Demand for Health Insurance: Financial and Informational role of Informal Networks

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Abstract

With an aim to increase healthcare access for poor households, many state and national governments, in India, have introduced free health insurance programs. At more than 50%, India has one of the world's highest out-of-pocket healthcare expenditure rates. It is then a puzzle that the utilization of many of these programs remain low. In this paper, we study the role of informal risk-sharing networks in explaining insurance-adoption behavior in the context of the *Arogyasri* health insurance program introduced in the erstwhile state of Andhra Pradesh between 2007 and 2008. We use household panel data from the Young Lives Survey (YLS) conducted between 2002 and 2016 to empirically study how the adoption of Arogyasri among poor households respond to their access to financial assistance from informal networks. We find that adoption and utilization are significantly higher for households with access to informal financial networks. However, adoption and utilization increases much more for households outside informal networks, after they experience health shocks. Information sharing role of informal networks do not seem to affect the decision to adopt insurance. We develop a simple theoretical framework to discuss the potential mechanisms through which informal network might affect adoption and utilization of formal health insurance. While public insurances are free, adoption and utilization involve pecuniary as well as non-pecuniary costs. We argue that for a given probability of receiving an idiosyncratic health shock, risk neutral individuals with heterogeneous costs, adopt the insurance only if they expect positive net benefits. Hence, households are more likely to adopt after receiving a shock since expected probabilities of future shocks go up. However, for individuals belonging to informal networks, financial implications of individual idiosyncratic shocks are borne by the entire network, either partly or fully. Hence, it is in the interest of the informal network to ensure that network members

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adopt and utilize the free insurance. We find considerable heterogeneity in these baseline effects. They primarily emanate from households without access to medical facilities. This suggests that informal networks facilitate adoption and utilization by reducing individual heterogeneity and uncertainty in pecuniary costs.

Keywords: health insurance; informal network; Adoption; Utilization; Demand

JELcodes: I13, I18,O17

1 Introduction

A staggering 14% of households in lower-middle income countries incur health expenditure that exceeds 10% of household income (WHO, 2023). Different countries have tried different delivery mechanisms for healthcare. While some have opted for public provision other have implemented different models of insuring the public where healthcare is provided privately. Over time, the emphasis of health policies moved from free provisioning of health care to arranging free health insurance that can pay for treatment at the private facilities. However, free health insurance programs run by different governments (central and state) did not see much success as the enrolment rate in most of such programs remained low. In this paper, we examine the role of community network in taking up of such insurance policies. Understanding the role of community network as it provides informal insurance and disseminates information regarding any government programs including insurance.

In India, the traditional approach of the government was to provide subsidized healthcare at public facilities. However, like in most developing countries, in India also public healthcare has suffered from overcrowding, crumbling infrastructure, staff shortage, chronic funding shortfall, lack of equipment and medicines among others (Mavalankar et al., 2003). While the private market has co-existed, the high out of pocket (OOP) expenditure for private healthcare makes it difficult to access for poor households. At more than 50%, India has one of the world's highest OOP healthcare expenditure rates. This unequal delivery system led to substantial and rising levels of health inequity that have been widely documented (Balarajan, Selvaraj, and Subramanian, 2011; Joe, Mishra, and Navaneetham, 2008). The segregation was made worse by the fact that less than 10% of the Indian population was covered by any form of health insurance (2007 report of the planning commission). Faced with a high demand for tertiary healthcare and an overburdened public healthcare infrastructure, India, along with many other developing countries, adopted a model of public-private-partnership where the government will pay the insurance premium for low-income households who will be covered by the insurance at various government and private hospitals. (Debnath and Jain, 2020). Since mid 2000, the central government and several state governments introduced these schemes across India.

With high demand for private healthcare, large out of pocket health expenditure and increasing demand for tertiary healthcare, it is then a puzzle that adoption, particularly utilization, of these free insurance programs offering subsidized private healthcare remains low. For instance, in our sample roughly 7% of the households utilized the health insurance scheme under study, even though 32% of the households experienced some health shock over the study period (see 3 for details).

The broader literature on low adoption of insurance products in low-income countries indicate co-payments and high insurance premium as important constraints preventing wider take-up.(Gaurav, Cole, and Tobacman, 2011). Other papers point to the possibility of a crowding out. For instance, Rosenzweig, 1988 finds that the extent of informal consumption smoothing arrangements reduces a household's engagement in formal mechanisms to reduce income risk.

However, the conventional theories of insurance demand do not explain lack of adoption of publicly financed free health insurance. Some have noted information constraints, ease of use and transportation costs as potential barriers to a wider utilization of insurance products even if they are subsidized. (Banerjee, Duflo, and Hornbeck, 2014; Debnath and Jain, 2020)

We investigate the role of informal networks in adoption of free public health insurance in India. An important aspect of insurance, in general, in the context of low-income countries is the presence of informal risk sharing strategies. There is a large literature that document the role of informal networks in mitigating shocks, both aggregate and idiosyncratic, either through direct transfers or through informal credit (Dror and Firth, 2014; Townsend, 1994). We ask whether and how these informal risk-sharing networks affect the adoption of market based insurance products even when there is no explicit adoption cost.

We investigate this question in the context of the *Arogyasri* health insurance program introduced in the erstwhile state of Andhra Pradesh between 2007 and 2008. We use household panel data from the Young Lives Survey (YLS) conducted between 2002 and 2016 to empirically study how the adoption of Arogyasri among poor households responded to their access to financial assistance and information from informal networks. We exploit the longitudinal nature of the data, along with a rich set of information on social, economic and demographic characteristics of households, to account for unobserved household heterogeneity. We find that adoption is significantly higher for households with access to informal financial networks. However, adoption increases for households outside these informal networks, after they experience health shocks. We do not find any evidence to support the informational role of informal networks in the adoption of this program. We find considerable heterogeneity in these baseline effects. Overall, the effects of the informal financial network are stronger when healthcare facilities are far away. This suggests that informal networks facilitate adoption by reducing individual heterogeneity in indirect costs like transportation.

Our paper is most closely related to Debnath and Jain, 2020 and Jowett, 2003. Both study the effect of informal networks on the adoption of subsidized or free public health insurance. Jowett, 2003 shows that informal networks crowd out subsidized formal public health insurance. Debnath and Jain, 2020, on the other hand, find that informal networks facilitate adoption of free insurance products and propose that informal networks help in information dissemination enabling network members to adopt the program. In our work, we explore this mechanism further and distinguish between information and financial networks. We do not find any evidence in support of the information dissemination role of informal networks. Instead we find that informal financial networks facilitate adoption of the insurance product.

To understand why informal financial networks enable insurance adoption we provide a simple theoretical framework. We argue that idiosyncratic shocks to individual network members have financial implications for all members in a risk-sharing network. Hence, it is in the interest of the informal network to ensure that all members take up the free insurance. In our model, people are different in terms of their perceived probability of a bad shock. We also assume that even though government insurance does not involve any premium, taking up of insurance involves some transaction costs. Therefore, an individual will only take up insurance if the expected cost of a bad shock is greater than the transaction cost of enrolling for insurance. Each individual has a different belief regarding the possibility of a bad shock and therefore, for every individual the expected cost of a bad shock assumes a different value.

If an individual is not a member of network she takes the decision by comparing her personal cost of bad shock with the (transaction) cost of insurance. We argue that the decision rules are quite different for the community members. If a community member does not take up insurance, in the event of a bad shock, his losses are compensated by his financial network. For example, suppose a member without insurance is met with an accident, loses her job and cannot repay the loan she took from other members. In such an event, the cost of not taking up the insurance gets transferred to the lenders. This is why, in our theory, a community evaluates the expected cost associated with a bad shock using some community level perception of the shock. The community level perception is like norm which could be an arbitrary belief, some past prior or the average perception. We have taken the latter approach and used the average value of the perceived probability to calculate the community level expected value. If the expected cost of the shock at community level is higher than that of the enrolment cost, every member of the community has to enrol for the insurance even if their individual beliefs indicate otherwise.

Hence, community members go for either of the corner solutions, either everyone takes up insurance or no one does. Non-members on the other hand, go for an interior solution with only a fraction of them taking up insurance. Our empirical results corresponds to the case where all members take up insurance making a member more likely to adopt insurance than a non-member. In our empirical section, we examine two more decisions – post-shock take up of insurance and utilization. Both hypotheses follow the same structure of analysis described above. In case of a non-member they do whatever is best for their individual pay-off while for members, they have to follow the community norm. We postulate that the community force its members to enrol for insurance as long as the community level expected benefit is more than the community level cost. Our empirical results are consistent with this theoretical results.

Our results make considerable departure from the existing literature which by and large postulates that community network facilitates insurance adoption by providing more information that reduces the transaction cost for enrolment. We, in this paper, disentangle the effect of information and financial effect and find that while membership in a financial network has a positive effect on the take up of free, public insurance, membership in an information network has no significant effect. The papers which found negative effect of network on take up, interpret the result as a crowding out effect where networks work as substitute for formal insurance. Our results indicate the opposite and we argue that a community being the fall back option for the members, encourages its members to take up public insurance which in turn reduces the financial burden of the community network. Consequently, our paper – that sees informal insurance as complementary to formal insurance – provides policy suggestions which are radically different from the ones coming from the existing literature.

