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Government health insurance and spatial peer effects: New evidence from India

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ABSTRACT

What is the role of spatial peers in diffusion of information about health care? We use the implementation of a health insurance program in Karnataka, India that provided free tertiary care to poor households to explore this issue. We use administrative data on location of patient, condition for which the patient was hospitalized and date of hospitalization (10,507 observations) from this program starting November 2009 to June 2011 for 19 months to analyze spatial and temporal clustering of tertiary care. We find that the use of healthcare today is associated with an increase in healthcare use in the same local area (group of villages) in future time periods and this association persists even after we control for (1) local area fixed effects to account for time invariant factors related to disease prevalence and (2) local area specific time fixed effects to control for differential trends in health and insurance related outreach activities. In particular, we find that 1 new hospitalization today results in 0.35 additional future hospitalizations for the same condition in the same local area. We also document that these effects are stronger in densely populated areas and become pronounced as the insurance program becomes more mature suggesting that word of mouth diffusion of information might be an explanation for our findings. We conclude by discussing implications of our results for healthcare policy in developing economies.

1. Introduction

Despite a plethora of schemes that offer healthcare services completely free of costs or at a highly subsidized rate, take up of hospital care is very low, especially in developing countries. Two key reasons can explain this finding. First, there is a paucity of information about benefits and costs of treatment and second, there is also little ability to comprehend such information even if it were available, leading to lack of faith about hospital care (See Bauhoff et al., 2011, Jehu-Appiah et al., 2011; Rajasekhar et al., 2011). In such situations, patients often rely on anecdotal evidence from their peers or neighbors on the benefits of treatment.

Health insurance has traditionally been viewed as a means to enable financial risk protection and improve access for patients and their families. Past evaluations of insurance programs have thus focused on how health insurance affects consumption smoothing, utilization of care by the insured and better health outcomes. We suggest another potential role of health insurance (especially in the case of universal health insurance schemes), which is its role in diffusing information on the benefits of treatment in hospitals. We thus postulate that in a setting where all residents are insured and can avail of healthcare benefits, peer effects from neighbors would lead to increased use of hospital care.

In order to examine this hypothesis, we draw from the peer effects literature. In particular, we study the role of peer effects in technology diffusion i.e. the spread of an idea within a community. This depends upon the innovation itself, communication channels, time, and a social system. Oster and Thornton 2009, Bollinger and Gillingham 2012, and Conley and Udry 2005, show that there are strong peer effects in the adoption of different innovations such as menstrual cups, photovoltaic panels and new methods of pineapple farming in developing as well as developed country contexts. In the health literature, past work (for example, Sorensen, 2006; Fowler and Christakis, 2008; Cohen and Soto, 2007; Dahl et al., 2012; Godlonton and Thornton, 2012; Bodine-Baron et al., 2013) document peer effects in a variety of contexts related to decisions in taking paternity leave, obesity, HIV testing, vaccination and in choosing health plans. In our paper, we consider the introduction of a new health insurance scheme to be similar to a new technology that could potentially impact health outcomes.

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A central challenge in this literature is identifying the causal effects of peers and distinguishing them from endogenous peer formation (Manski, 1993, 2000). Prior work has either used random assignment to peer groups or regression based approaches to identify the impact of exogenous variation in the behavior of peers on one's decisions. We follow the latter approach and exploit exogenous variation in the timing of a government scheme to identify peer effects.

Specifically, we use data from a new universal health insurance program (called the *Vajpayee Arogyashree Scheme* or VAS) to show that take-up for healthcare in a particular geographical unit leads to increased take-up by neighbors from the same area. This positive association between current and future use could arise for a variety of reasons. For example, common health related behaviors or environmental factors could lead to clustering of disease and healthcare use. Similarly current and future use could be correlated due to health policies that increase access to care or promote greater utilization over time. Finally, the correlation between current and future use of care could reflect diffusion of information about benefits of treatment. Put simply a successful surgery in a local area today might promote others in the same area to seek treatment or surgery in the future. We are interested in evaluating the degree to which the association between current and future use of healthcare is being driven by word of mouth diffusion of information rather than other competing explanations.

To isolate the impact of increase in take up due to spread of information from any other factor, we propose the following analytical strategy. Our dependent variable is the number of patients admitted in all VAS empanelled hospitals for a given condition, taluk (group of villages) and month. Several taluks form a district, and many districts make up an Indian state. Indian census data of 2011 indicate that Karnataka has a population of about 60 million and there are about 220 *taluks* in Karnataka across the state's *29 districts*.

Our key independent variable is the number of patients hospitalized for a given condition and taluk in the previous month. To account for any underlying trends that may influence take up of hospital care, we include taluk fixed effects, condition fixed effects and time fixed effects. To account for unobserved heterogeneity in disease prevalence and tertiary care hospitalizations, we control for local area specific health condition fixed. We also control for local area specific time fixed effects to allow for differential trends in health and insurance related to outreach activities varying geographically over time. We argue that the remaining identifying variation is exogenous and determined by the random occurrence and treatment of chronic conditions in the population. In other words, consider the thought experiment where two taluks who have the same underlying risk factors for a chronic disease but in one taluk a patient decides to seek hospital care for a chronic condition and in the other taluk patients do not seek hospital care. Will the hospitalization of the patient encourage others in the same taluk to seek hospital care in the future? This is what we investigate in our analysis.

We expect that information diffusion will have some decay. This means that a hospitalization this month leads to higher information diffusion in the next month, but the impact dies down in consecutive months. To account for this phenomenon, we borrow from the marketing literature and perform a grid search to find a value of depreciation that minimizes the root mean square error of the impact of present take up for tertiary healthcare on its lag. Our results indicate that after accounting for depreciation, 1 new tertiary care hospitalization today results in 0.35 additional future hospitalizations for the same condition in the same local area. We are also able to document that these effects increase with time as VAS matures and patients have more time to determine the outcomes of treatment.

If it is indeed the case that take up for hospital care increases because of diffusion of information through a network of geographic peers, the impact would also be evident amongst peers from neighboring taluks. To test this hypothesis, we control for take up for hospital care in a same condition and month but from a neighboring taluk. In line with our expectations, we find that the impact is statistically significant but not as strong as that within the same taluk.

Interestingly we also find that information diffusion gets stronger with time and is more significant in taluks with higher population density. In geographies with low population density, one new hospitalization, results in an increase in future hospitalizations by an additional 0.28 units, whereas in geographies with high population density, one new hospitalization today increases future hospitalizations by an additional 0.41 units. Since we are interested in studying increase in take up for healthcare only for tertiary illnesses, we believe that the impact of higher population density is through word of mouth publicity and not a mere increase in incidence of illness as tertiary illnesses are known to be non-communicable and occur typically with a low probability.

