

Impact of Private Health Insurance on Lengths of Hospitalization and Healthcare Expenditure in India: Evidences from a Quasi-Experiment Study

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Abstract

The health insurers administer retrospectively package rates for various inpatient procedures as a provider payment mechanism to empanelled hospitals in Indian healthcare market. This study analyzed the impact of private health insurance on healthcare utilization in terms of both lengths of hospitalization and per-day hospitalization expenditure in Indian healthcare market where package rates are retrospectively defined as healthcare provider payment mechanism. The claim records of 94443 insured individuals and the hospitalisation data of 32665 uninsured individuals were used. By applying stepwise and propensity score matching method, the sample of uninsured individual was matched with insured and 'average treatment effect on treated' (ATT) was estimated. Overall, the strategies of hospitals, insured and insurers for maximizing their utility were competing with each other. However, two aligning co-operative strategies between insurer and hospitals were significant with dominant role of hospitals. The hospitals maximize their utility by providing high cost healthcare in par with pre-defined package rates but align with the interest of insurers by reducing the number (length) of hospitalisation days. The empirical results show that private health insurance coverage leads to i) reduction in length of hospitalization, and ii) increase in per day hospital (health) expenditure. It is necessary to regulate and develop a competent healthcare market in the country with proper monitoring mechanism on healthcare utilization and benchmarks for pricing and provision of healthcare services.

Keywords: Health insurance, Healthcare, India

1. Introduction

An approach of cost-effective healthcare services has been of increasing interest to healthcare managers, health insurers, providers, patients, and governments. The provider payment mechanism has been considered one of the tools to address this issue (Barnum, Kutzin et al. 1995; Maceira and Reform 1998). Provider payment systems are defined as the way money is distributed from the government, insurance company, or other fund holder to a healthcare provider (Maceira and Reform 1998). There are six main payment methods such as line item budgets, global budgets, capitation, case-based payment, per diem, and fee-for-service; different payment systems generate different incentives for efficiency, quality, and utilization of healthcare facilities (Lave and Frank 1990; Swartz and Brennan 1996; Saltman and Figueras 1997; Maceira and Reform 1998; Wouters, Bennett et al. 1998).

There are four main stakeholders who will be affected by provider payment mechanisms: healthcare facilities (e.g., hospitals), and health professionals (e.g., physicians and nurses), patients, and insurers/payers. The provider payment mechanism produces different incentives for each of these stakeholders and there will be conflict of interest as the healthcare market, unlike

other markets, is characterized with asymmetric information resulting in both demand-induced and supplier-induced moral hazard (Arrow 1963; Akerlof 1970). One of the objectives for the insurers is to administer a preferred payment mechanism to reduce supplier-induced moral hazard and to maximize profits.

The privatization of Indian insurance market in 2000 led to the entry of several insurers, and the insurers began to empanel hospitals for delivery healthcare services to their customers. The prevailing health insurance products are mainly hospitalization schemes and do not cover outpatient expenses. The insurers administer predetermined package rates (similar to 'case-based payment') various inpatient procedures as provider payment mechanism across the empanelled hospitals. As against this practice, the provider payment mechanism for the general public who are uninsured is the conventional fee-for service. At the same time, the Indian healthcare market is still unregulated and lacks any benchmark for pricing and provision of healthcare services. Further, the consumers (and insured) are relatively less empowered than healthcare providers and insurers, which may have implication on the healthcare provision and utilization. In this context, the present paper aims to examine the impact of the private health insurance on the lengths of hospitalization and per day hospitalization expenditure in an unregulated healthcare market

with a retrospectively defined package rates as provider payment mechanism.

