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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 project 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. The 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 19% and first time claim amounts by 16% in the subsequent quarter. Simultaneously, as a placebo, neither other castes inside or outside the

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[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.

village, nor same caste peers outside the village in the same sub-district, have any 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.

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.[2] 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).[3] 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

[2] In India, the state and not the central government is primarily responsible for the provision of healthcare services.
[3] The fraction of households in AP who are classified as BPL is more than 90%, which makes eligibility for the scheme nearly universal.

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.[4]

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.

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 and economic transactions such as risk pooling and investments 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. 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.[5] 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.[6]

[4] 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.

[5] 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.

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

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 Rs. 26,680.

Lacking the characteristics of the non-claimants social networks cannot be measured at the individual level. Instead we collapse individual utilization from the claims data by village-caste-quarter cells separately for first-time users in a quarter and total users in the quarter. 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. 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. 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. Using presence of permanent (*Mandi*) or weekly (*Haat*) markets in a village we 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. Two villages were chosen at random from each rural subdistrict. 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. Table 3 shows that 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

We examine 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. Table 4 shows that *Aarogyasri* utilization is associated with significantly lower out-of-pocket healthcare expenditures after controlling for a number of household characteristics. Households using *Aarogyasri* reported Rs. 21591.6 lower expenditures for in-patient care and Rs. 1079.5 for out-patient care. 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.

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 will suggest that social networks are influential in increasing utilization. In order to eliminate the confounding factors that influence both total utilization in the prior period as well as subsequent first-time utilizations within the group we control for village-caste fixed effects. We introduce subdistrict-caste-quarter fixed effects to control for time-varying economic, social and political factors that might impact first time utilization. We adapt the same methodology 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 Main Results

Table 5 report the effects of caste networks on first time 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 19%. We find that other caste groups within the same village have virtually no effect on utilization. The table reports that the same caste members in other villages within the same sub-district have a negligible impact compared to the same caste within the village. This finding is consistent with healthcare decisions being very localized, with immediate family and friends as the central sources of information. Other groups outside the village, but within the same sub-district have an even smaller effect.

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 16%. Columns 5 and 6 also show that other castes within the village significantly effect claim amounts, although the magnitude is 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.

4.2 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. 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. 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.

Table 6 shows that network effects are almost entirely driven by men, so much so that the main effect is statistically insignificant in this model. 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 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, the type of procedure that is least likely to be communicable within a population group. The coefficients associated with cardiology, nephrology and urinary surgery, oncology and pediatrics 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, plastic surgery and dermatology, gastroenterology, critical care and orthopedics, rheumatology and prosthesis are an order of magnitude lower, 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 which is consistent with the earlier findings where network effects are largely driven by male claimants. Second, the coefficient associated with infectious diseases is also negligible.

4.3 Location and Social Networks

Demographic features and infrastructure 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. In a similar vein, phones, radios and other wealth measures might facilitate social interactions and could therefore complement network effects.

We find that the marginal effects of social networks are significantly greater in urban areas compared to the overall sample, supporting the hypothesis 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. 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 – 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.

We also examines the impact of local health facilities and market access in increasing effectiveness of social networks. Table 11 reports that the marginal effectiveness of social networks increases by approximately 4% in villages that are above the median in the health facilities index ($p < 0.01$). Both private and public health facilities have similar effects. 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 4.3% increase in the effectiveness of social connections.