As an additional robustness check, we control for heterogeneity in hospital type by splitting our sample of patients based on whether they enrolled in public or private hospitals. We find that while information diffusion is significant in both cases, take-ups based on past cases are stronger in the case of private hospitals. Our findings suggest that spatial diffusion of information might play an important role in explaining the take up of healthcare over and above other factors that could drive uptake of healthcare insurance schemes in these contexts (Panda et al., 2013, Sinha et al., 2006, Binnendijk et al., 2013 and Dror et al., 2007).

The paper proceeds as follows. Section 2 offers a summary of the institutional background that relates to our study. Our data and empirical framework are outlined in Section 3. Results are presented in Section 4 and we conclude in Section 5.

2. Institutional background

The government healthcare system in India offers medical services free of charge in public hospitals across the country. However, several individuals, including the poor, also seek treatment from private hospitals. As a result, out-of-pocket payments for hospital bills represent an estimated 69% of total health spending in India (Kumar et al., 2011; Ma and Sood, 2008). Such high out of pocket costs for healthcare can drive households into poverty and also limit the use of costly but lifesaving medical care.

While most schemes focus on primary illnesses, in recent times tertiary illnesses have posed a larger threat in developing economies due to the large costs associated with treatment. To address these concerns, several state governments and the national government in India have introduced government-sponsored insurance schemes for financing medical costs for tertiary care. Table 1a provides a summary some of the recently introduced health insurance schemes in India.

However as per results from a survey we conducted amongst healthcare professionals, we find that lack of information and knowledge about the schemes is one of the primary reasons for lack of use of such insurance schemes. One of our respondents highlighted that literate individuals have a much higher probability of availing benefits of this scheme as they are better able to understand the information given to patients.

Our survey also revealed that often the insurance schemes are misused by hospitals by tweaking bills, providing unnecessary care, and illegally making richer patients eligible for the scheme. To reduce such misuse, some government schemes impose a ceiling on the maximum amount to be reimbursed for each treatment. However, according to a doctor who works for one of the leading private hospitals in Bangalore, this ceiling on reimbursement implies that patients often don't get the best treatment because price ceilings force doctors to treat using an inferior but cheaper method.

Despite the shortcomings in implementation of these schemes, universal insurance has shown to reduce incidence of poverty and improve health outcomes at least in the Indian context. For instance, a World Bank report (La Forgia and Nagpal, 2012) finds that over the last

Table 1a
Summary of recently introduced health insurance schemes in India.

Scheme	Location	Target Population	Beneficiaries	Max Cover	Source of funds
Apka Swasthya Bima Yojana	Delhi	Existing enrolees in Delhi under RSBY	0.65 million in 2011	Rs 150,000 per family per year	Entirely by state government
Chief Ministers comprehensive health insurance scheme	Tamil Nadu	BPL or annual income below Rs.72,000, members of 26 welfare boards	15724432 in 2017	Rs 100,000 per family over 4 years	Entirely by state government
Rajiv Aarogyasri Healthcare Insurance Scheme	Andhra Pradesh	BPL or annual income below Rs.75,000	1,753,466 in 2013	Rs 150,000 per family per year	100% from State Government
Rashtriya Swasthya Bima Yojana	35 states in India	BPL families	36,332,475 in 2017	Rs 30,000 per family per year	75% central, 25% state government
Rajiv Gandhi Jeevandayee Arogya Yojana	Maharashtra	Families with ration cards in 36 districts in Maharashtra	45,075 in 2013	Up to Rs. 1, 50,000/- per family per year	Entirely by state government
Vajpayee Arogyashree Scheme-2009	Karnataka	BPL residing in covered areas	1.5 million in 2009	Rs 150,000 per family per year + Rs.50,000 buffer	Entirely by state government
Yashaswini - 2017	Karnataka	Members of the rural cooperative society	4,372,000 as of 2017	Rs 200,000 per person per year	58% from beneficiaries 42% from state

five years, government-sponsored schemes have contributed to a significant increase in the population covered by health insurance in India, higher than anywhere else in the world. Since 2010, over 25 percent of India's population (roughly 300 million people) have gained access to some form of health insurance of which 180 million were below the poverty line. Thus given their importance, understanding why takeup for tertiary care health insurance is so low despite so many people being covered by some form of government insurance is imperative to attain better health outcomes.

This paper uses data from only one state, namely Karnataka. Karnataka is a state located in the south of India and is considered to be among the better-off states in the country. However, there are large populations living in deep poverty (particularly in the rural northern part of the state) contributing to significant socio-economic disparity.

Over the past few years, there has been a tremendous improvement in certain health outcomes in Karnataka. For instance, there is a sharp decline in the maternal mortality ratio as well as infant mortality rates. The introduction of National Rural Health Mission (NRHM) in Karnataka in 2005 has resulted in the strengthening of infrastructure for secondary and tertiary illnesses, but the quality of care provided in government hospitals remains of concern. There has also been a tremendous growth in the private sector in the last decade. According to the district level household and facility survey, 60% of the population preferred treatment from the private sector for chronic illness. As a result, there has been a decline in the utilization of public health services in the last decade from 34% to 26% (71st National Sample Survey Office report of India).

Given the increasing incidence of tertiary illnesses, the government has introduced several insurance schemes for tertiary care in Karnataka as summarized in Table 1b. These government-sponsored insurance schemes are different from private voluntary insurance markets, in that beneficiaries of these schemes pay no premiums. Beneficiaries typically receive first dollar coverage as long as care is received in an empanelled or network hospital. Thus, these schemes are similar to government-financed insurance programs for the poor in other countries such as the Medicaid program in the U.S.

However given the overlap between these schemes, the government now plans to introduce a new scheme called Arogya Bhagya beginning November 2017 which will merge several different schemes. Under Aarogya Bhagya, the seven different health care schemes of Karnataka will be merged into one requiring a total of INR 869.4 crore (USD 130 million approximately) as the cost to the state exchequer.

In this paper, we use data from one particular scheme known as the Vajpayee Arogyashree Yojana (VAS) for 13 districts in Karnataka. VAS was introduced in Karnataka in 2009 and is one of the most beneficial schemes for the rural poor as it provides one of the highest level of coverage per person but does not require any co-payment from the beneficiaries. The scheme has defined a benefits package for 402 tertiary care services, which covers cardiology, oncology, neurology, nephrology, neonatology, burn care and trauma care. Residents in eligible divisions who possess a BPL card issued by the state government are automatically enrolled in VAS and eligible for all benefits. Anecdotal evidence shows that VAS has been effective in treating patients who would have otherwise had no access to hospital care. A recent study (Sood et al., 2014) also shows that areas that had benefitted from VAS experienced lower mortality (0.32%) compared to neighboring districts where VAS was introduced much later (0.90%) for below poverty line households. The authors find no difference in mortality rates for above-poverty line households. Eligible households also had significantly reduced out-of-pocket health expenditures for admissions to hospitals with tertiary care (Barnes et al., 2017).

