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ARTICLE

Publicly funded health insurance schemes and demand for health services: evidence from an Indian state using a matching estimator approach

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Abstract

Using Demographic and Health Survey data (2015–16) from the state of Andhra Pradesh, we estimate the differential probability of hysterectomy (removal of uterus) for women (aged 15–49 years) covered under publicly funded health insurance (PFHI) schemes relative to those not covered. To reduce the extent of selection bias into treatment assignment (PFHI coverage) we use matching methods, propensity score matching, and coarsened exact matching, achieving a comparable treatment and control group. We find that PFHI coverage increases the probability of undergoing a hysterectomy by 7–11 percentage points in our study sample. Sub-sample analysis indicates that the observed increase is significant for women with lower education levels and higher order parity. Additionally, we perform a test of no-hidden bias by estimating the treatment effect on placebo outcomes (doctor's visit, health check-up). The robustness of the results is established using different matching specifications and sensitivity analysis. The study results are indicative of increased demand for surgical intervention associated with PFHI coverage in our study sample, suggesting a need for critical evaluation of the PFHI scheme design and delivery in the context of increasing reliance on PFHI schemes for delivering specialised care to poor people, neglect of preventive and primary care, and the prevailing fiscal constraints in the healthcare sector.

Keywords: publicly funded health insurance schemes; moral hazard; supplier-induced demand; treatment effect analysis; India

1. Introduction

Publicly funded health insurance (PFHI) schemes have been introduced across developing countries, including India, as a tool to achieve universal health coverage. PFHI schemes in India target poor families and intend to achieve equity in the utilisation of health services (Prinja *et al*., 2017). In India, the first state to launch a PFHI was Andhra Pradesh in 2007, and in the subsequent year, the central government launched Rashtriya Swastyha Bima Yojana as a social protection scheme. Along similar lines, many Indian states are increasingly implementing their state-specific PFHI schemes since 2008. The growing focus on PFHI schemes in India is a consequential departure from the traditional public healthcare delivery model to a public–private partnership (PPP) model for delivering secondary and tertiary care (Khetrapal *et al*., 2019). Due to the deficient public health system, PFHI schemes in India have to rely on the unregulated private sector for delivering care under these schemes (Reddy and Mary, 2013*b*; Khetrapal *et al*., 2019). Existing evidence from India suggests that PFHI schemes play a critical role in improving access to secondary and tertiary care for poor people (Ranjan *et al*., 2018); however, there is limited evidence on the effectiveness of these schemes in improving the quality of service delivery (Khetrapal *et al*., 2019). Studies have found that there is an increase in out-of-pocket (OOP) expenditure even after the introduction of PFHI schemes that guarantee cashless treatment to poorer populations (Jayakrishnan *et al.*, 2016; Ranjan *et al.*, 2018). Researchers attribute this increased OOP to over-reliance on unregulated and for-profit private providers empanelled under these schemes (Jayakrishnan *et al.*, 2016; Ghosh, 2018). Further, owing to their insurance-based model, researchers raise concerns about the cost-effectiveness of these schemes due to the probable associated moral hazard (Ghosh, 2018). However, studies in the Indian context are lacking as health insurance markets are still in the nascent stage in India, with only 28.3 per cent of the total population covered by any form of health insurance and 12.8 per cent covered by PFHI schemes (Ranjan *et al.*, 2018).

There exists limited analysis on PFHI schemes and demand for health services in the Indian context. A few studies using bivariate or multivariate analysis indicate that insurance coverage is a significant predictor of surgical intervention, specifically hysterectomy (Desai *et al.*, 2014, 2017; Prusty *et al.*, 2018); however, experimental or quasi-experimental evidence is lacking. Our study contributes to this research gap by estimating the effect of PFHI coverage on the demand for health services (covered) using a quasi-experimental method.

