Social Networks and Health Insurance Utilization

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Abstract

This paper examines the role of social networks in increasing use of public welfare programs. In the context of health insurance programs, utilization by socially proximate peers helps individuals learn about program and treatment procedures while also signaling social appropriateness of using formal healthcare, all of which could increase program utilization. Using complete administrative data on claims from a publicly financed health insurance program in India, we estimate the impact of utilization by members of "naturally" occurring caste peers within the village on subsequent first-time utilization of the program. We find that a unit increase in peer utilization increases subsequent utilization by 20%, with negligible effects of out of network individuals. Peers have the strongest effect on the treatment of informationally intensive procedures such as oncology and cardiology. Combining the administrative data with village/ward level census data, reveals that networks are most effective in dense urban areas and where communication is easiest, suggesting that information through social networks complements more formal sources.

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1 Introduction

The use of many public programs is complex and difficult, requiring considerable information, expertise and help. For some types of people and diseases, using formal health services might be taboo, violating prevailing social norms on appropriate behavior. These factors might limit adoption, even if the program is otherwise beneficial for users. For example, in developing countries there are often few formal sources of information about program benefits or how to access them. In sectors such as privately provided healthcare, experts frequently have conflicts of interest. Social networks might influence adoption by providing more program information, offering expertise on how to make choices and signaling whether using the program is socially appropriate. Members within social groups might have strong in-group preferences and help each other use public programs.

This paper examines the role of social networks, specifically caste networks within a village or urban ward, in increasing utilization of *Aarogyasri*, a large publicly financed health insurance program operating in the state of Andhra Pradesh (AP), India since 2007.[1] We posit that local caste networks play a vital role in transmitting information about the *Aarogyasri* program. The kinds of information communicated might include eligibility criteria, procedures for contacting hospitals and availing treatment for specific diseases. Individuals may share information on which hospitals or doctors provide the best care. Caste utilization could signal that using formal healthcare is socially appropriate, an important consideration for women and other excluded groups.

Using administrative data on program claims between 2008 and 2013, we estimate how both the incidence and amount of first time claims is effected by past utilization within village-level caste networks. Our main finding is that a unit increase in *Aarogyasri* use and associated claim amounts in the same caste and village increases first time claims in the same group by 20% and first time claim amounts by 18% in the subsequent quarter . In contrast, same caste peers outside the village in the same sub-district have an impact that is about a hundred

[1] Formally called the *Rajiv Aarogyasri* Scheme (RAS), the program was significantly redesigned in 2014 when Andhra Pradesh was split into the two states of Telangana and Andhra Pradesh.

times smaller. Simultaneously, as a placebo, other castes inside or outside the village have no discernible effect on utilization.

We open up the black box of how networks operate by examining different types of heterogeneity that might effect network influence. First, networks have the strongest influence in oncology, cardiology and major surgical procedures which are arguably more complex, and the weakest influence in the treatment of infectious diseases and in general medicine which are perhaps less informationally intensive. This suggests that networks transmit specific information about treatment and procedures, rather than general program information. Network effects might be different by gender, since men interact with peers outside the home more than women. Conversely, women might be more removed from formal information channels and rely disproportionately on social networks. We find significantly greater effects of networks on men's rather than women's *Aarogyasri* use.

We examine the differential effect of networks by location by matching the administrative data with the 2011 Census of India. We analyze the effects of social networks when communication within the network is easier, for instance in urban areas and in regions with greater penetration of cell phones and radios. Our analysis suggests that better communication systematically enhances the influence of social networks.

A range of other factors are complementary to social networks. We find that household wealth and access to markets are complements rather than substitutes for information through community peers. Finally, when local health facilities help screen patients, then social ties are most effective for those patients who suffer from more serious diseases.

The empirical strategy, combined with the administrative data, allows us to overcome a number of econometric problems that plague studies on peer and network effects. The first set of problems are fundamental identification concerns (Manski 1993). How can we define appropriate social networks that are important for decision-making, yet not formed endogenously for facilitating information sharing? We rely on local caste networks within the villages as "naturally" defined communities of trust, exchange and information sharing.[2] Since individuals are

[2] See Munshi (2014) for a comprehensive review of the role of caste networks in economic decisions. Further discussion of caste groups as social networks is in Section 2.2.

assigned caste by birth and cannot switch to other castes, caste networks can be considered to be exogenously assigned. The presence of multiple castes within each village also permit straightforward falsification tests – if own caste networks are influential in healthcare decisions, then other castes should have significantly smaller effects on utilization as should both own and other castes outside the village. A second identification concern is separately identifying peer effects from common environmental conditions and other potentially correlated shocks. We circumvent this concern by including village-caste fixed effects, caste-time fixed effects and district-time trends to control for environmental, social and cultural factors that might influence health status, disease incidence and health seeking behavior. Furthermore, we focus on tertiary diseases which are unlikely to be communicable within a group. Indeed, analyzing the results by disease type shows that "infectious diseases" are the only major category with no social influence in *Aarogyasri* utilization. The third identification concern is discerning the direction of peer effects, for which we rely on the timing of insurance claims, assuming that earlier users influence subsequent claimants, rather than vice versa.

In addition to Manski (1993)'s concerns, our data and setting also allow us to circumvent other potentially significant challenges. First, by examining a full program that operates throughout the state, we avoid both the problem of low take-up that might arise if participants believe that the program might be discontinued before medical treatment is completed, as well as bias due to the implementing agency selecting areas where it has better operational capabilities, or where it believes the target population might be more receptive to the program. Additionally, Chandrasekhar and Lewis (2011) argue that estimating network effects with sampled data produces biased results as network nodes are systematically undercounted. Even sampling all the households within the village assumes that networks beyond the village are not influential, which might not be consistent with spatially widespread family and communities ties in developing countries (Fafchamps and Lund 2003; Munshi 2003; Cox and Fafchamps 2007). Since we use the census of all claims against the program, combined with household and village data from the Census of India, the estimation is performed with complete network data and yields unbiased estimates.

This study contributes to literature on the role of peer and social networks on public program participation. Dahl, Løken, and Mogstad (2014) examine social influences in the context of paternity leave policy in Norway, Cai, De Janvry, and Sadoulet (2015) in rainfall insurance adoption in China, Bertrand, Luttmer, and Mullainathan (2000) in welfare in the United States, Aizer and Currie (2004) on prenatal care in California, and Deri (2005) in health services in Canada. An important strand of the literature highlights the value of social connections, especially caste-based ties, in increasing access to and utilization of government programs in developing countries (Berg et al. 2013; Nagavarapu and Sekhri 2014; Kumar and Somanathan 2015).[3]

Our study also contributes an explanation for the low take-up of health insurance among poor households in developing countries, which has been a puzzle despite seemingly low barriers and significant welfare benefits from participation. In India, only 15% of households have any coverage, and efforts to increase adoption have been largely unsuccessful. See, for example, Rajasekhar et al. (2011) and Rathi, Mukherji, and Sen (2012) who illustrate challenges associated with take-up of the *Rashtriya Swastha Bima Yojana* (RSBY), a national health insurance program with similar features as *Aarogyasri*. Banerjee, Duflo, and Hornbeck (2014) discuss the failure of a pilot health insurance plan promoted by Spandana, a non-profit microfinance organization. And Capunoa et al. (2014) evaluate impacts of two interventions designed to increase enrollment in the Philippines Individual Payer Program. Highlighting the role of social networks helps understand a mechanism that could boost health insurance utilization, especially in an information scarce environment. From a policy perspective, our findings suggest that initial differences in program participation at the community level might lead to significant divergence in the long term levels of health insurance utilization and health outcomes. In addition, our results suggest that community-based mechanisms might be particularly effective in increasing adoption.