However, VAS's effectiveness potentially is also moderated by path dependence in the macro-healthcare environment within Karnataka, varying by geography. Table 1c shows the number of government run healthcare institutions in the 12 districts where VAS was first implemented. As seen in the table, the availability of healthcare facilities

Table 1b
Summary of recently introduced tertiary healthcare schemes in Karnataka.

Scheme and Inaugural Year	Amount covered	Illness covered	Coverage area/target population
Chief Minister's Relief Fund - 2018	Up to Rs.50,000	Cardiac surgeries	Mainly patients from Bangalore Urban and nearby districts
Rajiv Arogya Bhagya(2013)	Rs. 150,000 with copayment	All tertiary illnesses	Above Poverty Line(APL) card holders
Jyothi Sanjeevini Scheme - 2014	Ranges between Rs.16000 to Rs. 43000	7 broad specialities including Cardiology, Oncology, Genito Urinary Surgery, Neurology, Burns, Poly- trauma cases and neo- natal and Pediatric surgery.	State government employees and their dependent family members whose monthly income does not exceed Rs. 6000.
Mukhyamantri Santwana Harish Yojana - 2016	Max amount of Rs.25,000 per victim per episode.	Poly- trauma cases	All road traffic accident victims, who meet with accidents on the roads of Karnataka
Indira Suraksha Yojane - 2016	Rs. 150,000 per family per year	Secondary and tertiary care	Dependent members of the farmers who committed suicide in Karnataka
Senior citizen Rashtriya Swasthya Bima Yojana -2016	1,50,000 per family	Secondary and Tertiary care	Senior citizens aged 60 and above with RSBY Card.

Table 1c
Number of government run health providers in Karnataka in 2009.
Source: Rural health statistics from the Ministry of Health and Family Welfare.

Districts	Sub-centers	Primary health care centers	Community health care centers
Bagalkot	224	47	12
Belgaum	539	146	24
Bellary	272	70	13
Bidar	234	50	10
Bijapur	285	64	12
Dharwad	179	31	3
Gadag	174	35	6
Gulbarga	378	126	30
Haveri	290	68	11
Koppal	183	45	11
Raichur	196	52	9
Uttar Kannada	120	78	13

Table 2
Descriptive statistics on VAS-Hospitalizations.
Source: Suvarna Arogya Suraksha Trust (SAST).

Type of disease	Number of patients
BURNS (Patients suffering from severe burns on foot, leg, face, etc. and treating ulcers from burns)	185
CARDIOLOGY (Patients requiring cardiothoracic surgery, valve replacement, pacemaker implantation, closed heart disease)	3741
NEPHROLOGY (Patients suffering from renal diseases, enlargement of prostrate, etc)	670
NEUROLOGY (Patients requiring spine and brain related surgery)	812
ONCOLOGY (Patients suffering from mainly ovarian cancer, esophageal cancer, breast cancer, soft tissue and bone tumor)	901
NEONATOLOGY (Patients requiring pediatric treatments)	86
POLYTRAUMA (Patients suffering from severe fractures)	8

varies considerably across districts. As we discuss later, some of these unobserved heterogeneity coming from path dependence will be taken care of using fixed effects in our econometric analysis. Although the scheme was first introduced in late 2009, take up for the scheme was limited. Table 2 shows the distribution of hospitalizations across disease conditions, with a list of most common ailments within each condition. During our study period, heart disease accounted for the majority of hospitalizations followed by cancer and neurological diseases.

To create awareness about the scheme, VAS conducted several Information, Education and Communication (IEC) activities such as pamphlet distribution, advertisement through public address system, drum beating, posters, banners and self-help group meetings to popularize the health insurance scheme. In addition, a mega health camp was conducted at the district level where patients were screened for various illnesses and referred to network hospitals located in nearby urban areas for free tertiary care. Once a district had a mega health camp, smaller health camps followed every month to screen patients and refer them to specialty hospitals if they required treatment. Fig. 1 shows a Geographical Information System (GIS) based plot of the order in which mega health camps were conducted in districts under VAS. The impact of mega health camps has been positive, as is evident through the rise in new-VAS hospitalizations as shown in Fig. 2.

Fig. 3 shows the increase in VAS hospitalizations over time across all districts using some additional GIS plots. The left-most panel indicates that mega health camps first began in the north-eastern districts of Bidar and Gulbarga in Karnataka and thus we see the largest incidences of VAS hospitalizations in these districts. Between 7 and 12 months, hospitalizations mostly occur in Bellary, Raichur and Koppal while the last 7 months have hospitalizations from all districts under study. These figures show that hospitalization rates are responsive to mega health camps. Thus, the staggered implementation of health camps and other promotional activities could lead to different trends in hospitalization rates across districts or taluks. We control for the staggered implementation of health camps non-parametrically by including taluk specific time fixed effects in our regression models. However, what is interesting is that there are cases where we observe take-up for VAS even though the district has not had a mega health camp (Fig. 4). Districts neighboring Bellary (Raichur and Koppal) had mega health camps just a few weeks before Bellary. Our plots show that there are patients who enrolled for VAS soon after health camps in neighboring districts, once again suggesting the presence of peer-effects in take up for healthcare.

3. Data & methods

3.1. Data

We use data from administrative records maintained by SAST (*Suvarna Arogya Suraksha Trust*), the executing agency for VAS. The raw data includes (1) disease condition for over 6000 patients, (2) the geographical location of the patient, (3) the hospital where the treatment was done, and (4) the expenses borne out by the scheme at the patient level. The dataset we worked with finally was at the taluk-disease condition-time level and was for the first 19 months beginning from November 2009, which is when the VAS program was first

