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# ABSTRACT

## Demand for Health Insurance: Financial and Informational Role of Informal Networks*

We study why free public health insurance in India exhibits persistently low utilisation despite high out of pocket health expenses. Using panel data from the Young Lives Survey and the rollout of the Arogyasri scheme in Andhra Pradesh, we distinguish the roles of informal financial and information networks in shaping adoption. Empirically, households embedded in financial networks show higher take-up and utilisation, while information networks have no effect. To explain this pattern, we develop a simple theoretical framework in which informal financial networks act as mutual insurance: because members bear each other's uninsured losses, the network has an incentive to push all members to enrol when the expected cost of shocks exceeds enrolment transaction costs. This generates corner solutions for network members and interior solutions for non-members, consistent with observed bimodal take-up patterns. The model clarifies why financial—but not informational—ties complement public insurance and highlights community-based mechanisms for increasing adoption.

**JEL Classification:** I13, I18, O17

**Keywords:** health insurance, informal network, adoption, utilization, demand

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# 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 and Rosenfield, 2005). 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 in the early 2000s (Ranson et al., 2007). 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 utilisation, of these free insurance programs offering subsidized private healthcare remains low. For instance, despite proliferation of publicly financed free health insurances, NFHS data shows that only about 41% of the Indian households are covered by any kind of insurance (NFHS, 2021b). In our study sample roughly 7% of the households utilised the health insurance scheme, even though 32% of the households experienced some health shock over the study period (see Sec 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 where informal consumption smoothing arrangements reduces a household's engagement in formal mechanisms to reduce income risk (Rosenzweig, 1988).

However, the conventional theories of insurance demand do not explain lack of adoption of free social health insurance. Some have noted information constraints, ease of use and transportation costs as potential barriers to a wider utilisation 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 social 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). In a similar study, Chemin, 2018 found that among two possible treatments – subsidizing the insurance product and informal group meeting – informal group meetings have a significantly large effect on insurance take up. In our research, 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 study 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.

Households associated with a financial network are 3 percent points more likely to utilise *Arogyasri* compared to those without network association. With an average utilisation rate of 5% among those who experienced severe health shocks in the 2009 survey year (the first survey year after the introduction of *Arogyasri*), this implies that financial network association increased the probability of utilisation by 60%. In addition, takeup increases by 4% with membership of financial-network even when the baseline take-up rate, at over 80%, is substantially high. However, adoption increases for households who are not associated with informal networks, after they experience health shocks. We do not find any evidence supporting 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 such as 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 social health insurance. Jowett, 2003 shows that informal networks crowd out subsidized formal social 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, either everyone in the community takes up the 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 utilisation. 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 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 findings have considerable policy implication. In 2019-2021, more than half of Indian households did not even have a member enrolled in any health insurance. This is in spite of the proliferation of free social health insurance schemes at both the state and national level. Despite being cashless, take-up and utilisation of such programs have been low. Andhra Pradesh is a notable exception with high take-up rates. In the first survey year that we observe after the introduction of *Arogyasri* in April 2007, the average take-up rate was approximately 80%. Even then, if we compare take-up rate in 2009 between households with and without access to financial network in 2006, then the take-up is approximately 79% for households without network and 85% for households with network (Figure 3). We find a 4% average increase in take-up probability with network membership across survey years. This means that at low baseline values this could translate to a much higher increase. Qualitative and quantitative work have identified several barriers to adoption of free social health insurance in India such as lack of awareness, poor accessibility, problem with documents, difficulty navigating the health system, as well as limited insurance coverage in terms of empanelled hospitals and listed therapies (Dvara Research, 2025; Narasimhan et al., 2014; Ahlin, Nichter, and Pillai, 2016). Typically, policymakers have tried to solve the problem of low adoption by streamlining administrative processes and aggressive mass information campaigns. Our findings that network membership facilitates insurance adoption suggests that take up and utilisation of free health insurance can also be improved by leveraging community networks as the networks themselves will ensure that its members adopt the available outside option, i.e the social health insurance. In this respect, our findings and policy recommendations reflect the extant literature on expanding adoption of social programs through social networks (Banerjee, Chandrasekhar, et al., 2019). Through exploratory analysis we have shown that community networks formed at village levels can be a natural unit of intervention by policymakers to this end. Other potential units of intervention can be self-help groups, caste connections within and across villages, and women's groups, although limited sample size in our data prevents us from conducting analyses that has adequate statistical power at the level of these networks.

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. Section 7 presents the estimates for select sub-categories of networks. Finally, section 8 concludes the paper.

# 2 Policy Background

We study adoption in the context of the *Arogyasri* health insurance scheme. *Arogyasri* 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). Arogyasri 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 Arogyasri in Telengana, and Dr. YSR Arogyasri 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 Arogyasri 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 *Arogyasri* beneficiaries through Arogyamithra, 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 *Arogyasri* beneficiaries are not refused admission if it offers the required listed therapy.

In order to receive treatment, a beneficiary can approach either (1) Arogyamithra 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 Arogyamithra, 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 Arogyamithra and communicated to the concerned Arogyamithra of the referred NWH. Similar process is followed at health camps. If beneficiary directly approaches a NWH, after initial registration by the network Arogyamithra (NAM), they are attended at exclusive *Arogyasri* 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 Study 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 for five survey years covering the period 2002-2016. A timeline of the survey and introduction of *Arogyasri* is presented in Figure 4. The data contain detailed information on the YL child, household, and community characteristics, including questions on adoption of the social health insurance program, *Arogyasri*. The *Arogyasri* health insurance scheme was introduced in 2007. In the Young Lives data, survey years 2002 and 2006 cover the period prior to the introduction of *Arogyasri* and survey years 2009, 2013, and 2016 cover a period following the introduction of *Arogyasri*. We consider survey years 2006 through 2016, corresponding to survey survey years 2 through 5 for our study. While information on insurance adoption is available from year 2009, we use survey year 2006 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 network. While the IHDS has information on whether household has taken loans from informal sources, the 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 ex-post measure of informal financial network limits our study to only a selection of households who have actually faced financial exigencies.

## 3.2 Insurance Adoption

Our dependent variable is adoption, which we capture using two dimensions- take up and utilisation. We define take up as a binary variable based on the question on whether a household has *Arogyasri* card. We define utilisation as a binary variable based on the question on whether *Arogyasri* benefits have been accessed by the household. Figure 5 shows the trend in adoption of *Arogyasri* across survey survey years- survey year 3 in 2009, through survey year 5 in 2016.

Take-up of *Arogyasri* increases steadily over the three survey years although the initial extent of take-up is very high at 82% in 2009, within two years of the program's introduction in 2007. It is worthwhile to note here that take up of *Arogyasri* stands in contrast to the low penetration of health insurance at the national level. There are two reasons for this. First, Andhra Pradesh and *Arogyasri* in particular, is an exception with the overall health insurance coverage in the state being 70.2% as of 2019-2020 (NFHS, 2021a). Second, take-up rate in our data is specifically very high since the Young Lives is a study of poverty and inequality and hence focuses on disadvantaged families (Young Lives, 2023). However, While take up has steadily increased over the years, utilisation of *Arogyasri*, conditional on the household experiencing severe illness, has been low. Among households who have been affected by severe illness, the utilisation rates are 5.3% in 2009, 11.2% in 2013 and 6.8% in 2016. Extant literature has discussed the role of non-listed therapies, low quality of services under *Arogyasri*, and remote location of beneficiary's residence in explaining the low utilisation rate (Rao et al., 2012; Mannuru, 2019; Debnath and Jain, 2020). In this paper, we explore the extent to low utilisation can be explained by pre-existing informal ways of risk mitigation, when other factors that keep utilisation low are held constant.

## 3.3 Informal network

The prevalence of informal network for risk mitigation in village economies with underdeveloped financial markets is well known (Townsend, 1994), with network playing the dual role of providing financial assistance and facilitating information dissemination (De Weerdt and Dercon, 2006; Devillanova, 2008). Hence, we define informal network along these two dimensions.

Our 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. 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. To construct our measure of financial network we considered an union of these five responses. In addition, we consider the union of the following response categories- relying on relatives and friends in their own community if need arises, relying on relatives and friends in another community if need arises, having relied on the community for an actual need, having relied on relatives and friends for an actual need- and construct a binary measure of reliance on community. Thus our measure of informal financial network can also be considered as an union of access to community and access to informal loan. While we use our composite measure of informal financial network for the main analyses in this paper, we show additional analyses at the disaggregated levels of community and informal loan.

We define informal information network as a binary variable based on two questions: whether any member of the household is part of any social group and whether any member of the household has engaged with the community. Community engagement involves talking to other members of the locality about a problem, or taking action with other members of the locality, or taking part in awareness raising campaign, or taking part in protest march or demonstration. These localities are village (for rural areas) or municipal wards (for urban areas) of residence (Young-Lives, 2017). To construct the measure of information network, we take the union of the indicators for group membership and community engagement. While we use the composite measure of information network in our main analyses, similar to financial network, we also show analyses at the level of the major social group in our data- self help group, and community enagement.

Figure 6 presents proportions of households having access to financial and information networks during the period of our study and a brief description is available in Appendix Table A1. In Figure 7 and Figure 8 we present the disaggregation of financial and information networks as discussed above.

While conceptually we keep the financial and informational networks distinct, in reality networks play multiple roles. Figure 9 show 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. In our sample, about 50% of all households have both financial and information network, while about 30% have access to only informal financial network, and a little over 10% have access to only 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 define health shock as a binary variable for whether the YL child or any other usual member of the household has experienced severe illness. While we use both contemporaneous and lagged health shock in our empirical specification, due to restrictions imposed by the data, we are forced to consider only health shock to the child for contemporaneous health shock. Figure 10 shows the prevalence of health shock during our period of study and a brief description is available in Appendix Table A1.

## 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 Study. 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. Thus, in effect, we estimate the impact of households becoming a network member from being a non-member on insurance adoption.

### 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 survey year $t$. $\beta_{11}$ and $\beta_{21}$ 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 survey year, and its independent effect on take-up is captured by $\beta_{13}$. $HS_{it}$ 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 $\beta_{23}$. 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 utilised 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 survey year specific characteristics through inclusion of household fixed effects, $\alpha_i$, and survey year fixed effects, $\delta_t$, respectively.

At this point it is important to note that we consider the conditional effect of informal network on adoption probability, rather than the unconditional effect. This is because the unconditional effect of network shows the average difference in insurance adoption between networked and un-networked households, but averaged across those impacted by health shocks and those not impacted by health shocks. We illustrate this point in Figure 11.

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, whether household has higher then median consumption and an index of wealth level of household. We control for the following demographic characteristics- whether there is any educated child in the household and age of household head. Additionally, we account for access to alternative government safety net, eg. the NREGS [0] . We provide a summary of households based on these characteristics by their insurance status in Table 1 and include a brief description in Appendix Table A1.

## 4.2 Overlap

As presented in Figure 9, 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.

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

and

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

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 survey year 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 study 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-survey year level across regressions 1 through 4. Based on this criterion, there are about 500 clusters in our study sample, which allays concerns

[0] NREGS, or the National Rural Employmnet Guarantee Scheme was introduced in 2005 through a act in parliament to enhance the livelihood security of rural households across the country. The scheme provides at least 100 days of guaranteed wage employment in a financial year to every rural household whose adult members volunteer to do unskilled manual work (NREGS, 2025)

related to small number of clusters (Cameron, Gelbach, and Miller, 2008).

