2015) with health behaviors in Honduras, show that dissemination is most effective when first targeted at influential individuals in the network.

The remainder of the paper is structured as follows. In Section 2 we give the context of the study and describe the insurance scheme. Section 3 describes the promoters intervention. Section 4 discusses the data and main variables. In Section 5 we outline the estimation strategy. Results are presented in Section 6 and Section 7 concludes.

2 Context

Guinea-Bissau is the 12th poorest country in the world, with approximately 69 percent of its population living below the poverty line, according to the World Development Indicators 2020. The majority of the population lives in rural areas, and agriculture represents the main source of livelihood – employing approximately 80 percent of the country's population. Guinea-Bissau has been plagued with political instability, resulting in low provision of public goods and lack of social assistance programs.[3] The health situation in the country is characterized by the persistence of high morbidity and mortality in maternal, newborn and child and youth health. The country's average life expectancy is 58 years, which is lower than the average in Sub-Saharan Africa. The main causes of death are lower respiratory infections (accounting for 12 percent of deaths), maternal and neonatal complications (12 percent), HIV/AIDS (11 percent), malaria (8 percent), and diarrhoeal diseases (6 percent).[4]

Our study area is the village of Suzana in north-western Guinea-Bissau. At the time of our study, it had a population of approximately 1600 individuals across 334 households. The majority of the population belongs to the Felupe ethnic group. Similar to the rest of the country, subsistence agriculture is the primary means of livelihood. There is one health center in the village, which provides primary care, and it is staffed with two nurses and a midwife.

2.1 Community health insurance package

In 2013, the NGO VIDA, introduced a community health insurance program in the area called 'Mutualidades'. Over the years, the insurance program has been managed by a village committee in partnership with the NGO. While the introduction of the program was decided at the village level, enrolment decisions are taken at the individual level. Each insured adult pays a one-time membership fee of USD 1.78 (1000 FCFA),[5]and an upfront USD 6.41 fee, which corresponds to a whole year's worth of monthly fees, with the monthly fee being USD 0.53. After the first year of enrollment there is greater flexibility with fee payments, where individuals may decide to pay monthly, or several months upfront. The program covers all health acts at the local health center, essential drugs, and in case of an emergency also includes the transport cost of a medical evacuation to the nearest hospital.[6] Enrolled individuals receive an insurance card, which entitles the holder to the benefits. Children under 14 are also included in their guardian's health plan. During the first four years take up rates in the village were around 30%. However, around 90% of the households registered were at some moment in debt with the program, and on average households paid only 40% of monthly fees. This situation led the NGO running the program to undertake a process of regularization. This process consisted of evicting all households that had more than 6 months of debt. Households willing to register after being evicted, had to pay a complete year in advance. After this process, by 2018, adoption dropped

[3]See Group (2016).

[4]Latest available years, World Health Organization, 2019.

[5]For comparison, USD 1.78 corresponds approximately to the average daily wage of agriculture salaried workers in the region.

[6]The closest hospital is located at approximately one hour by car (36 km).

to 20% while the shared of paid fees raised to 80%.

3 Health insurance promoters

In order to raise adoption, and to remind households of payment obligations, the implementing agency supported the introduction of insurance promoters in August 2019. The insurance promoters were chosen among the village female leaders. [7] In a first stage, all the main village leaders were approached to become health insurance promoters, and each of these could then choose a second village leader to also be part of the project. In total 36 leaders were selected to attend a training session and become health insurance promoters. The training session was provided by the NGO running the program. It lasted for one day and included detailed information regarding the insurance product, its benefits, responsibilities of each insured member and the payment scheme. Each promoter received a promotional t-shirt and 6 calendars (Figure A1) with basic information about the insurance. The promoters were instructed to keep one of the calendars to themselves and distribute the remaining 5 calendars to other households in the village. Each calendar was embedded with a unique code for each promoter. Promoters were also informed that at a later stage all households in the village would be visited to check that calendars had been distributed.

4 Measurement and data

The data for this project is based on three sources: administrative data, household surveys and home visits. The administrative data was provided by the NGO running the program. This includes individual level information on insurance purchase decisions and fee payments for the whole village from the introduction of the insurance scheme in October, 2013 to July, 2020. This represents a total of 290 members (from 186 households) during the 2013-2020 period. The second data source is a household panel survey collected in 2016, 2018 and 2019, before the promoters' intervention, and comprising every household in the village at the time of the collection. A census of the village was initially carried out in 2016 and updated in every survey wave. The surveys targeted the female household head. The survey data contains information on individual and household level socio-economic characteristics, including household demographics, health expenses, assets, and social network contacts. Over the period from 2013 to 2020 a total of 378 households have lived in the village. At the 2019 survey, a total of 334 households (approximately 1600 individuals) were living in the village. Finally, we collected information on how the calendars were distributed across the village. To that purpose, three weeks after the promoters' training sessions we revisited every household in the village and checked for the presence of a calendar, along with the promoter's code embedded in the calendar.

[7] Village leaders' responsibilities include representing the community to outside individuals, representing their own neighborhood in village meetings, making decisions regarding public goods, and making sure that their fellow villagers are informed and have a saying regarding community decisions and activities.

4.1 Network data

The social network data were collected in 2016, 2018 and 2019. For the purpose of this study, we focus on the last data collection round. In a previous visit, we conducted a census of the village, including all household members. At the time of the census, we took a picture of the household respondent, and compiled a village photo album, which was later used to aid the network data collection. During the household survey, the respondents were asked to list village members that they regularly talked to, and to whom they may ask for money in times of need. Once the respondents finished listing all the network peers that they could recall, we used the photo album to aid the respondent in recalling possible forgotten network links. All the reported links were then pooled in a directed network graph, that reports links between households in the village. Since we did not use any sampling method for network data collection, but rather surveyed the entire population, we obtained a complete network map of the village. This combined with photo album data, allows us to avoid the common pitfalls of incomplete information on the structure of the network, where relevant network links may be unobserved (Chandrasekhar and Lewis, 2016).

4.2 Outcome measures

The primary outcome measure in this project is adoption of the insurance program at the household level. To better capture changes in adoption before and after the intervention, we compute our measures for periods of four months.[8] In particular, we focus on whether households are actively registered in the health insurance program, that is, if they are registered in the program and have an accumulated debt of less than 6 months.[9] Then, we define two outcomes on adoption and one outcome on fees paid. In particular we look at: (i) whether the household has at least one member actively registered during at least one month in a four-month period; (ii) the total number of household members per household actively registered for at least one month in a four-month period; (iii) the share of active months paid at the household level. This variable takes a maximum value equal to one if the household has paid all the fees until the current period for all the household members registered in the program. This measure captures whether the households are debt-free with the program, but do not take into account whether households are paying fees in advanced, which in this context is highly correlated with income seasonality, in particular with the Cashew nuts harvest in spring.

[8] We aggregate monthly data as we do not have much monthly variation. By using four-month periods we aggregate all data from 2019 after the intervention in one data point. Our results remain largely unchanged using monthly data.

[9] We impose a threshold of 6 months following the regularization guidelines implemented by the NGO running the program.

5 Estimation strategy

First, we estimate whether health insurance behavior changed after the intervention. To do so, we restrict our analysis to the period between 2018 and 2020, that is, after the process of regularization implemented by the NGO running the program. We estimate a single difference equation:

$$y_{it} = \alpha + \gamma Post_t + \theta_1 X_i + \epsilon_{it} \tag{1}$$

where y_{it} is the outcome of interest for household i at time t. As mentioned in the previous section, the dependent variables are aggregated in four-month periods. $Post_t$ is an indicator variable that takes the value of one for all time periods after the intervention, that is, after September 2019, and zero otherwise. The vector X_i contains observed household level characteristics, which include respondents' age, gender, religion and ethnic group, and the household neighborhood. ϵ_{it} is an idiosyncratic error term and it is clustered at the household level.