2. Methodology and Data

It is a cross sectional study with quasi-experiment study design. We applied the matching method to develop the quasi-experiment study design. The main challenge of an impact evaluation is to determine what would have happened to the beneficiaries if the program had not existed (Imbens and Wooldridge 2008). A beneficiary’s outcome in the absence of the intervention would be its *counterfactual*. In the absence of conducting a randomized experiment study, the method of matching has been widely used to estimate causal treatment effects. The standard framework in evaluation analysis to formalize this problem is the potential outcome approach or Roy-Rubin-model (Roy 1951; Rubin 1974). There are three main approaches of matching. i) Multivariate matching based on Mahalanobis distance (Cochran and Rubin 1973; Rubin 1980) ii) Coarsened Exact Matching (Iacus, King et al.) and iii) Propensity score matching (Rosenbaum and Rubin 1983).

We used the claim records of 94443 insured individuals (‘treated’ group) in 2007-08, provided by Insurance Regulatory and Development Authority and the hospitalisation data of 32665 uninsured individuals (‘untreated’ group) from a nationally representative sample survey by National sample Survey Office (NSSO) in 2004 (NSSO 2006). Since both data come from different period of time but no single reliable healthcare inflation estimate is available in India, the health expenditure data of uninsured are inflated at different rates (10%, 15% and 20% per annum for over a period of 4 years) based on informed research.

One of the preconditions for matching is the availability of a data set with large number of variables that are observable and common between both ‘treated’ and ‘untreated’ group. Though we have information on a large number of socioeconomic characteristics of the uninsured from the NSSO data, the information on same variables are limited in the unit level data provided by IRDA. However, we have some prior information on the socio economic patterning of insurance coverage from the IRDA (IRDA 2009). Therefore, we matched the insured data with the insured data by using two stage matching: 1) step-wise matching by using those variables that are available on the socio economic characteristics of the insured from both the IRDA and other secondary sources including prior research, and subsequently the 2) propensity score matching for those variables that are common between both insured and uninsured data sets.

2.1 Step-wise (stratified) matching

In the stepwise matching, based on the prior information we retain those observations that have characteristics similar to the treated group but keep the entire observations of the treated group constant. The variables that we used based on the prior

information are that the insured people are i) high income, ii) utilize private healthcare and iii) use paying special wards instead of general wards. Therefore, we retained the individuals with the above three characteristics in the uninsured (untreated) group. As stated earlier, the sample size is 94443 for treated and 32665 for untreated group. Table 1 shows changes in the sample size of untreated group before and after matching while step-wise matching.

Table 1. Changes in sample size of untreated group before and after step-wise matching

| Matching characteristics | Untreated group (before matching) | Untreated group (after matching) |
|------------------------------|-----------------------------------|----------------------------------|
| Belong to high income groups | N=32665 | N=19104 |
| Use private healthcare | N=19104 | N=11054 |
| Use paying ward | N=11054 | N=10709 |

2.2 Propensity score matching

In the second stage of the matching, we used the propensity score matching from the 10709 untreated and 94443 treated groups. The basic idea of propensity score matching is to replicate the randomized experiment in a non-experimental context. The matching constructs a statistical comparison group by modelling the probability of participating in the program on the basis of observed characteristics unaffected by the program (Rosenbaum and Rubin 1983) Individuals selected into treatment and non-treatment groups have potential outcomes in both states: the one in which they are observed and the one in which they are not observed (Winship and Morgan 1999). For the treated group, observed mean outcome under the condition of treatment is $E(Y_1|W=1)$ and unobserved mean outcome under the condition of non-treatment is $E(Y_0|W=1)$. Similarly, for the non-treated group we have both observed mean $E(Y_0|W=0)$ and unobserved mean $E(Y_1|W=0)$. Participants are then matched on the basis of this probability, or propensity score. The average treatment effect of the program is then calculated as the mean difference in outcomes across these two groups. Thus, first we calculated the propensity score by using the logit regression model. We regressed age and gender on the status of being insured ($Y=1$ if insured, $=0$ if uninsured) (see table 2).