[3] Beyond public programs, peers and broader networks have significant influence in agricultural technology adoption (Foster and Rosenzweig 1995; BenYishay and Mobarak 2015), educational (Sacerdote 2011; Calvó-Armengol, Patacchini, and Zenou 2009; Jain and Kapoor 2015) and labor market outcomes (Calvó-Armengol and Jackson 2004; Mas and Moretti 2009; Field et al. 2015), among others.

2 Background

2.1 *Aarogyasri* Health Insurance Program

The government of Andhra Pradesh introduced *Aarogyasri* as a cashless health insurance program for households living below the poverty line in April 2007.[4] The program provided "medical assistance to families below poverty line for the treatment of serious ailments such as cancer, kidney failure, heart and neurosurgical disease etc., requiring hospitalization and surgery/therapy". Under the scheme, Below Poverty Level (BPL) households in Andhra Pradesh were eligible and covered for medical expenditure towards 938 listed treatments up to Rs. 200,000 (USD 3300).[5] Of the total coverage, 75% is on family floater basis, i.e., unutilized coverage will be available to the other household members. The remaining coverage, Rs. 50,000 is available on the basis of recommendations of a technical committee. The insurance does not have any deductible or co-payment. All transactions are cashless, where a beneficiary can go to any authorized hospital and receive care without paying for the procedures covered under the scheme. As of May 2014, 663 public and private hospitals were empaneled under *Aarogyasri* in every district of AP.[6]

A notable feature of *Aarogyasri* program was high adoption among the target population, compared both with public and privately financed health insurance. Figure 1 shows the geographical spread of *Aarogyasri* claims across AP between 2007 and 2013. Not surprisingly, a large number of claims are from urban areas and few from the sparsely populated districts of Rayalseema and Telangana. Figures 2 and 3 show the number of surgeries performed under *Aarogyasri* over time, and the corresponding claims paid out by the trust (in million Rupees). As of December 2013, about 2.1 million procedures had been performed under the program with Rs. 52.05 billion (USD 868 million) claimed cumulatively by beneficiaries. Al-

[4] In India, the state and not the central government is primarily responsible for the provision of healthcare services.

[5] The fraction of households in AP who are classified as BPL is more than 90%, which makes eligibility for the scheme nearly universal.

[6] The *Aarogyasri* Trust pays health care providers on a case-by-case basis at a predefined rate. Hospitals must conduct free health camps for patients. Ambulances and help desks facilitate patient access at all primary health centers, area/district hospitals and network hospitals.

though a precise comparison between programs is not possible, utilization of the Rashtriya Swastha Bima Yojana (RSBY) which provided insurance coverage to BPL households in 25 states (specifically excluding AP), is between 11% and 55% in Amravati district in Maharashtra (Rathi, Mukherji, and Sen 2012) and "virtually zero" for RSBY in Karnataka (Rajasekhar et al. 2011). Among privately sponsored schemes, Banerjee, Duflo, and Hornbeck (2014) report that marketing health insurance (covering hospitalization and maternity expenses) bundled with a microfinance product led to 0.5% of village households insured, compared to 0.3% of households in control villages without the offer.

Without a convincing program evaluation of *Aarogyasri*, how can we assess the value of using *Aarogyasri*? Section 3.2 compares healthcare expenditures between households where at least one member was hospitalized in the previous year, and used *Aarogyasri* or not. Households using *Aarogyasri* report Rs. 21592 lower in-patient expenses than those that did not. Simultaneously, the difference in out-patient expenses was only Rs. 1079, suggesting that *Aarogyasri* is associated with lower out-of-pocket expenditures for tertiary care. These results also address concerns with graft associated with *Aarogyasri*, since it is possible that program utilization merely represents large scale corruption and unlikely to improve health. Since the estimate of reduction in healthcare expenditure from the independent survey (Rs. 21592) matches average claims from the administrative data (Rs. 24496), we are reasonably confident that large scale corruption is unlikely to be driving the results of the program.

2.2 Caste-based Social Networks

In India, caste is a "naturally" occurring social network. Individuals are born into a caste, and cannot change their caste assignment. Caste, or more specifically the jati, serves primarily as a means of social stratification and occupational transmission from one generation to another. At the same time, many social transactions such as marriage (Bidner and Eswaran 2015), and economic transactions such as risk pooling and investments (Ligon 1998; Banerjee and Munshi 2004) also take place within the caste. One implication is that contract enforcement is easier within compared to out of caste, since social sanctions can be used when formal mechanisms are unavailable (Munshi and Rosenzweig 2013). As a result, information from socially proximate caste peers is often regarded as more credible.

Our data reports the following demographic categories against each claim – Backward Classes/Castes (BC), Other Castes (OC), Scheduled Castes (SC), Scheduled Tribes (ST), Minorities and Others.[7] In Andhra Pradesh, BC communities constitute 52% of population, and are the dominant political and economic groups. Brahmins, Kshatriyas and other socially privileged groups constitute the OC category. SC consist of groups at the bottom of the traditional caste hierarchy, whereas ST are the geographically isolated tribal communities. Minorities represent non-Hindu religious groups, especially Muslims and Christians. The definition of Others is unclear, hence we exclude these claims from our analysis.[8]

3 Data

3.1 Data Source

We combine data from multiple sources: (i) administrative claims data from the *Aarogyasri* Trust from 2008 to 2013, (ii) the 2011 Census of India, and (iii) household survey data from 2013 of *Aarogyasri* users and non-users.

The administrative data consists of a complete record, including the date, of each claim against the trust, the amount approved and paid. An observation also contains details of the surgery or procedure performed (in 29 categories) and the hospital that filed the claim. Finally, a number of demographic characteristics such as age, gender, caste and village/ward of residence, are reported for each claimant. Table 1 shows that the average claimant age is slightly under 40 years and men comprise 55.8% of claimants. This table also shows the caste distribution of *Aarogyasri* users which matches the fraction of SCs and STs reported in the Census. The average amount claimed is Rs. 24,496.02, very close to the average preauthorized amount of

[7] Our measure of social networks is based on these official caste groups within a village. Given that most social interaction takes place at finer caste divisions (jati), our definition will underestimate the role of social networks on utilization.

[8] Claims under this category are less than half a percent of all claims, so we do not expect these to affect our empirical conclusions.

Rs. 26,680.

This dataset has several features that make it attractive for use in our analysis. First, since the dataset is a record of claims paid out by the *Aarogyasri* trust, subject to verification by state auditors, it reflects the complete census of all *Aarogyasri* users and claims.[9] Correspondingly, individuals absent from the database can be reliably classified as non-users. One implication is that the user networks constructed using this data will be networks with a complete count of nodes, in contrast to sampled survey data which will systematically undercount network nodes and bias the strength of networks effects. Additionally, the administrative data collected by computer suffers considerably less from self-reporting bias, measurement error, and missing data. For instance, out of 2,125,121 observations, only 68 are missing village information and none are missing age or caste information.

Ideally, the data would also contain the characteristics of the non-claimants, so that social networks could be measured at the individual level. Lacking this information, we collapse users by village-caste-quarter cells separately for first-time users in a quarter and total users in the quarter, adding '0' for cells with no claims. Table 1 shows that the average cell has 0.571 first-time and 0.895 total claims, whereas the other groups in the same village file 3.28 claims per quarter. 14.4% of the groups are located in urban wards.

We match each village reported in the claims dataset with village-level data on Household Amenities and Village Amenities from the 2011 Census of India. The household data allows us to integrate variables on ownership of mobile phones and radios, as well as to create an asset index.[10] As reported in Table A.1, for villages in Andhra Pradesh with at least one claim filed under *Aarogyasri* between 2008–2013, about 65 percent of the households reside in houses that are in good condition while 33 percent of them use treated tap water. Television and mobiles are most frequently owned household assets as 45 and 47 percent of the households

[9] *Aarogyasri*, like many public programs in developing countries, almost certainly experiences some fraudulent claims not associated with any real disability or disease. Hence, our definition of *utilization* is a claim, and not treatment against the claim.