To study the influence of promoters on households' adoption decision we employ a difference-in-difference specification at the household level. The equation we estimate is as follows:

$$y_{it} = \alpha + \beta Prom_{it} + \gamma Post_t + \delta Prom_{it} \times Post_{it} + \theta_1 X_i + \theta_2 \bar{X}_j + \epsilon_{it} \tag{2}$$

$Prom_{it}$ represents a peer promoter indicator for household i at time t. Where time t represents four months periods from January 2018 to July 2020. The coefficient δ can be interpreted as the effect of the peer promoters on households' health insurance behavior.

We use four different measures for the peer promoter indicator: the share of promoters in household i's social network that are registered in the insurance; a dummy variable that takes the value of one if household i has an above-median share of adopting peer promoters and zero otherwise; the share of promoters in the network; and lastly, a dummy variable that takes the value of one for above-median share of peer promoters and zero otherwise. The share of promoters in the network is constant across time, and refers to the number of promoters in the household network before the intervention (August, 2019). However, adoption across promoters is not constant and changes over time. [10]

As before, X_i is a vector of household-specific characteristics. To account for exogenous network effects which might lead to the estimation of spurious network effects (Manski, 1993) we introduce the average network level characteristics of the peers of i's network, $\bar{X}_j$. $\bar{X}_j$ includes the average age of network members, the proportion of female network members, proportion of network members from the main religions, and proportion of network members from the main

[10] The share of registered promoters is defined as: $Prom_{it} = \left(\frac{1}{N_i}\right) \sum_j^{N_i} y_{jit}^N$, where y_{jit}^N is the adoption decision of promoters' household j in the network of household i at time t. N_i is the total number of households in i social network and allows us to control for the effects of social network size.

ethnic group.

Lastly, we analyze how receiving the calendar influences households' adoption decisions. We employ the following specification:

$$y_{it} = \alpha + \beta Calendar_i + \gamma Post_t + \delta Calendar_i \times Post_{it} + \theta_1 X_i + \theta_2 \bar{X}_j + \epsilon_{it} \qquad (3)$$

where $Calendar_i$ is an indicator variable taking the value of one if household i received a calendar and zero otherwise.

In the results section we check whether the main results of the paper are robust to using the Post-Double Selection LASSO procedure to select control variables and households' fixed effects.

6 Results

6.1 Descriptive statistics

Table 1 contains descriptive statistics at the household and individual level. We report means for the subgroups of promoters and other village members, as well as differences between the two. Note that whenever possible we report characteristics for the universe of households that have ever lived in the village between 2016 (the first year of available census data) and 2019. The majority of respondents are female, within the age interval of 45 to 56 years old at the time of the survey.[11] Animism is the predominant religion in the village, followed by Catholicism. 87 percent of the households belong to the Felupe ethnic group, and agriculture is the main form of livelihood. In terms of network characteristics, villagers report on average 40 network links within the village, and approximately 9 network links with promoters. 20 percent of households have at least one household member registered at the insurance program, with the average number of household members registered being around 1.30. When comparing with the villager respondents, promoters are more likely to be female, younger, married, belong to the main ethnic group, and work in agriculture. The promoters also report larger households and spending more on health than the rest of the village. Promoters have more assets than the rest of the village, and a lower risk aversion coefficient. Regarding the network variables, promoters have a similar number of peers as the rest of the village but are better connected among themselves. Finally, promoters are more likely to have ever been enrolled in the insurance, but there is no statistically significant difference in having at least one active member, the number of active members or the number of months enrolled.

[11] This corresponds to the age interval 4.

6.2 Adoption of health insurance over time before health promoters' intervention

We begin with a descriptive exercise that documents adoption decisions over time. Figure 1 illustrates households' registration rate in the health insurance program since the start of the program until the last four-month period available. We distinguish between villagers' and promoters' take-up. Registration rates of promoters and of the rest of villagers tend to co-move over time, although the promoters' rate is overall twice as big. We observe two main moments in time. First, in mid-2017 when the organization running the program conducted a process of eviction of all beneficiaries who had a debt of more than 6 months. And second, in September 2019, when we observe a sharp jump in enrollment after the intervention, which remains stable in the first 7 months of 2020.

We now turn our analysis to the role of social networks in the adoption of health insurance over time. In particular we focus on the influence of peers' adoption rate, i.e., the proportion of other households in a household's network that are registered, on household's adoption decision. We restrict our analysis to the period before the intervention, that is from the last four months of 2013 (the introduction of the insurance) to August 2019 (before the promoters' intervention).

To investigate the influence of peers on households' decisions before the intervention, we distinguish between peer-villagers' and peer-promoters' adoption rates. 'Peer-promoters' adoption' refers to the proportion of adopting promoters in households' social networks, whereas 'peer-villagers' adoption' denotes the adoption decisions of other villagers in households' social networks. We assume that the composition of the network did not change significantly since 2013, and we construct our measure of the share of peers registered in the network using data from 2019. As described in Section 2.4.2, we focus our analysis on three outcome variables of interest: whether the household is registered, the number of household members registered per household, and the share of fees paid. The first two outcomes capture households' adoption decisions at the extensive and intensive margin, respectively. The share of fees paid captures whether households are up to date with their insurance payments. Figure 2 shows the results. Each panel shows estimates for the interaction between seven-year indicator variables and peer-villagers' adoption rates (in yellow) and peer-promoters' adoption rates (in grey) for one of our three main outcomes.[12] Confidence intervals are built using statistical significance at the 5 percent level. We find that peers' adoption decisions have a significant and positive effect on households' take-up in terms of both registration and payments across time. As we can see from the figure, peer-promoters' decisions seem to have a larger influence on households' behaviour than other peers' decisions. This pattern is observed for the three outcomes and for all years. However, while peer-promoters' decisions are correlated with the decision to adopt, and with paying the insurance fees on time, since the start of the program, peer-villagers' decisions are not correlated with payment behaviour after 2017. Except in this last case, we fail to reject

[12]We employ the following specification: $y_{it} = \alpha + \beta_1 \mathrm{PA}_{it} + \sum_t Y_t \pi_t + \sum_t (\mathrm{PA}_{it} \times Y_t)\delta_t + \theta_1 X_i + \theta_2 \bar{X}_j + \epsilon_{it}$, where PA_{it} is a measure of peers' adoption for household i in year t, Y_t accounts for year fixed effects, and δ_t captures how individual's behaviour is affected by peers' behaviour in year t.

the hypothesis that coefficients are equal across time.[13] Hence, we conclude that before the intervention, peer-promoters' decisions have a consistent positive and statistically significant effect on households' insurance decisions.

These results support the hypothesis that the identity of adopters in one's peer group matters for households' adoption decisions, further motivating our intervention which will be explored in the next session.