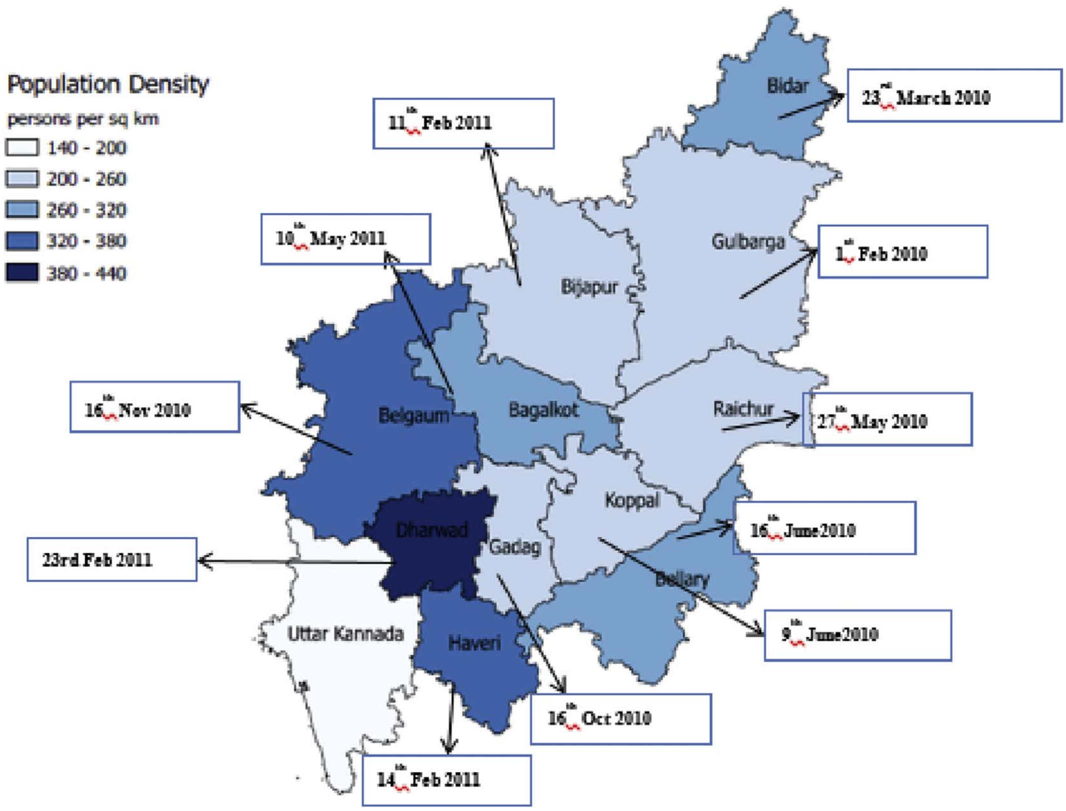

Fig. 1. VAS Mega Health Camps across Districts in Karnataka, India 2010–2011.
The figure also outlines the population density of these various districts as per figures available from census data in India as of 2011. The figure illustrates how authorities considered holding the mega-health camps as a mechanism to enhance enrollment in VAS, especially during the earlier periods in more sparsely populated districts than in the more densely populated ones. In the dataset we have 13 districts but we can show only 12 in the map below as the district of Gulbarga was recently split creating a new district Yadagiri. This change has been incorporated in the dataset, but the updated GIS maps are not yet available. Since the mega health camp was conducted in 2010, the date of mega health camp is the same for both Yadagiri and Gulbarga.
Source: SAST & Indian Census

implemented in Karnataka, India. As we are able to track the scheme right from its beginning, we create a panel dataset of number of patients enrolled in VAS for each medical condition in a geographical area every month. The unit of geographic consideration we explore is the *taluk* (collection of a few villages), which is an administrative division used in some South Asian countries. During the period of time for which we have access to administrative data, VAS was rolled out in *79 taluks* across *13 districts* in the state. Our unit of observation is thus at the *taluk-condition-month* level giving us 10,507 (79 × 7 × 19) observations in a balanced panel. The data we have is only for first visits and does not include data on patients who visited doctors for a follow up visit. In addition, the final data we were able to use for empirical

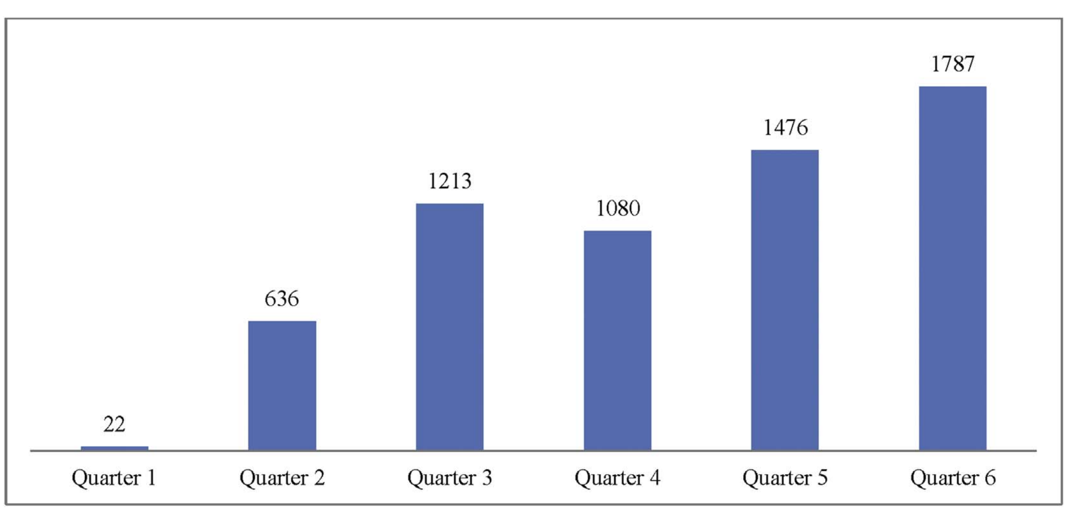

Fig. 2. Quarterly Flow of VAS Hospitalizations.
This figure outlines the rise in new-VAS hospitalizations each quarter during our period of analysis. The Y-axis is the flow of patients and the X-axis are the quarters that elapsed since initial launch. We split our data for 19 months into quarters, ignoring the last month. The take-up increased substantially over time.
Source: SAST.