Table 2. Logit model results for generating propensity scores

| Number of observations = 105044 | | | | |
|---------------------------------|-----------|---------------------|---------------------|-------|
| LR chi2(2) = 186.82 | | | | |
| Prob > chi2 = 0.0000 | | | | |
| | Coef. | 95% CI: lower limit | 95% CI: upper limit | P>z |
| age | -.0019246 | -.0028935 | -.0009556 | 0.000 |
| gender | -.2679455 | -.3081315 | -.2277596 | 0.000 |
| constant | 2.389453 | 2.342128 | 2.436777 | 0.000 |

Different matching criteria can be used to assign participants to non-participants on the basis of the propensity score. Doing so entails calculating a weight for each matched participant-non-participant set and the choice of a particular matching technique may therefore affect the resulting program estimate through the weights assigned. We used the following three methods for the matching as follows: Nearest-Neighbor matching, Radius (Caliper) matching, and Kernel matching methods.

2.2.1 Nearest-neighbor (NN) matching

In this method, each treatment unit is matched with the comparison unit with the closest propensity score. One can also choose *n* nearest neighbors and do matching (usually *n* = 5 is used).

2.2.2 Radius or Caliper matching

One problem with NN matching is that the difference in propensity scores for a participant and its closest nonparticipant neighbor may still be very high. This situation results in poor matches and can be avoided by imposing a threshold or “tolerance” on the maximum propensity score distance (*caliper*). This procedure therefore involves matching with replacement, only among propensity scores within a certain range.

2.2.3 Kernel matching

One risk with the Radius matching is that only a small subset of nonparticipants will ultimately satisfy the criteria to fall within the common support and thus construct the counterfactual outcome. The kernel matching uses a weighted average of all nonparticipants to construct the counterfactual match for each participant.

3. Results

Overall, the strategies of each stakeholder (insured, insurers and hospitals) for maximizing their utility are competing with each other in the Indian health insurance market. For the hospitals, the payment mechanism that is currently in place would give incentives to reduce services per case but increase number of cases (if per case rate is above marginal costs), and therefore incentivizes to improve efficiency per case. About the insured, they would try to access to good quality and expensive healthcare with minimum out-of-pocket health expenditure and also would

attempt the conversion of out-patient care in to in-patient care as the health insurance schemes do not cover out-patient care. On the other hand, however, the insured are relatively less empowered in the Indian market. Apart from deciding whether to seek care and from where, the insured/patients have relatively less role in generating demand-side moral hazard including the quantity and quality of healthcare. About the insurers, as always, they try to maximize their utility by minimizing the claim amount.

However, two aligning co-operative strategies are significant with dominant role of hospitals: between insurer and hospitals. At the same time, the hospitals maximize their utility by providing high cost healthcare in par with retrospectively defined package rates but align with the interest of insurers by reducing the number of hospitalisation days. It implies higher level of returns for hospitals with minimum inputs as the package rate is retrospectively fixed. As an outcome, we expect that there will be provision of expensive (in-patient) healthcare but at a less number of hospitalisation days for each illness episodes than the normal practice. In addition, the hospitals and insured maximize their utility function by converting some of the outpatient care procedures in to inpatient care (no referral system in the country) to become eligible for reimbursement.

We present empirical evidences by estimating the ATT in terms of length of hospitalization and per day health expenditure. Table 3 shows the ATT of length of hospitalisation (ATT= mean of length of hospitalisation of insured - mean of length of hospitalisation of uninsured). The ATT of length of hospitalisation is less for the insured which ranges from (-4.68) to (-4.72) days as various methods of matching. The combined mean of length hospitalisation days for both insured and uninsured group was 8.4 days, and the insured groups have a length of hospitalisation of almost half the times of the uninsured group.

Table 3. Impacts on Length of hospitalization

| | n. treat | n. control | ATT | Std. Err. | t |
|---------------------------|----------|------------|-------|-----------|--------|
| Nearest-Neighbor Matching | 94440 | 10591 | -4.68 | 0.14 | -31.56 |
| Radius Matching | 71677 | 10654 | -4.72 | 0.13 | -34.82 |
| Kernel Matching | 94442 | 10661 | -4.72 | 0.12 | -33.53 |

Table 4 shows the impact of health insurance on the per-day hospitalization expenditure. We presented the ATT after assuming annual inflation of the healthcare expenditure of the untreated group at various levels (0%, 10%, 15% and 20%) for over a period of four years.