6.3 Health promoters' intervention

This section presents the results of the promoters' intervention. Figure 3 shows single difference estimates before and after the intervention, while employing Equation 1. As before, our outcome variables of interest are whether the household is registered and the number of household members registered per household, both of which capture households' adoption decisions, and the share of fees paid, which refers to insurance payment decisions. In line with the descriptive analysis, we observe a 22 percentage point increase in the probability of households being registered for health insurance and an increase of 0.36 in the number of household members registered per household. Although both increase, the former does so more sharply, suggesting that the majority of new registrations come from new households. After the intervention, the share of fees paid increases by 19 percentage points. All coefficients are statistically significant at the 1 percent level.[14]

Having documented an increase in adoption rate in the village after the intervention, we now turn to examining the role of social networks in adoption decisions. Figure 4 illustrates how the adoption diffused through the village network. For graphical clarity, we omit the links between neighborhoods. From the figure, we can observe a clear increase in adoption decisions after September 2019. We further investigate the influence of promoters using Equation 2. As mentioned in Section 5, we employ four different measures of promoters' influence through the network: the share of registered promoters in household, having above-median share of adopting promoters; the share of promoters; and having above-median share of promoters. Tables 2 and 3 display the results of promoters' influence on households' registration and payment decisions.

In Table 2 we report the estimates on the share of adopting promoters in the network on our main outcome variables of interest. In the top panel we investigate the role of the rate of links and in the bottom panel we look at whether having a relatively high rate of links (above-median) with registered health promoters in the village affect households' decisions. These variables allow us to capture heterogeneous effects between households which are especially

[13] P-values from testing the null hypothesis $H_0: \delta_{2013} = \delta_{2014} = \delta_{2015} = \delta_{2016} = \delta_{2017} = \delta_{2018} = \delta_{2019}$ goes from 0.2094 to 0.3998, with the exception of the test done for peer-villager's interaction with year dummies on the share of total fees paid, from which the p-value is 0.0432.

[14] Figure C1 in the Online appendix shows the results of a placebo test. We re- estimate Equation 1 using data from January 2018 to May 2019, that is, after the process of regularization conducted by the NGO running the insurance program and before the health promoters intervention. To run a placebo test we define $Post_t$ as an indicator variable that takes the value of one for all time periods after September, 2018. If health insurance adoption increases at end or at the start of the year, Figure C1 would show positive coefficients. Conversely, estimates are very small and never statistically significant.

well connected to health promoters compared to other households who have less connections to health promoters registered in the program.

As shown in Table 2 (top panel) we do not find statistically significant results for the effect of peer-promoters' adoption after the intervention. Households with high promoters' adoption rate in their networks are more likely to adopt even before the intervention. An increase of 1 percent in health promoters' adoption rate leads to a 0.012 percentage-point increase in the probability of being registered, and to a 0.013 percentage point increase in the share of fees paid. The number of registered household members also increases marginally (around 0.021 members). All coefficients are statistically significant at the 1 percent level. Note that, in line with the results in Figure 3, overall adoption increased after the intervention. However, being linked with adopting promoters does not increase households' adoption.

To explore what drives this result we look at network heterogeneous effects by degree of connection to adopting promoters. We define highly connected households, as households whose peer-promoters' adopting rate is above village's sample median. Specifically, we define an indicator variable that takes value equal to one for households for whom at least 10.4% of the social network is constituted of registered health promoters (in numbers, it translates to know at least 4 registered health promoters), and zero otherwise.

The bottom panel in Table 2 shows the results. Results on the post-intervention time indicator and on the indicator variable measuring highly connected households are consistent with our previous estimates. In addition, we find that the interaction terms between both indicator variables are positive for the specifications on adoption and on number of household members registered. After the intervention, being highly connected to registered health promoters increases the probability of registering by 9.6 percentage points and increases the number of household members registered by 0.16 members. Both estimates are significant at the 5 percent level. Results also show a positive effect on the share of fees paid,statistically significant at 10 percent level. This result suggests that the health promoter intervention was successful in attracting households who were relatively high connected to the group of registered health promoters.

Table 3 replicates this analysis using the rate of peer-promoters in the social network, without considering whether they were registered in the health program before the intervention. We do not find statistically significant results for the effect of the share of promoters after the intervention on households' decision to register or on the share of monthly fees. The number of active household members is however the exception, where the coefficient is positive and statistically significant.

Our central findings are robust to using Post-Double Selection LASSO procedure and households' fixed effect, the results of which are presented in Section D of the Online appendix. Overall, we conclude that knowing more peer promoters does not influence adoption decisions after the intervention unless they are also adopting.

6.4 Calendar

We next investigate how receiving the calendar influences households' adoption decisions using Equation 3.[15] Results are presented in Table 4. Our main variable of interest is the interaction between the post-intervention indicator variable (*Post-September 2019*) and an indicator variable taking value equal to one if the household received a calendar (*calendar*). Households that received the calendar are 7.5 percentage points more likely to register in the insurance program, and receiving the calendar increases the number of household members registered by 0.217 members. Finally, we find, that the calendar also increases the share of total fees paid after the intervention. Results are statistically significant at the 5 percent level. Table 4 shows that even if there was selection into whom received the calendar, the calendar by itself has a valuable contribution on the mission of attracting new households to the program and keeping households out of debt.

7 Conclusion

In this paper, we study the influence of social networks on health insurance adoption in rural Guinea-Bissau. We exploit a rich social network dataset and administrative data of insurance take-up and payments, combined with an intervention, which mobilized female community leaders to endorse and promote the insurance scheme. Leaders attended a training course on community health insurance and received promotional material to disseminate through the community. Our empirical findings can be summarized as follows. First, we document that peer promoters' adoption decisions have a significant and positive effect on households' take-up in terms of both registration and payments of health insurance before the intervention, giving support to our promoters' intervention. Second, we find that after the promoters' intervention households' take-up of the health insurance scheme increases by 22 percentage points. Third, households that are well connected to insurance promoters are more likely to adopt if the promoters themselves have adopted too. Fourth, households that received promotional material from the insurance promoters are more likely to adopt and be out of debt.

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[15] In Section B.1 of the online appendix, we investigate the determinants of calendar diffusion. Our results suggest that promoters targeted the calendar distribution not only to their network partners, but also to households that might benefit more from the insurance.