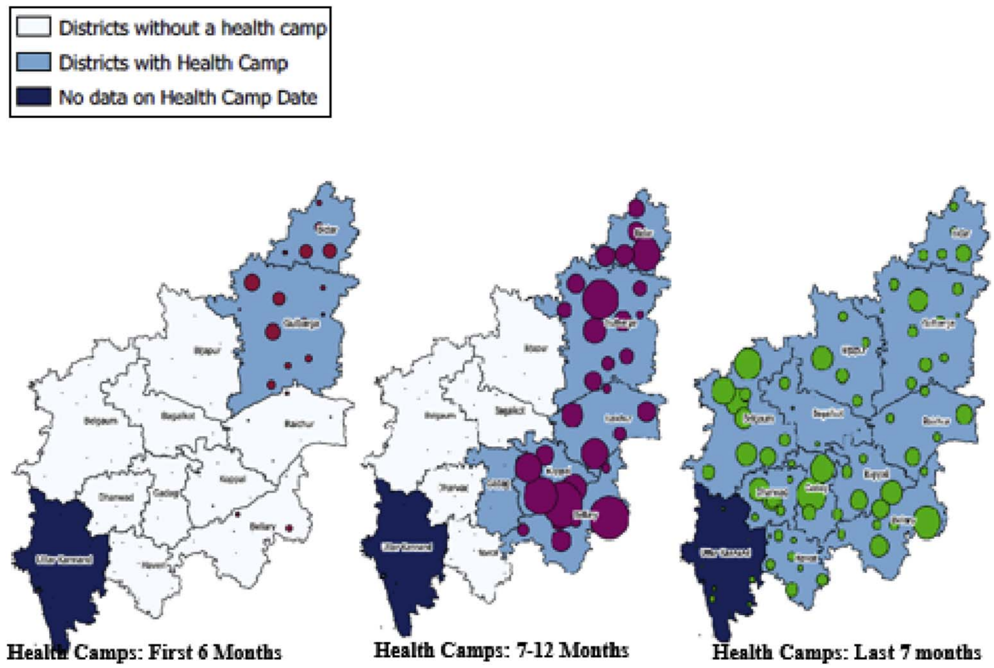

Fig. 3. Spatial Adoption of VAS in Karnataka, India.
Fig. 3 below shows the increase in take-up of VAS patients over time (indicated by circles) across all districts. Each circle corresponds to a taluk and the size of the circles reflects number of patients from that taluk in the given time frame. These figures are plotted using GIS software QGIS. The left-most panel indicates that mega health camps first began in the north-eastern districts of Bidar and Gulbarga and thus we see most incidences of VAS cases in these districts. Between 7 and 12 months, cases mostly occur in Bellary, Raichur and Koppal while the last 7 months have cases from all districts under study. The figure shows that incidence of VAS cases are responsive to mega health camps that are conducted at the district level and highlights the need for fixed effects that vary within the taluk but over time to capture for the unobserved effects of mega health camps over and above spatial flow of information.

analysis masked patient level information and related heterogeneous socio-economic status of patients and was only at the taluk-condition-month level. Our project received an ethics approval by the institutional review board at the University of Southern California.

3.2. Empirical methodology & construction of spatial stocks and flows

We are interested in examining whether people living in the same locality are influenced by their neighbors on decisions with respect to tertiary care.

We start by using the following model:

$$F_{t,\,c,\,g} = \alpha_0 + \beta_1 S_{t\text{-}1,\,c,\,g} + \tau_t + \mu_c + \theta_g + \Theta_g {}^*\mu_c + \Theta_g{}^* \tau_t + \varepsilon_{t,\,c,\,g} \quad (1)$$

where, $F_{t,\,c,\,g}$ is the number of tertiary care hospitalizations (current flow) in month t, for condition c and taluk g. We also include τ_t (time fixed effects), μ_c condition fixed effects, Θ_g (taluk fixed effects), and two-way fixed effects $\Theta_g {}^*\mu_c$ (taluk condition fixed effects) and $\Theta_g{}^* \tau_t$ (taluk time fixed effect). Current flow of hospitalization is a function of stock (sum of all cases starting from the first month) of hospitalization $S_{t\text{-}1,\,c,\,g}$ for the same condition, in the same taluk at time t-1. The stock of VAS hospitalizations in month t, for condition c, and taluk g is given by:

$$S_{t,\,c,\,g} = (1\text{-}\delta)\, S_{t\text{-}1,\,c,\,g} + F_{t,\,c,\,g} \quad (2)$$

To account for the fading-out effect of the impact of a previous take up on current take up we introduce a depreciation rate δ. The rate of depreciation is calculated using a grid search method (Lakdawalla et al., 2013; Ling et al., 2002). This involves running a regression in equation (1) using different depreciation rates and then choosing the depreciation rate that results in the best fit. We run the regression using values of δ, from 0 to 100% in increments of 10%. The estimated optimal depreciation rate (where the root mean square error is minimized) turns out to be 70%, which we use to compute the stocks $S_{t,\,c,\,g}$.

The total stock at time t calculated using the perpetual inventory method (2) can be written as:

$$S_{t,c,g} = \sum\nolimits_{t=0}^{t=T} (1-\delta)^t F_{t,c,g} \quad (3)$$

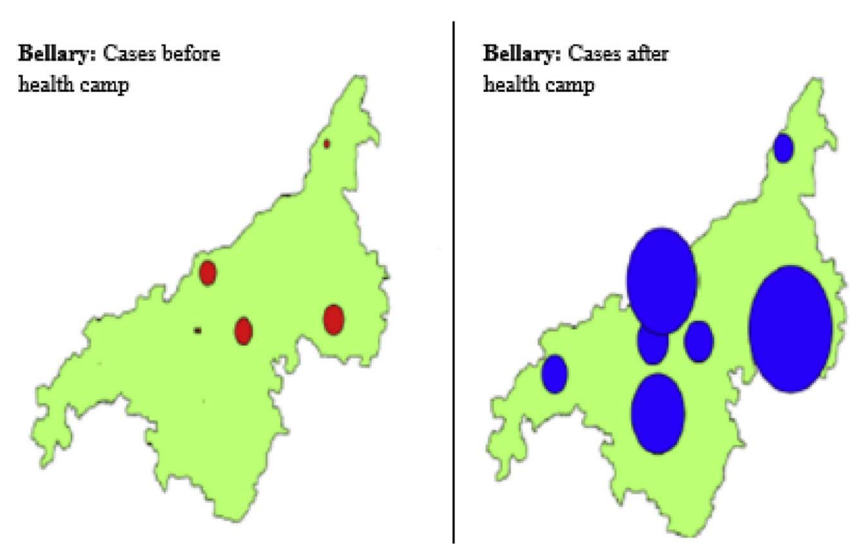

Fig. 4. Spatial Diffusion in a Sample District Before/After Health Camp.
Fig. 4 highlights spatial diffusion of VAS with health camps in a sample district of Bellary, in the south-eastern part of Karnataka. The map on the left shows incidence of VAS cases before the health camp in Bellary while the map on the right panel shows incidence of VAS cases after the health camp. The presence of VAS cases before the mega health camp indicate presence of information spillover but more importantly it also indicates that take-up is spread around those parts where first incidence occurs in a pre-health camp period, indicating the role of diffusion of information. Raichur and Koppal are two districts that are adjacent to Bellary and have had mega health camps a few weeks prior to the mega health camp in Bellary. The dots in the left panel thus suggest that patients may have heard about the VAS scheme from people in neighboring areas and signed themselves up for the scheme through their own initiative. The panel on the right shows take-up for VAS over a period of 18 months after the health camp. The size of the circles in the right panel indicates the number of patients from a particular taluk.

Table 3
Current spatial flow & lagged spatial stocks of VAS hospitalizations.