[10] The asset index is created using the responses to the following variables: Condition of house good, Main source of drinking water is tapwater from treated source, Radio/transistor, Television, Phone landline only, Phone mobile only, Phone both, Scooter/motorcycle/moped, Car/jeep/van, Households with TV, Computer, Type of structure is permanent, Total number of households availing banking services, Type of fuel used for cooking is LPG/PNG, Type of Fuel used for cooking is electricity.

owned them, respectively. Only one percent of the households reported owning a car. In order to explore complementarities between networks and communication devices and income, we create indicator variables that take the value one for a village if the fraction of households own mobiles, radios or assets are above the median, and 0 otherwise. Simultaneously, using Village Amenities data from the 2011 Census of India we also integrate provision of private and public health facilities and market access at the village level. As reported in Table A.2, mobile health clinics are the most pervasive in terms of health care access. 31 percent of the villages in our sample were visited by a mobile health clinic. Presence of primary health care centers and dispensaries are limited to 7 and 1 percent of the villages, respectively. For each village, we create two indicator variables that take the value one if the census reports the presence of a public health facility and private health facility and zero otherwise. Village markets in India can be permanent (*Mandi*) or weekly (*Haat*). About 12 percent of the villages had access to a daily regular market while about 18 percent of them had access to a weekly market. Only 2 percent of the villages had an Agricultural Marketing Society. We use these market access variables to create a single indicator for market access to explore whether access to a market dilutes or strengthens the network effects.

Finally, we use data on a comprehensive household survey on institutional and out-of-pocket expenditures on health care. The Out of Pocket Expenditure Survey (OPES) collected data in April and May 2013 from a cross-section of households located in all sub-districts of Andhra Pradesh (Nagulapalli 2014). Two villages were chosen at random from each rural sub-district. Three households were chosen using simple random sampling with replacement from these villages – one household that used *Aarogyasri* for at least one in-patient procedure in the last 365 days, a second household that underwent an in-patient treatment in the last 365 days, but did not use *Aarogyasri*, and a third household that did not have any member admitted in a hospital in the last year. This yields a sample of 5,753 households spread over 1918 villages. Table 3 shows summary statistics associated with this survey data, and compares these to similar ones from the Andhra Pradesh households of the National Sample Survey (NSS). All household characteristics in the OPES, including household size, distribution of religion and caste, and possession of Below Poverty Line cards are comparable to the NSS, allaying concerns that the OPES is not representative.

3.2 *Aarogyasri* and Healthcare Expenditures

While we select health insurance utilization as an outcome measure, the effects of *Aarogyasri* on welfare are unclear. An additional concern might be that corruption is the dominant driver of welfare and that social networks facilitate this corruption. In the absence of data on health outcomes or graft, the best we can do is to examine if *Aarogyasri* is associated with lower household expenses for tertiary care. This section examines the association between *Aarogyasri* use and both in-patient and out-patient healthcare expenditures using independent survey data of a cross-section of *Aarogyasri* users and non-users.[11]

The following specification estimates the association between using *Aarogyasri* and healthcare expenditures.

$$exp_{im} = \alpha_0 + \alpha_1 Aarogyasri_{im} + \alpha_2 \mathbf{Z}_{im} + subdistrict_m + \varepsilon_{im} \tag{1}$$

In this specification, exp_{im} is the healthcare expenditure reported by household i in subdistrict m. We separately examine out-patient and in-patient expenditures. *Aarogyasri* utilization is represented by an indicator variable $Aarogyasri_{im}$ that is 1 if the household used formal healthcare services in the last year and paid with *Aarogyasri*, and 0 if household used formal healthcare, but paid out of pocket. Therefore, the main coefficient of interest is α_1, which would be negative and statistically different from zero if *Aarogyasri* was associated with lower out-of-pocket expenditures. We control for a number of observable household characteristics ($\mathbf{Z}_{im}$) such as household size, caste and religion, source of drinking water, ration card type, sewage type, land ownership and household type. The specification includes sub-district fixed effects. Finally, the i.i.d error term ε_{im} is clustered at the district level.

Table 4 shows that *Aarogyasri* utilization is associated with significantly lower out-of-

[11] While we control for a number of observable characteristics in the comparison, users might be systematically different from non-users on unobservable dimensions. Hence, the analysis is not causal in nature.

pocket healthcare expenditures, especially for in-patient care covered by *Aarogyasri*. Households using *Aarogyasri* reported Rs. 21591.6 lower expenditures for in-patient care ($p < 0.01$), and Rs. 1079.5 for out-patient care ($p < 0.10$). Note that the coefficient for in-patient care is close to the average claim size (Rs. 24496.0) reported in the administrative data. These findings suggest that *Aarogyasri* is effective in decreasing tertiary care expenditures. Since these findings are from an independent household dataset, they are less likely to reflect systematic graft, and more likely to arise from program use.

4 Empirical Analysis

The primary objective of the empirical exercise is to estimate the effect of total utilization in the previous period on first-time utilization in the subsequent period. Positive correlations between total utilization by other members of the same caste in the same village with new, first-time *Aarogyasri* claims suggests that social networks are influential in increasing utilization. The critical identifying assumption is that the incidence of major diseases, which is the underlying driver of seeking tertiary care, is not correlated within the social group. This would be a concern, for instance, if the claims are for communicable diseases that might be transmittable within neighborhoods. However, communicable diseases form a negligible part of *Aarogyasri* claims, and instead the most popular claims are for oncology, trauma (accident) and cardiology, procedures that do not directly transmit within social groups. Our main specification, described in Section 4.1, includes controls to account for a number of other supply and demand-side factors that might impact *Aarogyasri* claims.

We adapt this specification to examine heterogeneity in network effects. Motivated by significant differences in both reliance on and access to social networks on the basis of gender, we examine whether social networks are more germane for women versus men. Additionally, examining the strength of network effects by disease or procedure type reveals the type of information that the networks likely convey. If networks are more important in the case of informationally complex procedures, such as the treatment of cancer or cardiovascular diseases, then users might be learning about specific doctors and procedures, rather than general program features such as where hospitals are located or how to contact *Aarogyasri* help desks.

We examine the impact of location-based economic and social characteristics under which social networks are more or less effective in increasing first-time utilization. Specifically, we uncover the role of urban location, or residence in villages with greater wealth, teledensity, market access or health facilities in enabling social networks as drivers of utilization. These results reveal the mechanisms through which social networks potentially operate, and point to policies that could facilitate the adoption of healthcare insurance.

4.1 Specification

The following equation is used to estimate the relationship between network and own utilization.

$$y_{vgt} = \beta_0 + \beta_1 Y_{vgt-1} + \beta_2 \sum_{-g} Y_{vt-1} + \beta_3 \sum_{-v} Y_{gt-1} + \beta_4 \sum_{-g,-v} Y_{t-1} + \phi_{vg} + \omega_{gt} + \tau_t + \delta * \tau_t + \epsilon_{vgt} \quad (2)$$

In this specification, the outcome variable y_{vgt} represents first-time claims by individual, aggregated to the village-caste-quarter level. We also examine claim amounts as an outcome variable, since users might learn how much to claim from their peers. The claimant's immediate social network is represented by Y_{vgt-1}, which is the total utilization (either claim incidence, or the claim amounts associated with utilization) by other members of the same caste g in the same village v in the previous quarter $t-1$. If network utilization is influential in driving new users to *Aarogyasri*, then we expect that $\beta_1 > 0$ and statistically different from zero. The specification also looks at other, socially further groups, as a natural control group for the effect of immediate peers. The term $\sum_{-g} Y_{vt-1}$ is the effect of total utilization by all members of other castes ($-g$) in the same village. We expect that the influence of these groups will be smaller, i.e., $\beta_2 < \beta_1$. Members of the same caste residing in different villages within the sub district should also have lower influence on utilization compared to more proximate peers, so $\beta_3 < \beta_1$.