Our paper is organised as follows. In section 2, we discuss the context of our study. In section 3, we summarize the data used for the empirical analysis. In section 4, we outline the empirical model and in section 5 we present the empirical findings. In section 6, we present a theoretical framework to understand the mechanisms. Finally, section 7 concludes the paper.

2 Policy Background

We study adoption in the context of the Rajiv Aarogyasri (RAS) health insurance scheme. RAS was introduced in 2007 for the state's BPL population by the government of undivided Andhra Pradesh, with an initial allocation of Rs.50 Cr. The scheme started on a pilot basis from 1st April,2007 in the poorest three districts of the state- Anantpur, Mahaboobnagar,and Srikakulam, and was extended in a phased manner to all the districts by 17th July,2008 (AHCT, 2009, AHCT, 2022). Aarogyasri Health Care Trust was set up as the concerned nodal agency for this scheme. After bifurcation of the state into Andhra Pradesh and Telengana, the scheme became known as Aarogyasri in Telengana, and Dr. YSR Aarogyasri in Andhra Pradesh.

This cashless health insurance scheme (Debnath and Jain, 2020) is operated on a public private partnership model, with the government paying the premium and incurred hospital bill (Yellaiah, 2013) on behalf of the beneficiary, while empanelled government and private hospitals implement the scheme (Reddy and Mary, 2013). The scheme covers 942 and 1044 listed therapies as part of inpatient service in telengana and Andhra Pradesh respectively (AHCT, 2022). However, no outpatient service is included in the scheme. The scheme covers pre-existing diseases, pre- and post-hospitalisation requirements, and free follow up services for patients under 125 follow-up packages (Aarogyasri, 2013). Poor families considered BPL by civil supplies department of state governments are deemed eligible for the scheme and are given Rajiv Aarogyasri Health Card. A total coverage of Rs. 2 lakhs per family per annum is provided on a floater basis, i.e, either the family can collectively use the amount or individual family member can utilise the amount. The scheme does not involve any deductibles or co-payments. In situations where cost of treatment exceeds coverage, a buffer amount is also provided on a floater basis.

Government and private hospitals who satisfy the standards of infrastructure, service, personnel, an equipment are deemed eligible to be empanelled. Upon verification of details, a hospital would be empanelled and would thereafter be known as network hospital. The hospital would then be required to provide listed medical services under pre-specified package rates. Network hospitals are required to undergo medical audit. In case of unsatisfactory performance, the provider would be referred to Disciplinary committee. Network hospitals are obligated to provide for registration and reception for Aarogyasri beneficiaries through Aarogyamithra, as well as, separate out-patient facility and ward for beneficiaries. The beneficiaries are to be provided quality food free of charge and offered follow-up treatment from those listed by the scheme. Empanelled hospitals are to ensure that Aarogyasri beneficiaries are not refused admission if it offers the required listed therapy.

In order to receive treatment, a beneficiary can approach either (1) Aarogyamithra counter at primary health centre (PHC), or (2) health camp organised by PHC or network hospital (NWH), or (3) NWH. In a PHC, after initial registration by the Aarogyamithra, the beneficiary is attended at the out-patient ward. If the situation requires tertiary care for a listed therapy, the beneficiary is referred to a relevant NWH. Otherwise, they are given medicines and discharged. In case of referral, various details of the beneficiary is noted by the Aarogyamithra and communicated to the concerned Aarogyamithra of the referred NWH. Similar process is followed at health camps. If beneficiary directly approaches a NWH, after initial registration by the network Aarogyamithra (NAM), they are attended at exclusive Aarogyasri out-patient ward and are offered medical investigations if necessary. If the case is suited for out-patient, the patient is discharged after giving diagnosis and prescription. If the case requires tertiary care under some listed therapy, it is converted to in-patient. For treatment under listed therapy, the NWH is required to submit pre-authorization through the Trust portal and deliver treatment. The beneficiary, at the time of successful discharge, receives a discharge summary, post-discharge medication and counselling regarding follow-up treatment. The scheme further requires that the beneficiary be reimbursed for transport charges. After 10 days since successful discharge of the beneficiary, the NWH is permitted to raise the claim.

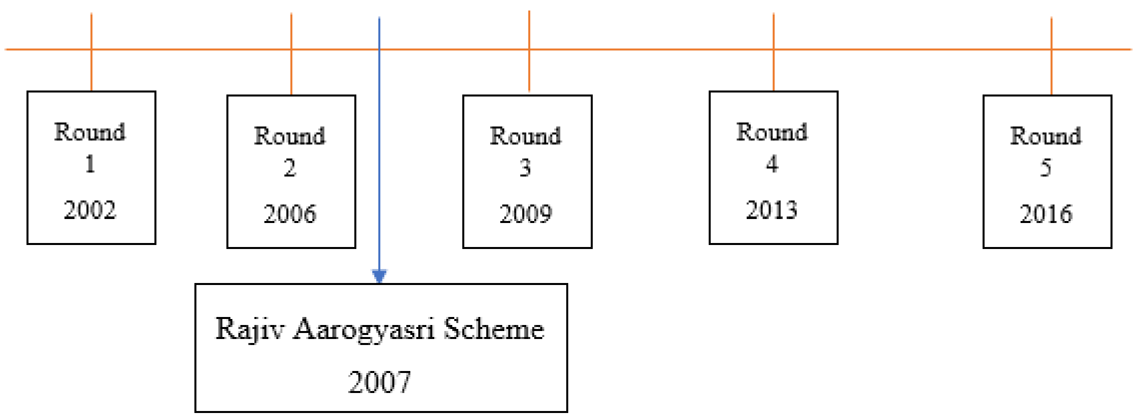
3 Data

3.1 Data source

We use the Young Lives Survey (YLS) panel data from the current day Indian states of Andhra Pradesh and Telengana for our study. The Young Lives is a study on childhood poverty, following 3000 children (referred to as the YL child), one from each household, across the states of Andhra Pradesh and Telengana, over a period of 15 years. Three regions across the two states are surveyed: Rayalaseema, Coastal Andhra, Telengana. (Young-Lives, 2017) The data are available over five rounds between 2002 and 2016. A timeline of the survey and introduction of RAS is presented in Figure 1. The data contain detailed information on the YL child, household, and community characteristics, including questions on adoption of the government health insurance program, Rajiv Aarogyasri. The Rajiv Aarogyasri health insurance scheme (RAS) was introduced in 2007. In the YLS data, rounds 1 and 2 cover a period prior to the introduction of RAS and rounds 3 to 5 cover a period post the introduction of RAS. We consider rounds 2 to 5 for our study. While information on insurance adoption is available from round 3, we use round 2 for lagged information wherever relevant. Moreover, while the data follow 3000 children, with 1000 belonging to old cohort (aged 8 years at the beginning of the survey) and 2000 belonging to young cohort (aged 1 year at the beginning of the survey), we focus on only the young cohort for our analysis. These two cohorts have been surveyed to explore different aspects of childhood poverty and hence have focused on different variables. The variables that we seek to study are primarily available in young cohort, which is why we consider this cohort for our analysis.

We favour the use of the Young Lives panel data over other sources of household level panel data sources such as the India Human development Survey (IHDS) or the National Family Health Survey (NFHS) (Desai and Vanneman, 2010; Desai and Vanneman, 2018). While all three of these datasets have information on health insurance, the NFHS data do not contain any information on informal networks. The IHDS, while has information on whether household has taken loans from informal sources, their measure of informality is only an ex-post one. The data does not contain any information on ex-ante measure of informal financial network, such as whether a household intends to use informal financial support. Such ex-post measure of informal financial network limits our study to only a subsample of households that have actually faced financial exigencies and risks making our measure of informality less comprehensive. Moreover, the IHDS contain information only on whether anyone in the household has health insurance, and not on actual utilisation of health insurance. The data also does not always distinguish between government and private health insurance.

Figure 1: Timeline of Young Lives survey rounds and Rajiv Aarogyasri Scheme

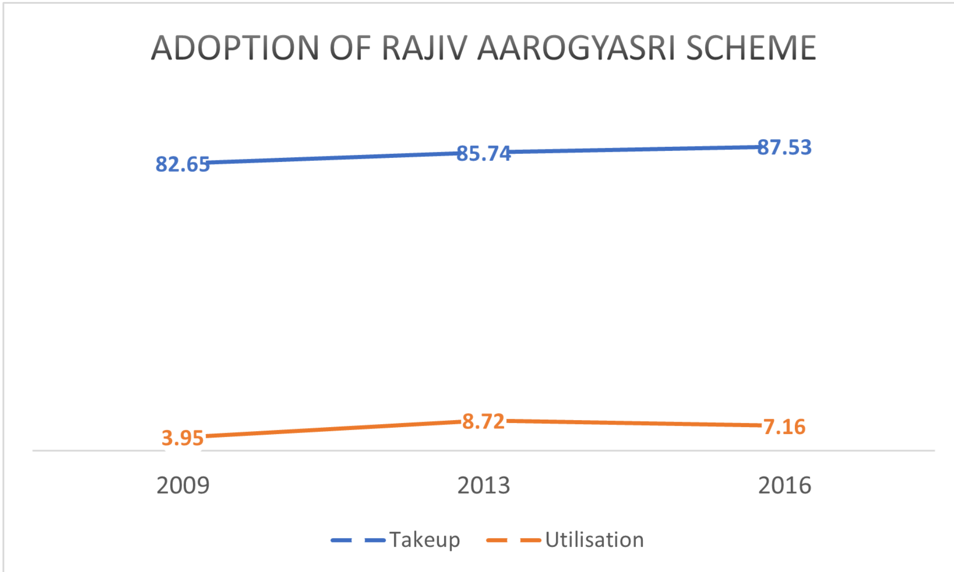


3.2 Insurance Adoption

The objective of our paper is to investigate household's adoption behavior of a free health insurance product, specifically the RAS. Adoption of a health insurance program has two aspects: whether a household has registered for the scheme, and whether a household has utilised the scheme. We use the terms take-up and utilisation, respectively, to refer to these two aspects. The measure of take up is based on the question on whether a household has Rajiv Aarogyasri card. The response is coded as a binary variable. The measure of utilisation is based on the question on whether Rajiv Aarogyasri benefits have been accessed by the household, the response to which, is coded as a binary variable.