Variables	(1)	(2)	(3)
	Countflow	Countflow	Countflow
Depreciated Stock	0.354***	0.259***	0.244***
	(0.015)	(0.019)	(0.020)
Constant	0.229***	−0.120	−0.327
	(0.024)	(0.076)	(0.210)
Optimal Depreciation Rate	0.7	0.7	0.7
Time Fixed Effects	Y	Y	Y
Taluk Fixed Effects	Y	Y	Y
Condition Fixed Effects	Y	Y	Y
Taluk*Condition Fixed Effects	N	Y	Y
Taluk*Time Fixed Effects	N	N	Y
Observations	10507	10507	10507
R-squared	0.316	0.356	0.491

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

Juxtaposing equations (1) and (3), our model allows a hospitalization today to have *long-lived effects* on future hospitalizations. Our empirical strategy has parallels in other work in health economics that study the *long lived effects* of economic variables. For example, a similar strategy has been used to study the effects of pharmaceutical advertising on future drug sales (Berndt et al., 1995; Rizzo 1999; Ling et al., 2002; Lakdawalla et al., 2013).

We interpret the coefficients as follows: a single hospitalization today increases stock contemporaneously by 1. Thus one new hospitalization today will increase stock the next month by 1-δ, 2 months from now by (1-δ)^2, etc. Also, a unit increase in stock today as per equation (3) will increase flow next period by β_1 (*see* equation (1)). Combining, the increase in flow from one new patient is therefore:

$$\beta_1 + \beta_1 * (1\text{-}\delta) + \beta_1 * (1\text{-}\delta)\hat{}2 + .. \tag{4}$$

Thus, summing up the geometric series implies that one new hospitalization today will yield β_1/δ future hospitalizations. We use a panel data Durbin Watson test and confirm that there is no autocorrelation within the data.

As shown in Table 1c, there is considerable variation in government run supply side factors across the districts. We thus include taluk fixed effects (θ_g) to account for time invariant unobserved differences across taluks such as access to hospitals or other health infrastructure, condition fixed effects (μ_c) to account for unobserved differences in treatment across conditions and time fixed effects (τ_t) to control for secular trends. To account for time invariant unobserved factors related to spatial disease prevalence and tertiary care hospitalizations, we control for local area specific health condition fixed (taluk*condition). We also control for local area specific time fixed effects to absorb differential unobserved trends in health and insurance related to outreach activities over time (taluk*time).

Estimates with lagged dependent variables and fixed effects might be biased since the error term, which is the difference between the error in period t and period t-1, is correlated with the lagged dependent variable, since it is also a function of the error term in period t-1. An alternative would be to implement an Arellano-Bond estimator using earlier lags as instruments which we test for in additional specifications as a robustness check below. This however may be problematic if the goal is to trace out the effects of utilization in all earlier periods. It however does seem that the above correlation would induce a downward bias of our estimate and hence our results are likely to be a lower bound.

We also explore a model in which the stock of hospitalization not only affects future flow in the same taluk but also in neighboring taluks. For each taluk, we manually identify neighbors (i.e. all surrounding taluks) from a map and we generate a new variable $NS_{t,c,n,}$ which is the sum of stock of patients from all taluks neighboring to the focal taluk g.

$$S_{t,\,c,\,g} = (1\text{-}\delta)\, S_{t\text{-}1,\,c,\,g} + F_{t,\,c,\,g} + (1\text{-}\,\delta) NS_{t,c,n} + \tau_t + \mu_c + \theta_g + \Theta_g * \mu_c + \Theta_g * \tau_t + \varepsilon_{t,\,c,\,g} \tag{5}$$

For the neighborhoods model, the optimal level of depreciation is found to be 100%, indicating that individuals lay far more emphasis on information diffusion from the focal taluk than from the neighboring taluk. We expect that the cross effects for neighboring taluks to be smaller given the possible depreciation of information over space. We also control for unobserved heterogeneity as discussed in our baseline specification.

Finally, we explore a model where we allow heterogeneous moderating effects by population density. We expect larger effects in more densely populated areas as word of mouth diffusion of information might be easier in more densely populated areas (Fig. 1). We thus split our sample into half: districts of high population density and districts of low population density and run the same specification on each subsample.

Similarly to account for heterogeneity in hospital type, we classify hospitals as being public or private and run a model similar to equation (1). We might expect a stronger spillover effect for private hospitals as private hospitals were largely unaffordable to the rural poor prior to the implementation of VAS. These hospitals also have better amenities and are less crowded than public hospitals. Thus, a hospitalization in a private hospital (which only the rich could afford prior to implementation of VAS) might create more word of mouth advertising compared to a hospitalization in a crowded public hospital.

In additional robustness checks, we implemented count-data models, notably negative binomial and zero inflated negative binomial regressions. Results here remain qualitatively similar to our baseline specifications.

4. Results & discussion

4.1. Baseline regression results on spatial diffusion of information about VAS

Model 1 in Table 3 estimates equation (1) using ordinary least squares and outlines how lagged spatial stocks of tertiary care hospitalizations impact contemporaneous flow of tertiary care hospitalizations at the taluk-condition-month level. The model controls for condition fixed effects, taluk fixed effects and time or month fixed effects. The coefficient estimates indicate that a one unit increase in lagged stocks increases contemporaneous flows of hospitalizations by 0.35. Model 2 adds taluk*condition time-invariant fixed effects (to account for taluk specific time-invariant condition level unobserved heterogeneity) and the results are qualitatively similar. Model 3, adds taluk-specific time fixed effects to control for time-varying effects of outreach activities like mega-health camps that would be incident at the taluk level. The results are qualitatively similar and lagged stocks continue to positively impact contemporaneous flows. The results indicate that a 1 unit increase in lagged stock of hospitalizations increases current hospitalizations by 0.24 units. Using equation (4) with coefficient estimates from Model 3 implies that one new hospitalization today will yield 0.244/0.7 or 0.35 new hospitalizations in future time periods. Table 7 documents robustness with count-data models for specifications in Table 3. Our results remain qualitatively similar to the baseline specifications in model 2 and 3 of Table 3.

Table 4 presents results from the specification where lagged stock of hospitalizations in a particular taluk not only influence current flows in own taluk but also current flows in neighboring or adjoining taluks. We expect these cross effects for neighboring taluks (coming from potentially information spillovers) to be smaller due to potential depreciation of information over space or geography. Neighboring taluks were manually created using Karnataka's maps. Model 2 in Table 4 shows that a one unit increase in lagged stocks of VAS hospitalizations in a

Table 4
Baseline results controlling for neighbor Taluk's effects.