Even more distant will be other castes in other villages $(-g, -v)$ in the same sub-districts, to the point that the influence of these groups to be negligible, so we expect β_4 to be close to zero (or slightly negative, reflecting mean reversion in utilization) and statistically indistinguishable from the null.

The main threat to this specification is from potentially omitted variables that influence both total utilization in the prior period as well as subsequent first-time utilizations within the group. The most significant of these are common environmental factors (for example, local air and water pollution) and socio-cultural practices (for instance, diet and nutrition or smoking) that drive health status and treatment within a caste group in a village. Demographic and social factors such as population size, fertility and death rates by caste group or spatial segregation might also indirectly effect health and healthcare utilization. Utilization might also be effected by the location of the village or town, such as the distance to district headquarters. To control for all these factors, we add village-caste fixed effects (ϕ_{vg}) in the specification.

Caste-quarter-year fixed effects ω_{gt} account for social and political factors, such as the statewide political offices held by the member of a particular caste or changes in caste-based affirmative action rules, that effect each caste differently and could impact health utilization. Broad state-wide trends such as economic growth or more specific factors like drug prices or changes in program policies might also effect utilization, so we account for these with a quarter-year specific fixed effect τ_t. District-specific time trends $\delta * \tau_t$ account for variation in supply side factors, most importantly empaneling or disempaneling hospitals under the program, or the introduction or withdrawal of certain specialties over time. This term also accounts for time varying environmental conditions that effect the ability of individuals to access the program, such as the weather, the quality of road access (Aggarwal 2015) or the quality of the local bureaucracy. Finally, the i.i.d. error term ϵ_{vgt} is clustered at the district level.[12]

To ensure that the results are directly attributable to village-caste networks and not to either

[12] Note that a fraction of seats in village councils is reserved for different caste categories. Since the members of the village councils and especially the heads could facilitate *Aarogyasri* utilization by caste, a concern is that changes in the councils' caste composition is a source of potential omitted variable bias. However, local government elections in Andhra Pradesh were held in 2006, before the start of *Aarogyasri*, and 2013 in the last quarter of our dataset. Therefore, the composition of the village councils did not vary over the time that we analyze, and the effects associated with the councils are absorbed by the village-caste fixed effects.

shared (but unobserved) environmental characteristics or spurious correlations in the data, we conduct a falsification exercise where first time claims are randomly rematched to different total claims cells in the data. We then estimate equation (2) with these rematched placebo networks. We expect that network effects should be absent in these results and the estimated coefficients (β_1, β_2 and β_3) will be both smaller in magnitude and statistically indistinguishable from the null.

4.2 Main Results

Columns 1-3 in Table 5 report the coefficients from estimating equation (2) on utilization. The main finding, reported in the first row of Column 3, is that a unit increase in *Aarogyasri* utilization by the caste peers in the previous period increases first-time utilization by 20%. The coefficient is stable to sequentially augmenting the specification with other networks in Columns 1, 2 and 3. Simultaneously, results in the second row confirm that utilization is driven by caste-specific networks instead factors that are common across groups within the village. We find that other caste groups within the same village have virtually no effect on utilization; the relevant coefficient is 0.0078 and statistically indistinguishable from the null. The table reports that the same caste members in other villages within the same sub-district have a small impact that is one-hundredth in magnitude compared to same caste within the village, albeit statistically significant (+0.0024, $p < 0.05$). This finding is consistent with caste networks extending beyond villages, but with those interactions less critical in driving utilization compared to caste peers within the village. Other groups outside the village, but within the same sub-district have an even smaller effect. The negative correlation that is statistically significant perhaps reflects mean reversion after a large number of claims (-0.0003, $p < 0.01$).[13]

We observe similar effects of own caste network with claim amount as the dependent variable, with a rupee increase in claims by the network also increasing subsequent claims by 18% ($p < 0.10$). Columns 5 and 6 also show that other castes within the village significantly effect

[13] Also noteworthy is that the empirical model, representing both demand and supply side factors, is effective in explaining first-time health insurance utilization. Specifically, the R-squareds representing goodness-of-fit are 0.75 for the number of claims (columns 1-3) and 0.68 for the claim amounts (columns 4-5).

claim amounts, although the magnitude is less than one-tenth of own caste. This suggests that while utilization is not necessarily correlated within villages or mandal, the amount claimed might be, perhaps due to supply-side factors such as hospital billing practices. As before, the effect of claims outside the village is many orders of magnitude lower than those within the village.

To confirm that the results in Table 5 represent the role of village-caste networks on healthcare utilization, Table 6 shows the results from estimating equation (2) with the match between first time claims and village-caste networks shuffled within the sub-district. The reported coefficients are very close to zero, and statistically indistinguishable from the null. The R-squareds also decline from 0.75 to 0.72 since variation in network variables are ineffective in explaining first-time utilization. Taken together, the evidence presented in Tables 5 and 6 suggests that caste networks have a large and significant role in increasing utilization of public healthcare insurance.

4.3 Heterogeneity by Claimant Gender and Procedure Type

This section explores the effects of variation in claimant gender and the type of procedure on the impact of social networks on healthcare utilization. The impact of social networks on utilization by gender is not theoretically clear. Women have lower mobility compared to men, so they might rely disproportionately on informal sources of program information such as friends and relatives. Utilization by other women might also signal that using formal healthcare is social appropriate.[14] Conversely, men might either be the critical decision-makers or have greater ability to access their connections, so network effects might be stronger. These mechanisms produce qualitatively opposite predictions on the impact of social networks on gender-based utilization, motivating the empirical analysis.

We interact claimant gender with the four network measures (Y_{vgt-1}, $\sum_{-g} Y_{vt-1}$, $\sum_{-v} Y_{gt-1}$,

[14] For example, Jain and Langer (2015) find that network relationships are more critical for women compared to men among Indian business school students, mirroring Ibarra (1997) who studies middle managers in American workplaces. Field et al. (2015) find that women who attend a business training program with a peer are more likely to start small businesses, suggesting that networks help facilitate out of the home activities among women.

$\sum_{-g,-v} Y_{t-1}$) and examine the impact on first time utilization. Table 7 shows that network effects are almost entirely driven by men (0.11, $p < 0.01$), so much so that the main effect is statistically insignificant in this model (0.083, $p > 0.10$). This suggests that utilization among men's networks is disproportionately influential in driving subsequent *Aarogyasri* use. From a policy perspective, our finding indicates that using networks might not be effective in increasing healthcare utilization by women, and that policy-makers should adopt other ways to encourage female participation.

Effect of social network on utilization of health care may vary by disease type. For example, networks might be ineffective in disseminating information for diseases that require patients to reveal private and sensitive information to their peers. Second, personal characteristics could determine both the peers and the illness an individual is most prone to. For instance, elderly citizens are most likely to have different peers and they are also more likely to suffer from geriatric diseases. In order to examine the effect of social networks on first time utilization by disease type, we categorize all new claims under *Aarogyasri* into sixteen categories.[15] We estimate the model specified in equation (2) and report the estimated effects of social networks on new utilization for each of the disease type in Tables 8.A and 8.B.