This study aims to estimate the effect of PFHI coverage on the probability of surgical intervention using a quasi-experimental method. We specifically estimate the effect of PFHI coverage on the probability of undergoing a hysterectomy (removal of the uterus) among women of reproductive age group (15–49 years). Hysterectomy is the surgical removal of the uterus and is the second most common procedure performed among women of reproductive age group in India (Prusty *et al.*, 2018). The reason we chose hysterectomy other than the availability of data is as follows. The increasing rates of hysterectomy in India, especially at a younger age, is a cause of concern among researchers and policymakers (Desai *et al.*, 2011, 2017; Prinja *et al.*, 2017; Kaur *et al.*, 2019) and thus, for the first-time information on hysterectomy was collected from women in the age group of 15–49 years during fourth round (2015–16) of National Family Health Survey (DHS-India) (Kaur *et al.*, 2019). Recent studies using Demographic and Health Survey (DHS) data from India found that insurance coverage is the most significant predictor of undergoing hysterectomy in the Indian context with the likelihood of hysterectomy being 1.9 times higher in women with insurance coverage (Prusty *et al.*, 2018). Moreover, community-based health insurance schemes have been consistently found to be associated with increasing rates of hysterectomy in other Indian states (Desai *et al.*, 2014; Kaur *et al.*, 2019), but experimental evidence is lacking. These studies have mainly used regression methods; however, to have causality claims we cannot rely on simple comparisons or even regression-adjusted comparisons as they may provide misleading estimates of causal effects (Caliendo and Kopeinig, 2008; Austin, 2011). For instance, those covered under PFHI might have a higher incidence of co-morbidities which perhaps could explain the higher association between PFHI coverage and chances of undergoing surgical intervention. Thus, in such a scenario getting a positive association may reflect bias arising from unobserved and uncontrolled differences in health status variables or other potential covariates. Experiments provide an ideal way to perform impact assessments; however, ethical consideration makes it difficult to conduct experiments in the healthcare market, and perhaps this is the reason many researchers rely on observational studies to establish the association between health insurance status and the use of health services. However, the endogenous nature of the health insurance status would bias the results, and researchers may end up overestimating the impact of health insurance on demand for health services (Barros *et al.*, 2008). Under such conditions, the use of quasi-experimentation methods such as matching methods is suggested. Among the matching techniques, propensity score matching (PSM) is the most popular treatment effect analysis approach using cross-sectional data (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 1999, 2002; Abadie and Imbens, 2011). Thus, to estimate the effect of PFHI coverage on the probability of undergoing surgery (a procedure covered) we use matching estimators, PSM, and coarsened exact matching (CEM) to create our treatment (having PFHI coverage) and control (no PFHI coverage) groups. Women who reported not having PFHI coverage formed our control group and women with PFHI coverage formed our treatment group. Additionally, as a test of no-hidden bias, we estimate the effect of PFHI coverage on healthcare services not covered under PFHI, namely 'Doctor's visit' and 'Preventive health check-up'. We expect that PFHI coverage would result in increased demand for services covered under the insurance plan (surgical intervention) while no effect is expected for services not covered. The different design of Aarogyasri scheme wherein there is no exclusion or screening and every poor household is by default covered (Bergkvist *et al*., 2014; Rao *et al*., 2016*b*; Prinja *et al*., 2017) with the only eligibility of having below poverty line (BPL) ration card (a document proof of poor socio-economic status in India), allows us to argue that the issue of endogeneity due to adverse selection in health insurance programmes would be minimum in our study. The increased demand, if any, due to insurance status may be patient-driven or supplier-induced.

2. PFHI scheme: design elements and demand for health services

The current study focuses on Andhra Pradesh's PFHI scheme Rajiv Aarogyasri Health Insurance Scheme (popularly known as Aarogyasri) (Rao *et al*., 2016*a*). This scheme (PFHI now onwards) provides a cashless treatment facility for a pre-defined list of surgical and medical procedures with an annual insurance coverage of USD 4,500 (INR 200,000) to all individuals of BPL families on a family floater basis, all family members collectively entitled to the insured sum (Yellaiah, 2013). This seems to be a generous coverage given average expenditure on hospitalisation in a private hospital in India is INR 38,400 (NFHS-4 report, 2017). The scheme covers all families with a BPL ration card (Rao *et al*., 2016*b*) which is issued by state's civil supplies department to families with an annual income below USD 1,384 (INR 75,000) in urban areas and USD 1,107 (INR 60,000) in rural areas. All the members of a BPL family are automatically enrolled including individuals with pre-existing medical conditions (Bergkvist *et al*., 2014; Rao *et al*., 2016*b*). The scheme focuses on secondary and tertiary level care, i.e. minor and major procedures while preventive and primary care (like outpatient visits and preventive health checks) are not covered. The benefits include procedure costs, all inpatient costs, including investigations, medicines, food and transport, and follow-up visits (Rao *et al*., 2016*b*).