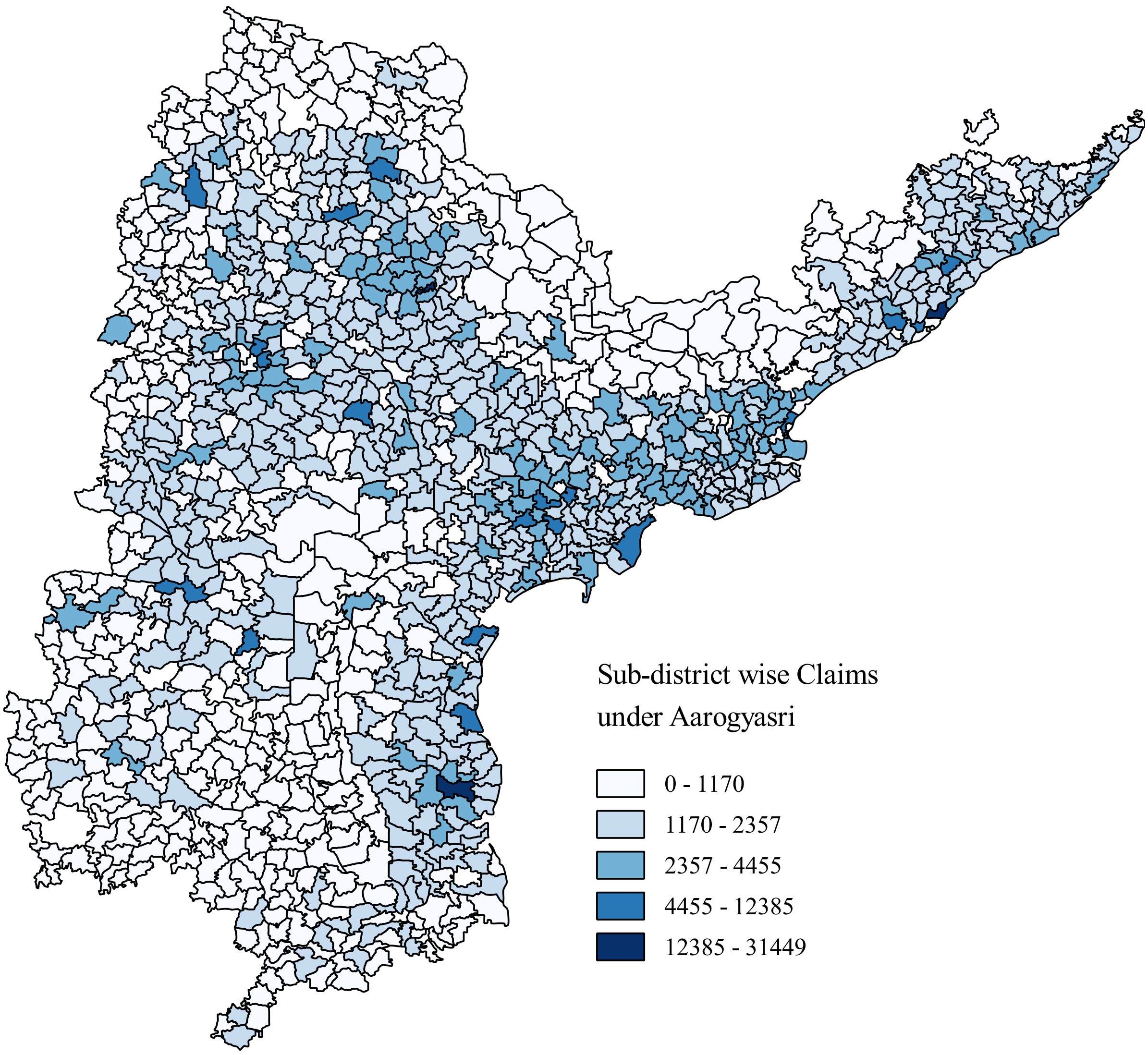
5 Current Status

We have integrated additional datasets such as the Census of India with the administrative claims data. Our empirical analysis on this merged data is almost complete. Our data analysis suggests that network claims are strongly correlated with subsequent unique claims. These effects are stronger in urban areas and in regions with greater penetration of cell phones and radios. 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.

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 use, 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. For publicly financed health insurance more specifically, researchers 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 use.