The results show that network effects are strongest in poly trauma (+0.03, $p < 0.01$), the type of procedure that is least likely to be communicable within a population group. The coefficients associated with cardiology (+0.03, $p < 0.10$), nephrology and urinary surgery (+0.02, $p < 0.05$), oncology (+0.02, $p < 0.01$) and pediatrics (+0.06, $p < 0.10$)are also relatively large and precisely estimated. What is notable is that these major procedures require significant information processing, and therefore information obtained from friends and family is potentially important for decision making. Conversely in Table 8.B, the coefficients associated with own group in same village for ophthalmology (+0.002, $p < 0.10$), plastic surgery and dermatology (+0.003, $p < 0.10$), gastroenterology (+0.002, $p < 0.01$), critical care (+0.001, $p < 0.05$) and orthopedics, rheumatology and prosthesis (+0.006, $p < 0.01$) are an order of magnitude lower,

[15]These categories are poly trauma, cardiology, nephrology and urinary surgery, oncology, neurology, general surgery and medicine, pediatrics, obstetrics and gynecology, ENT, ophthalmology, plastic surgery and dermatology, gastroenterology, pulmonology, critical care, orthopedic, rheumatology, and prosthesis, infectious disease.

perhaps because decision-making by patients is less complex for these procedures.

Network effects are virtually absent for treatment in two categories. First, the coefficient for Obstetrics and Gynaecology is small and negligible (+0.0002, $p > 0.10$), which is consistent with the findings in Table 7, where network effects are largely driven by male claimants. Second, the coefficient associated with infectious diseases is also negligible (+0.000003, $p > 0.10$). Since this disease category is the most likely to be correlated within a community, this finding helps addresses concerns of time-varying village-caste effects driving our overall results.

4.4 Location and Social Networks

The literature, such as Katz, Kling, and Liebman (2001)'s landmark evaluation of Moving to Opportunity, shows that neighborhood effects can influence healthseeking behavior as well as health outcomes. In Andhra Pradesh, migration is relatively low but different places vary in terms of quality and capacity of health infrastructure and the ability to access it. More pertinent for our analysis of social networks is the ability to communicate with other community members while making decisions to seek treatment. So location features such as density and teledensity may facilitate or hinder network effects. For instance, social networks might be more effective in urban areas, where density allows more opportunities for information exchange between members of the same community. Conversely, urban residents could more readily access alternate sources of program information, decreasing the need for community-based learning. Thus, the net impact of urban residence is an empirical question. In a similar vein, phones, radios and other wealth measures might facilitate social interactions and could therefore complement network effects. Conversely, these assets could substitute for social networks if they enable access to more formal sources of information.

We augment equation (2) by including terms describing location effects and interacting them with network variables.[16] The coefficients on the main and interacted variables are reported in Tables 5 and 9. We find that the marginal effects of social networks are significantly greater in urban areas (+0.25, $p < 0.01$) compared to the overall sample, supporting the hypoth-

[16] The main effect of the location variables is absorbed in the village-caste fixed effect.

esis that residence in urban areas is associated with more intense information exchange within caste networks to the extent of overcoming the effects of greater information from alternate sources. In contrast to the overall sample, other caste groups within the ward also have a small effect on healthcare utilization. However, the coefficient is negative for urban wards (-0.021, $p < 0.01$), perhaps indicating reversion to the mean. This is not surprising since both the mean and maximum utilization in urban wards is much greater than rural areas.

Location effects are also reported in Table 10 which shows the effect of three variables – whether the village is above the median in the fraction of households that own a mobile phone, the fraction of households that own a radio, or in the wealth index (described in Section 3) – in enabling the impact of social networks on *Aarogyasri* utilization. In columns 1 to 3, we find that the effect of social network utilization is greater when the village is above median in the ownership of mobile phones and radios, and in richer villages. This finding is maintained in column 4 where all three factors are introduced in the regression, suggesting that the net effect of these assets is to facilitate communication within the network rather than access other sources of information.

This section also examines the impact of local health facilities, both private and public, and market access in increasing effectiveness of social networks. Primary health facilities might play an important role in screening patients for tertiary care. So information on using tertiary care obtained through social networks might be particularly useful when the patient is more likely to require a major procedure.

Table 11 reports that the marginal effectiveness of social networks increases by approximately 3.5% in villages that are above the median in the health facilities index ($p < 0.01$). Both private and public health facilities have similar effects.

Finally, Table 11 also reports the marginal effects of the market access index on increasing the effects of social networks. Above median market access is associated with a similar 3.4% increase in the effectiveness of social connections ($p < 0.01$). The combined results of this table suggest that investment in primary health and access infrastructure is likely to significantly improve healthcare utilization.

5 Conclusion

This paper investigates the role social networks in driving utilization of a public welfare program. Set in the context of a large, publicly-financed tertiary care insurance program, we examine whether utilization within a "naturally" occurring social group can drive subsequent first-time utilization. We have a number of underlying mechanisms in mind. Social connections might transmit information about the program location and how to access it as well as information on the treatment of specific diseases. Community peers might also have an important demonstration effect – by using the program they show that it is socially appropriate to do so, which might especially be a concern for marginalized groups.

Our paper uses administrative data from the program combined with village level characteristics from the census to estimate networks off a complete record of program users. By doing so, we are able to avoid a number of econometric problems that affect research on network effects based on sample surveys. In addition, the combination of a fixed effects approach and a number of falsification exercises offers us greater confidence that the estimated relationships are causal in nature, instead of reflecting spurious correlations in the data. Our main finding is that a unit increase in utilization within the village-caste in the previous quarter increases subsequent first time use by 20%. These effects are relatively large – suggesting an important role for network based policies to promote program use. Further, by examining how these peer effects vary by gender, type of procedure and household and village characteristics, our study affords a nuanced understanding of these network effects.

Our results should be read with a few caveats. Just because we found evidence of network effects in this setting does not imply that the results are necessarily universal. The results might be different by type of program. For instance, social networks might be less important as an explanation for utilization if programs are straightforward to use or if no social stigma is associated with program use. The results might also be effected if other networks, such as those of class, occupation or educational background, are more germane than caste networks in effecting individual decisions. Finally, while we investigate public health insurance utilization as an outcome measure, the impact on overall welfare, as measured by improvements in overall health, remain unexamined.

Nonetheless, our work has important implications both for increasing utilization of welfare programs, and for the provision of healthcare in developing countries. By uncovering the role of network effects on healthcare utilization, our findings suggest that welfare programs should incorporate network based learning, in addition to direct information provision, to increase participation. This approach has been tried, for instance in the case of Mahadalits in Bihar with positive results (Kumar and Somanathan 2015). For publicly financed health insurance more specifically, Berg et al. (2013) also find that the effectiveness of community liaisons in encouraging enrollment in RSBY is negatively correlated with social distance. Future research, with a sharper focus on implementation, could help understand and operationalize the network-based approach to increasing healthcare utilization.