Figure 2 shows change in adoption of RAS over the three rounds, starting from round 3 in 2009, up to round 5 in 2016.

Figure 2: Adoption of Rajiv Aarogyasri Scheme



Notes: Figures reported are in percentages. Figures for utilisation are for households with RAS

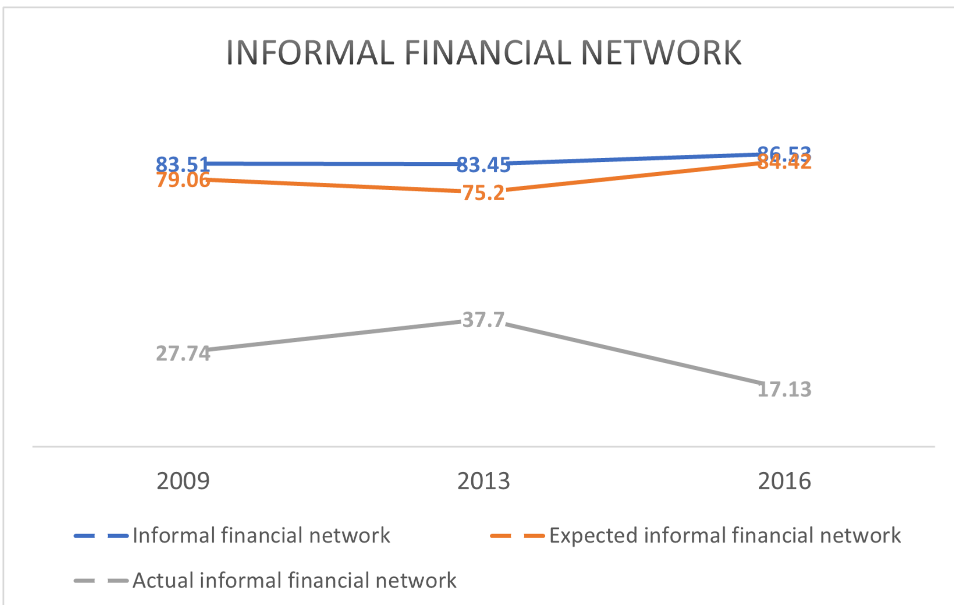
Take-up of RAS increases steadily over the three rounds although the initial extent of take-up is very high at 82% in 2009, within two years of the program's introduction in 2007. However, While take up has steadily increased over the years, utilisation of RAS has been low. This is even when 32% of the households in our sample experienced health shock to at least one member since 2007. We define health shock as any transitory episode of illness, excluding long-term health problems and permanent disabilities. Such low levels of utilisation has been attributed to non-listed therapies, low quality of services under RAS and remote location of beneficiary's residence (Rao et al., 2012; Mannuru, 2019; Debnath and Jain, 2020). We explore the extent to which it is explained by pre-existing informal ways of risk mitigation, as is common in underdeveloped rural communities across the world.

3.3 Informal network

The prevalence of informal network for risk mitigation in village economies with underdeveloped financial markets is well known (Townsend, 1994). In case of health shocks, informal networks can play a dual role of providing financial assistance and/or facilitating information dissemination (De Weerdt and Dercon, 2006; Devillanova, 2008). Hence, we define informal networks along these two dimensions.

The measure of informal financial network is based on two questions: how the household would raise money in one week, and how the household responded to a shock. For the question on how the household would raise money, households that responded that they would be relying on relatives and friends in their own community, or relatives and friends in another community, or on informal loan, were deemed to have informal financial network. Similarly, for the question on how the household responded to shocks, households that responded to having relied on the community, or on relatives and friends, were deemed to have informal financial network. While the former is treated as a measure of expected informal financial network, the latter is considered as a measure of actual informal financial network. The measure of informal financial network used in the paper combines the expected and the actual and treats the presence of either expected financial network, or the presence of actual financial network, or both, as the household having informal financial network. Proportions of households having access to informal financial networks during the period 2009-2016 are shown in Figure 3. At 83%, a large fraction of households have access to some form of informal financial network. While expectations seem to be very optimistic compared to actual assistance received, we must note that actual assistance is conditional on receiving a shock.

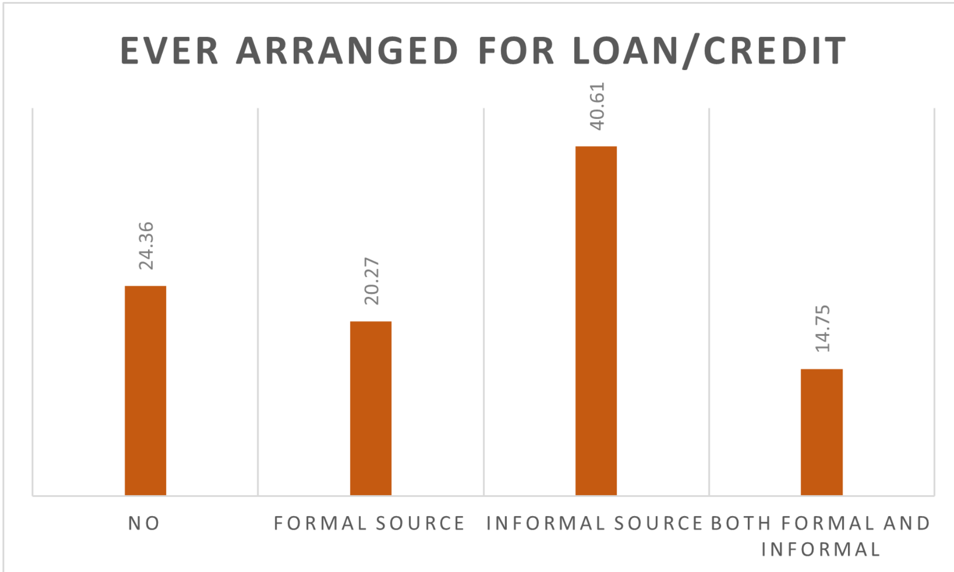
Figure 3: Informal financial network



Notes: Figures for actual and expected financial network are for all households in the sample.

There can be some concerns regarding whether response to the question on how household would raise money in one week, can be an appropriate measure of expected informal network. It can be argued that households might expect to rely on informal networks only as a temporary emergency measure, and not as an alternative to formal financing. In this context we offer suggestive evidence that the question on how household would raise money, does indeed reflect household's reliance on informal network. In particular, we argue that if households with expected informal network, based on the above question, do in fact rely less on formal credit, then our measure can be considered appropriate.

Figure 4: Ever arranged for loan/credit

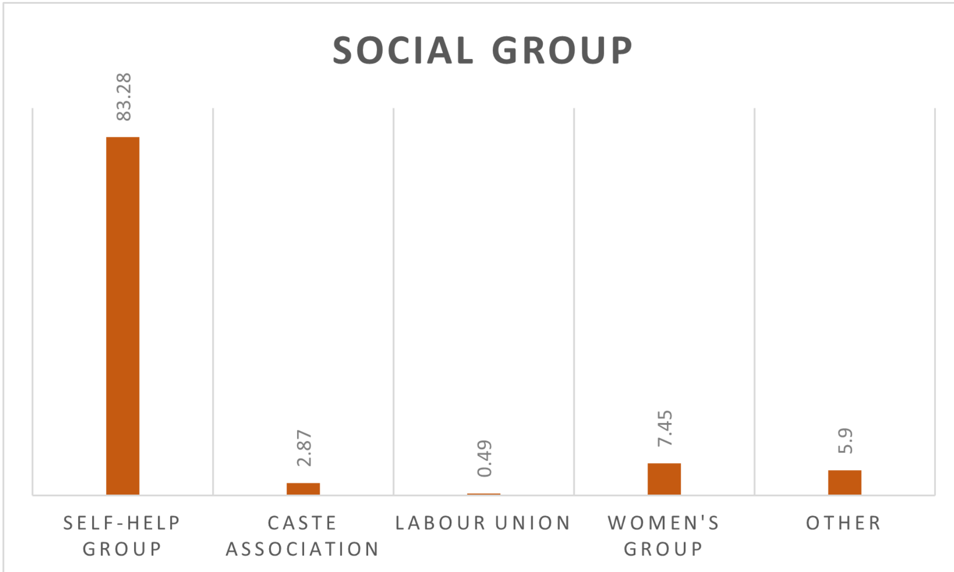


Notes: Figures reported are in percentages. Sample includes households with expected informal financial network.