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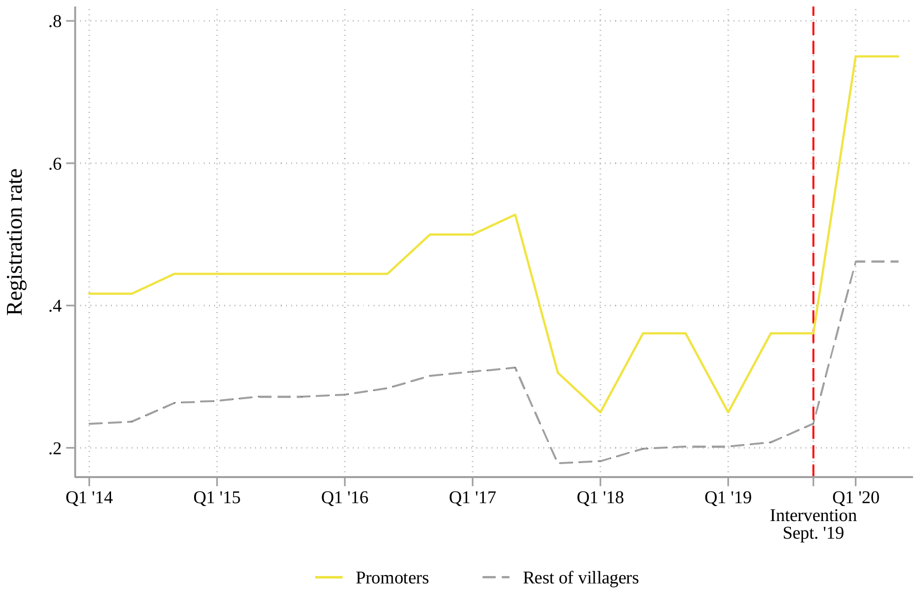
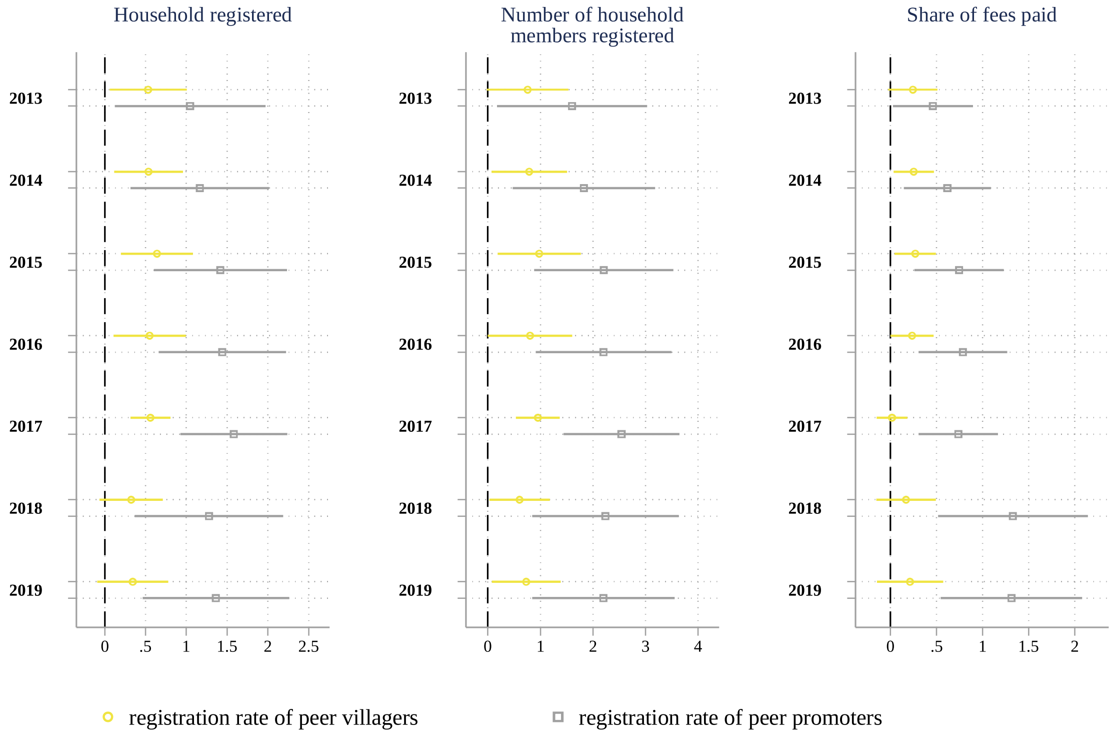
Figures and tables

Figure 1: Registration rate over time - villagers vs. health promoters



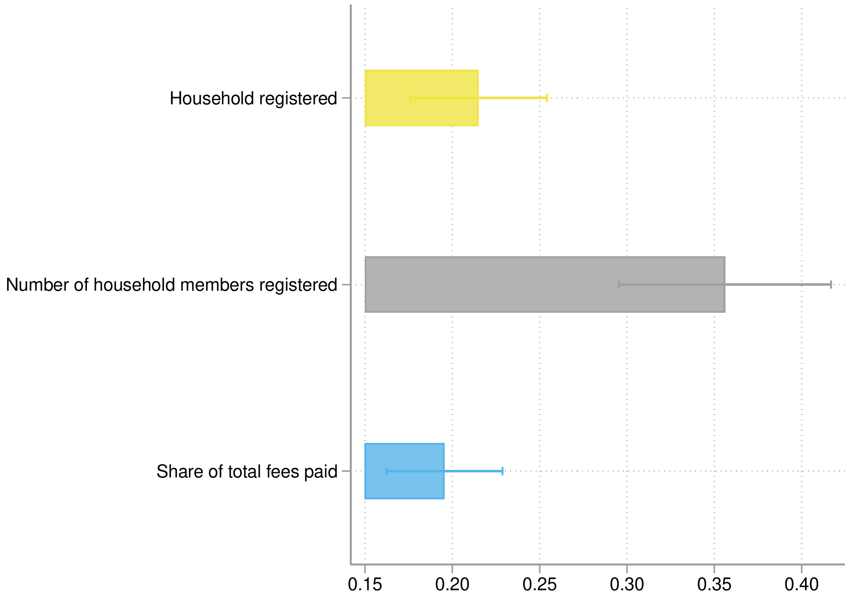
Note: Registration rates over time for the subgroup of health promoters and for the rest of the villagers. Registration rates are in four-months averages from September 2013 to July 2020.

Figure 2: Registration over time - network effects on households' registration and payment decisions.



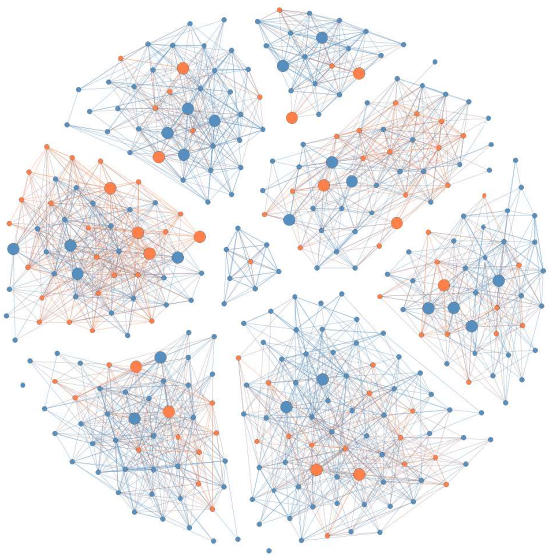
Note: Estimates based on OLS regressions. Top bars in yellow represent the point estimates and the 5 percent level confidence intervals of the interactions between a year indicator variable and the registration rate of peer-villagers. Bottom bars in grey represent the point estimates and the 5 percent level confidence intervals of the interactions between a year indicator variable and the registration rate of peer-promoters. Dependent variables are four-month averages. All specifications include year fixed effects and individual, household and network characteristics. The full list of controls is presented in Section 5. Standard errors are clustered at the household level.

Figure 3: Health promoters' intervention - Single difference

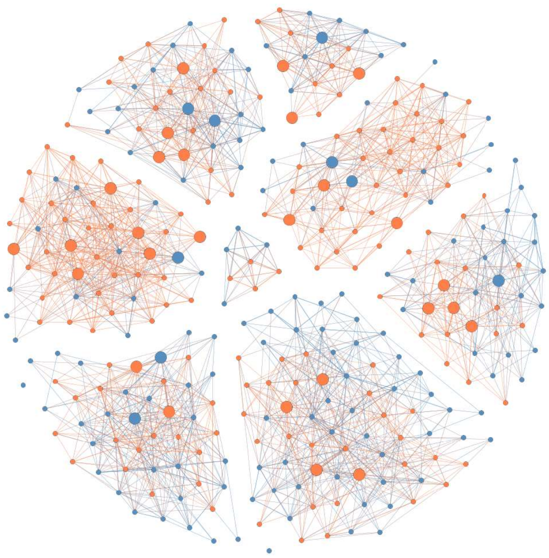


Note: Estimates based on OLS regressions using Equation 1. Estimation sample includes all households interviewed in August 2019, except those including health promoters. Dependent variables are four-month averages. All specifications include individual, household, and network characteristics. The full list of controls is presented in Section 5. Confidence intervals are built using statistical significance at the 5 percent level. Standard errors clustered at the household level.