# 5 Results

## 5.1 Baseline

Table 2 presents OLS estimates of equations 1 and 2 where access to financial network is the variable of interest. Columns 1 and 2 present the results for take-up while columns 3 and 4 present 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 in our full specification in column 1. 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 *Arogyasri* compared to households with access to informal finance, when faced with a health shock. We observe similar patterns for utilisation of *Arogyasri*.

Even though utilisation is conditional on take-up, the effects of access to informal network on utilisation are similar. Households with access to informal financial network have a 3.0 percentage points higher probability of utilising formal health insurance compared to households without access to informal finance in our full specification in column 3. Once again, for households without access to an informal financial network, the probability of utilisation is much higher after experiencing a health shock, compared to those who are network members. Households without informal network are 4.9 percentage points more likely to utilise *Arogyasri* compared to households with access to informal finance, when faced with a health shock.

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

Table 3 presents OLS estimates of equations 1 and 2 where access to information network is the variable of interest. Columns 1 and 2 present results for take-up while columns 3 and 4 present results for utilisation. Information network is not found to have any significant impact on adoption decisions, in terms of either take-up or utilisation.

## 5.2 Overlap

As discussed in Section 3.3 and illustrated in Figure 9, 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 2 and 3. To address this we next present the results from estimation of equations 3 and 4 in Table 4. Columns 1 and 2 present results for take-up while columns 3 and 4 present results for utilisation. The results are very similar to our findings in tables 2 and 3. Households with access to financial network are more likely to register for and utilise 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 utilisation 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 3.5 percentage points in our full specification in column 1. 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 2. The size of the effect of informal financial network on utilisation is also similar to what we obtained in Table 2. Households with access to informal financial network are 3.1 percentage points more likely to utilise *Arogyasri* in the full specification in column 3, while experience of a health shock has a higher marginal impact on utilisation, by almost 5 percentage points, for households without network ties.

The substantial overlap between financial and information network further raises the question of whether the two types of networks are complementary. To understand complementarity effects, we compare people with access to both financial and informational network to those with access to any one kind of network or without access to any network. Table 5 presents the results of this estimation. We do not find any evidence of complementarity between the two types of networks. This finding is consistent with our previous estimates in Table 3 and Table 4 where information network itself does not have any impact on the decision to adopt insurance.

However, considering the magnitude of the effect sizes we find that the average increase in take-up is only 4%. This is perhaps because, as shown in Figure 5, more than 80% of households are already registered for *Arogyasri* at the time of the survey in 2009, the first survey year post *Arogyasri* introduction. The *Arogyasri* program in Andhra Pradesh is known to be one of the best implemented social health insurance programs in the country and the government took active steps in distributing the insurance cards widely among the poor population (Bergkvist et al., 2014; Reddy and Mary, 2013).

However, in terms of utilisation, we find very large effects. Our estimates suggest a 3 percent point increase in the probability of utilisation when someone is member of a financial network compared to not being member of a network. With an overall utilisation rate of 5% among those experiencing severe health shocks in the 2009 survey year (the first survey year after the introduction of *Arogyasri*), this implies that financial network membership increased the probability of utilisation by 60%. Since our measure of utilisation is binary, our estimates are not perfectly comparable to Debnath and Jain, 2020, which is the closest to our paper. However, they too find an increase in utilisation for those who are part of an informal network.

They find that a unit increase in adoption by peers in the previous quarter increases utilisation by nearly 3.2%. In their context, utilisation is measured as reduction in inpatient medical expenses. However, our findings depart from Debnath and Jain, 2020 in that we also find that it is the risk-sharing role of informal networks, rather than information-sharing, that promotes adoption of free social health insurance.

To understand why informal financial networks might enable insurance adoption we develop a simple theoretical structure.

However, before we move to the theoretical framework, we briefly revisit our identification strategy of using household fixed effects to estimate the effect of changes in network membership for a household across survey years on insurance adoption.

### 5.3 Network formation

Our identification assumption is that controlling for household fixed effects addresses all time-invariant factors that shape both insurance adoption and membership in a network. In effect we are estimating the effect on insurance adoption of a household becoming a member from being a non-member. An important question here is why do households that were non-members become members? And are these factors driving network membership exogenous with respect to insurance adoption? Extant literature suggests that several potential factors like migration, underdevelopment (Meghir et al., 2022; Chandrasekhar, Kinnan, and Larreguy, 2018) can drive informal network formation. However, most of these are endogenous with respect to household characteristics. One potential exogenous determinant of network formation is income shock. In our context, since most households are engaged in agriculture, a weather shock is a well known determinant of network membership. While idiosyncratic shocks, like job loss, health shock could also drive network membership, these would again be endogenous since the outcome variable is a household level decision. In our data we observe a household's experience of a natural disaster. We use this as an indicator of aggregate shock and find that exposure to aggregate shock significantly affects network membership. Households are more likely to have access to a financial network when they have experienced a natural disaster shock in the previous period. We then use the experience of natural disaster shock in the previous period as an instrument for network membership in the current period. Our IV regression has a strong first-stage, while the 2 SLS estimates support our main findings that take-up is higher for households with access to financial network. Appendix Table A2 reports the first stage and IV results. Due to severe limitations in the incidence of disasters, it is not possible for us to estimate the full specification for IV estimation. Hence we have to exercise caution in interpreting these results.

# 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 utilise 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.

We assume that while the health insurance is free, enrollment and utilisation of the free health insurance entails substantial transaction cost. Both quantitative and qualitative research have documented the presence of substantial transaction cost which drives a wedge between on-paper costs and actual costs faced by households. Such costs are present for both enrolment and utilisation. Qualitative studies on publicly funded health insurance in general and *Arogyasri* in particular highlight the pervasive lack of awareness about the programme which acts as barrier to enrolment (Narasimhan et al., 2014; Ahlin, Nichter, and Pillai, 2016). Case studies reveal confusion about whether *Arogyasri* is still available, which health facilities are empanelled, and whether certain diseases are covered under the program. In some cases, households did not have ration card which is a prerequisite for *Arogyasri* enrolment. Disadvantaged individuals also reported having difficulty navigating the health system despite having a valid ration card. Such problems were especially prevalent in rural regions. Many rural regions do not have adequate transport to reach primary health centre which prevents both enrolment and utilisation of the health insurance scheme. In addition, several chronic health conditions are not covered under *Arogyasri* which also limits utilisation. Quantitative studies mirror these findings (Dvara Research, 2025). Citizen survey about exclusion from comparable social health insurance in an Indian state finds very limited enrolment and utilisation even amongst respondents who were aware of the free health insurance scheme. Major reasons for non-enrolment were technical issues, document requirements, and overcharging at the point of enrolment. The survey also revealed additional barriers to utilisation where individuals enrolled in the health insurance scheme did not receive free treatment or received only partial coverage. Major reasons for absent or partial coverage were the hospital not being empanelled, the treatment not being covered, document mismatch, inability to get health insurance card validated, for not having the card on their person at the time of admission, in addition to undisclosed reasons. utilisation also requires visiting the nearest empanelled hospital which poses additional challenge. However, 70% of the private hospitals are in urban locations which raises the transaction costs.

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 utilisation ) 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 utilisation 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 $\tau$. 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 enrollment, i.e.

$$q_i K > \tau \tag{6}$$

This condition boils down to

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

We assume that the transaction cost of enrollment ($\tau$) 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 pessimist individuals who have higher perceived probabilities of bad shock will enrol for public insurance. We have presented this scenario in Figure 1.

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. The transaction cost of enrollment ($\tau$) is incurred by the individual member, but that means that in aggregate, the total transaction cost is borne by the community. But the community leaders do 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 $\overline{q} > \frac{\tau}{K}$.

At this point, it is warranted that we discuss the nature of punishment that is meted out to the defectors i.e., who, despite the directive from the community leaders, do not enroll in the insurance program. We argue that the community punishes the defector by denying her different public goods and services that she receives from the community. Instead, could the community punish the defector by simply refusing to provide any help when she gets a health shock? If the community decides to take such a punishment strategy. a member will take up such insurance only when $q_i K > \tau$ and the resulting equilibrium will not be any different from the non-member equilibrium. In this case, also members with $q_i \in [q_l, q^*)$ take up the insurance and members with $q_i \in [q^*, q_h)$ will not take up insurance. Even if the community does not pay for uninsured individuals' health costs in case the shock happens, the total personal cost members bear will be part of the community's total cost measurement, and thus, following this strategy, the net cost incurred by the community will be $[1 - \Phi(q^*)]\overline{q}K$

where $\Phi(q^*) = \int_{q_l}^{q^*} \phi(q)dq$ and $\overline{q}$ is the community leader's perceived probability of a bad shock. The cost comes from the uninsured members.

Now, consider the case where the community imposes a punishment that is not contingent on a health shock. This could be denial of any community goods and services, such as banning a family from the place of community worship. For comparability, we keep the cost of such punishment equal to K as well. In this case, $K > q_h K > q^* K > \tau$ and therefore, all members will be accepting insurance. The critical difference between this strategy and the earlier one is that, under the threat of the strategy, all members take up insurance and therefore, in equilibrium the community does not incur any cost.

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 ($\tau$)? 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 2. 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.

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 ($\tau$) 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 utilise 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 utilisation 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 fact that in India a *free public insurance* is not actually free and the clients have to entail certain costs that are not reimbursed are documented and analyzed by Dupas and R. Jain, 2024. They looked at the case of Bhamashah Swasthya Bima Yojana (BSBY) – a state backed free insurance program from the Indian state of Rajasthan. The cost of filing is $\gamma$ 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 utilises 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 utilise 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 ($\gamma$). 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 utilise 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 utilise insurance than non-members.*

First of all, our empirical strategy is geared towards getting rid of all unobserved heterogeneity that might be creating an omitted variable bias. Hence, in the best-case scenario, we should have the network membership status randomly assigned. Our theoretical model emulates the best-case scenario by assigning membership status randomly. Secondly, if we want to directly make the empirical strategy and the theoretical model comparable, we may interpret the model in the following manner: suppose in period 1, every individual was a non-member, and then in period 2, all of them became members. The comparison we make in the model between members and non-members is essentially a comparison between the decisions of representative individuals in period 1 and those in period 2. That way the same model will embed the empirical results directly. Finally, our theoretical framework implies that take-up and utilisation will have corner solution for households that are members of informal network. Empirically, one unit of such informal network can be a village. To this end, we look at the distribution of village-level take-up rates. If take up has corner solution, then we would ideally find two types of villages- one with perfect take-up, and the other with no take-up. Figure 12 show that a large majority of villages fall in these two categories, closely implying a bimodal distribution. Network can also be formed at caste-village level: villagers belonging to the same caste may form network. To this end, we compare average take up rates among people belonging to dominant caste in the villages. The reason for defining a network as membership of dominant caste of the village follows from our earlier assumption of community membership not being a choice. We argued that community membership may not be a choice if it is synonymous to ethnic identity. This scenario arises if half the population belongs to a closely knit ethnic identity. At that point co-ethnic members automatically become member of a community. This is the dominant caste in a village and we would expect a bimodal distribution of take-up rate for them. The rest of the population who are ethnically diverse and do not belong to a community will be the non-majority castes in our empirical framework. Consistent with our theoretical framework, we once again find a near bimodal distribution of take-up rate for the dominant caste in Figure 13.