PFHI is implemented through a PPP between the state government, an insurance company, and healthcare providers (both public and private). The state government is responsible for financing the scheme and overall regulation and monitoring, the insurance company handles the claims management system and hospitals/providers ensure cashless treatment to the scheme beneficiaries. The insurance-based model of healthcare delivery, specifically, when there is no co-payment (the patient needs to pay a portion of medical expenses), reduces the marginal cost of care for the patient and may promote overuse of healthcare services (Cutler and Zeckhauser, 2000; Vera-Hernández, 1999; Barros *et al*., 2008). On the other hand, payment methods adopted under insurance-based healthcare delivery models could affect the prescription behaviours of healthcare providers (Ellis and McGuire, 1986).

PFHI scheme has adopted a prospective payment system (PPS) for regulating the behaviour of private providers. PPS is a method of reimbursement based on a pre-defined fixed payment as per the treatment provided. However, the existing evidence from developed countries, which rely on insurance-based models since the 1980s, found that moral hazard (supplier-induced) in the form of increasing/decreasing care or reducing the quality of care follows a PPS (Ellis and McGuire, 1986; Cutler, 1995; Cutler and Zeckhauser, 2000; Tan and Melendez-Torres, 2018). With this background, this study postulates that PFHI coverage would be associated with increased demand for surgical intervention which could either be patient-driven or supplier-induced.

We expect a patient-driven demand as there are no copayments or co-insurance associated with PFHI coverage and the marginal cost of care for the patient is close to zero. Moreover,

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there are no alternative affordable treatment options available to poor women suffering from bleeding disorders (Desai, 2016). Further, we argue that the increased demand may be supplier-induced when the surgery is performed in a private hospital, given this scheme follows a prospective payment mechanism, and payments are per procedure (Ellis and McGuire, 1986; Cutler, 1995; Khetrapal *et al.*, 2019). Thus, private providers have every incentive to recommend for more procedures. Moreover, there is no gate-keeping mechanism wherein referral by a primary physician is a must for consulting a surgeon (Reddy and Mary, 2013*a*; Rao *et al.*, 2016*b*). Patients can directly go to specialists and bypass primary care. PFHI schemes are dominated by for-profit private providers (La Forgia and Nagpal, 2012). Specifically for the Aarogyasri scheme, studies have found that since its inception in 2007, close to 70 per cent of patients have been treated in private hospitals, and healthcare service delivery under the scheme is dominated by for-profit private hospitals (Reddy and Mary, 2013*a*, 2013*b*).

Further, a very high prevalence rate of hysterectomy in Andhra Pradesh (8.9 per 100) in comparison to the India average (3.2 per 100) warrants the attention of researchers. A recent study on the prevalence of hysterectomy in India reports that though India's average rate of hysterectomy (3.2 per 100) is way lower than that prevalent in Western countries; however, the rates of hysterectomy in Andhra Pradesh (8.9 per 100) are comparable to Western countries like USA and UK (Desai *et al.*, 2019). Further, the study points towards lower average age at hysterectomy in India as compared to Western countries. This is perhaps linked to lower average age at marriage and child-bearing, and perceptions of the limited utility of the uterus beyond childbearing. Thus, in our analysis, we expect that women with higher order parity (number of children born) will have higher chances of hysterectomy given perceptions of the limited utility of the uterus beyond child-bearing (Desai, 2016).

