Public Insurance, Reimbursement Design and Access to Healthcare in India*

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Preliminary and Incomplete - Please do not circulate

Abstract

Our article studies the design of reimbursement rates in the context of a large-scale publicly funded health insurance program in India by exploring its effects on the quality of care, diagnostic facilities provided by the hospitals and welfare of the patients. Under this insurance program implemented in the state of Andhra Pradesh, close to 40 million eligible households get free treatment from hospitals, and the hospitals are reimbursed by the government. The level of reimbursement is the key decision variable for the government. Setting the level too low implies that not enough private hospitals will participate, and the program will have capacity shortfalls and potentially lower quality. Setting the level too high implies that the fiscal burden will be high, which might be unsustainable in the future. To study this problem, we gather a unique and novel dataset that records the universe of claims made by the patients in the state of Andhra-Pradesh. Our data covers patient characteristics as well as details of diagnosis for each patient. Additionally, we collect detailed data on hospital characteristics, including provision of hospital facilities, quality of care as well as entry and exit of hospitals over time. We build a structural model and estimate the underlying incentives for patient's choice of hospital, hospitals' decision to participate in the insurance program as well as the provision of quality of care conditional on participation. Given the parameter estimates, in our counterfactual exercise, we vary the reimbursement rates, simulate hospitals' decisions to participate and provision of quality, and compute corresponding consumer welfare. Our preliminary estimates suggest that adopting an alternative reimbursement policy that varies in urban and rural markets may save the Government up to 15% of its cost without compromising the access and quality of health care.

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1 Introduction

As the world's population ages, provision of tertiary healthcare is emerging as a major policy challenge.[1] This challenge is particularly acute in developing countries where private healthcare markets are underdeveloped, motivating a role for the government in the sector. Given limited state capacity for operating tertiary care facilities, one approach for government intervention is through piece-rate reimbursements to private hospitals that perform medical procedures. Although this relatively blunt approach has found favor in countries such as India, the Philippines and Thailand (Annear and Huntington, 2015), the quality of care at private hospitals for each procedure and patient is difficult to monitor and regulate. Such publicly financed healthcare in weak governance regimes implies that quality monitoring is primarily in the hands of the patients who seek care. Even when captive within the publicly financed system, patients can choose between different private hospitals. Hospitals are disciplined by competition for profitable patients, and make system entry and quality decisions accordingly. However, the direction and magnitudes of these decisions are not clear. Hospitals could choose better quality to increase the quantity of patients, or reduce quality and costs to increase margins. How hospitals and patients respond to the levels of reimbursement rates has important consequences for patient welfare and public finances, yet poorly understood by economists and policymakers.

This paper develops and estimates a structural model of public reimbursement for treatment at private facilities, with several interesting features that emerge from the setting and the data. First, the government reimburses private hospitals for procedures performed at any facility, regardless of quality of care or outcomes, with variations in the rate as the essential policy tool. In a developing country setting, quality of care indicators are often unspecified or unregulated in contrast to Medicare where these indicators are heavily monitored

[1]As perspective, South East Asia had 9.1 million deaths in 2016 due to non-communicable diseases that are typically treated with tertiary care, in contrast to 6.3 million in 2000. In the same period, the number of deaths due to communicable, maternal, perinatal and nutritional conditions, typically treated in primary care settings fell from 5.4 million to 3.4 million, indicating both an absolute and relative increase in the importance of tertiary healthcare (Global Health Estimates, 2016).

and regulated. Second, patients are concentrated differently across various markets, and are also differently informed about the quality of care offered by hospitals. Similarly, hospitals operate in different locations, with heterogeneity in the costs associated with entering the program and in providing incremental levels of care. Given that hospital capacity is limited, costs to private hospitals also includes the opportunity cost of not serving patients not covered under the scheme. Thus, profit-maximizing private hospitals endogenously choose to participate in the program and the quality to offer based on the reimbursement rate, patient characteristics and market competition.

The key policy tradeoff is deciding the per-procedure reimbursement. Setting reimbursements high implies that a large number of hospitals participate, leading to more capacity and potentially greater consumer welfare. Setting the level too high however implies that taxpayers bear a greater fiscal burden. For hospitals, participation in markets where competition is high could squeeze margins, leading to either increases in quality as hospitals compete for more patients, or decreases in quality as hospitals seek to expand margins by cutting costs. Finally, patients have to choose between different providers – higher quality might come at greater costs, for instance, of transportation from home to the hospital. In our model, we assume that full-information agents understand these tradeoffs and make choices that optimize their payoffs.