# 7 Heterogeneity analysis

## 7.1 Transaction cost

In Section 6, 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($\tau$). 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 4 for different measures of proximity to healthcare facilities - (a) localities with hospital, (b) localities with health centre, and (c) rural vis-a-vis urban areas. A locality in the Young Lives study is used to indicate the village (for rural households) or municipal ward (for urban households) of residence of 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 utilisation of the insurance.

Like in Table 4 informal information network is not found to have any effect on the probability of take-up or utilisation 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 utilisation in such a situation. These findings suggest that informal networks enables households to takeup and utilise formal insurance by complementing formal insurance in terms of mitigating unplanned indirect expenditure that are typically not covered by health insurance.

### 7.2 Network types

As discussed in Section 3.3 and illustrated in Figure 7 and Figure 8, our measure of informal financial network can be considered as an union of access to community based financial network and access to informal loan from moneylenders, while informal information network can be disaggregated into membership of social groups and community engagement. In this section, we look at the impact of financial and information network at these disaggregated levels.

Table 9 shows estimates of equations 1 and 2 separately for community based financial network (columns 2 and 5) and informal loan (columns 3 and 6), in addition to the composite measure of financial network (columns 1 and 4). Consistent with our theoretical framework, we find that the effect of the financial network is driven by community based financial networks and not by informal loans from moneylenders. In Table 10 we present the heterogeneity results for informal information network. To this end, we estimate equations 1 and 2 separately for membership of self-help group (columns 2 and 5) and community engagement (columns 3 and 6), in addition to the composite measure of information network (columns 1 and 4). Consistent with the effect of the overall information network, we do not find any effect for any of the sub categories of information network.

## 8 Conclusion

The paper sought to study the impact of informal network on adoption of a formal social health insurance in India. Low adoption of formal health insurance, despite availability of free social health insurance has been a puzzle in the Indian context. Against this backdrop, we looked at the role of informal network, by acknowledging the dual role such network 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.

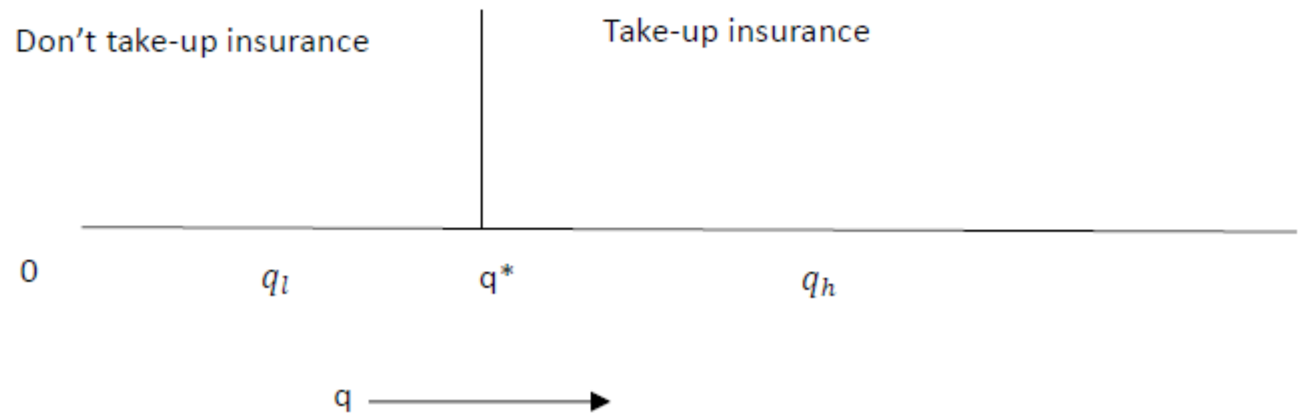
We find that the members of financial network are more likely to take up insurance than the non-members. We also find that information network does not play any role in the process of insurance take-up. Most of the existing papers in the literature cannot empirically observe the distinction between information 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.

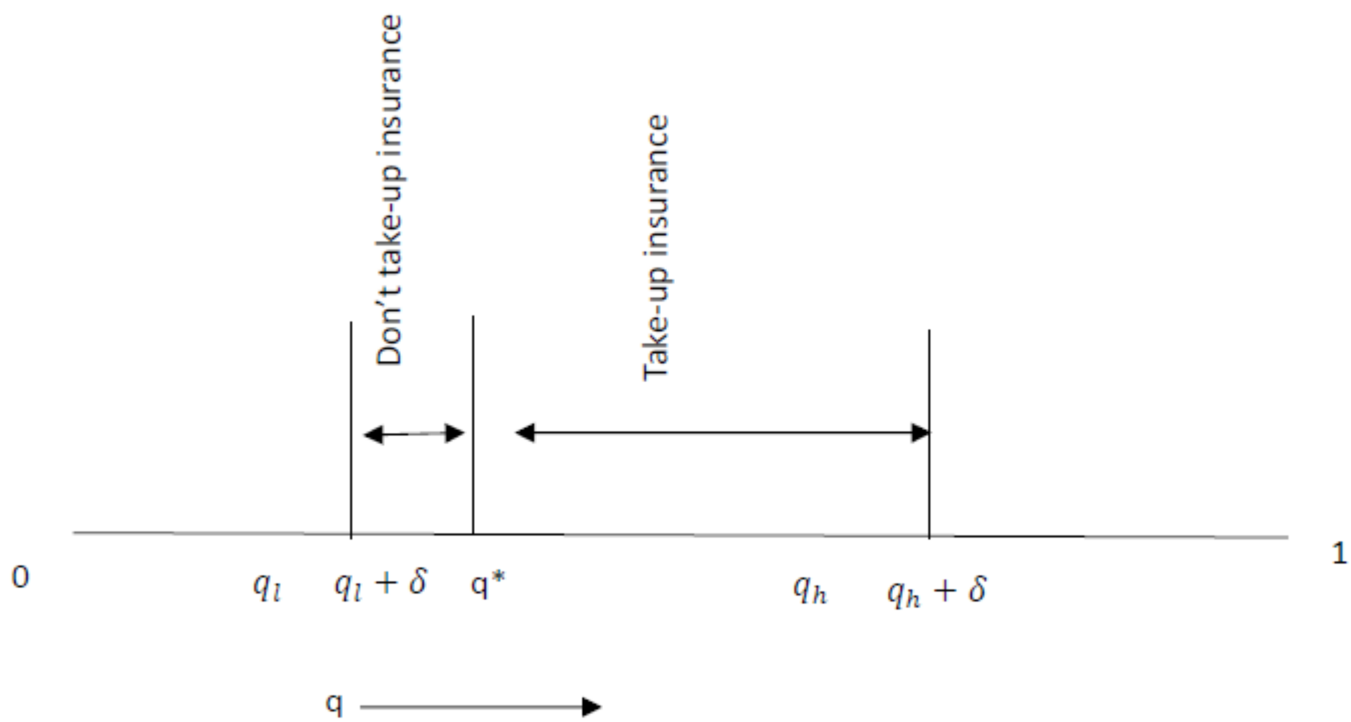
Our approach has many significant policy implications. Our results suggest that providing more information regarding public information may not improve its take up rate. In this case, the interest of the community network and the state is aligned – both institutions want to increase the take up rate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

Figure 1: Pre-shock decision rule for non-members



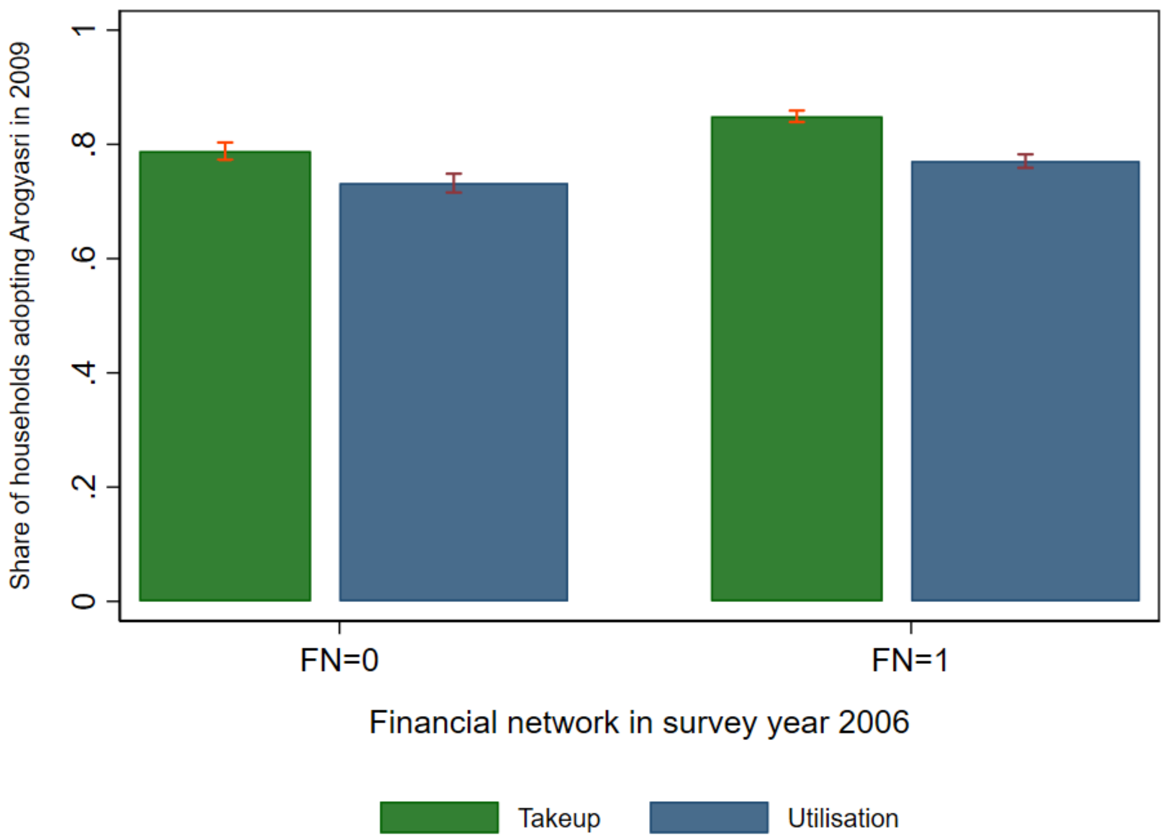

NOTES: This figure represents the non-members' decision to take up insurance before shock based on individual's perceived probability of heath shock ($q$). The minimum and maximum value of the perceived probability are $q_l$ and $q_h$ respectively. The value $q^*$ represents the individual whose shock perception is such that she is indifferent between taking up and not taking up insurance. People with $q < q^*$ are optimists and they don't take up insurance. On the other hand, people with $q > q^*$ and they take up insurance. Related discussion can be found in Section 6.