With this background, we estimate the differential probability (for women aged 15–49 years) of undergoing hysterectomy by PFHI coverage in a matched sample. Further, we perform a sensitivity analysis of our estimates wherein we test the sensitivity to increasing odds of unobservable affecting selection into the treatment group (Becker and Caliendo, 2007). As per our knowledge, this is the first study in the Indian context examining the causal linkage of PFHI and the demand for health services covered. Our study contributes to the scant literature on the demand for health services and PFHI schemes in developing countries.

3. Methodology

3.1 Data

We use data from India's fourth round of National Family Health Survey (NFHS-4) (2015–16) for the state of Andhra Pradesh. The purposive selection of Andhra Pradesh for this study is justified as Andhra Pradesh is a pioneer in PFHI implementation in India; secondly, the rate of hysterectomy (our interest variable) is highest in the state of Andhra Pradesh (Desai *et al.*, 2019); thirdly, the PFHI model of Andhra Pradesh requires no enrolment in the scheme (Reddy and Mary, 2013*a*, 2013*b*; Yellaiah, 2013) and thus, the issue of selection bias into the treatment is minimum in this study setting. NFHS is a district-level household survey that uses a multi-stage stratified sampling method and is representative at the state level (NFHS-4, 2017). It collects information on socioeconomic variables, health services utilisation, health insurance status, and morbidity with a focus on reproductive and child health services. Information on household social and economic welfare using durable asset holdings and other endowments in agriculture, water and sanitation, and housing was also collected to construct a wealth index. In 2015–16, for the first time, it collected information on the prevalence of hysterectomy. The questions related to 'whether undergone hysterectomy' was asked to women who reported amenorrhea (absence of menstruation) of more than 6 months in the age group of 15–49 years ($N = 3{,}440$).

We obtain our final sample after dropping observations with missing values for covariates used in the study [social category/caste ($n = 14$) and sterilised ($n = 62$)]. As our focus is on the effect of

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the Aarogyasri scheme thus, we drop all observations ($n = 515$) who reported undergoing hysterectomy before the launch of Aarogyasri. As the benefits covered, co-payments and eligibility requirements are very different across insurance types and our focus is the effect of PFHI schemes, thus we remove observations with other types of health insurance plans ($n = 76$). Finally, our working sample size is 2,768 women in the age group of 15–49 years.

3.2 Variables: treatment, outcome, and covariates

Our treatment variable is coverage in Andhra Pradesh's state-specific PFHI (Aarogyasri scheme) which is recorded as a dummy with '1' as covered and '0' otherwise. Our main outcome variable is 'whether undergone hysterectomy' recorded as a dummy variable with '1' as yes and '0' as no. As a test of no-hidden bias we use two placebo outcome variables namely, 'visit to doctor/any health facility in last three months' (doctor's visit) and 'visit to a health facility for a health check-up in last three months' preceding the survey' (health check-up). The propensity score (PS) of treatment assignment (i.e. the probability of PFHI coverage in our sample) is estimated using household-level variables (wealth index, social category, religion, rural/urban residence) and individual-level variables (age, education, obstetric history, undergone sterilisation, parity (number of children ever born), reported presence of non-communicable diseases (NCDs)).

The wealth index is a composite measure of a household's living standard calculated using household data on ownership of selected assets such as televisions, scooters, livestock, materials used for housing construction, and types of water access and sanitation facilities. The social category was recorded as categorical variable with four categories, including Scheduled Castes (SCs), Scheduled Tribes (STs), Other Backward Categories (OBC), and General Category. SCs and STs are among the most marginalised groups and have poor socioeconomic conditions. Religion was recorded as a categorical variable with four categories, including Hindus, Muslims, Christians, and Others. Age was recorded as completed years as a continuous variable. Education is recorded as completed years of schooling as a continuous variable. Bad obstetric history involved self-reported incidence of stillbirth/miscarriage/abortion and was recorded as a dichotomous variable. The presence of NCDs included self-reported presence of any of these diseases, namely asthma, cancer, diabetes, hypertension, and thyroid. The choice of covariates is guided by existing literature on factors determining PFHI coverage (Devadasan *et al*., 2011; Ghosh, 2014; Ghosh and Gupta, 2017; Nandi *et al*., 2018) and literature on predictors of hysterectomy (Desai *et al*., 2017; Prusty *et al*., 2018; Desai *et al*., 2019) in Indian context.