Figure 4: Network map by neighborhoods - Health insurance adoption



(a) Before September, 2019



(b) After September, 2019

Note: Visual representation of the network links within neighborhoods in the village. Each node represents a household. Larger notes represent health promoters' households. Smaller notes represent the remaining households in the village. Households enrolled in the health insurance are depicted in orange, non-enrolled households are represented in blue. The lines between nodes indicate the existence of a network link. Network links are depicted in orange when both nodes are enrolled in the health insurance, in blue when both nodes are not enrolled, and in grey otherwise.

Table 1: Descriptive statistics

		Mean		
	observations	villagers	promoters	diff. (s.e)
	(1)	(2)	(3)	(4)
Female	378	0.83	1.00	0.17***
				(0.02)
Age (interval)	378	4.27	3.56	-0.71***
				(0.19)
Married	376	0.48	0.83	0.36***
				(0.07)
Catholic	378	0.27	0.31	0.04
				(0.08)
Animist	378	0.61	0.64	0.03
				(0.08)
Felupe	377	0.87	0.97	0.10***
				(0.03)
Works in agriculture	378	0.73	0.89	0.15***
				(0.06)
Household characteristics:				
Number of household members	378	4.55	7.00	2.45***
				(0.47)
Sick household members	329	1.26	1.28	0.02
				(0.21)
Sick household members not visitING a doctor	329	0.24	0.14	-0.10
				(0.06)
Total health expenditures (interval)	328	12.39	13.81	1.41
				(1.32)
Well-being index (1-5)	329	2.52	2.33	-0.19
				(0.21)
Asset index (0-21)	332	5.17	6.33	1.16***
				(0.43)
Risk aversion index	329	2.86	2.44	-0.42*
				(0.25)
Network:				
Total links within the village	330	40.32	43.67	3.35
				(4.42)
Links with health promoters	330	8.54	11.31	2.76***
				(0.97)
Health - insurance program:				
Household registered	378	0.20	0.25	0.05
				(0.08)
Number of household members registered (conditional)	78	1.30	1.44	0.14
				(0.24)
Number of months registered	378	70.34	91.22	20.88
				(33.13)
Share of fees paid	378	0.17	0.24	0.07
				(0.07)

Note: Column (1) reports number of observations. Columns (2) and (3) report the mean for the villagers and for the group of health promoters, respectively. Column (4) reports the difference between columns (2) and columns (3). Standard errors clustered at the household level are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table 2: Adoption and payment - Health promoters adoption rate in network

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post-September 2019	0.136***	0.149***	0.128***
	(0.035)	(0.051)	(0.030)
Peer-promoters' adoption rate	1.193***	2.052***	1.287***
	(0.440)	(0.653)	(0.405)
Post-September 2019 × Peer-promoters' adoption rate	0.022	0.509	-0.099
	(0.329)	(0.453)	(0.284)
Observations	2344	2344	2344
R^2	0.17	0.16	0.17
Mean outcome variable	0.22	0.30	0.19
Post-September 2019	0.108***	0.166***	0.100***
	(0.029)	(0.041)	(0.027)
High peer-promoters' adoption rate	0.106**	0.193***	0.120***
	(0.044)	(0.074)	(0.041)
Post-September 2019 × High peer-promoters' adoption rate	0.096**	0.159**	0.070*
	(0.046)	(0.073)	(0.041)
Observations	2344	2344	2344
R^2	0.17	0.16	0.17
Mean outcome variable	0.22	0.30	0.19

Note: Estimates based on OLS regressions using Equation 2. Estimation sample includes all households interviewed in August 2019, except those including health promoters. Dependent variables are four-month averages. All specifications include individual, household and network characteristics. The full list of controls is presented in Section 5. Standard errors clustered at the household level are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table 3: Adoption and payment - Rate of links with health promoters in network

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post-September 2019	0.219***	0.276***	0.206***
	(0.044)	(0.061)	(0.037)
Rate of peer-promoters	0.396	0.905*	0.459
	(0.320)	(0.514)	(0.287)
Post-September 2019 × Rate of peer-promoters	-0.021	0.357	-0.046
	(0.187)	(0.279)	(0.155)
Observations	2344	2344	2344
R^2	0.15	0.15	0.15
Mean outcome variable	0.22	0.30	0.19
Post-September 2019	0.207***	0.287***	0.188***
	(0.027)	(0.034)	(0.023)
High rate of peer-promoters	0.056	0.154**	0.053
	(0.051)	(0.078)	(0.046)
Post-September 2019 × High rate of peer-promoters	0.015	0.134**	0.016
	(0.038)	(0.059)	(0.032)
Observations	2344	2344	2344
R^2	0.15	0.15	0.15
Mean outcome variable	0.22	0.30	0.19

Note: Estimates based on OLS regressions using Equation 2. Estimation sample includes all households interviewed in August 2019, except those including health promoters. Dependent variables are four-month averages. All specifications include individual, household, and network characteristics. The full list of controls is presented in Section 5. Standard errors clustered at the household level are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table 4: Adoption and payment - Calendar

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post-September 2019	0.165***	0.215***	0.146***
	(0.028)	(0.035)	(0.024)
Calendar	0.146***	0.200**	0.126***
	(0.050)	(0.079)	(0.046)
Post-September 2019 × Calendar	0.075**	0.217***	0.077**
	(0.038)	(0.054)	(0.032)
Observations	2312	2312	2312
R^2	0.17	0.16	0.17
Mean outcome variable	0.23	0.31	0.19

Note: Estimates based on OLS regressions using Equation 3. Estimation sample includes all households interviewed in August 2019, except those including health promoters. Dependent variables are four-month averages. All specifications include individual, household, and network characteristics. The full list of controls is presented in Section 5. Standard errors clustered at the household level are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

A Calendar

Figure A1: Calendar

B Auxiliary results

B.1 Calendar diffusion

In this section we investigate the determinants of calendar diffusion. More specifically, we explore whether households are more likely to receive a calendar if they have a network connection with the promoters, their demographic characteristics and dyadic level characteristics. To that end we employ a dyadic framework, in which we take the directed dyad as the unit of observation, i.e., we do not assume that network connections are reciprocal, and only consider dyads between the village members and the promoters. We estimate the following specification:

$$c_{ij} = \alpha + \beta Link_{ij} + \delta w_{ij} + \alpha_i + \alpha_j + \upsilon_{ij} \tag{4}$$

Let the binary variable c_{ij} denote calendar received by household i from the promoter j. $Link_{ij}$ represents the existence of link between households before the intervention, taking the value of one if i mentioned promoter j as a network partner and zero otherwise. w_{ij} is a vector of variables that describes the relation between i and j, which includes whether the respondents belong to the same ethnic group, same religion, same gender and live in the same neighborhood.

Following de Weerdt, Genicot, and Mesnard (2019), we use a two-way fixed effect model, α_i and α_j, and include a fixed effect for household i and j, respectively. υ_{ij} are dyadic - cluster robust standard errors (Cameron and Miller, 2014).

In order to estimate how the characteristics of nodes influence the diffusion of calendar we drop household i fixed effects and replace it with i's characteristics. Our estimation then is:

$$c_{ij} = \alpha + \beta Link_{ij} + \delta w_{ij} + \theta W_i + \alpha_j + \upsilon_{ij} \tag{5}$$

where W_i include years of education, age, number of household members, household health expenditures in the last 12 months, number of household members that were sick in the last month, number of household members that were sick but did not seek medical help, household vulnerability index, well-being index, asset ownership index, coefficient of risk aversion and previous insurance adoption in the household.