Figure 4 considers households' expectation of access to informal financial assistance and shows proportions of these households who had to arrange for a loan or credit in the last 12 months. Amongst these households, around 20% relied exclusively on formal source, while around 40% relied on informal source of financing and 14% relied on both. The figure indicates that households with expectations of informal financial assistance indeed rely less on formal sources of financing.

Two distinct measures are used to gauge the presence of informal information network. One measure indicates whether any member of the household is part of any social group. The social groups considered in the data are primarily self-help groups, although, labour unions, occupational groups and caste associations are also included. Households having at least one member as a part of a social group is considered to have access to group membership. A large majority of households are associated with SHGs as shown in Figure 5. The second measure indicates the extent of community engagement of the household. In our data, community refers to the village (for rural areas) or municipal wards (for urban areas) of residence (Young-Lives, 2017). If any member of the household has talked to other members of the community about a problem, or taken action with other members of the community, or taken part in awareness raising campaign, or taken part in protest march or demonstration, or any combination of the four engagements, then the household is considered to have access to community engagement.

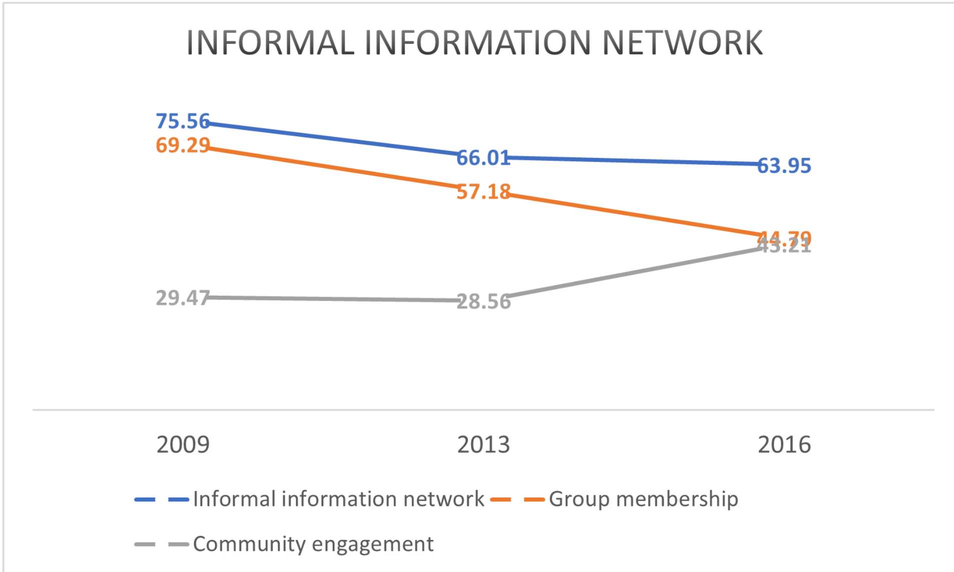
Figure 5: Social Groups



Notes: Figures reported are in percentages. Figures are for households with at at least one member part of any group.

Based on these two dimensions, a composite measure of informal information network is constructed. A household is said to have access to informal information network if they have access to either group membership, or community engagement, or both. Figure 6 presents proportions of households having access to informal information network during the period 2009-2016.

Figure 6: Informal information network



Notes: Figures reported are in percentages. Figures for group membership and community engagement are for all households in the sample.

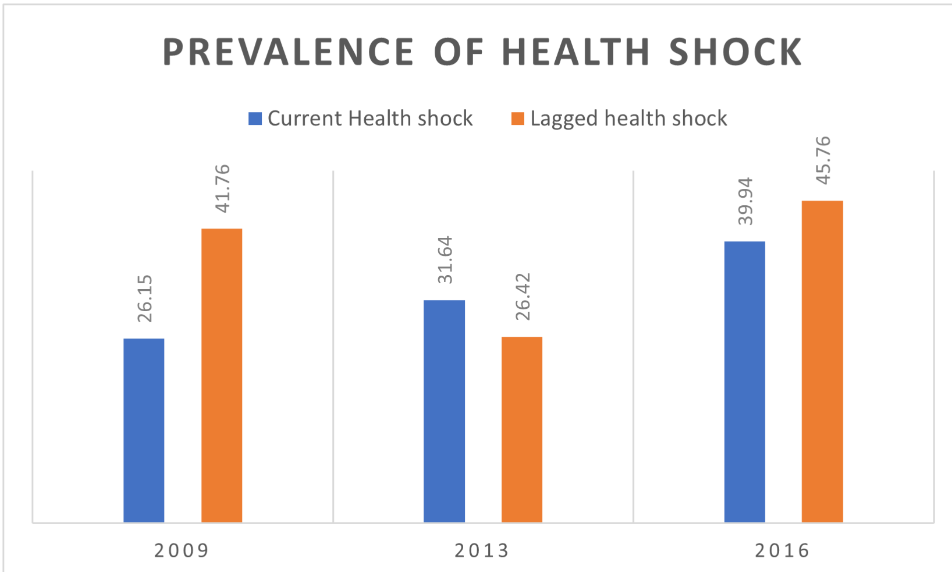
Proportion of households having access to informal information network has experienced a decline over the period of the study. This decline is driven by a fall in group membership. This is in contrast to community engagement which has seen an increase between 2009 and 2016.

While theoretically we keep the financial and informational network distinct, in reality networks play multiple roles and hence it is difficult to keep them separate. Table 1 shows the distribution of informal financial network and informal information network in our study sample and the overlap between the two types of networks. There appears to be considerable a overlap between informal financial network and informal information network. Hence, in our empirical analysis we account for the overlap by including both information and financial network simultaneously in our regression specifications.

3.4 Health shock

We expect the effect of informal network on adoption to be moderated by experience of illness of the household. Thus, we also consider the presence of health shock in our analysis. We consider both current health shock and lagged health shock for this purpose. A household is considered to have faced lagged health shock if severe illness has been experienced by either the YL child, or their father or mother, or any other member of the household in the previous round. Similarly, we define current health shock to have occurred in the present round to the household. However, due to restrictions imposed by the data, we are forced to consider only health shock faced by the child in the current round. Prevalence of current health shock and lagged health shock has been shown in Figure 7. A sizable fraction of households in our sample are seem to have experienced severe illness over the period under study. Severe illness have been seen to affect both the YL child and rest of the members of the household.

Figure 7: Health shock



Notes: Figures reported are in percentages

4 Empirical Specification

To understand how informal networks influence the adoption of formal insurance products we estimate a household fixed effects model using panel data from the Young Lives Survey. The identification of the effect rests on the assumption that inclusion of household fixed effects controls for time invariant household specific unobserved characteristics, such as risk preference, social and religious associations, that can affect both network formation and adoption of formal health insurance. Apart from household specific time invariant characteristics, there can also be time specific factors like community wide covariate shocks that can affect both network formation and adoption of formal health insurance. To account for such time specific factors, we also include time fixed effects in our empirical specification. However, in addition, there can be household level time varying factors that can confound our estimates. We account for a wide range of time varying household characteristics which are discussed below.

4.1 Baseline

Informal networks can perform two distinct roles: financial transfers and information dissemination. We study the effects of these two types of networks separately. Furthermore, adoption of formal health insurance has two aspects: take up and utilisation. Therefore, we study the effect of each type of network on the two aspects of adoption independently.

We estimate the effect of informal network, conditional on health shock, on the probability of adoption of formal health insurance through the following empirical specifications:

$$Takeup_{it} = \beta_{10} + \beta_{11}N_{it} + \beta_{12}N_{it} * HS_{i,t-1} + \beta_{13}HS_{i,t-1} + \gamma_1 X_{it} + \alpha_i + \delta_t + u_{1it} \quad (1)$$

and

$$Utilisation_{it} = \beta_{20} + \beta_{21}N_{it} + \beta_{22}N_{it} * HS_{it} + \beta_{23}HS_{it} + \gamma_1 X_{it} + \alpha_i + \delta_t + u_{2it} \quad (2)$$

where N stands for Financial network or Informational network. Equations 1 and 2 capture the effect of network(financial or informational), in the presence of a health shock, on the probability of take-up and utilisation respectively. N_{it} is a binary variable that indicates whether household i has access to informal network (financial or informational) in round t. β_{11} and β_{21} measure the independent effects of financial network on take-up and utilisation respectively. $HS_{i,t-1}$ is a binary variable that indicates whether the household has faced any health shock in the previous round, and its independent effect on take-up is captured by β_{13}. HS_{it} is a binary variable that indicates whether household has faced any health shock in the current period, and its independent effect on utilisation is captured by β_{23}. It is important to note the difference between these two specifications in terms of the use of health shock. For take-up, a health shock in the recent past can induce households to make a choice on whether or not to register for formal health insurance going forward. For this reason, we consider the presence of health shock in the previous period while studying the effect of financial network on take up. On the other hand, occurrence of a current health shock would be more relevant for utilisation since utilisation can happen only when the household is already registered and must be utilized at the time the shock happens. For this reason, we consider presence of health shock in the current period while studying the effect of informal network on utilisation. We account for time-invariant household specific characteristics and round specific characteristics through inclusion of household fixed effects, α_i, and round fixed effects, δ_t, respectively.