Figure 2: Post-shock decision rule for non-members



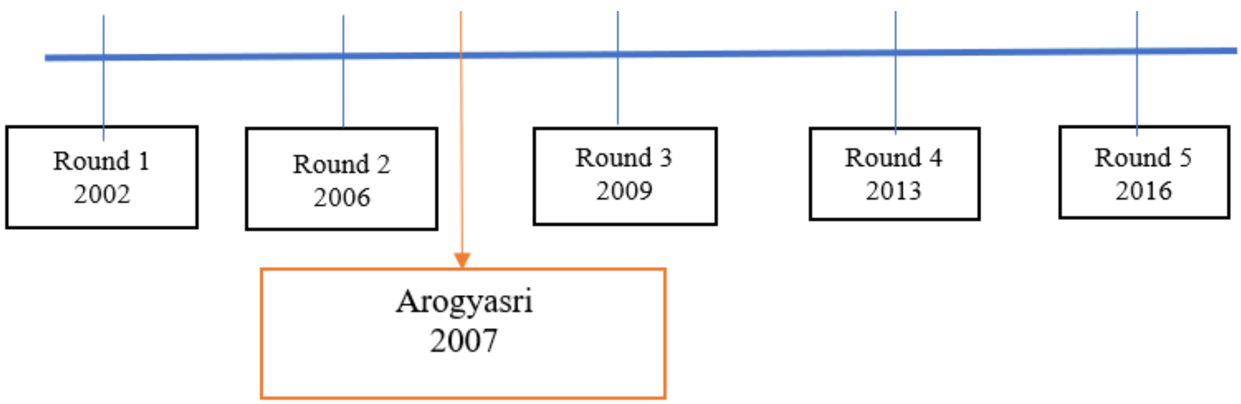

NOTES: This figure represents the non-members' decision to take up insurance after a health shock. After a shock, every one's perceived probability increases by $\delta$. Consequently, the minimum and maximum of the distribution of $q$ now becomes $q_l + \delta$ and $q_h + \delta$. The critical value $q^*$ however remains the same which implies that more non-members are likely to take up insurance compared to the pre-shock scenario. Related discussion can be found in Section 6.

Figure 3: *Arogyasri* adoption in 2009 classified by network status before introduction of scheme



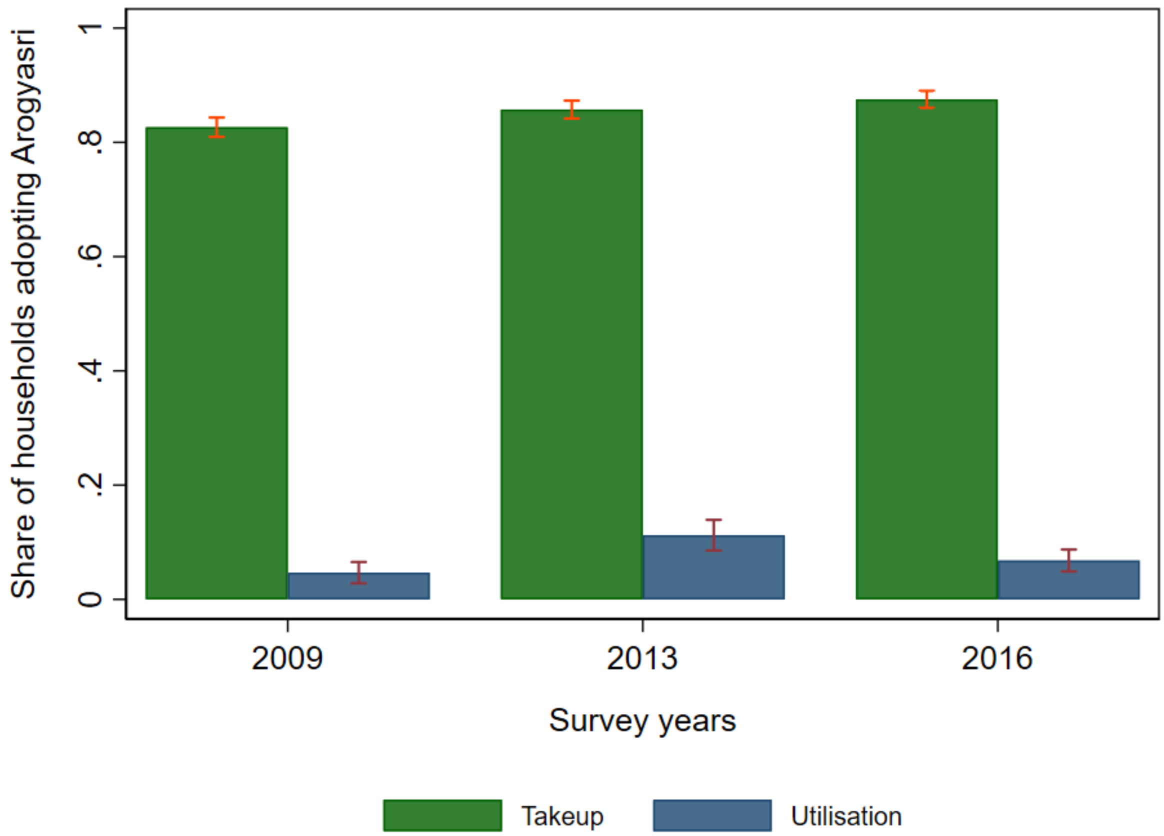

NOTES: This figure plots the share of households who took up and utilised *Arogyasri* in 2009 (the survey year immediately following the introduction of *Arogysri*) classified by their network status in 2006 (the survey year immediately preceding the introduction of *Arogyasri* in April 2007). Related discussion can be found in Section 1. Source: Authors' own calculation from Young Lives data.

Figure 4: Timeline of Young Lives survey years and *Arogyasri*



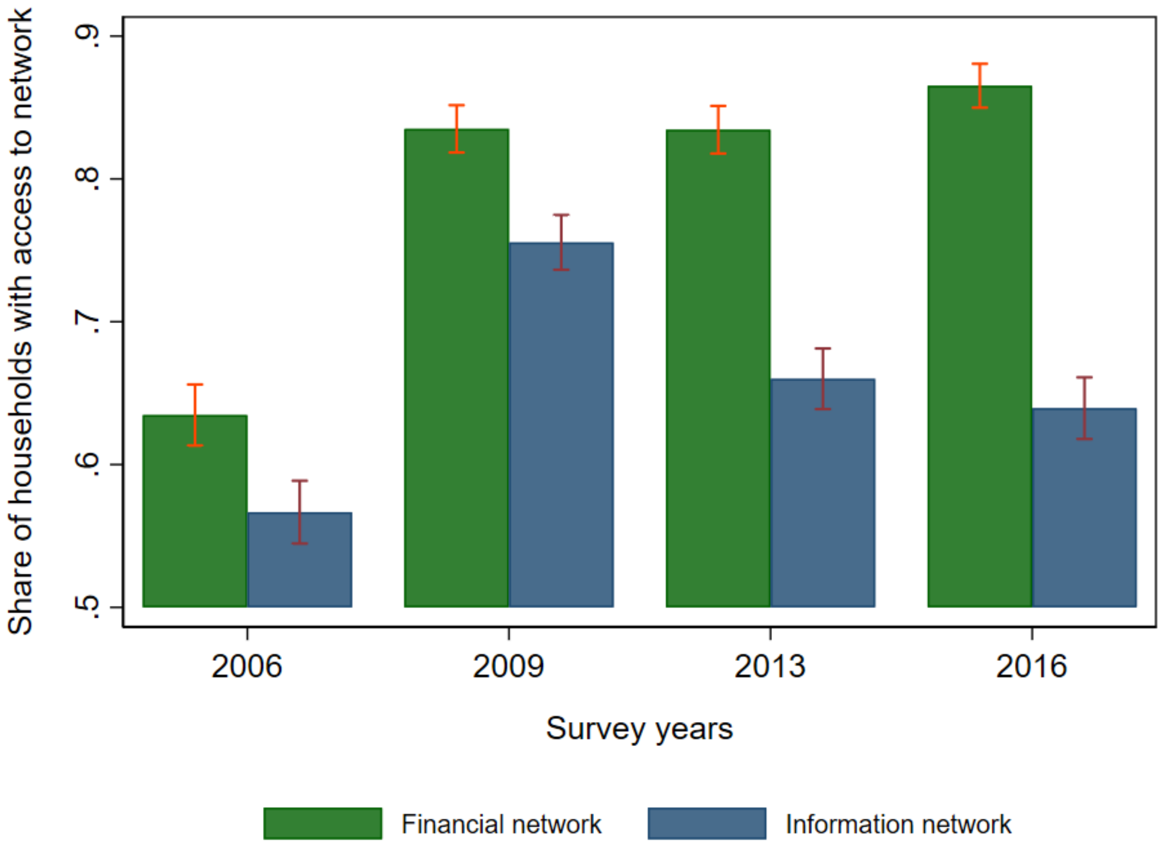

NOTES: This figure presents the timeline of the Young Lives survey years and the introduction of *Arogyasri*. *Arogyasri* was introduced in April 2007 and the roll out of the scheme was completed by July 2008. The Young Lives study had conducted five rounds of survey in the period 2002-2016. We discuss *Arogyasri* in further detail in Section 2 and discuss the Young Lives Study in Section 3.1

Figure 5: Trends in *Arogyasi* take up and utilisation



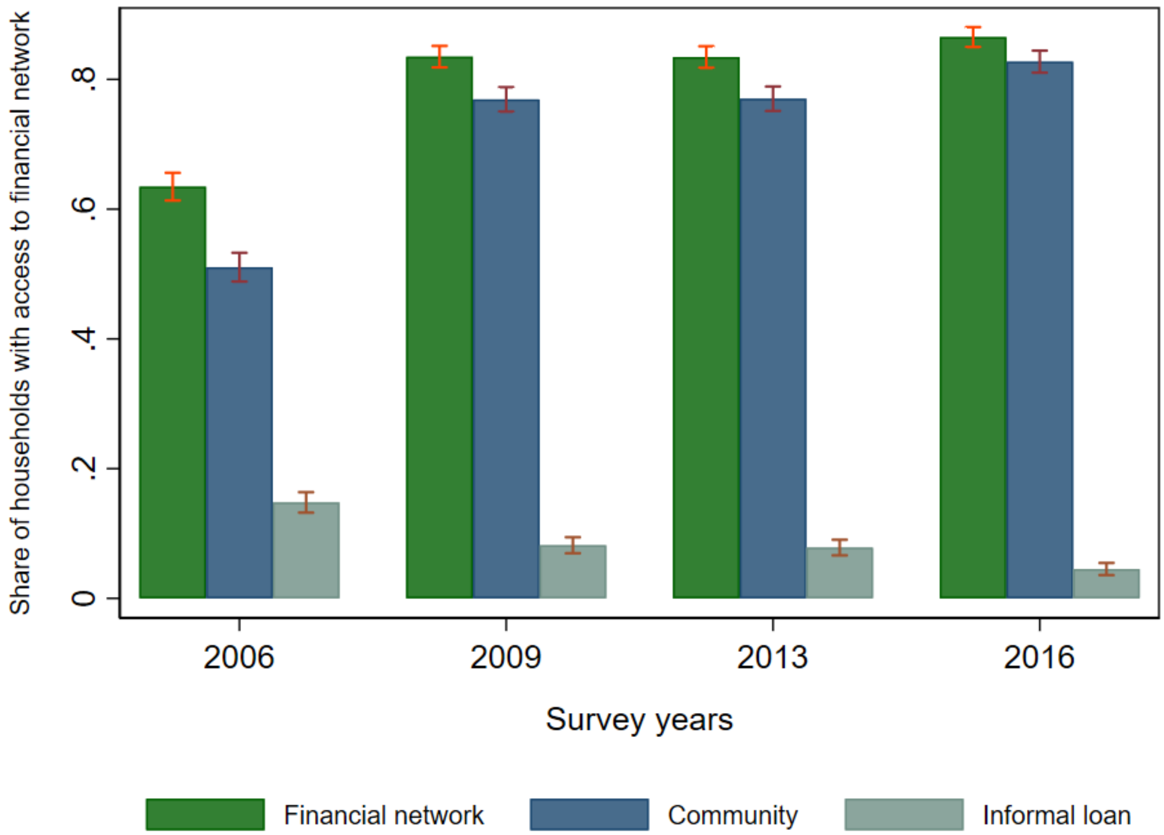

NOTES: This figure plots the share of households who have taken up and utilised *Arogyasri* during the period 2009-2016. The utilisation figures are conditional on experience of severe illness in the contemporaneous survey year. *Arogyasri* was introduced during 2007-2008, thus, we can capture adoption from survey year 2009 through survey year 2016. Further discussion on construction of adoption variables can be found in Section 3.2. Source: authors' own calculation from Young Lives data.