We investigate these tradeoffs and attendant welfare implications in the context of the Aarogyasri healthcare program in India. Implemented in 2007 in Andhra Pradesh state, the program reimbursed private hospitals for tertiary medical services for poor patients. More than 3.1 million used the program between 2007 and 2015 for 900 types of major procedures, choosing from more than 600 hospitals. Private hospitals could choose which therapeutic classes to participate in, and enter and exit the program over time. A key feature of the program is that the government changed the per-procedure reimbursement rates in 2013, which permits analysis of how hospital and patient behavior changed as a consequence.

To allow clear measurement of care quality, we focus on long bone fracture surgery, a frequently performed procedure with exogenous incidence.Quality is measured by two metrics – (1) the number of days between the patient arriving at the hospital and when the procedure is performed, with shorter intervals indicating better quality, and (2) the time between the procedure and when the patient is discharged from the hospital, with longer recovery times suggesting more time for the fracture to set and better patient outcomes. Another advantage of examining long bone surgery is that hospitals cannot manipulate the type of surgery for long bone fracture, substituting a procedure with lower margins for one with higher margins as reimbursement rates change.

We estimate the structural model using individual level claims data collected by the program administrator. The dataset contains information on the date of the claim, the procedure and discharge, the procedure performed and the identity of the hospital, and several characteristics of the patient, including the village or urban ward where they live. Using this data, we estimate the choice model with maximum likelihood methods, the quality parameters with generalized methods of moments, and fixed costs parameters with inequality bounds. With this structural model, we are able to provide a simple functional rule to approximate optimal reimbursement rates as a function of market characteristics, and then evaluate the impact of a counterfactual policy that varies reimbursement in different markets on patient outcomes, public finances and social welfare.

Our preliminary analysis uncovers several interesting results. We find robust evidence of existence of trade-off between distance traveled by patients to reach a hospital and hospital quality. We find that, on an average, patients are willing to travel 28 extra kilometers to avoid with one extra day of wait time and 30 extra kilometers to reach a hospital that provides one extra day of length of stay. In the supply side, we estimate that the average cost of accepting a patient is around 528 INR. Additionally, an extra day of stay costs 648 INR for hospitals in in rural regions and 1098 INR for hospitals in urban regions. Similarly, reducing wait time by a day costs 234 INR to hospitals in rural region and 298 INR in urban regions. Our fixed cost estimates suggest that in urban region, the estimated cost of hospital participation is around 140 thousand INR per quarter, while in rural regions, the cost of participation is around 114 thousand INR per quarter. Note that in the current set up, the level of reimbursement is fixed at 30,000 INR per patient across all markets. In our counterfactual exercise, we consider a different reimbursement design where we set 23,000 INR reimbursement for rural region and 28,000 INR for urban regions. We simulate the hospital entry decisions and quality choices made by hospitals. We find that 95% of the hospitals participate and provide comparable quality as before. However, government could have saved close to 12-15% of its revenue spent on reimbursement payments given this new design. In our work in progress, we are in the process of evaluating different reimbursement designs and characterize the optimal reimbursement plan.

This paper contributes to several strands of the literature. First, we contribute to the literature on how government regulation and public financing influence private healthcare provision. Most research in this domain is in the context of the United States, examining how public subsidies influence enrollment in health insurance (Finkelstein, Taubman, Wright, Bernstein, Gruber, Newhouse, Allen, Baicker, and Group, 2012). In India, (Mohapatra and Chatterjee, 2018) examine the role of price caps on pharmaceutical prices, availability and consumer welfare.

We also contribute to the literature on the design of healthcare markets. This literature has focused on the design of healthcare systems in Massachusetts and the United States overall. We contribute to the literature on healthcare system design by rigorously analyzing the reasons for, as well as the implications of, differential geographic reimbursement design.

2 Context

2.1 The Aarogyasri healthcare program

The government of Andhra Pradesh introduced Aarogyasri as a cashless health insurance program for households living below the poverty line in April 2007. The program provided "medical assistance to families below the 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 program, Below Poverty Level (BPL) households in Andhra Pradesh were eligible and covered for medical expenditure towards 938 listed treatments up to INR 200,000 (USD 3300) per year. The insurance does not have any deductible or co-payment. All transactions are cashless, where a beneficiary can go to an authorized hospital and receive care without paying for the procedures covered under the scheme. Aarogyasri reimburses healthcare providers on a case-by-case basis at a prespecified rate. While most public hospitals were automatically enrolled in the program, private hospitals could apply to participate. As of December 2015, 643 public and private hospitals were empaneled under Aarogyasri. Figure 1 shows that hospitals in the program are spatially concentrated in large cities (especially Hyderabad, Vishakapatnam and Vijaywada) and the headquarters of different districts.[2]