In addition to household fixed effects and year specific effects, we control for time varying household characteristics that are likely to be correlated with insurance adoption decisions as well as a household's association with an informal network, financial or informational. X_{it}

is a matrix of these time-variant household specific control variables. Specifically we account for three categories of correlates: economic characteristics of the household, demographic characteristics of the household, and access to other government safety nets. The economic characteristics that are controlled for in our analysis are whether the household is primarily an agricultural household, amount of landholding and livestock ownership, consumption class and wealth level of household. Demographic characteristics such as presence of educated child in the household and age of household head are also controlled for in our analysis. Furthermore, we take account of whether a household has access to other government safety net such as NREGS. A description of the included variables can be found in Appendix Table A1.

Table 2 provides a summary of households based on their insurance status. As regards, economic characteristics of households, a greater proportion of households with RAS are found to be engaged in agriculture as their primary occupation and have higher livestock holding, even though households with and without RAS have similar extent of landholding and both are primarily small landholders with less than 2 acres of land. Further, the households with insurance are characterized by lower average consumption and lower levels of wealth compared to households without RAS.

In terms of demographic characteristics, almost all the households have children who are enrolled in school education. There is also not a significant difference in the fraction of children enrolled in higher education, between the insurance takers and non-takers. Average age of household heads is found to be similar across these two types of household. Apart from this, a greater proportion of households with RAS are found to have access to other government programs such as NREGS, compared to households without RAS.

Compared to households without RAS, a greater proportion of households with RAS are found to be situated in rural areas, and in areas lacking medical facilities. A greater proportion of households with RAS belong to socially underprivileged communities, compared to those without RAS.

4.2 Overlap

As reported in Table 5, a significant proportion of households have access to both informal financial network and informal information network. Substantial overlap between financial network and information network gives rise to the possibility that our estimates for financial network also includes the effect of information network and vice-versa. To address this problem, we consider a specification where probability of adoption of formal health insurance is regressed on both financial network and information network. Equations 3 and 4 outline this new specification.

$$Takeup_{it} = \beta_{30} + \beta_{31}FN_{it} + \beta_{32}FN_{it} * HS_{i,t-1} + \beta_{33}HS_{i,t-1} + \beta_{34}IN_{it} + \beta_{35}IN_{it} * HS_{i,t-1} + \gamma_{31}X_{it} + \alpha_i + \delta_t + u_{3it} \quad (3)$$

and

$$Utilisation_{it} = \beta_{40} + \beta_{41}FN_{it} + \beta_{42}FN_{it} * HS_{it1} + \beta_{43}HS_{it} + \beta_{44}IN_{it} + \beta_{45}IN_{it} * HS_{it} + \gamma_{41}X_{it} + \alpha_i + \delta_t + u_{4it} \quad (4)$$

Equations 3 and 4 allow us to isolate the effect of one type of informal network by controlling for the effect of the other type of informal network. As in earlier cases, we further augment the equation by including time-variant household specific control variables, household fixed effects, and round fixed effects.

In all our specification discussed above, behavior of households within the same cluster are likely to be correlated. The sampling design of the Young Lives survey suggests that a random sample of communities were selected out of all the available communities within each region under a district, and at the next stage, households were randomly selected from these sampled communities (Young-Lives, 2017). Based on this design and following Abadie et al., 2023, we cluster standard errors at community-round level across regressions 1 through 4. Based on this criterion, there are about 500 clusters in our study sample, which allays concerns related to small number of clusters Cameron, Gelbach, and Miller, 2008).

5 Results

5.1 Baseline

Table 3 presents OLS estimates of equations 1 and 2 where access to financial network is the variable of interest. Column 1 presents the results for take-up while column 2 presents the results for utilisation.

Households with access to informal financial network have a 3.5 percentage points higher probability of insurance take-up compared to households without access to informal finance. However, experience of a health shock increases adoption rates by a higher margin for households without access to informal finance. Specifically, households without informal network are 4.4 percentage points more likely to sign up for RAS compared to households with access to informal finance, when faced with a health shock. We observe similar patterns for utilisation of RAS.

Even though utilization is conditional on take-up, the effects of access to informal network on utilization are similar. Households with access to informal financial network have a 3.02 percentage points higher probability of utilising formal health insurance compared to households without access to informal finance. Once again, for households that have experienced health shock, the probability of utilization is much higher for households without access to an informal financial network compared to those who are network members. As expected, experience of a health shock raises the probability of utilisation by 4.81 percentage points, although experience of a health shock in the previous period does not alter the probability of registering for RA in the current period. This is perhaps because as shown in Figure 2 a very high fraction of households are already registered for RAS at the time of the survey round 3, the first round post RAS introduction.

Thus, for both take up and utilisation, informal financial network is found to complement formal health insurance. Households without access to informal financial assistance, are more likely to adopt only when faced with an adverse health shock.

Table 4 presents OLS estimates of equations 1 and 2 where access to information network is the variable of interest.

Column 1 presents results for take-up while column 2 presents results for utilisation. In terms of either registration or utilization, information network is not found to have any significant impact on adoption decisions.

5.2 Overlap

As discussed in Section 3, there is significant overlap between information and financial network. Households that are better connected financially also have a stronger information network. Hence, there is a possibility that the omitted network type is confounding the estimates in Tables 3 and 4. To address this we next present the results from estimation of equations 3 and 4 in Table 5. Column 1 presents results for take-up while column 2 presents results for utilisation. The results are very similar to our findings in Tables 3 and 4. Households with access to financial network are more likely to register for and utilize the Arogyasri insurance even though access to information network does not have any effect on insurance adoption decisions. In addition, as before, we find that the marginal effect of a health shock on adoption of health insurance is higher for households without access to financial network compared to households connected to financial network.

The magnitudes of the effects in the combined regression are also close to the estimates in the separate regressions. Access to informal financial network increases the probability of take up of formal health insurance by 3.49 percentage points. While the effect of the interaction with health shock is not significant at conventional levels, the coefficient size is very close to what we found in Table 3. The size of the effect of informal financial network on utilization is also similar to what we obtained in Table 3. Households with access to informal financial network are 3.03 percentage points more likely to utilize Arogyasri, while experience of a health shock has a higher marginal impact on utilizaton, by almosy 5 percentage points, for households without network ties.

In a way, our findings are similar to Debnath and Jain, 2020, that informal networks facilitate adoption of free public health insurance. However, we also find that it is the risk-sharing role of informal networks, rather than information-sharing, that promotes adoption of free public health insurance. To understand why informal financial networks might enable insurance adoption we develop a simple theoretical structure. We argue that idiosyncratic shocks to individual network members have financial implications for all members in a risk-sharing network. Hence, it is in the interest of the informal network to ensure that all members take up the free insurance.

6 Conceptual framework

Our theoretical framework is written in the context of a free public health insurance scheme and models the decision of people to register for and utilize the free insurance provided by the government. While we empirically estimate these decisions for a health insurance product, our theoretical structure is more general and is applicable to many other free insurance product.

Specifically, we model how the choice made by the members of a financial network is different from that of a non-member. There is no trivial answer to this question as public insurance is free and yet, we do not observe everyone taking up the insurance. In this regard, we examine the role of community in the decision process.

In reality, a community provides various public goods and services. In our model, we focus only on the community as an insurance provider and therefore, our definition of community is restricted to financial network. A financial network typically provides insurance to its members through cheap loans. There also several ways to model community. We choose to treat community as a group of people with a cultural core which acts as a social planner. The core or central body of the community takes into account the welfare of the community and takes the decision for the entire community. The key difference between a community member and a non-member is that a non-member can decides whether to take up insurance while a member has to do whatever the community decides for her. But how does the community punish a defector? Besides health, there are several other areas where an individual may get bad shocks and may need insurance. If a member does not follow community's directive regarding taking up (and utilization) of health insurance, she will not get other non-health insurance provided by the community. We assume that the cost of such a sanction is so high that community members always adhere to community guidelines.

In our model, community membership is not a choice. The total population is of measure 2 and half of this population are randomly allocated to community membership while the rest half remain non-members. There are several ways to justify this assumption. One possibility is that community membership is synonymous to ethnic identity; half the population belongs to a closely knit ethnic identity and automatically becomes member of a community. The rest of the population are ethnically diverse and do not belong to a community. It is also possible that there is some kind of pro-social trait that one is born with and once someone has that trait, she joins a community.

Let us now discuss two decisions made by an individual – take up of insurance and its utilization once a bad shock happens.

6.1 Decision to take up insurance

Before health shock

Agents know about the possibility of a health shock but they differ in terms of their prior belief of the shock. The shock entails a cost of K. We rank individuals based on their prior belief. For the i^{th} agent, the probability of a health shock is q_i where for $i > j$, $q_i > q_j$. The expected cost of health shock for the i^{th} individual is q_iK. The health insurance is public and therefore, no premium is needed. However, there are some transaction costs involved in the enrollment process which may take the form of going to the government office, standing in the queue, filling out the forms etc. Let us denote such costs by τ. Note that, q_i is randomly distributed following a distribution function. We further assume that $q_i \in [q_l, q_h]$ such that $0 < q_l, q_h < 1$. Within this interval, q_i follows the probability mass function $\phi(.)$. We specify the probability mass function below:

$$\begin{aligned} Pr(q_i = q) &= 0 \text{ if } q_i < q_l \\ &= \phi(q) \text{ if } q_i \in [q_l, q_h] \\ &= 0 \text{ if } q_i > q_h \end{aligned} \tag{5}$$

Note that $\int_{q_l}^{q_h} \phi(q)dq = 1$. A non-member individual i decides to take up insurance if cost of not taking up insurance is more than the transaction costs for enrolment, i.e.