Figure 6: Trends in access to financial and information networks



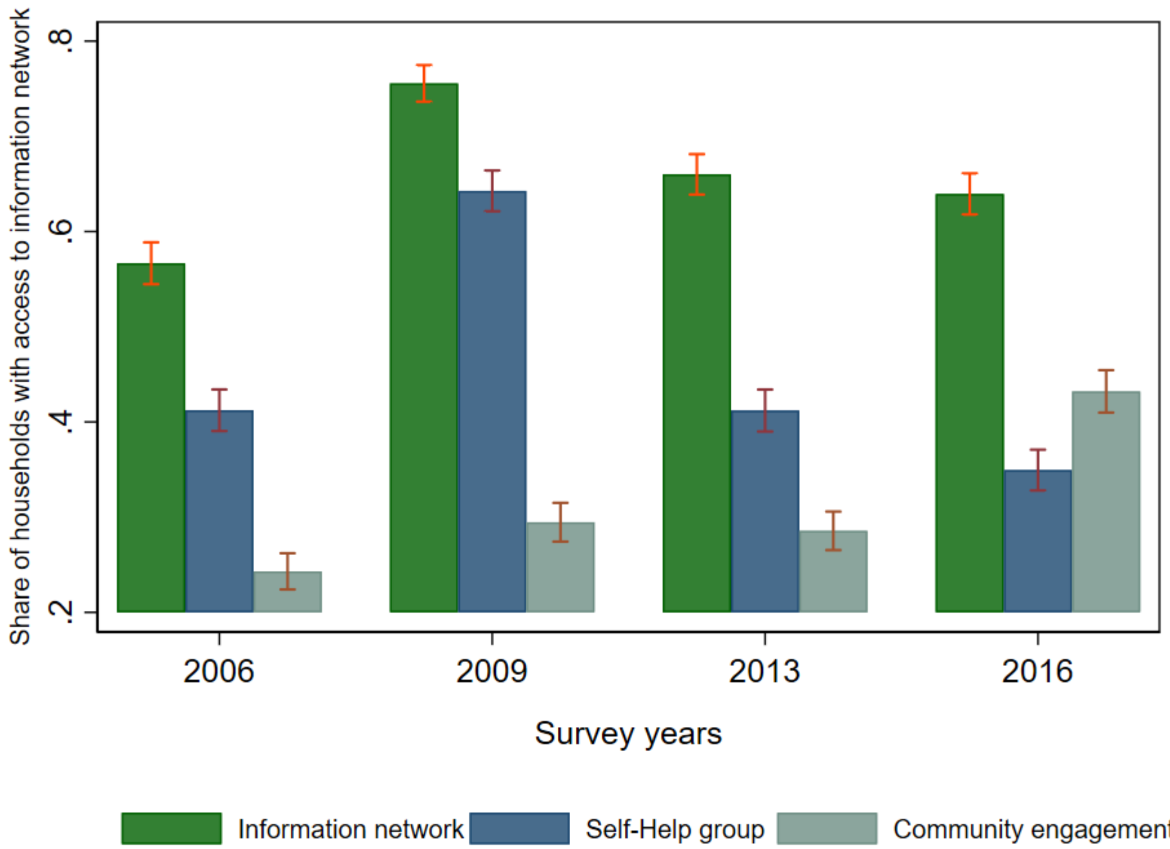

NOTES: This figure plots the share of households who have access to financial network and information network during our study period 2006-2016. Further discussion on construction of financial and information networks variables can be found in Section 3.3. Source: authors' own calculation from Young Lives data.

Figure 7: Trends in access to financial network: sub-categories



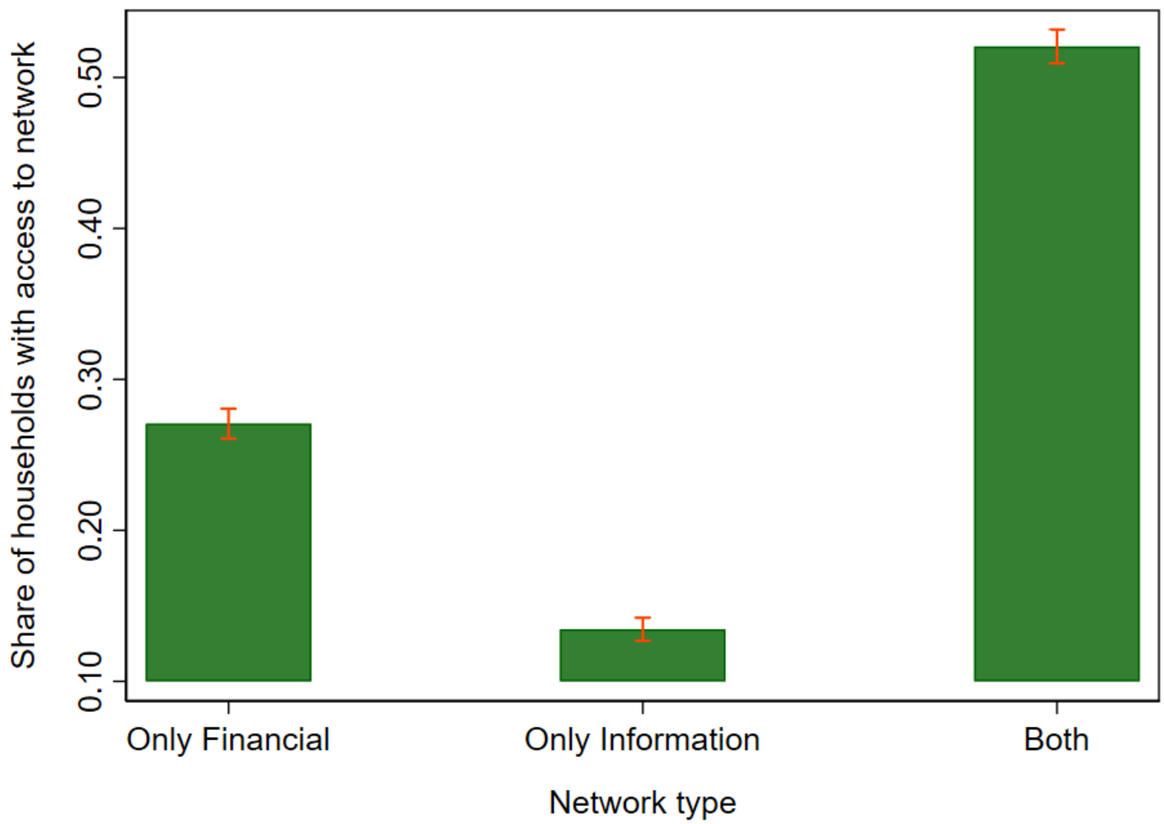

NOTES: This figure plots the share of households who have access to different sub-categories of financial network along with the composite measure of financial network during our study period 2006-2016. Further details on construction of these variables can be found in Section 3.3. Source: Authors' own calculation from Young Lives data.

Figure 8: Trends in access to information network: sub-categories



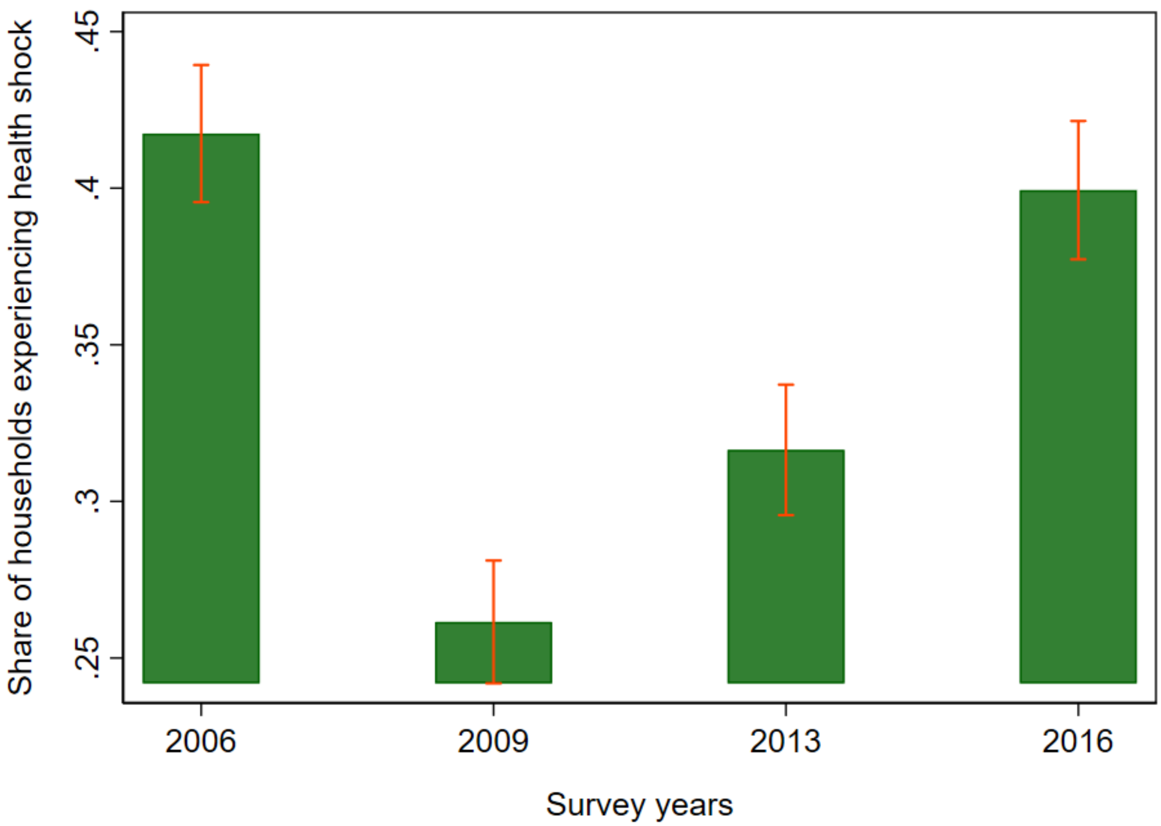

NOTES: This figure plots the share of households who have access to different sub-categories of information network along with the composite measure of information network during our study period 2006-2016. Further details on construction of these variables can be found in Section 3.3. Source: Authors' own calculation from Young Lives data.