2.2 Longbone surgery

Our analysis focuses on longbone surgery, which is one of leading procedures performed under the program – out of 3.1 million procedures between 2007 and 2015 under all categories, long bone surgeries were 12% of all procedures. Simultaneously, the long term trend in the number of hospitals that offer long bone surgery is increasing over time (Figure 2), although this masks considerable entry and exit.[3] What is notable is the significant increase in the number of participating hospitals before the first quarter of 2009 when the reimbursement rates for "open reduction and internal fixation for long bone fractures" changed from INR 15,000 to INR 22,000 per procedure, and then again in 2014 corresponding to a second rate increase to INR 30,000 per procedure.

[2] Debnath and Jain (2018) describe program features more extensively, including an estimation of reduction in household healthcare expenditures as a consequence of the program.

[3] Hospitals incur significant fixed costs on program entry. These include the costs of equipment (X-ray machines, CT scan and MRI machines), personnel (orthopaedic surgeons, anaesthetists and nurses), therapy and infrastructure (plaster rooms, physiotherapy facilities, occupational therapy facilities, and radiology and imaging facilities).

We focus on long bone surgery because this procedure has two readily observed proxies for quality in the administrative records. First, longer wait times, also called *delay to surgery*, are associated with increased risks of mortality (Zuckerman, Skovron, Koval, Aharonoff, and Frankel, 1995; Hamlet, Lieberman, Freedman, Dorey, Fletcher, and Johnson, 1997; Bergeron, Lavoie, Moore, Bamvita, Ratte, Gravel, and Clas, 2006), so hospitals can improve service quality by decreasing the time an Aarogyasri patient has to wait for surgery. Staying in the hospital after surgery allows the fracture to set, thus longer length of stay is a widely used measure of quality (Westacott, Abosala, and Kurdy, 2010).[4]

3 Data and Descriptive Evidence

3.1 Data source

Our main data source is from the administrative records of the Aarogyasri Trust, which report each claim against the program from 2008 to 2015. The data identifies each unique claimant, the procedure associated with the claim, the hospital where the surgery is performed, the pre-authorization date and amount, and the dates when surgery is performed and the patient eventually discharged. These allow us to calculate, for each procedure and patient, the *wait time* from the pre-authorization date to when the surgery is performed, and the *length of stay* which is the number of days from the date when the surgery is performed to when the patient is discharged. The patient's place of residence (village or urban ward), age and gender are recorded in the dataset. We augment this dataset with the precise latitude and longitude of each hospital as well as each village and urban ward. We also record the reimbursement rate for "Surgical Correction Of Longbone Fracture" prevailing at the date of the procedure.

[4] An alternate response might be to improve physician quality. However, physician skills are poor in India (Das, Holla, Mohpal, and Muralidharan, 2016), and the supply of physicians is relatively inelastic (Potnuru, 2017).

3.2 Descriptive analysis

We study the insurance plan implemented in Andhra Pradesh, a large state in India with population of around 80 million. Figure 1 shows the map of the state and plots the locations of private and public hospitals. As is clear from the map, there are very few public hospitals in the state while there are many more private hospitals. Hence, participation of private hospitals in the insurance scheme is crucial to ensure access to hospitals.

Figure 2, shows the number of hospitals participating in the program over time. We observe a change in reimbursement rate around June of 2013 when reimbursement rate increased from 15,000 INR per patient to 30,000 INR per patient. There are two key points to highlight here. First, higher reimbursements after June 2013 clearly attracted more private participation suggesting, reimbursement rates can be used as an instrument to encourage participation. Second, we observe quite a lot of entry and exit of hospitals during our sample period. This enables us to use a structural model to back out the participation cost of hospitals across different markets in the state.