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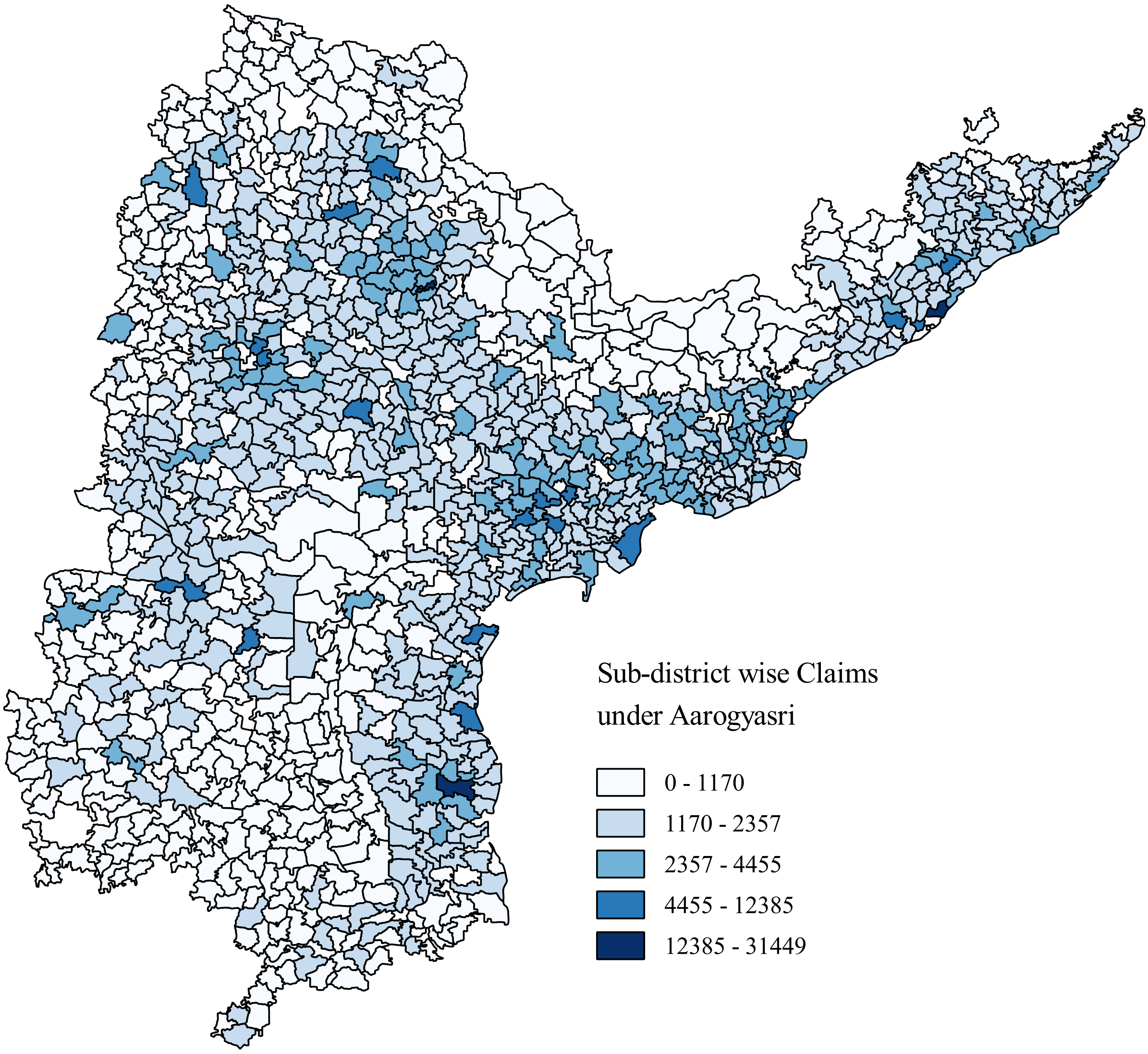
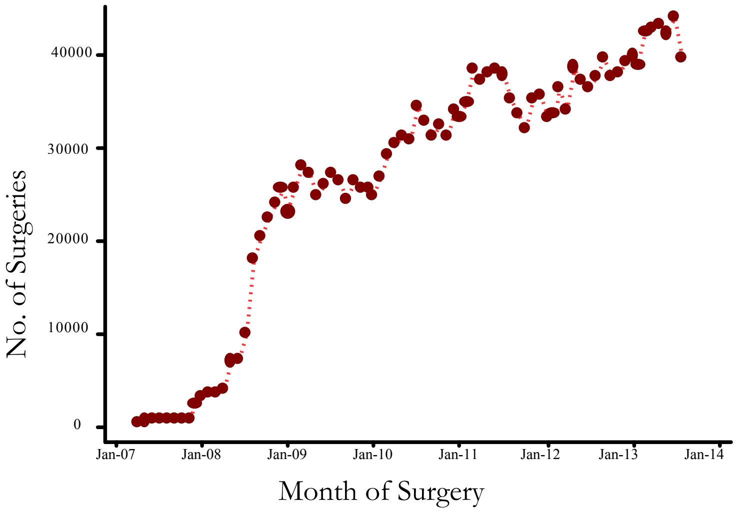
FIGURE 1: Claims under *Aarogyasri* in Andhra Pradesh (2008-2013).



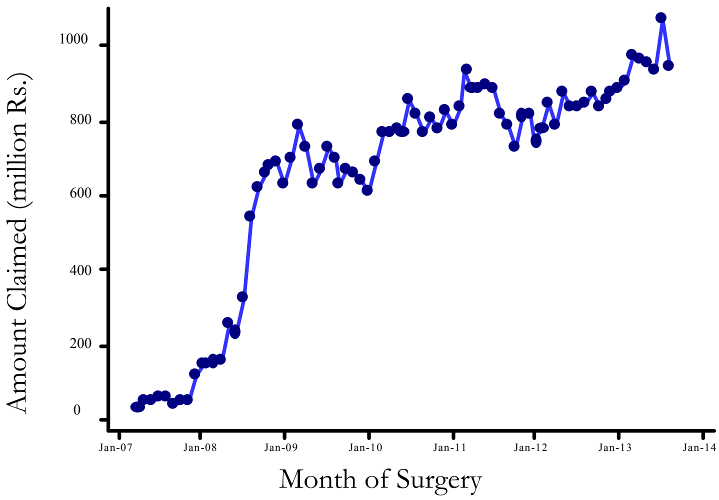
Notes: Data consists of all claims filed under the public health insurance program *Aarogyasri* for the period 2008-2013 in the state of Andhra Pradesh.

FIGURE 2: Surgeries per Month.



Notes: Data consists of all claims filed under the public health insurance program *Aarogyasri* for the period 2008-2013 in the state of Andhra Pradesh.

FIGURE 3: Claim Amount per Month.



Notes: Data consists of all claims filed under the public health insurance program *Aarogyasri* for the period 2008-2013 in the state of Andhra Pradesh.

TABLE 1: Summary Statistics for *Aarogyasri* Patient Claims Data.

Variable	Observations	Mean	Std. Dev.
Age	2125121	39.54	18.53
Gender is Male	2125121	0.558	
Backward caste	1111476	0.523	
Other caste	426,655	0.201	
Scheduled Caste	314,965	0.148	
Scheduled Tribe	80,418	0.038	
Minorities	182,502	0.086	
Others	9,105	0.004	
Preauthorization amount	2125118	26680.12	25888.25
Claim amount	2125118	24496.02	24758.64

Notes: Data consists of all patient claims filed under the public health insurance program *Aarogyasri* for the period 2008-2013 in the state of Andhra Pradesh.

TABLE 2: Summary Statistics for Village-Caste Panel Data.

Variable	Mean	Std. Dev.	Min	Max
First time claims	0.57	2.05	0	442
Total claims	0.89	3.35	0	678
First time claim amount	17036.39	62310.28	0	11200000
Total claim amount	21836.61	80939.81	0	15300000
Other group claims	3.28	9.66	0	978
Other group claim amounts	80244.35	230267.6	0	21700000
Other group claims in mandal	73.34	130.98	0	2346
Other group claim amounts in mandal	1785784	3085190	0	47700000
Urban groups	0.144	0.351	0	1
No. of Observations	2367576			

Notes: Data consists of all patient claims filed under the public health insurance program *Aarogyasri* for the period 2008-2013 in the state of Andhra Pradesh, collapsed at the village-caste-quarter level. The claims are distributed over 30,061 villages; categorized over six groups: backward castes, minorities (mainly Muslims), scheduled castes, scheduled tribes, other castes, and others; for 24 year-quarters. If no claims were filed by a caste group from a village between 2008-13 they are excluded from the panel.

TABLE 3: Comparison of Household Characteristics between National Sample Survey and Out of Pocket Survey.