Figure 9: Share of households with access to network- only one type and both types



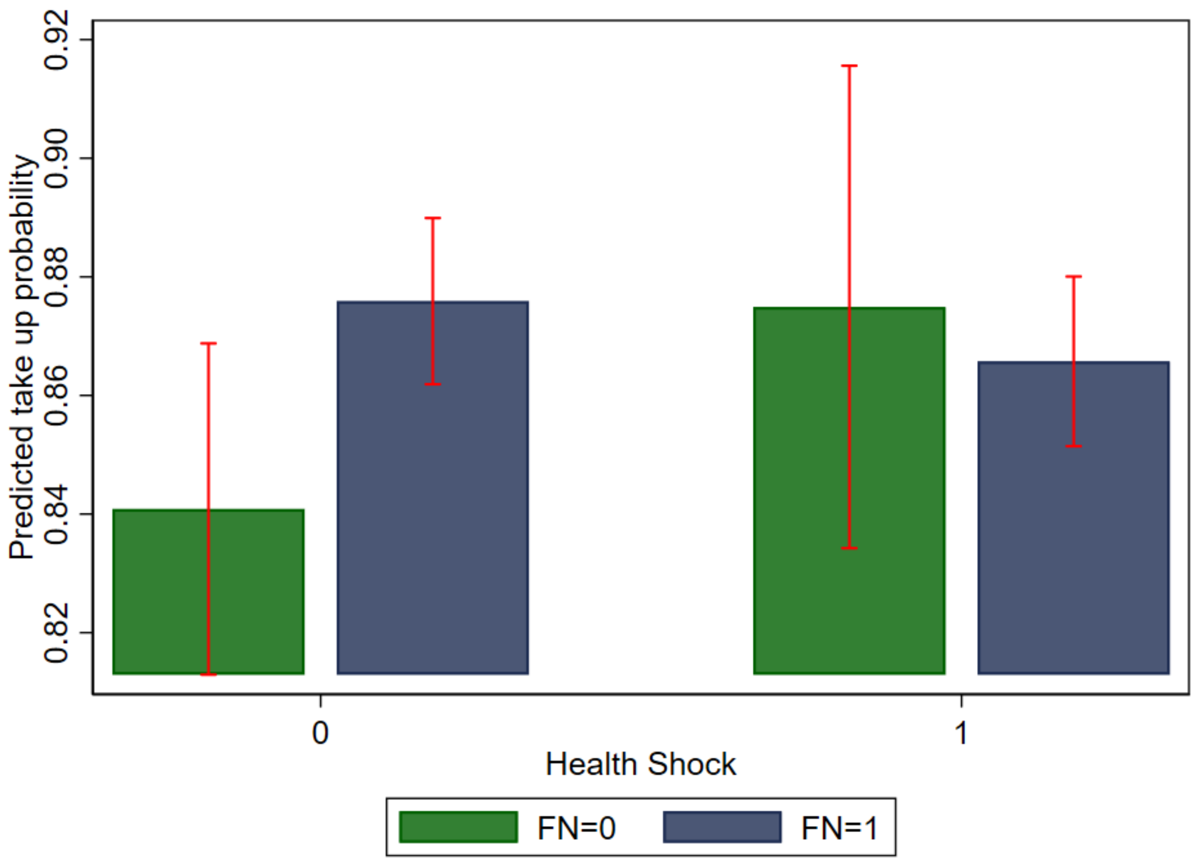

NOTES: This figure plots the share of households who have access to only financial network, only information network, and both financial and information network during our study period 2006-2016. Further details on construction of financial and information networks and related discussion can be found in Section 3.3. Source: Authors' own calculation from Young Lives data.

Figure 10: Share of households with experience of severe illness



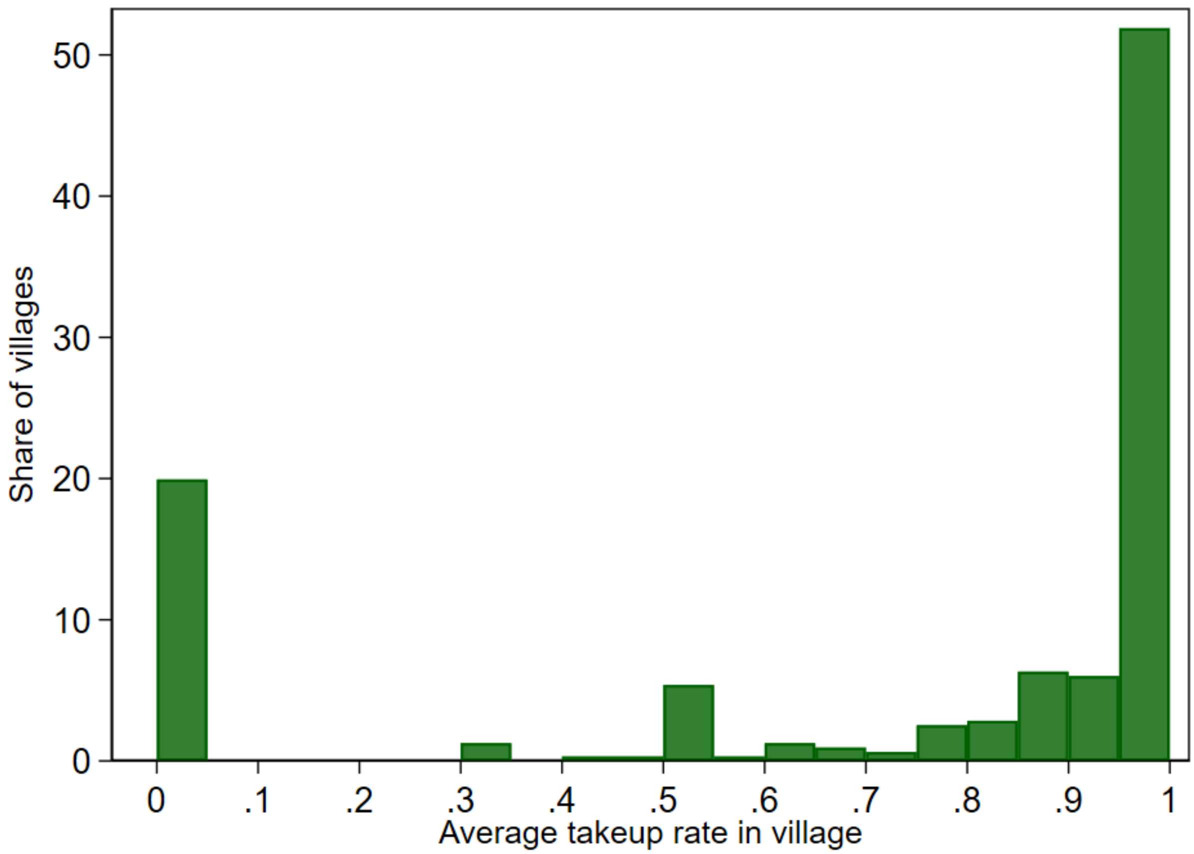

NOTES: This figure plots the share of households who experienced a severe illness, i.e health shock, during our study period 2006-2016. Further details on construction of health shock variable can be found in Section 3.4. Source: Authors' own calculation from Young Lives data.

Figure 11: Predicted take up probability by network status and experience of health shock



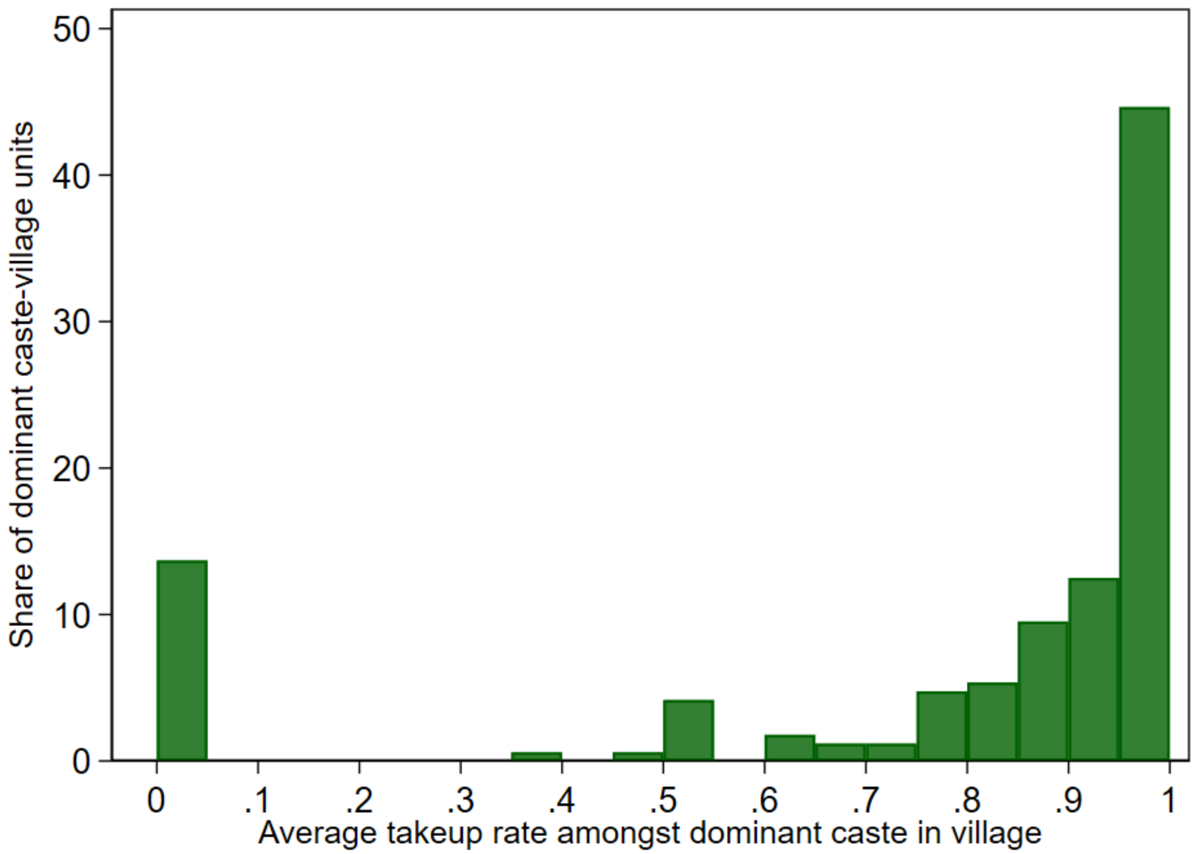

NOTES: This figure plots the predicted take up probability amongst household with and without access to financial network, classified by experience of health shock in the contemporaneous survey year during the period 2009-2016. Related discussion can be found in Section 4.1. Source: Authors' own calculation from Young Lives data.

Figure 12: Distribution of average take up rate in village




NOTES: This figure plots the distribution of village-level average take up rate during the period 2009-2016. Related discussion can be found in Section 6. Source: Authors' own calculation from Young Lives data.

Figure 13: Distribution of average take up rate amongst dominant caste in village




NOTES: This figure plots the distribution of average take up rate amongst dominant caste in a village during our the period 2009-2016. Related discussion can be found in Section 6. Source: Authors' own calculation from Young Lives data.