In table 1, we provide suggestive evidence that patients derive negative utility from distance. In the table, we divide patients in terms of the number of choices they have in their choice set. For example, the 8-th row in the table corresponds to the number of patients who have 8 choices in their choice set. As we document in the table, even when patients have 8-10 choices in the choice set, in more than 55% of the cases, patients choose nearest three choices. Table 2 reports the results from regression analysis that looks into the trade-off the patients face when they do not choose the nearest hospital. The dependent variable in the regression is the log of extra distance traveled by a patient when the patient does not choose the nearest hospital. We regress it on a set of of variables that capture the quality difference between the chosen hospital and the minimum distance hospital. For example, difference in median los stands for the difference in the length of stay provided by the chosen hospital compared to the nearest hospital in the patient's choice set. Similarly, we control for differences in wait time, number of beds, as well as accreditation status where a high quality hospital is accredited by the government while low quality hospitals do not qualify for the status. We find strong evidence of quality-distance trade-off, a patient chooses to travel extra to gain higher length of stay, lower wait time, higher number of beds. The patient is also likely to choose a hospital with accreditation status by traveling extra distance. Our descriptive evidence motivate the modeling choice in the next section.

4 Model

This section presents a model capturing the patients' choice of hospitals, as well as hospitals' willingness to participate in the program and choice of quality provision conditional on participation. We model this as a two stage static game. In the first stage, a hospital that is already empaneled decides whether to stay in the program or exit the program. Similarly, a hospital that previously did not impanel in the program, chooses whether to stay of out of the program or get empaneled. In the second stage, an empaneled hospital decides on the specific quality to offer in the market, which depends on level of competition and hospital-procedure level cost for quality.

Two important assumptions qualify this analysis. First, we assume that each hospital is making the decisions for a given procedure independent of other procedures. This assumption is facilitated by Aarogyasri program rules that hospitals can independently participate in different therapeutic categories. In addition, many inputs, such as speciality physicians and advanced medical equipment, are not fungible across different procedures. Second, while the hospitals solve dynamic optimization problems, we estimate a static analysis that is a first order approximation of the dynamic problem because of the complexity as well as high dimensionality of the dynamic problem.

4.1 Demand: Patients choose hospital

A patient with long bone fracture qualified under Aarogyasri, chooses a hospital for treatment. The choice set of a patient includes any hospital in the patent's district, its nearest big city and the hospitals in the state capital that are registered under Aarogyasri. In our data, we observe patients from a specific district visiting various hospitals. The super-set of these hospitals is treated as the choice set for each patient in our demand analysis.

Each patient chooses whether to choose one of the hospitals in its choice set or choose an outside option. An outside option may include any hospital or treatment option not included in Aarogyasri scheme. A patient's utility from a given option is represented by the following equation.

$$u_{ijt} = \beta_1 f(\text{Distance}_{ijt}) + \beta_2 \text{Quality Index}_{jt} + \beta_{hj} \text{ Hospital Dummy}_j + \xi_{jt} + \varepsilon_{ijt} \tag{4.1}$$

where the quality index for a hospital is given by the following expression.

$$\text{Quality Index}_{jt} = \gamma_1 \text{ los}_{jt} + \gamma_2 \text{wait time}_{jt} \tag{4.2}$$

Here los_{jt} is the average length of stay in the hospital in a given period. Additionally, we assume that $\varepsilon_{ij} \sim$ IID EV Type 1 distribution.

Since each patient can choose at most one hospital, the probability that patient i chooses hospital j is given by

$$p_{ijt} = \frac{\exp(\delta_{ijt})}{\sum_{j \in \mathbf{C}_{ijt}} \exp(\delta_{ijt})} \tag{4.3}$$

where δ_{jt} is given by

$$\delta_{ijt} = \beta_1 f(\text{Distance}_{ijt}) + \beta_2 \text{Quality Index}_{jt} + \beta_{hj} \text{ Hospital Dummy}_j + \xi_{jt}$$

4.2 Supply stage 2: Hospitals choose quality

Hospital j offers quality l to maximize profit

$$\Pi_{jt} = [p_t - ac(q_{jt}, l_{jt}; \alpha, \omega_{jt})] \; q(l_{jt}, l_{-jt}, p_t; \beta) \tag{4.4}$$

where q_{jt} denotes the number of patients served by hospital j, time t, ω_{jm} stands for mean average cost shock for hospital, (l_{jt}, l_{-jt}) stands for qualities by hospital j and its competitors and time t. Finally, α stands for the cost parameters to be estimated. The hospital maximizes its profit by choosing quality. Higher quality attracts more patients, but also incurs higher cost. Hence, each private hospital chooses quality to maximize its profit subject to the quality chosen by competitors in the market.

4.3 Supply stage 1: Hospitals choose to participate in the network

In the beginning of every period, a hospital arrives with one of the two state variables - either the hospital is already empaneled from previous period or the hospital is not empaneled from previous period. Hospitals compute expected profit from staying in the scheme for a given period ($E\pi_{jt}$) and compares it with fixed cost of participating in the insurance scheme. An empaneled hospital decides to stay in the scheme if $E\pi_{jt}$ exceeds the scrap value that the hospital earns from leaving the program. Similarly, a hospital not yet empaneled decides to join if $E\pi_{jt}$ exceeds the fixed cost of entry.