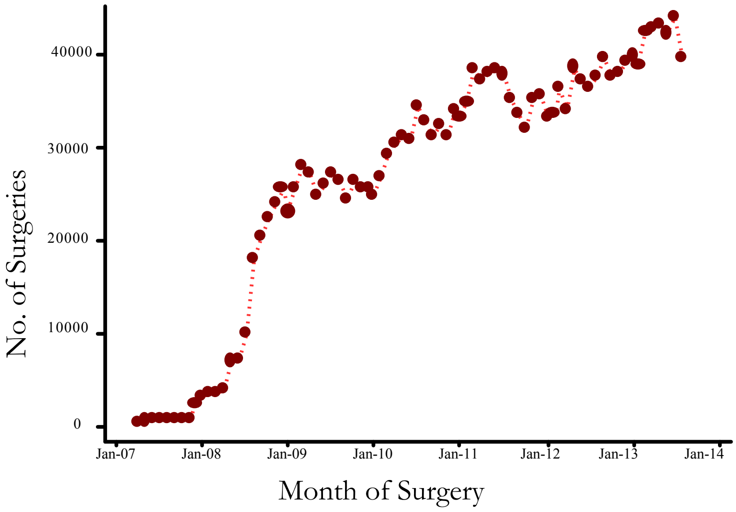
Currently we are incorporating the comments that we received at several seminars and conferences. So far we have presented our findings at Boston University, Tufts Fletcher School, and the Indian Statistical Institute's Annual Conference on Economic Growth and Development. We anticipate presenting the paper at a number of other venues in the near future including the Royal Economic Society Conference at University of Sussex in March 2016 and the University of Connecticut and University of California Santa Cruz in April 2016.

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



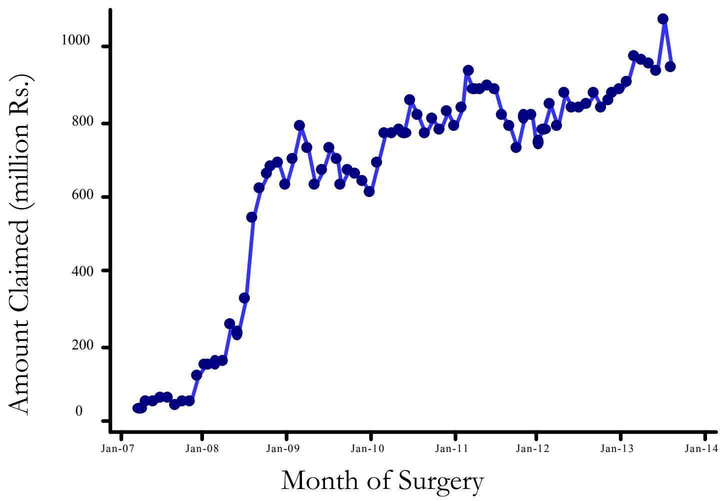
Notes: Data consists of all claims filed under the public health insurance program *Aarogyasri* for the period 2008-2013 in the state of Andhra Pradesh.

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.

	National Sample Survey		OOP Survey	
	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$_{t-1}$	0.19**	0.19**	0.19**			
	(0.07)	(0.08)	(0.07)			
Claim, oth groups$_{t-1}$		0.012	0.012*			
		(0.01)	(0.01)			
Claim, same group in sub-dist.$_{t-1}$			0.000047			
			(0.00)			
Claim, oth groups in sub-dist.$_{t-1}$			-0.00015			
			(0.00)			
Claim amount, own group$_{t-1}$				0.17*	0.16*	0.16*
				(0.08)	(0.08)	(0.08)
Claim amount, oth groups$_{t-1}$					0.019***	0.019***
					(0.00)	(0.00)
Claim amount, same group in sub-dist.$_{t-1}$						0.00028
						(0.00)
Claim amount, oth groups in sub-dist.$_{t-1}$						-0.00031
						(0.00)
Average	.57	.57	.57	17034.69	17034.69	17034.69
No. of Observations	2258922	2258922	2258922	2258922	2258922	2258922
R Squared	0.10	0.10	0.10	0.043	0.046	0.046

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 Social Networks on Healthcare Utilization under *Aarogyasri* by Gender.

	(1)	(2)	(3)
Male	0.072***	0.069***	0.054***
	(0.01)	(0.01)	(0.01)
Claim, own group$_{t-1}$	0.015	0.018	0.0076
	(0.03)	(0.04)	(0.03)
Claim, own group$_{t-1}$ $\times$ Male	0.23***	0.21***	0.24***
	(0.05)	(0.04)	(0.05)
Claim, oth groups$_{t-1}$		-0.014*	-0.011
		(0.01)	(0.01)
Claim, oth groups$_{t-1}$ $\times$ Male		0.051***	0.045***
		(0.01)	(0.01)
Claim, oth groups in sub-dist.$_{t-1}$			-0.0024**
			(0.00)
Claim, oth groups in sub-dist.$_{t-1}$ $\times$ Male			0.0068**
			(0.00)
Claim, same group in sub-dist.$_{t-1}$			-0.029***
			(0.01)
Claim, same group in sub-dist.$_{t-1}$ $\times$ Male			0.068***
			(0.01)
Average	.34	.34	.34
No. of Observations	3777336	3777336	3777336
R Squared	0.031	0.034	0.058