Table 4. Impacts on per-day hospitalization expenditure (inflated at various rates for over a period of four years)

| | Number of treatment group | Number of control group | Inflated at 0% per annum for untreated group | | | Inflated at 10% per annum for untreated group | | | Inflated at 15% per annum for untreated group | | | Inflated at 20% per annum for untreated group | | |
|--|---------------------------|-------------------------|--|-----------|---|---|-----------|---|---|-----------|---|---|-----------|---|
| | | | ATT | Std. Err. | t | ATT | Std. Err. | t | ATT | Std. Err. | t | ATT | Std. Err. | t |
| | | | | | | | | | | | | | | |

| | | | | | | | | | | | | | | |
|---------------------------|-------|-------|------|----|----|------|-----|----|------|-----|----|------|-----|----|
| Nearest-Neighbor Matching | 94440 | 10591 | 4441 | 99 | 44 | 3240 | 134 | 24 | 2639 | 152 | 17 | 2038 | 170 | 11 |
| Radius Matching | 71677 | 10654 | 4227 | 93 | 44 | 3035 | 125 | 24 | 2414 | 141 | 17 | 1814 | 158 | 11 |
| Kernel Matching | 94440 | 10604 | 4405 | 98 | 43 | 3189 | 126 | 25 | 2581 | 148 | 17 | 2003 | 154 | 12 |

4. Discussion and Conclusion

We found that that private health insurance coverage leads to i) reduction in the length of hospitalization days and ii) increase in per day health expenditure. In general, evidences from the literatures suggest that health insurance coverage leads to both supplier-induced and demand induced moral hazard. Accepting the fact that patients are relatively less empowered in the Indian healthcare market than hospitals, we can assume that there is scope for supplier induced demand. In this regard, we should be observing higher levels of both the length of hospitalisation and healthcare expenditure. However, surprisingly, our study did not find such a clear trend but showed a very mixed trend with an increase in per day healthcare expenditure but with a decline in the days of hospitalisation for the insured.

The underlying reason for a mixed trend in healthcare utilisation can be explained with the provider payment mechanism that is currently in place in the Indian health insurance market. Given the retrospectively defined package rates for the in-patient procedures as provider payment mechanism and the absence of any standard treatment protocol, the hospitals maximize their profit by reducing the number of hospitalisation days. As the package rate is retrospectively negotiated and fixed, the hospitals will maximize their return by minimizing the inputs required to treat the patients. Towards this end, the hospitals reduce the number of hospitalisation days for the insured so that they can save the resources in terms not allocating more days of doctors, nursing and other supporting staffs for treating the insured patients. On the other hand, the patients will be satisfied with less number of days of hospitalisation and same for the insurers because the room rents are not part of the package rates and thus it can be saved. Furthermore, the hospitals and insured maximize their utility function by converting some of the outpatient care procedures in to in-patient care (no referral system in the country) to become eligible for reimbursement.

There are several limitations for this study. First of all, we lack very clear and detailed information on the nature of contract between insurer and hospitals. Furthermore, though we have considered the behavior of hospitals in our study we could not consider the role of doctors as they are other important stakeholders in the healthcare market. Further, the study also has some weakness in terms of its study design that can affect our empirical results: i) we had compared two different data sets of insured and uninsured where the first one is self reported (possibility of recall bias) but the latter is more objectively reported data by insurance companies, ii) any differences in types of illness and

levels of hospitals between insured and uninsured, if any, was not accounted in the present study, and iii) the matching exercise is performed with limited number of observable characteristics.

The findings from this study revealed that the private health insurance results in welfare loss to the economy through irrational utilisation of healthcare. In the long run, it would also lead to increased premium. Therefore, it is necessary to regulate and develop a competent healthcare market in the country with proper monitoring mechanism on healthcare utilisation and benchmarks for pricing and provision of healthcare services.

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5. References

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