5 Estimation

For a given individual we collect all hospitals that is visited by someone from the same village for any purpose (not just long bone surgery) and we include those hospitals in the choice set of the patient. Probability that individual i with K choices in the choice set, chooses hospital j, is given by

$$p_{ij} = \frac{\exp(\delta_{ij})}{\sum_{k=1}^{K} \exp(\delta_{ik})}$$

where

$$\delta_{ij} = \beta_1 f(\text{Distance}_{ij}) + \beta_2 \text{Quality Index}_j + \beta_{hj} \text{ Hospital Dummy}_j + \xi_j$$

We estimate the utility parameters using maximum likelihood estimation.

Our quality estimation follows the techniques developed in Fan (2013). Essentially, we use demographic instruments to control for endogeneity of quality choices. Our rich regional heterogeneity enables us to estimate the quality parameters using GMM.

Our fixed cost estimation follows the moment inequality approach developed in Pakes, Porter, Ho, and Ishii (2015).[5]. If a hospital is already empaneled, the hospital chooses whether to stay empaneled, or leave the program to collect scrap value. If a hospital is not empaneled, the hospital chooses whether to remain not-empaneled, or enter the program by paying a fixed cost.

If a hospital chooses to move from not-empaneled to empaneled, it must be that the hospital gains from this action. This implies

$$\underbrace{\pi_o^{ne}}_{\text{Unobs.}} \leq \underbrace{\pi_o^{e}}_{\text{Unobs.}} + \underbrace{\pi_{aar}}_{\text{Obs.}} - \underbrace{FC}_{\text{to be estimated}} \tag{5.1}$$

Note that we assume additive separability of Aarogyasri and non-Aarogyasri profits. Here, π_o^{ne} represents the hospital's outside profit when the hospital is not-empaneled. π_o^e is the hospital's profit from non-Aarogyasri outside patients when hospital is empaneled. π_{aar} stands for hospital's profit from Aarogyasri scheme. FC stands for fixed cost that the hospital has to pay to get empaneled. Note that in our data, π_{aar} is observable while π_o^{ne} and π_o^e are unobservable. Rearranging the expression in equation 5.1, we have

[5]This approach has also been used in recent works including Eizenberg (2014), Ho and Pakes (2014), Fan and Yang (2018), and Wollmann (2018) amongothers

$$FC \leq \pi_{aar} + (\pi_o^e - \pi_o^{ne}) \tag{5.2}$$

Note that the inequality that we can construct from observable variables is given by

$$FC \leq \pi_{aar} \tag{5.3}$$

Let us assume $(\pi_o^e - \pi_o^{ne}) \leq 0$. This assumption implies that when the hospital is empaneled, and allows both Aarogyasri and non-Aarogyasri patients, the hospital's outside profit from **non-aarogyashri** patients is less compared to hospital's outside profit when hospital is not empaneled and allows **only non-aarogyashri** patients for treatment in the hospital. This assumption holds when Aarogyashri patients and non-aarogyashri patients are substitutes, and hospital resources get divided between aarogyashri and non-aarogyashri patients. On the other hand, in case of complementarity, when allowing more aarogyashri patients also attracts more non-aarogyashri patients, this assumption will be violated.

Note that given inequality (5.2), if $(\pi_o^e - \pi_o^{ne}) \leq 0$, inequality (5.3) is automatically satisfied whenever the inequality (5.2) is satisfied.Hence, inequality (5.2) implies (5.3), and hence we can use (5.3) instead of (5.2) for estimation.

6 Estimation Results and Counterfactual Exercise

We report the results from demand estimation in table 4. Coefficient of distance is negative and statistically significant suggesting that patients derive strong dis-utility from traveling to a distant hospital. Additionally, waiting longer for surgery also derives negative utility while staying one extra day in hospital derives positive utility. Using the parameter estimates, we can compute 'willingness to pay' in terms of traveling distance. Our estimates suggest that, on an average, patients are willing to travel 28 extra kilometers to avoid with one extra day of wait time and 30 extra kilometers to reach a hospital that provides one extra day of length of stay.