Table B1 shows the results. In column 1, we can observe that being connected with a promoter increases the likelihood of receiving the calendar. The magnitude is 2 percentage points, statistically significant at the 1 percent level. In addition, households are more likely to have a calendar if they belong to the same ethnic group and live in the same neighborhood as the promoter. We are also interested in understanding how individual and household characteristics influence the calendar diffusion. The estimates for the impact of these variables in column 2 have been obtained by dropping household fixed effects. It is interesting to note that having a higher number of household members sick that did not visit a doctor, and a lower well-being index increases the probability of receiving the calendar, while the remaining characteristics do not seem to influence calendar diffusion. These results suggest that promoters may have targeted the distribution of calendars to those households that might benefit more from health insurance.

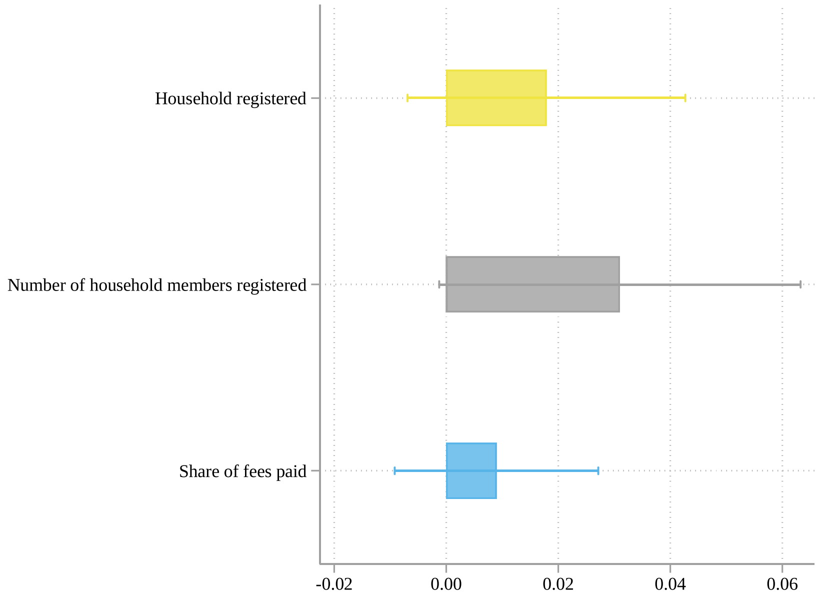
Table B1: Calendar diffusion

	Had a calendar	
	(1)	(2)
Links with promoters	0.020***	0.018***
	(0.006)	(0.004)
Years of education		-0.001
		(0.000)
Age (interval)		-0.001
		(0.001)
Household members		0.001
		(0.001)
Health expenditures without *Mutualidades* (interval)		0.000
		(0.000)
Sick household members		-0.000
		(0.001)
Sick household members not visiting a doctor		0.003*
		(0.002)
Vulnerability index		-0.000
		(0.000)
Well-being index		-0.002*
		(0.001)
Asset index		0.000
		(0.001)
Household registered in *Mutualidades*		0.004
		(0.003)
Risk aversion		-0.000
		(0.001)
Same ethnic group	0.042***	0.007**
	(0.014)	(0.004)
Same religion	0.003	0.002
	(0.005)	(0.003)
Same neighborhood	0.092***	0.092***
	(0.010)	(0.006)
Same gender		0.003
		(0.003)
Observations	31644	31644
R^2		
Mean dep. variable	0.01	0.01
Demographics	yes	yes
Fixed effects household j	yes	yes
Fixed effects household i	yes	no

Note: Estimates based on OLS regressions using Equations 4 and 5. *** p<0.01, ** p<0.05, * p<0.1.

C Placebo test

Figure C1: Placebo test using data from 2018 until August, 2019 - Single difference



Note: Estimates based on OLS regressions using Equation 2, where $Post_t$ is an indicator variable that takes the value equal to one for all the periods after August, 2018. Estimation sample includes all households interviewed in August 2019, except those including health promoters. Dependent variables are four-month averages. All specifications include individual, household and network characteristics. The full list of controls is presented in Section 5. Standard errors clustered at the household level are reported in parentheses.

D Robustness of estimates

D.1 Fixed effects - Household

Table D1: Adoption and payment - Health promoters adoption rate in network

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post-September 2019	0.110***	0.124***	0.102***
	(0.032)	(0.044)	(0.027)
Peer-promoters' adoption rate	1.453***	2.464***	1.337***
	(0.299)	(0.490)	(0.260)
Post September 2019 × Peer-promoters' adoption rate	0.031	0.441	0.008
	(0.266)	(0.407)	(0.223)
Observations	2352	2352	2352
R^2	0.19	0.23	0.21
Mean dep. variable	0.22	0.30	0.19
Post September 2019	0.111***	0.175***	0.102***
	(0.024)	(0.031)	(0.021)
High peer-promoters' adoption rate	0.065***	0.104***	0.063***
	(0.025)	(0.036)	(0.022)
Post September 2019 × High peer-promoters' adoption rate	0.112***	0.202***	0.097***
	(0.034)	(0.049)	(0.030)
Observations	2352	2352	2352
R^2	0.18	0.20	0.20
Mean dep. variable	0.22	0.30	0.19

Note: Estimates based on fixed effect regressions. Estimation sample includes all households interviewed in August 2019, except those in which a health promoter lives. Dependent variables are four-months averages. All specifications include individual, household and network characteristics. The full list of controls is presented in Section 5. Standard errors clustered at the household level are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table D2: Adoption and payment - Rate of links with health promoters in network

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post September 2019	0.217***	0.278***	0.203***
	(0.043)	(0.061)	(0.037)
Post September 2019 × Rate of peer-promoters	-0.014	0.368	-0.039
	(0.186)	(0.278)	(0.155)
Observations	2352	2352	2352
R^2	0.15	0.17	0.17
Mean dep. variable	0.22	0.30	0.19
Post September 2019	0.206***	0.290***	0.186***
	(0.027)	(0.034)	(0.023)
Post September 2019 × High rate of peer-promoters	0.016	0.136**	0.018
	(0.038)	(0.059)	(0.032)
Observations	2352	2352	2352
R^2	0.15	0.17	0.17
Mean dep. variable	0.22	0.30	0.19

Note: Estimates based on OLS regressions using Equations 2. Estimation sample includes all households interviewed in August 2019, except those in which a health promoter lives. Dependent variables are four-months averages. All specifications include individual, household and network characteristics. The full list of controls is presented in Section 5. Standard errors clustered at the household level are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table D3: Adoption and payment - Calendar

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post September 2019	0.164***	0.218***	0.144***
	(0.028)	(0.035)	(0.024)
Post September 2019 × Calendar	0.074**	0.214***	0.076**
	(0.037)	(0.054)	(0.032)
Observations	2336	2336	2336
R^2	0.15	0.18	0.17
Mean dep. variable	0.23	0.30	0.19

Note: Estimates based on OLS regressions using Equations 3. Estimation sample includes all households interviewed in August 2019, except those in which a health promoter lives. Dependent variables are four-months averages. All specifications include individual, household and network characteristics. The full list of controls is presented in Section 5. Standard errors clustered at the household level are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