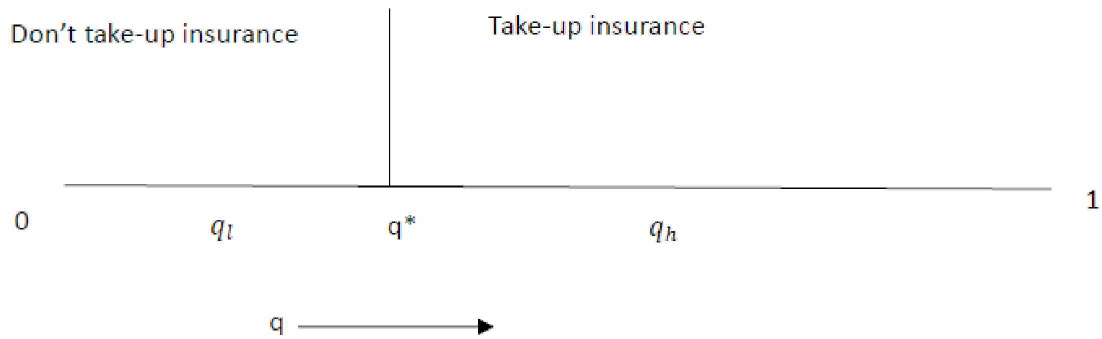
$$q_iK > \tau \tag{6}$$

This condition boils down to

$$q_i > \frac{\tau}{K} = q^* \tag{7}$$

We assume that the transaction cost of enrollment (τ) is always less than the actual health cost K and hence, $0 < \frac{\tau}{K} < 1$. There are three possible ranges in which q^* can fall. If $q^* < q_l$ all non members will take up insurance. If $q^* > q_h$ none of the non-members will take up insurance. The more interesting case is when $q_l < q^* < q_h$. In this range sufficiently

Figure 8: Pre-shock decision rule for non-members



pessimist individuals who have higher perceived probabilities of bad shock will enrol for public insurance. We have presented this scenario in figure 8:

Equation 7 implies that in this range, the fraction of non-members taking up public insurance would be $1 - \Phi(q^*)$ where $\Phi(q^*) = \int_{q_l}^{q^*} \phi(q)dq$.

Let us now look at the decision making process of the community leaders who make the process of their members. In case of the community, it covers the cost of bad shock if the person is not covered. Similarly, if a member decides to enroll, the community pays for the τ. But the community leaders does not know the actual risk perception of different individuals. They evaluate the possibility of a bad health shock by the average perception $\overline{q}$ where $\overline{q} = \int_{q_l}^{q_h} q\Phi(q)dq$. Hence, the leaders decide that all members should take up insurance as long as $\overline{q} > \frac{\tau}{K}$.

What happens if $\overline{q} \leq \frac{\tau}{K}$? The community does not see any reason for anyone to take up the insurance. But it does not stop anyone as long as one pays for its own transaction cost. Hence, under this condition, members just behave like non-members – the i^{th} member takes-up insurance as long as $q_i > \frac{\tau}{K}$. Essentially, we see an asymmetry in the community's decision making. When $\overline{q}K > \tau$, all community members take up insurance but only a fraction of the non-members take up insurance. But whenever, $\overline{q}K \leq \tau$, the expected cost of a bad shock as perceived by the community is not big enough to justify the transaction cost of enrolment. Therefore, the community does not give any mandate and members, like the non-members, take the decision by comparing their individual specific expected cost of a bad shock with the transaction cost. In this case, members and non-members will behave alike. In our first proposition, we summarize the result for the case where $\overline{q}K > \tau$

Proposition 1 *For a sufficiently high value of medical treatment cost relative to the cost of enrollment, all community members take up formal insurance. For non-members, only* $(1 - \Phi(q^*))$ *fraction take up insurance.*

But how do we know if the expected cost of a bad shock as perceived by the community ($\overline{q}K$) is less or greater than the transaction cost of enrollment (τ)? There is no way to find it directly. But one may imagine that the cost of bad shock will be higher in rural areas and in areas where hospitals and health centres are not near. In such an area, taking a patient to hospital will take long time which in turn will complicate the medical condition. This idea finds support in our heterogeneity analysis where we show that the positive relation between financial network membership and taking up of insurance is driven by rural areas and areas which do not have health facilities (see tables 6, 7 and 8). In urban areas and areas with hospitals and health centres, there is no significant difference between members and non-members.

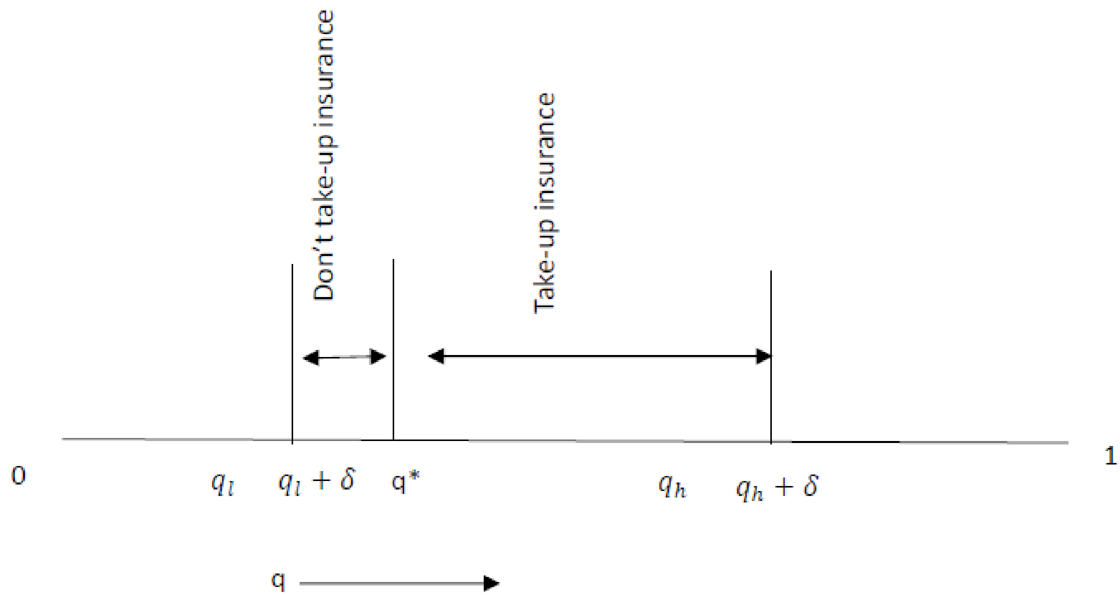
After health shock

In the last subsection we examined the decision to enroll in public insurance based on agent's belief about the possibility of a health shock. Let us now consider the decision after a bad shock has happened. It is reasonable to assume that post-health shock everyone will update their belief of a shock in an upward manner. If pre-shock perceived probability was q, the after-shock perceived probability is $q' = q + \delta$. This implies that the probability distribution will look like the following structure.

$$\begin{aligned} Pr(q_i = q) &= 0 \text{ if } q_i < q_l + \delta \\ &= \phi(q) \text{ if } q_i \in [q_l + \delta, q_h + \delta] \\ &= 0 \text{ if } q_i > q_h + \delta \end{aligned} \tag{8}$$

Note that Note that $\int_{q_l+\delta}^{q_h+\delta} \phi(q)dq = 1$. For a non-member the decision making rules remain the same i.e. they take-up insurance if $q_i > \frac{\tau}{K} = q^*$. Now the decision rule looks like figure 9. It shows, that in response to belief updating, the non-takers region has shrunk while that of the takers has expanded. Hence, after a health shock, the chance of non-takers taking up health insurance has further expanded.

Figure 9: Post-shock decision rule for non-members



Let us now examine the decision taken by the members in response to the health shock. Remember, for the members it is always a corner solution – either all members take it up or no one takes up insurance depending on the relative position of q^* and $\overline{q}$. In the pre-shock scenario, we assumed that the value of the medical bill (K) is relatively high relative to transaction cost of enrollment (τ) which ensures low value of q^* which in turn satisfies the condition $q^* < \overline{q}$. Under this condition, all members take up insurance. Now after the health shock and belief updation, the new average value of risk perception becomes $\overline{q} + \delta$. From our assumption in the previous subsection it automatically follows that $q^* < \overline{q} < \overline{q} + \delta$. This would mean that if all members took up insurance before receiving any shock, they would continue to do so even after the shock. On the other hand, there will be new takers among non-members who did not have insurance before the shock. Together, these two results lead to our second proposition:

Proposition 2 *After a bad shock is realized, non-members are more likely opt for the insurance than the members.*

6.2 Decision to utilize public insurance

Besides the perceived belief of a health shock, agents are heterogeneous in another aspect which plays a critical role in their decision regarding utilization insurance. Once a health shock has happened, filing insurance claims involves some form of transaction costs. But agents are uncertain whether they would get reimbursement for all the claimed items. The cost of filing is γ which is same for everyone. However, agent i believes that only p_i fraction of their claim (Y) would be reimbursed where $p_i \in [0, 1]$. The decision making process for members and non-members are the same as before – non-members decide for themselves by doing their own cost-benefit analysis while community leaders decides for the members.