We report the results from average cost estimation in table 5. Our results suggest that that the cost of accepting a patient is around 528 INR. Additionally, an extra day of stay costs 648 INR for hospitals in in rural regions and 1098 INR for hospitals in urban regions. Similarly, reducing wait time by a day costs 234 INR to hospitals in rural region and 298 INR in urban regions.

Finally, we divide the state into urban and rural regions and compute region-specific fixed cost of participation. Our results are reported in table 6. In urban region, the estimated cost of hospital participation is around 140 thousand INR per quarter, while in rural regions, the cost of participation is around 114 thousand INR per quarter.

Our results uncover the regional heterogeneity in terms of average costs and fixed costs across markets. This suggests that providing single reimbursement rate across all markets may lead to inefficient level of expenditure; hence, designing reimbursements taking into account market characteristics may save significant expenses for the government.

Note that in the current set up, the level of reimbursement is fixed at 30,000 INR per patient across all markets. In our counterfactual exercise, we consider a different reimbursement design where we set 23,000 INR reimbursement for rural region and 28,000 INR for urban regions. We simulate the hospital entry decisions and quality choices made by hospitals. We find that 95% of the hospitals participate and provide comparable quality as before. However, government could have saved close to 12-15% of its revenue spent on reimbursement payments given this new design. In our work in progress, we are in the process of evaluating different reimbursement designs and characterize the optimal reimbursement plan.

7 Conclusion

Access to health care is universal policy concern. Different developed countries have designed various public insurance programs to provide health care to their vulnerable population. In developing countries like India, there are additional challenges. A large part of the population in developing countries will be unwilling to pay even a small amount of premium and co-payment for enrolling in insurance program. Additionally due to limited state capacity as well as underdeveloped private markets, public-private partnership model has been adopted to provide health care in most developing countries. We study the reimbursement design problem in the context of such an insurance scheme implemented in a large state in India. Under the scheme, a poor individual gets free treatment from a hospital and hospital gets a flat reimbursement amount from the government that is identical across all markets in the state. In particular, hospitals operating both in urban and rural regions receive same reimbursement while treating a patient. Our structural analysis reveals that the cost of hospital participation as well as cost of providing quality vary significantly across urban and rural regions. Our counterfactual analysis suggests that adopting a simple alternative rule that reimburses differentially across rural and urban markets would lower the cost of the government by 15% without compromising hospital access and quality of service. In the current work in progress, we are working on designing the optimal reimbursement design that maximizes consumer welfare subject to budget constraint of the government. In a recent ambitious move announced in 2018, the Indian government is planning to scale up similar insurance program to cover 500 million individuals across 30 states in India, and our exercise will enable us to develop a practical policy tool to design reimbursement rates as a function of market and hospital characteristics that can be portably used across states.

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Figure 1: **Hospital locations**