Variables	(1)	(2)
	Countflow	Countflow
Depreciated Stock	0.156***	0.144***
	(0.027)	(0.026)
Depreciated Neighbor Stock	0.060***	0.059***
	(0.009)	(0.009)
Constant	−0.2858***	−0.158
	(0.0274)	(0.123)
Time Fixed Effects	Y	Y
Taluk Fixed Effects	Y	Y
Condition Fixed Effects	Y	Y
Taluk*Condition Fixed Effects	Y	Y
Taluk*Time Fixed Effects	N	Y
Optimal Depreciation Used	1	1
Observations	10507	10507
R-squared	0.375	0.506

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

taluk increases current flows in own taluk by 0.144 and in neighboring taluks by 0.059. Again, the results are robust to inclusion of taluk specific time fixed effects. In unreported robustness checks we controlled for health camp effects by adding a dummy for months after a health camp in a particular district. Results are qualitatively similar.

4.2. Dynamics of spatial diffusion of VAS & the role of population density

Table 5 presents results that explore how the spatial diffusion of information increases over time. Broadly our finding resonate with the hypothesis that initially word of mouth diffusion of information is not very effective as the insurance program is new and people are uncertain about the benefits of treatment. However, as more time elapses, the insurance program matures and individuals have more time to ascertain the benefits of treatment; it is then that the diffusion of information becomes more effective in influencing other patients to use treatment. The results indicate that in the first six months after inception of the insurance program, an increase in lagged spatial stocks of VAS hospitalizations increase current flow of hospitalization by 0.051and by 18 months since the launch of the insurance program, an increase in lagged stocks increases current flows by 0.242 units. Using equation (4), this also implies that one new hospitalization today will yield 0.07 future hospitalizations during the first 6 months, 0.26 future hospitalizations during the first 12 months, and 0.35 future hospitalizations by the end of 18 months in our dataset. While we are able to observe that peer effects increase with program maturity we would need data over a longer time period to see when peer effects stabilize.

Borrowing on past work in sociology, we next try to understand the moderating role of population density in spatial diffusion of information about VAS. Model 1 and 2 in Table 6 outline these set of results across taluks which come under districts with low and high population density. Model 1 shows that in taluks with low population density, one new hospitalization, adopting equation (4), results in an increase in future hospitalizations by 0.28, whereas in Model 2, in taluks of high population density, one new hospitalization today increases future hospitalizations by 0.41 units. This is consistent with the literature in sociology that has predicted that geographical areas with higher population density will witness a higher diffusion of information than those with lower density in population (Granovetter 1983; Valente 1996; Dobbin et al., 2007).

We also estimate separate effects for private versus public hospitals. Prior to implementation of VAS the rural poor received care primarily in overcrowded public hospitals and only the rich could afford care in private hospitals which were less crowded and had better amenities. VAS contracted with private hospitals so that the rural poor could receive free care at both private and public hospitals. Most of VAS patients are treated in private hospitals, and in our present dataset we have a total of 57 private hospitals and 11 public hospitals. We expect the spillover effect to be stronger for private hospitals, as patients in these hospitals likely had a better experience due to better amenities

Table 5
The dynamics of spatial effects in adoption of VAS.

Variables	(1)	(2)	(3)
	Countflow	Countflow	Countflow
	First 6 Months	First 12 Months	First 18 months
Depreciated Stock	0.051	0.181***	0.242***
	(0.121)	(0.036)	(0.022)
Constant	0.177	−0.537	−0.371
	(0.318)	(0.350)	(0.245)
Time Fixed Effects	Y	Y	Y
Taluk Fixed Effects	Y	Y	Y
Condition Fixed Effects	Y	Y	Y
Taluk*Condition Fixed Effects	Y	Y	Y
Taluk*Time Fixed Effects	Y	Y	Y
Optimal Depreciation Rate	0.7	0.7	0.7
Observations	2765	6083	9401
R-squared	0.488	0.583	0.505

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

Table 6
Moderating effects of population density on spatial adoption of VAS.

Variables	(1)	(2)
	Countflow	Countflow
	Low Population Density	High Population Density
Depreciated Stock	0.196***	0.284***
	(0.027)	(0.025)
Constant	0.086	6.739*
	(0.163)	(3.873)
Time Fixed Effects	Y	Y
Taluk Fixed Effects	Y	Y
Condition Fixed Effects	Y	Y
Taluk*Condition Fixed Effects	Y	Y
Taluk*Time Fixed Effects	Y	Y
Optimal Depreciation Rate	0.7	0.7
Observations	5187	5320
R-squared	0.478	0.506

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

Table 7
Robustness with count data models in VAS hospitalizations.

Variables	(1)	(3)
	Countflow	Countflow
	Negative Binomial Regressions	Zero-Inflated Negative Binomial Regressions
Depreciated Stock	0.058***	0.083***
	(0.004)	(0.011)
Constant	−5.756***	−3.432***
	(1.001)	(0.289)
Optimal Depreciation Rate	0.7	0.7
Time Fixed Effects	Y	Y
Taluk Fixed Effects	Y	Y
Condition Fixed Effects	Y	Y
Observations	7695	10507
Log Likelihood	−5406.69	−6653.95

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

Table 8
Heterogeneity in baseline results by private/public hospitals.

Public Hospitals	(1)	(2)	(3)	(4)
	Countflow	Countflow	Countflow	Countflow
Depreciated Stock	0.092***	0.102***	−0.029**	−0.040***
	(0.007)	(0.008)	(0.011)	(0.0110)
Constant	−0.552	−0.042	0.000	−0.350
	(0.022)	(0.035)	(0.013)	(0.0361)
Optimal Depreciation Rate	0.1	0.1	0.1	0.1
Time Fixed Effects	Y	Y	Y	Y
Taluk Fixed Effects	Y	Y	Y	Y
Condition Fixed Effects	Y	Y	Y	Y
Taluk*Condition Fixed Effects	N	N	Y	Y
Taluk*Time Fixed Effects	N	Y	N	Y
Observations	9954	9954	9954	9954
R-squared	0.255	0.359	0.371	0.467
Private Hospitals	(1)	(2)	(3)	(4)
	Countflow	Countflow	Countflow	Countflow
Depreciated Stock	0.380***	0.388***	0.286***	0.268***
	(0.021)	(0.021)	(0.027)	(0.026)
Constant	0.394***	−0.065	0.407***	−0.159
	(0.110)	(0.178)	(0.095)	(0.232)
Optimal Depreciation Rate	1.0	1.0	1.0	1.0
Time Fixed Effects	Y	Y	Y	Y
Taluk Fixed Effects	Y	Y	Y	Y
Condition Fixed Effects	Y	Y	Y	Y
Taluk*Condition Fixed Effects	N	N	Y	Y
Taluk*Time Fixed Effects	N	Y	N	Y
Observations	9954	9954	9954	9954
R-squared	0.356	0.487	0.399	0.532

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

and less overcrowding at private hospitals. The results presented in Table 8 confirm this hypothesis. We recreate our panel data separately for public and private hospitals and regress the number of patients in a given taluk, condition and month on its lag for each hospital type.