Table 1: Pre-*Arogyasri* summary statistics

| Variable | | With Arogyasri Mean (SE) | Without Arogyasri Mean (SE) |
|---|---|---|---|
| *Economic characteristics* | | | |
| | Main occupation agriculture,% | 26.57<br>(0.01) | 16.21<br>(0.02) |
| | Land holding,acres | 2.07<br>(0.09) | 1.77<br>(0.26) |
| | Livestock, rupees | 7878.3<br>(504.66) | 6439.7<br>(1022.23) |
| | Higher than median consumption,% | 46.39<br>(0.01) | 66.26<br>(0.02) |
| | Wealth index | 0.43<br>(0.004) | 0.56<br>(0.01) |
| *Demographic characteristics* | | | |
| | Any child with school education,% | 68.73<br>(0.01) | 61.25<br>(0.02) |
| | Age of household head, years | 38.4<br>(0.29) | 39.02<br>(0.65) |
| | Scheduled Caste/Scheduled Tribe,% | 32.58<br>(0.01) | 22.98<br>(0.02) |
| | Backward Caste,% | 48.74<br>(0.01) | 44.47<br>(0.02) |
| *Access to alternative safety net* | | | |
| | Has NREGS card,% | 38.14<br>(0.01) | 16.21<br>(0.02) |
| *Locality characteristics* | | | |
| | Urban,% | 20.76<br>(0.01) | 46.98<br>(0.02) |
| | Has hospital,% | 25.81<br>(0.01) | 43.47<br>(0.02) |
| | Has health centre,% | 31.63<br>(0.01) | 50.83<br>(0.02) |

NOTES: This table presents a summary statistics of a set of household characteristics in the survey year immediately preceding the introduction of *Arogyasri* classified by their take up status in the survey year immediately following the introduction of the scheme. The variables have been grouped in four categories: economic characteristics, demographic characteristics, access to alternative safety nets, and locality characteristics. Related discussion can be found in Section 4.1

Table 2: Effect of financial network on adoption of formal health insurance

| | (1) Takeup | (2) Takeup | (3) Utilisation | (4) Utilisation |
|---|---|---|---|---|
| Financial network | 0.035** | 0.035** | 0.030** | 0.030** |
| | (0.017) | (0.017) | (0.014) | (0.014) |
| Health shock lag | 0.034 | 0.038 | | |
| | (0.024) | (0.024) | | |
| Financial network X Health shock lag | -0.044* | -0.043* | | |
| | (0.026) | (0.026) | | |
| Health shock | | | 0.049* | 0.050* |
| | | | (0.029) | (0.029) |
| Financial network X Health shock | | | -0.049* | -0.051* |
| | | | (0.030) | (0.030) |
| Observations | 5,254 | 5,254 | 4,558 | 4,558 |
| R-squared | 0.655 | 0.648 | 0.438 | 0.436 |
| Baseline mean | .863 | .863 | .042 | .042 |
| Survey-year FE | YES | YES | YES | YES |
| Household FE | YES | YES | YES | YES |
| Control | YES | NO | YES | NO |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

NOTES: This table presents results from estimation of the effect of informal financial network, conditional on health shock, on the probability of adoption of formal health insurance. Adoption is measured through two binary dependent variables for whether a household has taken up Arogyasri and whether household has utilised Arogyasri. Columns (1) and (2) present the results for takeup and columns (3) and (4) present the results for utilisation. For columns (1) and (2), the point estimates on **Financial network** and **Financial network X Health shock lag** correspond to $\beta_{11}$ and $\beta_{12}$ respectively in Equation 1.For columns (3) and (4), the point estimates on **Financial network** and **Financial network X Health shock** correspond to $\beta_{21}$ and $\beta_{22}$ respectively in Equation 2. In columns (1) and (3) we further control for our set of covariates- whether household is primarily an agricultural household, amount of landholding and livestock ownership, whether household has higher than median average consumption, an index for household wealth, whether there is any school educated child in the household, age of household head, and whether a household has access to common government safety net such as NREGS. Columns (2) and (4) present the estimates without inclusion of time variant household level control variables. In addition, all models include household fixed effects and survey-year fixed effects. Standard errors, clustered at the community-survey year level, are reported in parentheses. Constants are not reported. Discussion of the results can be found in Section 5.1.

Table 3: Effect of information network on adoption of formal health insurance

| | (1) Takeup | (2) Takeup | (3) Utilisation | (4) Utilisation |
|---|---|---|---|---|
| Information network | 0.014 | 0.018 | -0.004 | -0.004 |
| | (0.013) | (0.013) | (0.014) | (0.014) |
| Health shock lag | -0.014 | -0.008 | | |
| | (0.020) | (0.019) | | |
| Information network X Health shock lag | 0.014 | 0.014 | | |
| | (0.024) | (0.023) | | |
| Health shock | | | 0.029 | 0.028 |
| | | | (0.021) | (0.021) |
| Information network X Health shock | | | -0.032 | -0.030 |
| | | | (0.024) | (0.025) |
| Observations | 5,255 | 5,255 | 4,558 | 4,558 |
| R-squared | 0.655 | 0.648 | 0.438 | 0.436 |
| Baseline mean | .863 | .863 | .042 | .042 |
| Survey-year FE | YES | YES | YES | YES |
| Household FE | YES | YES | YES | YES |
| Control | YES | NO | YES | NO |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

NOTES: This table presents results from estimation of the effect of informal information network, conditional on health shock, on the probability of adoption of formal health insurance. Adoption is measured through two binary dependent variables for whether a household has taken up Arogyasri and whether household has utilised Arogyasri. Columns (1) and (2) present the results for takeup and columns (3) and (4) present the results for utilisation. For columns (1) and (2), the point estimates on **Information network** and **Information network X Health shock lag** correspond to $\beta_{11}$ and $\beta_{12}$ respectively in Equation 1.For columns (3) and (4), the point estimates on **Information network** and **Information X Health shock** correspond to $\beta_{21}$ and $\beta_{22}$ respectively in Equation 2. In columns (1) and (3) we further control for our set of covariates- whether household is primarily an agricultural household, amount of landholding and livestock ownership, whether household has higher than median average consumption, an index for household wealth, whether there is any school educated child in the household, age of household head, and whether a household has access to common government safety net such as NREGS. Columns (2) and (4) present the estimates without inclusion of time variant household level control variables. In addition, all models include household fixed effects and survey-year fixed effects. Standard errors, clustered at the community-survey year level, are reported in parentheses. Constants are not reported. Discussion of the results can be found in Section 5.1.

Table 4: Effect of informal network on adoption of formal health insurance

| | (1) Takeup | (2) Takeup | (3) Utilisation | (4) Utilisation |
|---|---|---|---|---|
| Financial network | 0.035** | 0.035** | 0.031** | 0.031** |
| | (0.017) | (0.017) | (0.014) | (0.014) |
| Health shock lag | 0.022 | 0.026 | | |
| | (0.030) | (0.030) | | |
| Financial network X Health shock lag | -0.043 | -0.042 | | |
| | (0.026) | (0.026) | | |
| Information network | 0.013 | 0.017 | -0.004 | -0.004 |
| | (0.013) | (0.013) | (0.014) | (0.014) |
| Information network X Health shock lag | 0.017 | 0.016 | | |
| | (0.024) | (0.023) | | |
| Health shock | | | 0.072** | 0.072** |
| | | | (0.035) | (0.036) |
| Financial network X Health shock | | | -0.050* | -0.051* |
| | | | (0.030) | (0.030) |
| Information network X Health shock | | | -0.032 | -0.030 |
| | | | (0.024) | (0.024) |
| Observations | 5,254 | 5,254 | 4,558 | 4,558 |
| R-squared | 0.656 | 0.649 | 0.438 | 0.436 |
| Baseline mean | .863 | .863 | .042 | .042 |
| Survey-year FE | YES | YES | YES | YES |
| Household FE | YES | YES | YES | YES |
| Control | YES | NO | YES | NO |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

NOTES: This table presents results from estimation of the effect of informal financial and information networks, conditional on health shock, on the probability of adoption of formal health insurance. Adoption is measured through two binary dependent variables for whether a household has taken up Arogyasri and whether household has utilised Arogyasri. Columns (1) and (2) present the results for takeup and columns (3) and (4) present the results for utilisation. For columns (1) and (2), the point estimates on **Financial network** and **Information network** correspond to $\beta_{31}$ and $\beta_{34}$ respectively in Equation 3, while the point estimates on **Financial network X Health shock lag** and **Information network X Health shock lag** correspond to $\beta_{32}$ and $\beta_{35}$ respectively in Equation 3. For columns (3) and (4), the point estimates on **Financial network** and **Information network** correspond to $\beta_{41}$ and $\beta_{44}$ respectively in Equation 4, while the point estimates on **Financial network X Health shock** and **Information network X Health shock** correspond to $\beta_{42}$ and $\beta_{45}$ respectively in Equation 4. In columns (1) and (3) we further control for our set of covariates- whether household is primarily an agricultural household, amount of landholding and livestock ownership, whether household has higher than median average consumption, an index for household wealth, whether there is any school educated child in the household, age of household head, and whether a household has access to common government safety net such as NREGS. Columns (2) and (4) present the estimates without inclusion of time variant household level control variables. In addition, all models include household fixed effects and survey-year fixed effects. Standard errors, clustered at the community-survey year level, are reported in parentheses. Constants are not reported. Discussion of the results can be found in Section 5.2.

Table 5: Complementarity between financial and information network

| | (1)<br>Takeup | (2)<br>Utilisation |
|---|---|---|
| Both networks | 0.021* | 0.009 |
| | (0.011) | (0.012) |
| Health shock lag | -0.004 | |
| | (0.016) | |
| Both networks X Health shock lag | 0.002 | |
| | (0.019) | |
| Health shock | | 0.023 |
| | | (0.018) |
| Both networks X Health shock | | -0.027 |
| | | (0.023) |
| Observations | 5,254 | 4,558 |
| R-squared | 0.655 | 0.437 |
| Network type | Both networks | Both networks |
| Baseline mean | .863 | .042 |
| Survey-year FE | YES | YES |
| Household FE | YES | YES |
| Control | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

NOTES: This table presents results from estimation of the effect of having access to both financial and information network, conditional on health shock, on the probability of adoption of formal health insurance. Adoption is measured through two binary dependent variables for whether a household has taken up Arogyasri and whether household has utilised Arogyasri. Column (1) presents the result for takeup while column (2) presents the result for utilisation. We further control for our set of covariates- whether household is primarily an agricultural household, amount of landholding and livestock ownership, whether household has higher than median average consumption, an index for household wealth, whether there is any school educated child in the household, age of household head, and whether a household has access to common government safety net such as NREGS. In addition, all models include household fixed effects and survey-year fixed effects. Standard errors, clustered at the community-survey year level, are reported in parentheses. Constants are not reported. Discussion of the results can be found in Section 5.2.

Table 6: Heterogeneity analysis: proximity to hospital

| | (1)<br>Takeup | (2)<br>Takeup | (3)<br>Utilisation | (4)<br>Utilisation |
|---|---|---|---|---|
| Financial network | -0.007 | 0.051*** | 0.048 | 0.024* |
| | (0.039) | (0.020) | (0.045) | (0.014) |
| Health shock lag | -0.068 | 0.043 | | |
| | (0.082) | (0.033) | | |
| Financial network X Health shock lag | 0.027 | -0.065** | | |
| | (0.070) | (0.030) | | |
| Information network | 0.032 | 0.004 | -0.000 | -0.016 |
| | (0.037) | (0.014) | (0.032) | (0.016) |
| Information network X Health shock lag | 0.026 | 0.018 | | |
| | (0.062) | (0.025) | | |
| Health shock | | | 0.070 | 0.068 |
| | | | (0.071) | (0.043) |
| Financial network X Health shock | | | -0.007 | -0.055 |
| | | | (0.073) | (0.034) |
| Information network X Health shock | | | -0.025 | -0.020 |
| | | | (0.059) | (0.028) |
| Observations | 901 | 3,964 | 662 | 3,606 |
| R-squared | 0.736 | 0.588 | 0.524 | 0.431 |
| Baseline mean | .729 | .896 | .074 | .039 |
| Survey-year FE | YES | YES | YES | YES |
| Household FE | YES | YES | YES | YES |
| Control | YES | YES | YES | YES |
| Hospital | YES | NO | YES | NO |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

NOTES: This table presents results from heterogeneity analysis of binary dependent variables for whether a household has taken up formal health insurance and whether a household has utilised formal health insurance. Columns (1) and (2) estimate the coefficients in Equation 3 while Columns (3) and (4) estimate the coefficients in Equation 4. Each of the columns present results for the specific sub-sample indicated. Standard errors, clustered at the community-survey year level, are reported in parentheses. Constants are not reported. Further discussion located in Section 7.