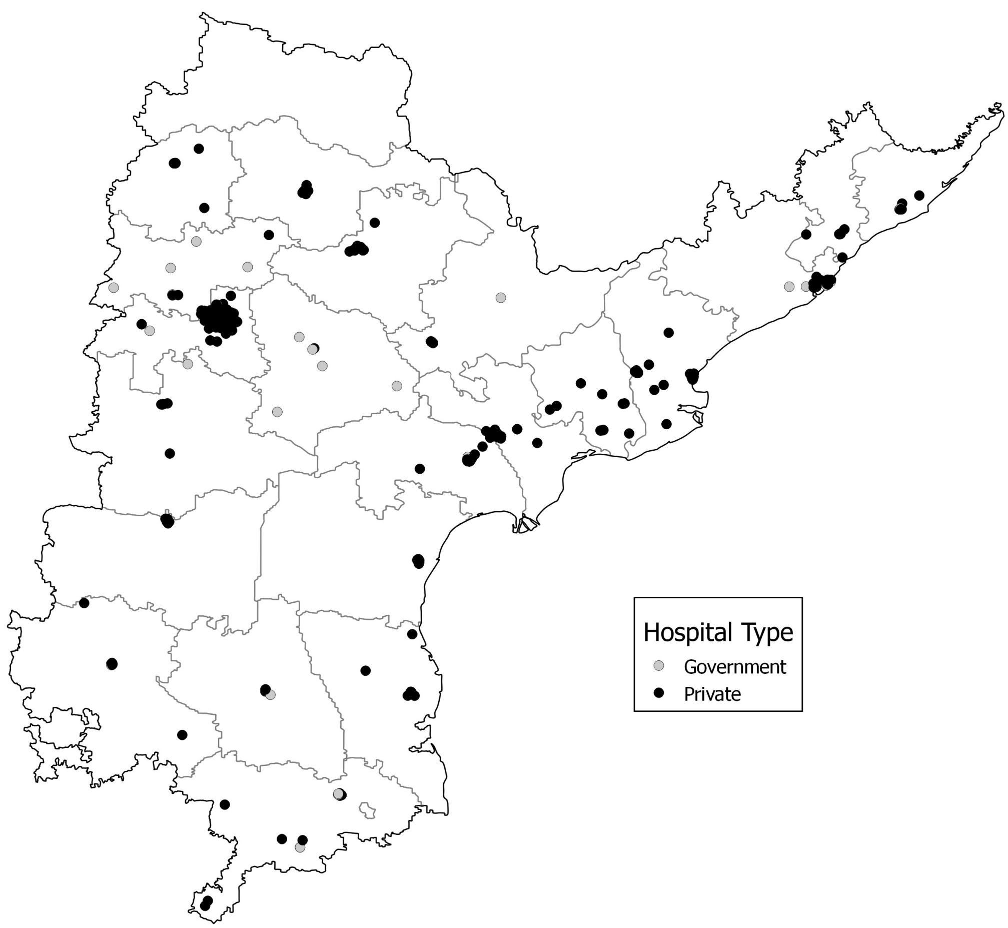

Figure 2: **Entry and exit of long bone surgery hospitals**

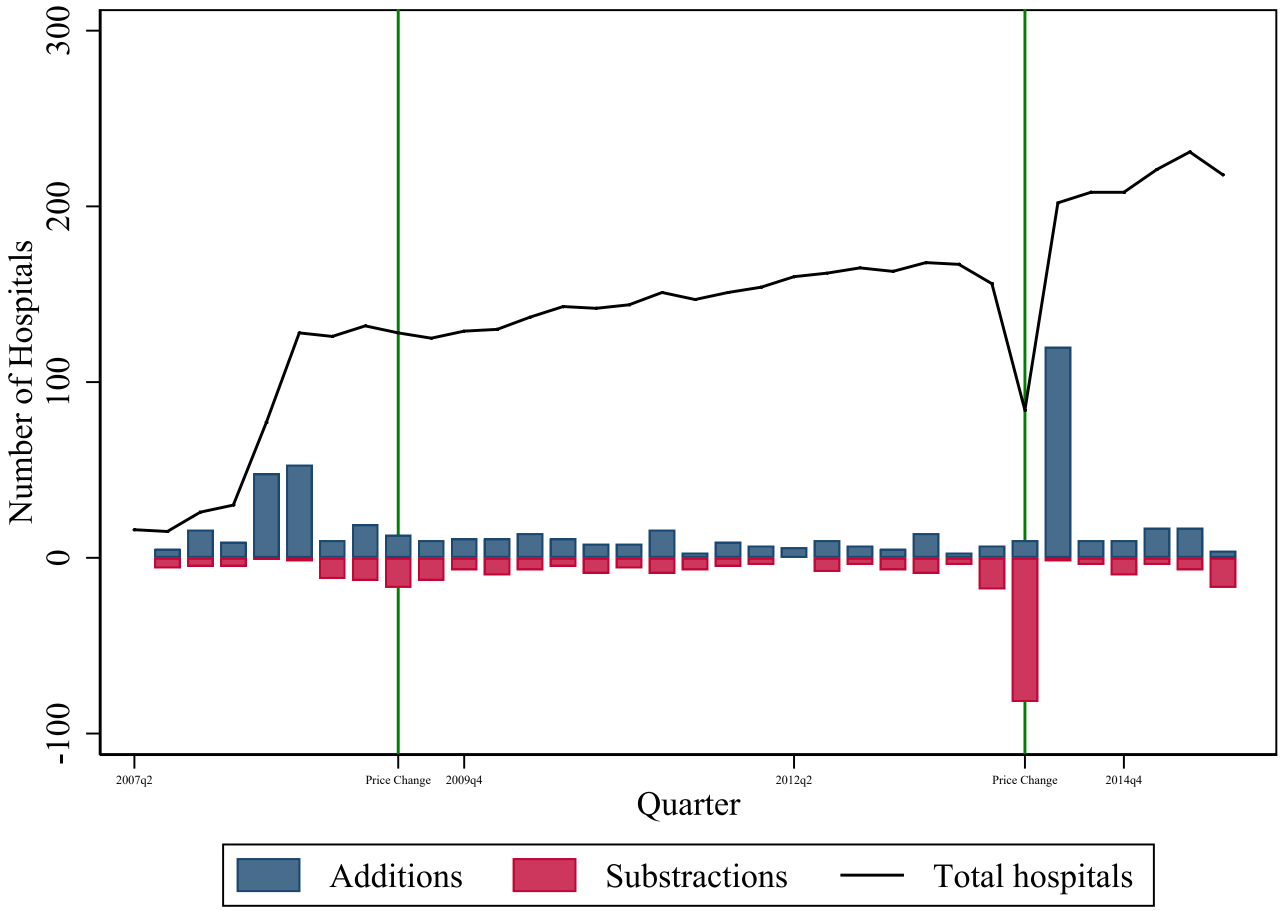

Table 1: Distance and Hospital Choice

No. of Hospitals in Choice set	No. of Patients	% choosing nearest choice	% choosing one of nearest 2 choices	% choosing one of nearest 3 choices	% choosing one of nearest 4 choices	% choosing one of nearest 5 choices
2	1447	53	100	-	-	-
3	3232	62	86	100	-	-
4	7263	42	71	89	100	-
5	11529	36	63	83	93	100
6	14654	29	49	69	84	92
7	16603	29	47	64	77	86
8	17691	23	39	56	68	78
9	16179	26	42	55	68	76
10	18928	22	39	55	65	73
11	19205	21	36	52	63	70
12	13531	19	34	49	59	66
13	13907	15	31	45	54	62
14	7789	16	27	38	47	53
15	5868	18	32	44	52	59
16	4513	12	24	35	43	49
17	3657	13	26	36	44	50
18	1723	15	28	34	40	49
19	1063	17	33	47	48	52
$\geq$ 20	1686	10	23	31	37	40
Total	180,468	25	42	57	68	76

Notes: This table lists consumers with different number of choices in the choice set. The columns report the fraction of patients that choose nearest choice, nearest 2 choices, nearest 3 choices, nearest 4 choices, and nearest 5 choices.

Table 2: Distance and Quality Trade-off

VARIABLES	log(Dist Chosen Hosp) -log(Dist Nearest Hosp)
Diff in median LOS	0.00145***
	(0.000358)
Diff in median wait time	-0.00357***
	(0.000990)
Log Diff in no of beds	0.00688***
	(0.000861)
Diff in Accreditation Status	0.0243***
	(0.00181)
Diff in no of hospitals (within 4km)	0.0139***
	(0.000331)
Diff in no of months since hospital enrollment	1.82e-05***
	(1.21e-06)
Constant	0.206***
	(0.0144)
Observations	69,083
R-squared	0.232
Year FE	X
Patient Location FE	X

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