Non-members decide to file insurance claim if

$$p_i Y > \gamma$$

This is same as the following condition:

$$p_i > \frac{\gamma}{Y} = p^* \tag{9}$$

The parameter p_i essentially captures an individual's trust on the state run institutions. A non-member files a claim and utilizes the public insurance if she has sufficiently high trust on the state run institutions. We assume that p_i is distributed according a distribution function $\Psi(.)$. Hence, $(1 - \Psi)$ fraction of the non-members utilize insurance.

For the member, the decision is taken based on the trust level of the average person $\overline{p} = \int_0^1 p\Psi(p)dp$. This implies that all community members take up the insurance if $\overline{p} > \frac{\gamma}{Y}$. This condition is likely to be satisfied it the amount of the medical bill (Y) is much higher than the cost of filing (γ). This is a reasonable condition to assume. Hence, we find that as long as medical bill sufficiently higher than the cost of filing, all members will utilize public insurance while only a fraction of the non-members will use it. This gives us our last proposition:

Proposition 3 *If the cost of making the insurance claims is sufficiently low relative to the medical bill, the community members are more likely to utilize insurance than non-members.*

7 Informal Network and Indirect Costs

In theory, we argued that it is in the interest of the informal networks to facilitate adoption of health insurance because idiosyncratic shocks to individual network members have financial implications for all members in the network. However, this could be achieved through easier information dissemination within the network, in which case both risk-sharing and information sharing role of networks could be instrumental in insurance adoption. Since we do not find any evidence to suggest that information flow within the network enables insurance adoption, we conduct further investigation to better understand the role of informal financial networks.

In the current section, we directly test what we discussed around proposition 1. We showed that (financial) network members and non-members differ in terms of insurance take-up when the expected cost of bad shock ($\overline{q}K$) is greater than the transaction cost of enrolment(τ). This could be true if the cost associated with a bad shock (K) is quite high. We argue that the value of K is likely to be very high in rural areas and areas which do not have hospitals and health centres around. In urban areas and areas with hospitals, K is not that high and consequently, we don't expect any difference between members and non-members in terms of insurance take-up. In this section, we run heterogeneity test to test the hypothesis directly.

Specifically, we conduct heterogeneity tests on the estimates obtained in Table 5 for different measures of proximity to healthcare facilities - (a) localities with hospital close by, (b) localities with health centre close by, and (c) rural vis-a-vis urban areas. We define a hospital or health center to be close by if it is situated within the same village (for rural households) or municipal ward (for urban households) as the household.

Table 6 shows the estimates separately for localities with hospital and localities without hospital. Table 7 and Table 8 show similar estimates comparing regions with and without a health center and rural and urban regions, respectively. Access to informal financial network matters for insurance take-up only when there are no hospitals or health care centers nearby or for rural regions. There is no comparable effect when there is a hospital or healthcare center close by or for urban regions. A similar difference, although weaker, is also observed for utilization of the insurance.

Like in Table 5 informal information network is not found to have any effect on the probability of take-up or utilization and irrespective of the proximity to a healthcare facility.

The results seem to be driven by the distance to a hospital. In the absence of a hospital nearby, a household would have to travel to other regions to access health care. This would require expenses on account of transportation, accommodation and other related costs which are both uncertain in amount and unlikely to be fully compensated by insurance. Informal financial transfers from a household's network is likely to facilitate insurance take-up and utilization in such a situation. These findings suggest that informal networks enable households to takeup and utilize formal insurance by complementing formal insurance in terms of mitigating unplanned indirect expenditure that are typically not covered by health insurance.

8 Conclusion

The paper sought to study the impact of informal network on adoption of formal public health insurance in India. Low adoption of formal health insurance, despite availability of free government health insurance has been a puzzle in the Indian context. Against this backdrop, we looked at the role of informal networks, by acknowledging the dual role such networks can play. On one hand, we looked at informal financial network, for their possible role in providing informal insurance through transfer of financial resources. On the other hand, we considered informal information network for their possible role in dissemination of information.

We find that the members of financial network are more likely to take up insurance than the non-members. We also find that information network does not play any role in the process of insurance take-up. Most of the existing papers in the literature cannot empirically observe the distinction between information and financial network. On one hand, when a positive relation has been found between network and insurance, the network has been interpreted as an informational network that facilitates take-up by providing more information (and thereby, reduces transaction costs). On the other hand, whenever a negative relationship between network and formal insurance has been found, it is interpreted as a financial network that crowds out formal insurance.

Our paper makes its departure from the existing literature on two counts. First, in our study, we directly observe the differential impact of financial and informational network. Second, unlike other studies, we find positive impact of financial network and no effect of informational network the take up rate of public insurance. In our conceptual framework, we argue that, financial network works as a community insurance. Public insurance, even if does not charge any premium, involves transaction cost of enrolment. Hence, if an individual believes that the chance of a bad shock is too low, she may avoid enrolment. If a non-member choose to not enrol, in the event of a bad shock, the cost of bad shock is borne by that individual herself. But if a community member fails to enrol in public insurance, in the event of a bad shock, the community has bail him out making non-enrolment costly for the entire community network. Therefore, a community member is pushed by his community to take up insurance, making the take up rate higher among the community members than the non-members.

In our heterogeneity analysis, we find that the results are consistent with our theoretical postulate. The results are stronger in rural areas and in areas where hospitals are far. These are the places where the real costs of treatment is much higher. Therefore, if a community member in these regions fails to take up insurance, the expected cost burden for the community network will be very high. In such areas, the communities will give their members strong push to take up public insurance.

Our approach has many significant policy implications. Our results suggest that providing more information regarding public information may not improve its take up rate. In this case, the interest of the community network and the state is aligned – both institutions want to increase the take up rate of public insurance. Therefore, the state must design policies that include the roles for community leaders.

References

Aarogyasri (2013). *Guidelines for Rajiv Aarogyasri Scheme*. URL: https://www.ysraarogyasri.ap.gov.in/documents/10181/0/Scheme_Manual.pdf/e67a112b-%206407-4ce5-b50d-a52c18399e3d (visited on 2022).

Abadie, Alberto et al. (2023). "When should you adjust standard errors for clustering?" In: *The Quarterly Journal of Economics* 138.1, pp. 1–35.

AHCT (2009). *annualreport*. URL: https://www.ysraarogyasri.ap.gov.in/documents/7e0a%20-%204384%20-%20ba66%20-%20a5286770a02f (visited on 2022).

– (2022). *Listed Therapies*. URL: https://aarogyasri.telangana.gov.in/ASRI2.0/r (visited on 2022).

Balarajan, Yarlini, Selvaraj Selvaraj, and SV Subramanian (2011). "Health care and equity in India". In: *The Lancet* 377.9764, pp. 505–515.

Banerjee, Abhijit, Esther Duflo, and Richard Hornbeck (2014). "Bundling health insurance and microfinance in India: There cannot be adverse selection if there is no demand". In: *American Economic Review* 104.5, pp. 291–297.

Cameron, A Colin, Jonah B Gelbach, and Douglas L Miller (2008). "Bootstrap-based improvements for inference with clustered errors". In: *The review of economics and statistics* 90.3, pp. 414–427.

De Weerdt, Joachim and Stefan Dercon (2006). "Risk-sharing networks and insurance against illness". In: *Journal of Development Economics* 81.2, pp. 337–356. ISSN: 0304-3878. DOI: https://doi.org/10.1016/j.jdeveco.2005.06.009. URL: https://www.sciencedirect.com/science/article/pii/S0304387806000666.

Debnath, Sisir and Tarun Jain (2020). "Social connections and tertiary health-care utilization". In: *Health Economics* 29.4, pp. 464–474.

Desai, Sonalde and Reeve Vanneman (2010). "National Council of Applied Economic Research, New Delhi (2010). India Human Development Survey (IHDS), 2005. ICPSR22626-v8". In: *Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]*, pp. 06–29.

– (2018). *IHDS-II*. URL: https://www.icpsr.umich.edu/web/DSDR/studies/36151/publications (visited on 2022).

Devillanova, Carlo (2008). "Social networks, information and health care utilization: Evidence from undocumented immigrants in Milan". In: *Journal of Health Economics* 27.2, pp. 265–286. ISSN: 0167-6296. DOI: https://doi.org/10.1016/j.jhealeco.2007.08.006. URL: https://www.sciencedirect.com/science/article/pii/S0167629607001038.

Dror, David M and Lucy A Firth (2014). "The demand for (micro) health insurance in the informal sector". In: *The Geneva Papers on Risk and Insurance-Issues and Practice* 39, pp. 693–711.

Gaurav, Sarthak, Shawn Cole, and Jeremy Tobacman (2011). "Marketing complex financial products in emerging markets: Evidence from rainfall insurance in India". In: *Journal of marketing research* 48.SPL, S150–S162.

Joe, William, Udaya S Mishra, and Kannan Navaneetham (2008). "Health inequality in India: evidence from NFHS 3". In: *Economic and Political Weekly*, pp. 41–47.