	NSS		OPES	
	Mean	Std. dev.	Mean	Std. dev.
Household size	3.87	1.72	3.98	1.52
Religion: Hindu	0.92	0.27	0.89	0.31
Religion: Muslim	0.05	0.23	0.05	0.21
Religion: Others	0.02	0.15	0.06	0.25
Caste: Scheduled Caste	0.20	0.40	0.22	0.42
Caste: Scheduled Tribe	0.07	0.26	0.16	0.36
Caste: Others	0.73	0.45	0.62	0.49
BPL Card	0.94	0.24	0.98	0.14
No. of Observations	3925		5753	

Notes: The Out of Pocket Expenditure Survey (OPES), collected in April and May 2013, is a household survey covering all sub-districts of Andhra Pradesh (Nagulapalli 2014). The National Sample Survey (NSS), Round 68 is a district level representative household survey collected between July 2011 and June 2012 by the Ministry of Statistics and Programme Implementation.

TABLE 4: Effects of *Aarogyasri* on Out-of-Pocket Healthcare Expenses.

	In-patient expenses	Out-patient expenses
Used Aarogyasri	-21591.6***	-1079.5*
	(1849.8)	(524.6)
No. of Observations	2609	639
R Squared	0.13	0.08

Notes: We use data from the Out of Pocket Expenditure Survey (2013). *Used Aarogasri* is an indicator taking the value one for households that used *Aarogyasri* for at least one in-patient procedure in the last 365 days, and zero otherwise. All specifications control for household size, caste and religion, source of drinking water, ration card type, sewage type, land ownership and household type, and sub-district fixed effects. Errors are robust and clustered at the district level.

TABLE 5: Effects of Social Networks on Healthcare Utilization under *Aarogyasri*.

Dependent variable	Utilization of health care under *Aarogyasri*					
	First time utilization			First time claim amounts		
	(1)	(2)	(3)	(4)	(5)	(6)
Claim, own group$_{t-1}$	0.21***	0.20**	0.20**			
	(0.07)	(0.07)	(0.08)			
Claim, oth groups$_{t-1}$		0.0074	0.0078			
		(0.01)	(0.01)			
Claim, same group in sub-dist.$_{t-1}$			0.0024**			
			(0.00)			
Claim, oth groups in sub-dist.$_{t-1}$			-0.00031***			
			(0.00)			
Claim amount, own group$_{t-1}$				0.19**	0.18**	0.18*
				(0.08)	(0.09)	(0.09)
Claim amount, oth groups$_{t-1}$					0.014**	0.015**
					(0.01)	(0.01)
Claim amount, same group in sub-dist.$_{t-1}$						0.0040***
						(0.00)
Claim amount, oth groups in sub-dist.$_{t-1}$						-0.00043***
						(0.00)
Average	.57	.57	.57	17036.39	17036.39	17036.39
No. of Observations	2268927	2268927	2268927	2268927	2268927	2268927
R Squared	0.75	0.75	0.75	0.68	0.68	0.68

Notes: Data consists of villages with at least one claim filed under *Aarogyasri* between 2008-2013 in the state of Andhra Pradesh. All specifications include quarter and village specific group fixed effects, and district wise time trend. We consider six groups: backward castes, minorities (mainly Muslims), scheduled castes, scheduled tribes, other castes, and others. Errors are robust and clustered at the district level.

TABLE 6: Effects of Shuffled Social Networks on Healthcare Utilization under *Aarogyasri*.

Dependent variable	Utilization of health care under *Aarogyasri*					
	First time utilization			First time claim amounts		
Average		.57			17034.69	
	(1)	(2)	(3)	(4)	(5)	(6)
Claim, own group$_{t-1}$	0.00012	0.00012	0.00012			
	(0.00)	(0.00)	(0.00)			
Claim, oth group$_{t-1}$		-0.000053	-0.000053			
		(0.00)	(0.00)			
Claim, same group in sub-dist.$_{t-1}$			0.00000070			
			(0.00)			
Claim, oth groups in sub-dist.$_{t-1}$			-0.000013			
			(0.00)			
Claim amount, own group$_{t-1}$				0.000011	0.000011	0.000011
				(0.00)	(0.00)	(0.00)
Claim amount, oth group$_{t-1}$					-0.000068	-0.000068
					(0.00)	(0.00)
Claim amount, same group in sub-dist.$_{t-1}$						-0.000016
						(0.00)
Claim amount, oth groups in sub-dist.$_{t-1}$						-0.0000088
						(0.00)
Average	.57	.57	.57	17034.69	17034.69	17034.69
No. of Observations	2268927	2268927	2268927	2268927	2268927	2268927
R Squared	0.72	0.72	0.72	0.66	0.66	0.66

Notes: Data consists of villages with at least one claim filed under *Aarogyasri* between 2008-2013 in the state of Andhra Pradesh. All specifications include quarter and village specific group fixed effects, and district wise time trend. We consider six groups: backward castes, minorities (mainly Muslims), scheduled castes, scheduled tribes, other castes, and others. Errors are robust and clustered at the district level.

TABLE 7: Effects of Social Networks on Healthcare Utilization under *Aarogyasri* by Gender.

	(1)	(2)	(3)
Male	0.050***	0.045***	0.038***
	(0.01)	(0.00)	(0.00)
Claim, own group$_{t-1}$	0.085	0.083	0.082
	(0.06)	(0.06)	(0.06)
Claim, own group$_{t-1}$ $\times$ Male	0.11***	0.11***	0.10***
	(0.01)	(0.00)	(0.00)
Claim, oth groups$_{t-1}$		0.0087**	0.0086***
		(0.00)	(0.00)
Claim, oth groups$_{t-1}$ $\times$ Male		0.0017	0.0028
		(0.00)	(0.00)
Claim, oth groups in sub-dist.$_{t-1}$			-0.00023
			(0.00)
Claim, oth groups in sub-dist.$_{t-1}$ $\times$ Male			-0.00019
			(0.00)
Claim, same group in sub-dist.$_{t-1}$			0.0029***
			(0.00)
Claim, same group in sub-dist.$_{t-1}$ $\times$ Male			0.00056
			(0.00)
Average	.34	.34	.34
No. of Observations	3784742	3784742	3784742
R Squared	0.64	0.64	0.64

Notes: Data consists of villages with at least one claim filed under *Aarogyasri* between 2008-2013 in the state of Andhra Pradesh. All specifications include quarter and village specific group fixed effects, and district wise time trend. We consider six groups: backward castes, minorities (mainly Muslims), scheduled castes, scheduled tribes, other castes, and others. Errors are robust and clustered at the district level.

TABLE 8.A: Effects of Social Networks on Healthcare Utilization under *Aarogyasri*.

	Poly Trauma	Cardiology	Nephrology & Urinary Surgery	Oncology	Neurology	General Surgery & Medicine	Pediatrics	Ob/Gyn
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Claim, own group$_{t-1}$	0.03***	0.03*	0.02**	0.02***	0.009***	0.004***	0.06*	0.0003
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)
Claim, oth groups$_{t-1}$	0.002	-0.001	0.0001	0.0006	0.0006	-0.0004	-0.005	-0.0004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Claim, same group in sub-dist.$_{t-1}$	0.0007**	0.00010	0.0002**	0.0003*	0.00009	-0.0001	-0.00005	-0.0002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Claim, oth groups in sub-dist.$_{t-1}$	-0.0001	-0.0002**	-0.0002*	-0.0001**	0.00003	-0.00001	-0.0002	-0.000004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Average	.373	.367	.299	.296	.239	.224	.146	.072
No. of Observations	656213	656213	656213	656213	656213	656213	656213	656213
R Squared	0.4	0.6	0.4	0.3	0.3	0.4	0.5	0.2

Notes: Data consists of villages with at least one claim filed under *Aarogyasri* between 2008-2013 in the state of Andhra Pradesh. All specifications include quarter and village specific group fixed effects, and district wise time trend. We consider six groups: backward castes, minorities (mainly Muslims), scheduled castes, scheduled tribes, other castes, and others. Errors are robust and clustered at the district level.