Notes: This table reports the regression results for the patients that do not choose the nearest hospital and choose a different hospital in the choice set by traveling extra distance.

Table 3: Length of Stay and Hospital Market Share

VARIABLES	Length of Stay
Log(No of patients)	0.0753***
	(0.0186)
Log(Patient Age)	0.347***
	(0.0148)
Gender	0.136***
	(0.0184)
Log(Distance)	0.0771***
	(0.0139)
Constant	-193.3***
	(36.42)
Observations	121,851
R-squared	0.520
Hospital FE	X
Time FE	X

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

Notes: This table shows the regression results from hospital level length of stay over time and shows that hospitals that provide higher length of stay also gain higher market share.

Table 4: Results from Demand Estimation

Dependent Var:	Choice
Distance (in km.)	-0.0038***
	(0.0009)
Wait Time	-0. 107***
	(0.0034)
Length of Stay	0.1216***
	(0.0041)
Dist×Age	-0.0024***
	(0.0002)
Dist×Female	-0.0047***
	(0.0003)
LOS×TimeTrend	0.0001
	(0.0001)
Hospital Dummy	Yes
Number of obs: 1375720	
Number of cases:150595	
Years considered: 2011-2015	
Standard errors in parentheses	

Notes: This table presents the results from estimation of hospital choice models.

Table 5: Results from Quality Estimation

Estimation of Average Cost Parameters	
Constant	528***
	(90.1)
Length of stay × Rural	648***
	(54.1)
Length of stay × Urban	1098***
	(256.8)
Wait time×Rural	234
	(178.7)
Wait time×Urban	298*
	(182.1)
Number of obs: 11720	
Standard errors in parentheses	

Notes: This table presents the results from estimation of cost of quality supplied by hospitals.

Table 6: Results from Fixed Cost Estimation

Estimation of Fixed Cost (in INR)	
Urban Region	135,936
Rural Region	113,552

Notes: This table presents the results from estimation of hospital participation costs.