D.2 Post-Double Selection (PDS) LASSO procedure

Table D4: Adoption and payment - Health promoters adoption rate in network

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post-September 2019	0.110***	0.124***	0.102***
	(0.032)	(0.044)	(0.027)
Peer-promoters' adoption rate	1.453***	2.464***	1.337***
	(0.299)	(0.490)	(0.260)
Post September 2019 × Peer-promoters' adoption rate	0.031	0.441	0.008
	(0.266)	(0.407)	(0.223)
Observations	2352	2352	2352
R^2	0.19	0.23	0.21
Mean dep. variable	0.22	0.30	0.19
Post September 2019	0.111***	0.175***	0.102***
	(0.024)	(0.031)	(0.021)
High peer-promoters' adoption rate	0.065***	0.104***	0.063***
	(0.025)	(0.036)	(0.022)
Post September 2019 × High peer-promoters' adoption rate	0.112***	0.202***	0.097***
	(0.034)	(0.049)	(0.030)
Observations	2352	2352	2352
R^2	0.18	0.20	0.20
Mean dep. variable	0.22	0.30	0.19

Note: This table replicates Table 2. The difference is that specifications individual, household and network-level controls which are selected using the Post-Double Selection LASSO procedure. Standard errors clustered at the household level are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table D5: Adoption and payment - Rate of links with health promoters in network

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post September 2019	0.217***	0.278***	0.203***
	(0.043)	(0.061)	(0.037)
Post September 2019 × Rate of peer-promoters	-0.014	0.368	-0.039
	(0.186)	(0.278)	(0.155)
Observations	2352	2352	2352
R^2	0.15	0.17	0.17
Mean dep. variable	0.22	0.30	0.19
Post September 2019	0.206***	0.290***	0.186***
	(0.027)	(0.034)	(0.023)
Post September 2019 × High rate of peer-promoters	0.016	0.136**	0.018
	(0.038)	(0.059)	(0.032)
Observations	2352	2352	2352
R^2	0.15	0.17	0.17
Mean dep. variable	0.22	0.30	0.19

Note: This table replicates Table 3. The difference is that specifications individual, household and network-level controls which are selected using the Post-Double Selection LASSO procedure. Standard errors clustered at the household level are reported in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

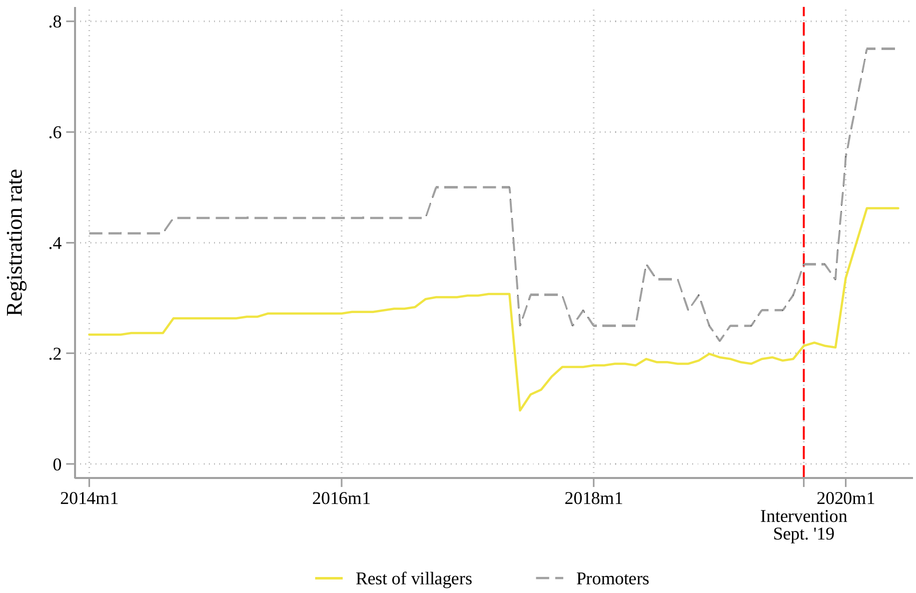
Table D6: Adoption and payment - Calendar

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post September 2019	0.164***	0.218***	0.144***
	(0.028)	(0.035)	(0.024)
Calendar	0.033	0.073	0.017
	(0.049)	(0.071)	(0.042)
Post September 2019 × Calendar	0.074**	0.214***	0.076**
	(0.038)	(0.053)	(0.032)
Observations	2336	2336	2336
R^2			
Mean dep. variable	0.23	0.30	0.19

Note: This table replicates Table 4. The difference is that specifications individual, household and network-level controls which are selected using the Post-Double Selection LASSO procedure. Standard errors clustered at the household level are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