TABLE 8.B: Effects of Social Networks on Healthcare Utilization under *Aarogyasri*.

	ENT	Opthalmology	Plastic Surgery & Dermatology	Gastroenterology	Pulmonology	Critical Care	Orthopedic, Rheumatology & Prosthesis	Infectious Disease
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Claim, own group$_{t-1}$	0.010**	0.002*	0.003*	0.002***	0.01*	0.001**	0.006***	0.000003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Claim, oth groups$_{t-1}$	0.0003	0.0002	-0.0005*	0.00008	-0.0007	0.000004	0.00010	-0.0000007
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Claim, same group in sub-dist.$_{t-1}$	0.0004**	0.0000008	0.00002	0.00003	-0.00006	-0.00003	0.0001	0.00000005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Claim, oth groups in sub-dist.$_{t-1}$	-0.00008***	-0.000004	-0.00002	0.000003	-0.000009	-0.00001	-0.00003**	-0.0000003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Average	.072	.029	.029	.028	.017	.012	.07	0
No. of Observations	656213	656213	656213	656213	656213	656213	656213	656213
R Squared	0.3	0.2	0.2	0.2	0.3	0.1	0.2	0.2

Notes: Data consists of villages with at least one claim filed under *Aarogyasri* between 2008-2013 in the state of Andhra Pradesh. All specifications include quarter and village specific group fixed effects, and district wise time trend. We consider six groups: backward castes, minorities (mainly Muslims), scheduled castes, scheduled tribes, other castes, and others. Errors are robust and clustered at the district level.

TABLE 9: Location Effects of Social Networks on Healthcare Utilization – Urban vs. Rural

	(1)	(2)	(3)
Claim, own group$_{t-1}$	0.074***	0.067***	0.065***
	(0.01)	(0.01)	(0.01)
Claim, own group$_{t-1}$ $\times$ $Urban$	0.24***	0.25***	0.25***
	(0.04)	(0.05)	(0.05)
Claim, oth groups$_{t-1}$		0.018***	0.018***
		(0.00)	(0.00)
Claim, oth group$_{t-1}$ $\times$ $Urban$		-0.021***	-0.020***
		(0.01)	(0.01)
Claim, oth groups in sub-dist.$_{t-1}$			-0.00045***
			(0.00)
Claim, oth groups in sub-dist.$_{t-1}$ $\times$ $Urban$			0.00035***
			(0.00)
Claim, same group in sub-dist.$_{t-1}$			0.0032***
			(0.00)
Claim, same group in sub-dist.$_{t-1}$ $\times$ $Urban$			-0.0033***
			(0.00)
Average	.57	.57	.57
No. of Observations	2268927	2268927	2268927
R Squared	0.76	0.76	0.76

Notes: Data consists of villages with at least one claim filed under *Aarogyasri* between 2008-2013 in the state of Andhra Pradesh. All specifications include quarter and village specific group fixed effects, and district wise time trend. We consider six groups: backward castes, minorities (mainly Muslims), scheduled castes, scheduled tribes, other castes, and others. Errors are robust and clustered at the district level.

TABLE 10: Location Effects of Social Networks on Healthcare Utilization - Household Assets

	(1)	(2)	(3)	(4)
Claim, own group$_{t-1}$	0.041***	0.040***	0.026***	0.0077
	(0.01)	(0.01)	(0.01)	(0.01)
Claim, oth groups$_{t-1}$	0.016***	0.016***	0.015***	0.015***
	(0.00)	(0.00)	(0.00)	(0.00)
Claim, oth groups in sub-dist.$_{t-1}$	-0.0000032	-0.0000095	-0.000019	-0.000017
	(0.00)	(0.00)	(0.00)	(0.00)
Claim, own group$_{t-1}$ $\times$ Mobile	0.035***			0.023**
	(0.01)			(0.01)
Claim, own group$_{t-1}$ $\times$ Radio		0.035***		0.024***
		(0.00)		(0.01)
Claim, own group$_{t-1}$ $\times$ Richer			0.049***	0.037***
			(0.01)	(0.01)
No. of Observations	1787675	1787675	1787675	1787675
R Squared	0.61	0.61	0.61	0.61

Notes: Data consists of villages with at least one claim filed under *Aarogyasri* between 2008-2013 in the state of Andhra Pradesh. All specifications include quarter and village specific group fixed effects, and district wise time trend. We consider six groups: backward castes, minorities (mainly Muslims), scheduled castes, scheduled tribes, other castes, and others. *Landline*, *Mobile*, *Landline & Mobile*, and *Radio* are indicator variables for villages where the fraction of households with the respective asset is higher than the rural median. *Richer* is an indicator variable taking the value one for villages with asset index greater than the rural median. Errors are robust and clustered at the district level.

TABLE 11: Location Effects of Social Networks on Healthcare Utilization - Village Amenities.

	(1)	(2)	(3)	(4)
Claim, own group$_{t-1}$	0.0072**	-0.00062	0.020***	-0.022***
	(0.00)	(0.00)	(0.00)	(0.00)
Claim, oth groups$_{t-1}$	0.013***	0.013***	0.013***	0.012***
	(0.00)	(0.00)	(0.00)	(0.00)
Claim, oth groups in sub-dist.$_{t-1}$	0.000030	0.000034	0.000050	0.000055
	(0.00)	(0.00)	(0.00)	(0.00)
Claim, own group$_{t-1}$ $\times$ Public health facility	0.056***			0.034***
	(0.01)			(0.01)
Claim, own group$_{t-1}$ $\times$ Private health facility		0.061***		0.035***
		(0.01)		(0.00)
Claim, own group$_{t-1}$ $\times$ Access to market			0.051***	0.034***
			(0.01)	(0.01)
No. of Observations	1751979	1751795	1751979	1751795
R Squared	0.58	0.58	0.58	0.58

Notes: Data consists of villages with at least one claim filed under *Aarogyasri* between 2008-2013 in the state of Andhra Pradesh. All specifications include quarter and village specific group fixed effects, and district wise time trend. We consider six groups: backward castes, minorities (mainly Muslims), scheduled castes, scheduled tribes, other castes, and others. *Public* and *Private health facility* are indicator variables for access to corresponding healthcare facilities. *Access to market* is an indicator that takes the value one if a village has either a permanent (*Mandi*), temporary weekly (*Haat*) market or a Agricultural marketing Society. Errors are robust and clustered at the district level.

Appendix A

TABLE A.1: Summary Statistics for Household Amenities Data.

Variable	Mean	Std. Dev.
Household condition good	64.70	24.75
Treated Tap Water	33.06	35.35
Asset Radio	7.36	9.55
Asset Television	45.26	21.93
Asset Landline only	3.00	4.33
Asset Mobile only	47.00	21.30
Asset Telephone Mobile Both	2.27	3.80
Asset Bike	11.77	10.69
Asset Car	1.17	2.91

Notes: Village level amenities data is from the Census of India (2011) merged with *Aarogyasri* patient claims data collapsed at the village-caste-quarter level. All variables report the percentage of households in a village with the described facility or asset.

TABLE A.2: Summary Statistics for Village Amenities Data.

Variable	Mean	Std. Dev.
Primary Health Centre	0.07	.26
Dispensary	0.01	.12
Mobile Health Clinic	0.31	.46
Family Welfare Centre	0.003	.05
Mandis/Regular Market	0.12	.32
Weekly Haat	0.18	.39
Agricultural Marketing Society	0.02	.16

Notes: Village level amenities data is from the Census of India (2011) merged with *Aarogyasri* patient claims data collapsed at the village-caste-quarter level. All reported variables are binary taking the value one if the corresponding amenity is present in a village and zero otherwise.