4.3. Threats to validity and additional robustness checks

While we try our best to address all concerns about our identification strategy, there still might remain certain threats to validity as is usually the case with empirical work. In this section, we discuss these limitations and present some additional robustness checks we perform to address these issues.

We argue that with taluk, condition and month fixed effects as well as the for local area specific time fixed effects and condition fixed effects, we are able to control for all other factors that may influence take up for tertiary healthcare. However a potential threat would be if hospitals change their focus to cater to the local, newly covered population or selectively chose patients. If the types of health conditions of the newly insured population are different from those of the previously insured (or those previously able to pay out of pocket), it may take time for hospitals to change their staffing or focus in order to treat these newly covered patients.

It is possible that using the lag of the dependent variable as our primary independent variable leads to biased estimates. In Table 9 we present results from an Arellano Bond dynamic panel estimation where takeup for VAS in previous time periods is used as an instrumental variable. Our results remain consistent.

A final cause of concern is the presence of cross-condition peer effects. A patient's positive experience at the hospital could lead to a friend or family member visiting the hospital for care for another disease, but this would not be picked up by the estimation. In Table 10 we present a matrix of cross conditions results i.e. our dependent variable

Table 9
Robustness with dynamic panel estimation.

Variables	(1)
	Countflow
L.countflow	0.315***
	(0.0141)
Constant	0.461***
	(0.0187)
Observations	9401
Number of panel	553

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

is now number of patients who enrolled for VAS for condition '1' in a given month and taluk and the independent variable includes the number of patients enrolled for VAS for condition '2' in the same taluk but previous month. Our results show that in all cases, previous enrollment has a positive impact on current take up, and in most cases the impact is statistically significant suggesting positive externalities in our peer effects across conditions.

5. Conclusion

Health insurance has traditionally been viewed as a means for financial risk protection or improving access to care for the poor, although there is some debate about whether health insurance is optimal way of financing health care for the poor. In this paper, we highlight another potential role of insurance, which relates to the diffusion of information about the benefits of treatment in hospitals. Understanding the information diffusion role of health insurance maybe particularly salient in the developing world where use of tertiary care is low and people are skeptical about the benefits of treatment. We postulate that in these settings, rational agents, economically poor patients in this case, will rely on anecdotal evidence or learn from experience of family, friends and neighbors – in making a choice about availing healthcare. Thus insurance induced increase in healthcare utilization can have important spillover effects of increased healthcare utilization. These spillover effects might also be relevant for other outreach activities such as education campaigns and health camps. Overall, the results suggest that increases in utilization induced by health insurance or other outreach activities can have multiplier effects by increasing future health care use through peer effects.

We find that 1 new hospitalization today results in 0.35 future hospitalizations for the same condition in the same local area, and the results are qualitatively similar across conditions. We also show that these effects increase as the health insurance program becomes more established. Finally, the role of health insurance in spatially diffusing information seems to be more pronounced in densely populated areas where word of mouth diffusion of information might be easier.

These findings have several important policy implications. First, following past work by Remler et al. (2002) our results highlight that any modeling effort to understand the impact of health insurance expansion should carefully consider our findings. In fact any cost-benefit evaluation of insurance programs should account for such spillover effects on the healthcare utilization of the peers of the insured. Second, empirical evaluation of insurance programs that use uninsured peers as a control group would under estimate the true effects of insurance on healthcare utilization due to the potential positive spillover effects on uninsured peers. While in this context, we are only able to study spillovers amongst insured patients as the entire village is covered under the VAS scheme, in other contexts, perhaps in future work, it would be interesting to study the impact of insurance induced increase in healthcare utilization by peers who are not covered by health insurance. Third, whether these spillover effects enhance or diminish

Table 10
Robustness to test for externalities across disease conditions.

Variables	condition1	condition2	condition3	condition4	condition5	condition6	condition7
L.condition2	0.0281***		0.0819***	0.108***	0.127***	0.0216***	0.000806*
	(0.00275)		(0.00571)	(0.00630)	(0.00607)	(0.00246)	(0.000427)
L.condition3	0.0607***	1.175***		0.384***	0.423***	0.0281**	0.000233
	(0.0123)	(0.111)		(0.0284)	(0.0281)	(0.0110)	(0.00186)
L.condition4	0.0716***	1.312***	0.344***		0.394***	0.0693***	0.00431***
	(0.0109)	(0.0974)	(0.0220)		(0.0250)	(0.00967)	(0.00166)
L.condition5	0.0700***	1.403***	0.316***	0.361***		0.0681***	0.00532***
	(0.0107)	(0.0945)	(0.0218)	(0.0247)		(0.00950)	(0.00163)
L.condition6	0.0591*	1.817***	0.283***	0.517***	0.531***		0.00819*
	(0.0303)	(0.279)	(0.0647)	(0.0725)	(0.0726)		(0.00455)
L.condition7	0.122	2.831*	0.912**	1.426***	0.495	0.902***	
	(0.177)	(1.646)	(0.379)	(0.428)	(0.431)	(0.155)	
Observations	1422	1422	1422	1422	1422	1422	1422
R-squared	0.069	0.073	0.126	0.172	0.236	0.051	0.003

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

social welfare will depend on whether consumers were over using or under using healthcare prior to insurance expansion. We argue that in the setting for this research, patients were likely underutilizing care prior to insurance as even though tertiary care is highly effective it is unaffordable for the vast majority of the poor in India. Thus, in our setting the spillover effects likely enhanced the social benefits of insurance.

That said, much more remains to be done. Specifically, future work could more fully describe the exact nature of information flows (through social networks) between the focal patient and his peers and the extent to which such information flows strengthen or destroy misconceptions about the benefits and costs of treatment. One can also tie in issues related to repeat visits to hospitals in the case of treatment of tertiary conditions for which we didn't get access to data.

Finally despite our strenuous efforts we failed to get access to promotional efforts for VAS across taluks varying over time and disease condition. This is a limitation in that promotional efforts like health camps or other forms of "advertising" might potentially focus on different conditions in different regions and that could be driving our results. If health camps tailor their approach to the local population, they may induce people with conditions most common to the region to visit the hospital. This would generate within condition changes in hospitalization through "advertising" associated with health camps rather than peer effects. Our conversations with doctors from some of the empaneled hospitals suggested minimal efforts in health camps customized to the local population, but we recognize that this is one area which deserves more attention in future research despite our efforts to econometrically control for this in our study.

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