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)
Own group	0.02***	0.01*	0.010**	0.02***	0.005***	-0.001	0.04*	-0.0004
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
Oth groups	0.002	-0.002	0.0003	-0.0004	0.0006	-0.0010	-0.002	-0.0001
	(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 Obs.	609352	609352	609352	609352	609352	609352	609352	609352
R Squared	0.008	0.005	0.004	0.005	0.0008	0.0002	0.05	0.0002

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	Gastroentero-logy	Pulmono-logy	Critical Care	Orthopedic, Rheumatol-ogy & Prosthesis	Infectious Disease
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Own group	0.006***	0.001	0.002*	0.001***	0.008*	0.0009**	0.004***	0.000005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Oth groups	0.0005*	0.00003	-0.0003	0.00004	-0.0003	0.0003**	0.00006	-0.000006
	(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 Obs.	609352	609352	609352	609352	609352	609352	609352	609352
R Squared	0.004	0.0008	0.0010	0.0005	0.03	0.0006	0.002	0.000006

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$_{t-1}$	0.067***	0.061***	0.065***
	(0.01)	(0.01)	(0.01)
Claim, own group$_{t-1}$ × $Urban$	0.24***	0.25***	0.24***
	(0.04)	(0.05)	(0.05)
Claim, oth groups$_{t-1}$		0.019***	0.019***
		(0.00)	(0.00)
Claim, oth group$_{t-1}$ × $Urban$		-0.018**	-0.019**
		(0.01)	(0.01)
Claim, oth groups in sub-dist.$_{t-1}$			-0.00031
			(0.00)
Claim, oth groups in sub-dist.$_{t-1}$ × $Urban$			-0.0010
			(0.00)
Claim, same group in sub-dist.$_{t-1}$			0.0035***
			(0.00)
Claim, same group in sub-dist.$_{t-1}$ × $Urban$			-0.0034***
			(0.00)
Average	.57	.57	.57
No. of Observations	2258922	2258922	2258922
R Squared	0.14	0.15	0.15

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$_{t-1}$	0.022***	0.026***	0.0092**	-0.0079
	(0.00)	(0.01)	(0.00)	(0.01)
Claim, oth groups$_{t-1}$	0.017***	0.017***	0.017***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)
Claim, oth groups in sub-dist.$_{t-1}$	0.000092	0.000081	0.000095	0.00012
	(0.00)	(0.00)	(0.00)	(0.00)
Claim, own group$_{t-1}$ $\times$ Mobile	0.037***			0.026***
	(0.01)			(0.01)
Claim, own group$_{t-1}$ $\times$ Radio		0.030***		0.019***
		(0.00)		(0.01)
Claim, own group$_{t-1}$ $\times$ Richer			0.049***	0.037***
			(0.01)	(0.01)
No. of Observations	1779418	1779418	1779418	1779418
R Squared	0.010	0.0098	0.011	0.011

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$_{t-1}$	-0.024***	-0.038***	-0.0086***	-0.064***
	(0.00)	(0.00)	(0.00)	(0.01)
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.$_{t-1}$	0.000039	0.000054	-0.000056	0.0000011
	(0.00)	(0.00)	(0.00)	(0.00)
Claim, own group$_{t-1}$ $\times$ Public health facility	0.071***			0.040***
	(0.01)			(0.01)
Claim, own group$_{t-1}$ $\times$ Private health facility		0.083***		0.051***
		(0.01)		(0.01)
Claim, own group$_{t-1}$ $\times$ Access to market			0.066***	0.043***
			(0.01)	(0.01)
No. of Observations	1743906	1743722	1743906	1743722
R Squared	0.0026	0.0028	0.0026	0.0036

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.

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