Table 7: Heterogeneity analysis: proximity to health centre

| | (1) Takeup | (2) Takeup | (3) Utilisation | (4) Utilisation |
|---|---|---|---|---|
| Financial network | 0.010 | 0.057** | 0.033 | 0.024 |
| | (0.025) | (0.025) | (0.029) | (0.016) |
| Health shock lag | -0.043 | 0.057 | | |
| | (0.055) | (0.039) | | |
| Financial network X Health shock lag | 0.005 | -0.074** | | |
| | (0.044) | (0.036) | | |
| Information network | 0.017 | 0.008 | -0.001 | -0.017 |
| | (0.025) | (0.016) | (0.022) | (0.019) |
| Information network X Health shock lag | 0.040 | 0.010 | | |
| | (0.042) | (0.028) | | |
| Health shock | | | 0.081 | 0.068 |
| | | | (0.064) | (0.046) |
| Financial network X Health shock | | | -0.010 | -0.062 |
| | | | (0.053) | (0.038) |
| Information network X Health shock | | | -0.019 | -0.024 |
| | | | (0.051) | (0.029) |
| Observations | 1,633 | 3,232 | 1,329 | 2,939 |
| R-squared | 0.732 | 0.568 | 0.486 | 0.426 |
| Baseline mean | 0.824 | .893 | .07 | .033 |
| Survey-year FE | YES | YES | YES | YES |
| Household FE | YES | YES | YES | YES |
| Control | YES | YES | YES | YES |
| Health Centre | YES | NO | YES | NO |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

NOTES: This table presents results from heterogeneity analysis of binary dependent variables for whether a household has taken up formal health insurance and whether a household has utilised formal health insurance. Columns (1) and (2) estimate the coefficients in Equation 3 while Columns (3) and (4) estimate the coefficients in Equation 4. Each of the columns present results for the specific sub-sample indicated. Standard errors, clustered at the community-survey year level, are reported in parentheses. Constants are not reported. Further discussion located in Section 7.

Table 8: Heterogeneity analysis: urbanity

| | (1) Takeup | (2) Takeup | (3) Utilisation | (4) Utilisation |
|---|---|---|---|---|
| Financial network | 0.015 | 0.049** | 0.054 | 0.021 |
| | (0.033) | (0.020) | (0.044) | (0.015) |
| Health shock lag | -0.066 | 0.045 | | |
| | (0.070) | (0.034) | | |
| Financial network X Health shock lag | 0.037 | -0.062** | | |
| | (0.060) | (0.031) | | |
| Information network | 0.025 | 0.010 | -0.023 | -0.003 |
| | (0.032) | (0.014) | (0.032) | (0.016) |
| Information network X Health shock lag | 0.017 | 0.014 | | |
| | (0.055) | (0.024) | | |
| Health shock | | | 0.027 | 0.090** |
| | | | (0.070) | (0.043) |
| Financial network X Health shock | | | 0.035 | -0.074** |
| | | | (0.072) | (0.034) |
| Information network X Health shock | | | -0.020 | -0.034 |
| | | | (0.058) | (0.028) |
| Observations | 1,162 | 4,052 | 868 | 3,672 |
| R-squared | 0.731 | 0.583 | 0.482 | 0.430 |
| Baseline mean | .728 | .894 | .074 | .037 |
| Survey-year FE | YES | YES | YES | YES |
| Household FE | YES | YES | YES | YES |
| Control | YES | YES | YES | YES |
| Urban | YES | NO | YES | NO |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

NOTES: This table presents results from heterogeneity analysis of binary dependent variables for whether a household has taken up formal health insurance and whether a household has utilised formal health insurance. Columns (1) and (2) estimate the coefficients in Equation 3 while Columns (3) and (4) estimate the coefficients in Equation 4. Each of the columns present results for the specific sub-sample indicated. Standard errors, clustered at the community-survey year level, are reported in parentheses. Constants are not reported. Further discussion located in Section 7.

Table 9: Heterogeneity analysis: types of financial network

| | (1) Takeup | (2) Takeup | (3) Takeup | (4) Utilisation | (5) Utilisation | (6) Utilisation |
|---|---|---|---|---|---|---|
| Financial network | 0.035** | | | 0.030** | | |
| | (0.017) | | | (0.014) | | |
| Health shock lag | 0.034 | 0.026 | -0.004 | | | |
| | (0.024) | (0.019) | (0.009) | | | |
| Financial network X Health shock lag | -0.044* | | | | | |
| | (0.026) | | | | | |
| Community | | 0.029* | | | 0.025* | |
| | | (0.015) | | | (0.013) | |
| Community X Health shock lag | | -0.037* | | | | |
| | | (0.022) | | | | |
| Informal loan | | | -0.009 | | | 0.012 |
| | | | (0.022) | | | (0.024) |
| Informal loan X Health shock lag | | | 0.004 | | | |
| | | | (0.034) | | | |
| Health shock | | | | 0.049* | 0.022 | 0.009 |
| | | | | (0.029) | (0.026) | (0.012) |
| Financial network X Health shock | | | | -0.049* | | |
| | | | | (0.030) | | |
| Community X Health shock | | | | | -0.019 | |
| | | | | | (0.028) | |
| Informal loan X Health shock | | | | | | -0.036 |
| | | | | | | (0.042) |
| Observations | 5,254 | 5,254 | 5,240 | 4,558 | 4,558 | 4,548 |
| R-squared | 0.655 | 0.655 | 0.657 | 0.438 | 0.437 | 0.438 |
| Baseline mean | .863 | .863 | .865 | .042 | .042 | .043 |
| Survey-year FE | YES | YES | YES | YES | YES | YES |
| Household FE | YES | YES | YES | YES | YES | YES |
| Control | YES | YES | YES | YES | YES | YES |
| Network type | Financial Network | Community | Informal Loan | Financial Network | Community | Informal Loan |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

NOTES: This table presents results from heterogeneity analysis of binary dependent variables for whether a household has taken up formal health insurance and whether a household has utilised formal health insurance. Columns (1) through (3) estimate the coefficients in Equation 1 while Columns (4) through (6) estimate the coefficients in Equation 2. Each of the columns present results for the specific type of financial network indicated. Standard errors, clustered at the community-survey year level, are reported in parentheses. Constants are not reported. Further discussion located in Section 7.2.

Table 10: Heterogeneity analysis: types of information network

| VARIABLES | (1) Takeup | (2) Takeup | (3) Takeup | (4) Utilisation | (5) Utilisation | (6) Utilisation |
|---|---|---|---|---|---|---|
| Information network | 0.014 | | | -0.004 | | |
| | (0.013) | | | (0.014) | | |
| Health shock lag | -0.014 | -0.009 | -0.007 | | | |
| | (0.020) | (0.013) | (0.012) | | | |
| Information network X Health shock lag | 0.014 | | | | | |
| | (0.024) | | | | | |
| Self-Help group | | -0.001 | | | -0.016 | |
| | | (0.013) | | | (0.013) | |
| Self-Help group X Health shock lag | | 0.010 | | | | |
| | | (0.017) | | | | |
| Community engagement | | | 0.011 | | | -0.014 |
| | | | (0.013) | | | (0.013) |
| Community engagement X Health shock lag | | | 0.011 | | | |
| | | | (0.022) | | | |
| Health shock | | | | 0.029 | -0.003 | 0.018 |
| | | | | (0.021) | (0.015) | (0.014) |
| Information network X Health shock | | | | -0.032 | | |
| | | | | (0.024) | | |
| Self-Help group X Health shock | | | | | 0.016 | |
| | | | | | (0.020) | |
| Community engagement X Health shock | | | | | | -0.027 |
| | | | | | | (0.022) |
| Observations | 5,255 | 5,255 | 5,255 | 4,558 | 4,558 | 4,558 |
| R-squared | 0.655 | 0.654 | 0.655 | 0.438 | 0.437 | 0.438 |
| Baseline mean | .863 | .863 | .863 | .042 | .042 | .042 |
| Survey-year FE | YES | YES | YES | YES | YES | YES |
| Household FE | YES | YES | YES | YES | YES | YES |
| Control | YES | YES | YES | YES | YES | YES |
| Network type | Information Network | Self-Help Group | Community Engagement | Information Network | Self-Help Group | Community Engagement |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

NOTES: This table presents results from heterogeneity analysis of binary dependent variables for whether a household has taken up formal health insurance and whether a household has utilised formal health insurance. Columns (1) through (3) estimate the coefficients in Equation 1 while Columns (4) through (6) estimate the coefficients in Equation 2. Each of the columns present results for the specific type of information network indicated. Standard errors, clustered at the community-survey year level, are reported in parentheses. Constants are not reported. Further discussion located in Section 7.2.

# Appendix

Table A1: Description of variables

| Variable | Description |
|---|---|
| Financial network | Household has access to informal financial network |
| Information network | Household has access to informal information network |
| Health shock | Household has experienced severe illness |
| Agriculture | Agriculture is primary occupation of household |
| NREGS card | Household has NREGS card |
| Higher education | Household has children enrolled in higher education |
| School education | Household has children enrolled in school education |
| SC-ST | Household belongs to SC-ST community |
| BC | Household belongs to BC community |
| Urban | Households is located in urban area |
| Hospital | Household has hospital in the locality |
| Health center | Household has health center in the locality |
| Consumption class | Household monthly total consumption expenditure (current price) is above medi |
| Wealth | Composite index of household wealth |
| Land | Acres of agricultural and non agricultural land owned |
| Livestock | Monetary value of livestock owned (in rupees) |
| Age of household head | Age of household head |

NOTES: This table presents a brief definition of all the variables used in our analysis. The discussion on network variables can be found in Section 3.3, that on health shock in Section 3.4, and that on control variables in Section 4.1. Section 7.1 contains the discussion on locality based variables- urbanity, presence of hospital, amd presence of health centre.

Table A2: Effect of financial network on take up: instrumental variable approach

| | (1)<br>first<br>Financial network | (2)<br>second<br>Take-up |
|---|---|---|
| Aggregate shock lag | 0.0952*** | |
| | (0.0116) | |
| Financial network | | 1.055*** |
| | | (0.171) |
| Observations | 5,199 | 5,199 |
| R-squared | 0.014 | |
| Survey-year FE | YES | YES |
| Household FE | NO | NO |
| Control | NO | NO |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

NOTES: This table presents results from an instrumental variable estimation of the effect of having access to financial network on the probability of takeup of formal health insurance. We instrument financial network with an indicator variable for whether household has faced any aggregate shock in the previous survey year. Aggregate shock is measured using a question on whether a household experienced a natural disaster. Column (1) presents the first stage of this estimation and the point estimate on **Aggregate shock lag** captures the effect of experiencing natural disaster in the previous period on the probability of having access to financial network in the current period. Column (2) presents the IV result. We do not include household fixed effect or household level time-variant covariates and include survey-year fixed effects. We do not cluster standard errors and report them in parentheses. Constants are not reported. Further discussion located in Section 5.3

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