Jowett, Matthew (2003). "Do informal risk sharing networks crowd out public voluntary health insurance? Evidence from Vietnam". In: *Applied economics* 35.10, pp. 1153–1161.

Mannuru, Manjuram (2019). “Utilization of Rajiv Aarogyasri Health Scheme by rural policyholders of Chittoor district in Andhra Pradesh”. In:

Rao, Mala et al. (2012). “A rapid evaluation of the Rajiv Aarogyasri community health insurance scheme in Andhra Pradesh, India”. In: *BMC proceedings*. Vol. 6. Springer, pp. 1–2.

Reddy, Sunita and Immaculate Mary (2013). “Rajiv Aarogyasri Community Health Insurance Scheme in Andhra Pradesh, India: a comprehensive analytic view of private public partnership model”. In: *Indian journal of public health* 57.4, pp. 254–259.

Rosenzweig, Mark R (1988). “Risk, implicit contracts and the family in rural areas of low-income countries”. In: *The Economic Journal* 98.393, pp. 1148–1170.

Townsend, Robert M (1994). “Risk and insurance in village India”. In: *Econometrica: journal of the Econometric Society*, pp. 539–591.

WHO (2023). *Global Health Observatory data repository*. URL: https://apps.who.int/gho/data/view.main.FINANCIALPROTECTIONWBINCOMEGROUP01v?lang=en (visited on 2023).

Yellaiah, J (2013). “Health insurance in India: Rajiv Aarogyasri health insurance scheme in Andhra Pradesh”. In: *IOSR Journal of Humanities and Social Science* 8.1, pp. 7–14.

Young-Lives (2017). “Young lives survey design and sampling (round 5): United Andhra Pradesh”. In: *Young Lives*.

9 Tables

Table 1: Distribution of financial network and information network

	Financial network	Information network
With Access	84.49	68.53
Only	*31.43*	*15.49*
Both	*68.57*	*84.49*
N=	4852	3938

**figures reported are in percentage*

Table 2: Descriptive statistics

Variable	With RAS Percentage		Without RAS Percentage	
Agricultural household	49.96		25.87	
NREGS card	67.92		22.01	
Higher education	0.47		0.36	
School education	97.79		97.01	
SC-ST	32.24		22.54	
BC	49.85		45.31	
Urban	21.4		46.48	
Hospitals in locality	17.51		44.08	
Health center in locality	32.61		55.21	
	With RAS		Without RAS	
	Mean	SD	Mean	SD
Consumption	9198.41	8154.53	12061.29	10461.4
Wealth	.56	.17	.66	.17
Land	1.86	3.52	1.89	6.79
Livestock	21865.58	94192.86	11000.66	47529.55
Head age	41.01	8.42	41.57	9.08
N=	5746			

**consumption and livestock values are reported in INR*
**wealth is an index lying between 0 and 1*
**land is reported in acres*

Table 3: Effect of financial network: interaction with health shock

	(1) takeup	(2) utilisation
Financial network	0.0348**	0.0302**
	(0.0169)	(0.0145)
Health shock lag	0.0339	
	(0.0240)	
Financial network X Health shock lag	-0.0440*	
	(0.0262)	
Health shock		0.0481*
		(0.0291)
Financial network X Health shock		-0.0495*
		(0.0298)
Constant	0.681***	-0.0857
	(0.0602)	(0.0586)
N	5251	4555
Household FE	Yes	Yes
Control variables	Yes	Yes
Clustered SE	Yes	Yes

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 4: Effect of information network: interaction with health shock

	(1) takeup	(2) utilisation
Information network	0.0136	-0.00376
	(0.0131)	(0.0142)
Health shock lag	-0.0137	
	(0.0204)	
Information network X Health shock lag	0.0142	
	(0.0235)	
Health shock		0.0290
		(0.0207)
Information network X Health shock		-0.0327
		(0.0245)
Constant	0.699***	-0.0622
	(0.0613)	(0.0579)
N	5252	4555
Household FE	Yes	Yes
Control variables	Yes	Yes
Clustered SE	Yes	Yes

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 5: Effect of informal network: interaction with health shock

	(1) takeup	(2) utilisation
Financial network	0.0349**	0.0303**
	(0.0169)	(0.0145)
Health shock lag	0.0216	
	(0.0301)	
Financial network X Health shock lag	-0.0426	
	(0.0262)	
Information network	0.0129	-0.00401
	(0.0131)	(0.0141)
Information network X Health shock lag	0.0167	
	(0.0236)	
Health shock		0.0722**
		(0.0355)
Financial network X Health shock		-0.0499*
		(0.0299)
Information network X Health shock		-0.0327
		(0.0244)
Constant	0.672***	-0.0848
	(0.0609)	(0.0590)
N	5251	4555
Household FE	Yes	Yes
Control variables	Yes	Yes
Clustered SE	Yes	Yes

Standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6: Effect of informal network: presence and absence of hospital in the locality

	(1)	(2)	(3)	(4)
	takeup		utilisation	
	hospital far	hospital near	hospital far	hospital near
Financial network	0.0513***	-0.00749	0.0244*	0.0464
	(0.0197)	(0.0388)	(0.0139)	(0.0440)
Health shock lag	0.0436	-0.0663		
	(0.0332)	(0.0810)		
Financial network X Health shock lag	-0.0653**	0.0265		
	(0.0305)	(0.0702)		
Information network	0.00441	0.0321	-0.0153	0.00175
	(0.0137)	(0.0373)	(0.0165)	(0.0323)
Information network X Health shock lag	0.0179	0.0240		
	(0.0253)	(0.0617)		
Health shock			0.0677	0.0702
			(0.0424)	(0.0708)
Financial network X Health shock			-0.0545	-0.00380
			(0.0339)	(0.0716)
Information network X Health shock			-0.0211	-0.0279
			(0.0280)	(0.0597)
Constant	0.740***	0.137	-0.0467	0.0830
	(0.0675)	(0.192)	(0.0581)	(0.482)
N	3962	901	3604	662
Household FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Hospital	Absent	Present	Absent	Present
Clustered SE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 7: Effect of informal network: presence and absence of health centre in the locality

	(1)	(2)	(3)	(4)
	takeup		utilisation	
	center far	center near	center far	center near
Financial network	0.0565**	0.0103	0.0234	0.0317
	(0.0249)	(0.0255)	(0.0162)	(0.0285)
Health shock lag	0.0574	-0.0431		
	(0.0391)	(0.0553)		
Financial network X Health shock lag	-0.0745**	0.00581		
	(0.0358)	(0.0441)		
Information network	0.00784	0.0174	-0.0161	-0.000260
	(0.0157)	(0.0244)	(0.0186)	(0.0223)
Information network X Health shock lag	0.00964	0.0385		
	(0.0280)	(0.0415)		
Health shock			0.0665	0.0790
			(0.0464)	(0.0638)
Financial network X Health shock			-0.0600	-0.00741
			(0.0382)	(0.0530)
Information network X Health shock			-0.0254	-0.0195
			(0.0293)	(0.0514)
Constant	0.725***	0.602***	-0.0509	-0.112
	(0.0771)	(0.108)	(0.0650)	(0.155)
N	3230	1633	2937	1329
Household FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Health centre	Absent	Present	Absent	Present
Clustered SE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 8: Effect of informal network: rural or urban region

	(1)	(2)	(3)	(4)
	takeup		utilisation	
	rural	urban	rural	urban
Financial network	0.0450**	0.0165	0.0219	0.0489
	(0.0207)	(0.0333)	(0.0148)	(0.0435)
Health shock lag	0.0464	-0.0707		
	(0.0340)	(0.0715)		
Financial network X Health shock lag	-0.0639**	0.0495		
	(0.0300)	(0.0610)		
Information network	0.00708	0.0288	-0.00519	-0.0135
	(0.0141)	(0.0331)	(0.0164)	(0.0320)
Information network X Health shock lag	0.0137	0.0122		
	(0.0244)	(0.0559)		
Health shock			0.0892**	0.0263
			(0.0424)	(0.0682)
Financial network X Health shock			-0.0753**	0.0419
			(0.0340)	(0.0698)
Information network X Health shock			-0.0325	-0.0301
			(0.0278)	(0.0577)
Constant	0.693***	0.445***	-0.0759	-0.0306
	(0.0676)	(0.165)	(0.0566)	(0.267)
N	4075	1166	3676	872
Household FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Region	Rural	Urban	Rural	Urban
Clustered SE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Appendix

Table A1: Description of variables

Variable	Description
Financial network	Proportion of households having access to informal financial network
Information network	Proportion of households having access to informal information network
Health shock	Proportion of households with experience of severe illness
Agriculture	Proportion of households with agriculture as primary occupation
NREGS card	Proportion of households having NREGS card
Higher education	Proportion of households having children in higher education
School education	Proportion of households having children in school education
SC-ST	Proportion of households belonging to SC-ST community
BC	Proportion of households belonging to BC community
Urban	Proportion of households located in urban area
Hospital	Proportion of households having hospital in the locality
Health center	Proportion of households having health center in the locality
Consumption	Monthly total consumption expenditure (current price)
Wealth	Composite index of household wealth
Land	Acres of agricultural and non agricultural land owned
Livestock	Monetary value of livestock owned. Expressed in rupees
Age of household head	Age of household head