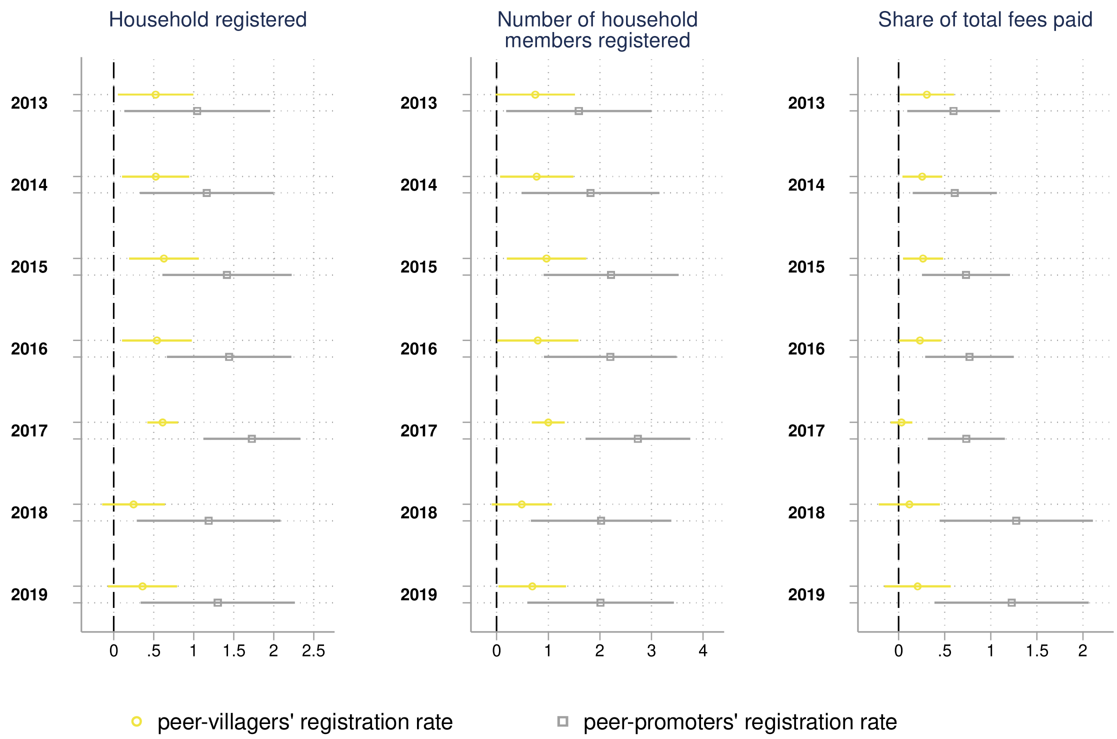
Monthly data

Figure D1: Registration rate over time - villagers vs. health promoters



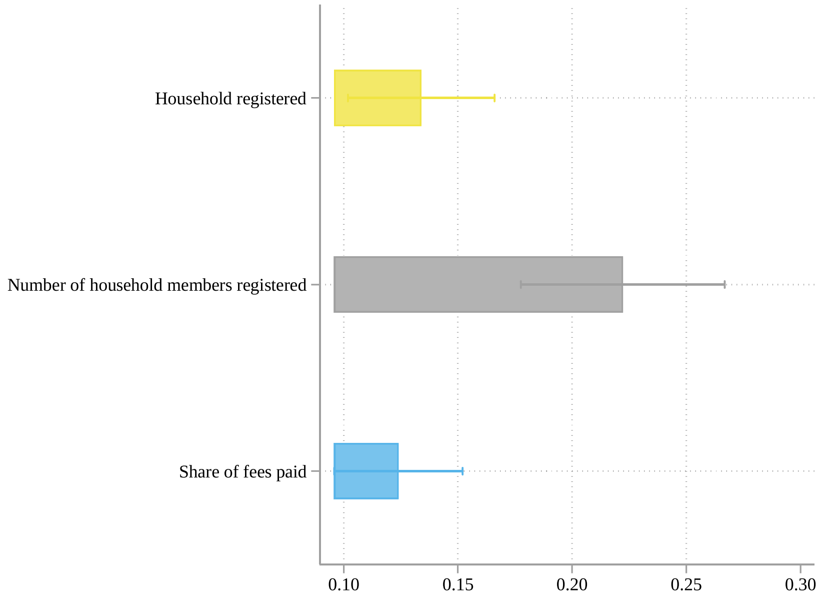
Note: Registration rates over time for the subgroup of health promoters and for the rest of the villagers. Monthly registration rates from September 2013 to July 2020.

Figure D2: Registration over time - network effects on households' registration and payment decisions.



Note: Estimates based on OLS regressions. Top bars in yellow represent the point estimates and the 5 percent level confidence intervals of the interactions between a year indicator variable and the registration rate of peer-villagers. Bottom bars in grey represent the point estimates and the 5 percent level confidence intervals of the interactions between a year indicator variable and the registration rate of peer-promoters. All specifications include year fixed effects and individual, household and network characteristics. The full list of controls is presented in Section 5. Standard errors are clustered at the household level.

Figure D3: Health promoters intervention - Single difference



Note: Estimates based on OLS regressions using Equation 1. Estimation sample includes all households interviewed in August 2019, except those including health promoters. All specifications include individual, household and network characteristics. The full list of controls is presented in Section 5. Confidence intervals are built using statistical significance at the 5 percent level. Standard errors clustered at the household level.

Table D7: Adoption and payment - Health promoters adoption rate in network

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post-September 2019	0.017	0.009	0.026
	(0.025)	(0.034)	(0.022)
Peer-promoters' adoption rate	1.196***	1.927***	1.312***
	(0.416)	(0.606)	(0.391)
Post-September 2019 × Peer-promoters' adoption rate	0.581*	1.157***	0.364
	(0.314)	(0.444)	(0.283)
Observations	8790	8790	8790
R^2	0.15	0.15	0.15
Mean outcome variable	0.21	0.28	0.18
Post-September 2019	0.030	0.065**	0.034*
	(0.022)	(0.028)	(0.020)
High peer-promoters' adoption rate	0.137***	0.226***	0.148***
	(0.040)	(0.066)	(0.037)
Post-September 2019 × High peer-promoters' adoption rate	0.111***	0.159***	0.080**
	(0.039)	(0.058)	(0.036)
Observations	8790	8790	8790
R^2	0.14	0.13	0.14
Mean outcome variable	0.21	0.28	0.18

Note: Estimates based on OLS regressions using Equation 2. Estimation sample includes all households interviewed in August 2019, except those including health promoters. All specifications include individual, household and network characteristics. The full list of controls is presented in Section 5. Standard errors clustered at the household level are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table D8: Adoption and payment - Rate of links with health promoters in network

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post-September 2019	0.154***	0.198***	0.149***
	(0.037)	(0.047)	(0.032)
Rate of peer-promoters	0.445	0.910*	0.482*
	(0.302)	(0.471)	(0.274)
Post-September 2019 × Rate of peer-promoters	-0.092	0.120	-0.114
	(0.158)	(0.212)	(0.135)
Observations	8790	8790	8790
R^2	0.11	0.11	0.11
Mean outcome variable	0.21	0.28	0.18
Post-September 2019	0.134***	0.190***	0.124***
	(0.023)	(0.028)	(0.021)
High rate of peer-promoters	0.062	0.150**	0.058
	(0.048)	(0.072)	(0.044)
Post-September 2019 × High rate of peer-promoters	0.002	0.072	0.002
	(0.033)	(0.046)	(0.029)
Observations	8790	8790	8790
R^2	0.11	0.11	0.10
Mean outcome variable	0.21	0.28	0.18

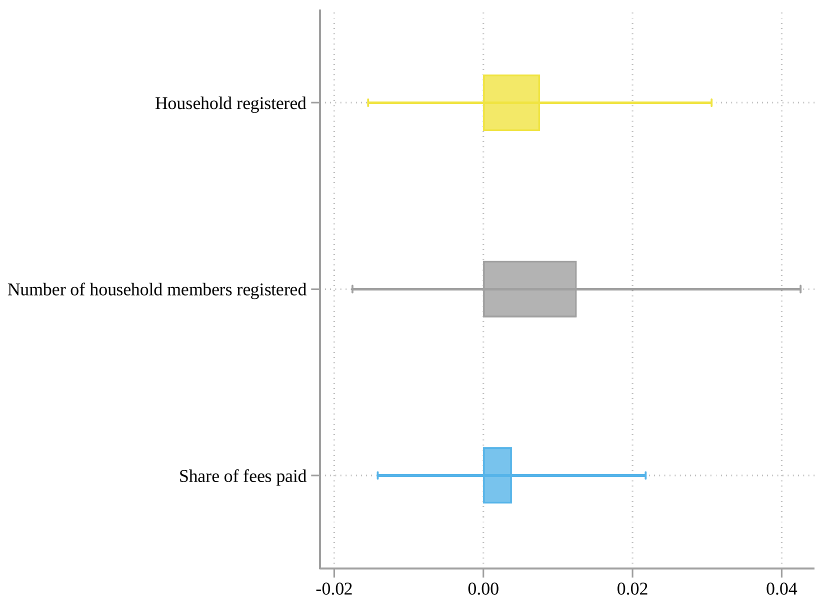
Note: Estimates based on OLS regressions using Equation 2. Estimation sample includes all households interviewed in August 2019, except those including health promoters. All specifications include individual, household and network characteristics. The full list of controls is presented in Section 5. Standard errors clustered at the household level are reported in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table D9: Adoption and payment - Calendar

	Household registered	Number of household members registered	Share of total fees paid
	(1)	(2)	(3)
Post-September 2019	0.103***	0.134***	0.093***
	(0.023)	(0.026)	(0.020)
Calendar	0.137***	0.181**	0.122***
	(0.049)	(0.075)	(0.045)
Post-September 2019 × Calendar	0.047	0.141***	0.047*
	(0.032)	(0.042)	(0.028)
Observations	8670	8670	8670
R^2	0.12	0.12	0.12
Mean outcome variable	0.21	0.28	0.18

Note: Estimates based on OLS regressions using Equation 3. Estimation sample includes all households interviewed in August 2019, except those including health promoters. All specifications include individual, household and network characteristics. The full list of controls is presented in Section 5. Standard errors clustered at the household level are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Figure D4: Placebo test using data from 2018 until August, 2019 - Single difference



Note: Estimates based on OLS regressions using Equation 2, where $Post_t$ is an indicator variable that takes the value equal to one for all the periods after August, 2018. Estimation sample includes all households interviewed in August 2019, except those including health promoters. All specifications include individual, household and network characteristics. The full list of controls is presented in Section 5. Standard errors clustered at the household level are reported in parentheses.