3.3 Analytical strategy

We assess the impact of PFHI on the demand for health services using three outcome variables: (i) doctor's visit and (ii) health check-ups, and (iii) hysterectomy done. Although our main focus is on 'Whether Hysterectomy is done', we include 'doctor's visit' and 'health check-ups' to conduct a test of 'no hidden bias', as suggested in the literature on matching methods (Steiner and Cook, 2013). As a test of 'no hidden bias' we include a non-equivalent dependent variable, which is similar to the outcome measure but presumed not to be affected by the treatment status. Our presumption is based on the fact that the Aarogyasri scheme covers only the cost of surgical procedures and not the 'visit to doctor'. Thus, we expect that there would be no impact of the scheme on demand for an outpatient visit (doctor's visit) or on preventive health care (health check-ups) under the assumption of no hidden bias. However, in the presence of hidden bias we may expect to get pseudo-treatment effects (Reichardt, 2019: 148). Thus, the inclusion of the placebo outcome variables helps us to test the assumption of 'no hidden bias' and test the robustness of our treatment estimates.

We perform treatment effect analysis using PSM and CEM (as a robustness check) in Stata (v15.1) to find the impact of having PFHI coverage on the demand for health services. PSM is a popular method to estimate the treatment effects with cross-sectional data (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 1999; Austin, 2011). In this method, we first estimate the PS, which is the conditional probability of assignment to a particular treatment given a set of covariates (Austin, 2011). We used PSM with replacement as we had fewer observations in our control group in comparison to our treatment group. For the construction and assessment of PS, we follow a step-wise method as proposed by Garrido *et al.* (2014). The step-wise method includes: (i) variable selection for PS estimation; (ii) checking for the balance of PS across treatment and comparison groups; (iii) checking for the balance of covariates across treatment and comparison groups within blocks of PSs before and after matching; and (iv) treatment effect estimation. Additionally, we perform sub-sample analysis. The decision to have a sub-sample analysis based on age-cohorts, parity, and education level was guided by the empirical evidence wherein age, education, and parity are considered to be significant predictors of demand for health care, specifically, hysterectomy (Desai *et al.*, 2017; Prusty *et al.*, 2018).

3.4 PS estimation

A PS is the probability of getting assigned to the treatment group conditional on a set of covariates (Rosenbaum and Rubin, 1983; Austin, 2011):

$$PS = P(T = 1|X).$$

If the potential outcome (Y) is independent of the treatment assignment given a set of covariates (X), then Y is also independent of the treatment assignment conditional on X (Rosenbaum and Rubin, 1983; Abadie and Imbens, 2006; Caliendo and Kopeinig, 2008). PS is used as a univariate summary of all the observed variables.

In observational studies, $p(X)$ is unknown and is estimated through a probabilistic model. We use the logit model to estimate the PS and include all pre-treatment observed variables that can potentially affect both treatments as well as the outcome. Our logit model for PS estimation is as follows:

$$\log(p/1-p) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \mu$$

To adjust for selection bias, we include all baseline covariates (X) that can potentially affect treatment assignment, including wealth quintile, age, education level, social class, and religion. These factors have been consistently found to be associated with enrolment in PFHI schemes in the Indian context (La Forgia and Nagpal, 2012; Bergkvist *et al.*, 2014; Rao *et al.*, 2016*b*; Ghosh and Gupta, 2017). As suggested by Austin (2011), to ensure robust treatment estimates we include potential confounders that could affect treatment outcomes as well, including parity, sterilisation status, and bad obstetric history and reported the presence of any NCD.

3.5 Balance of PS across treatment and control groups

After the estimation of the PS for each of observations in our sample we subjectively assess the common support/overlap in the range of PSs by examining the graph of PS (see Figure 1) (Garrido *et al.*, 2014). The PS for all of our observations lies within the common support region and thus, in the process of matching only two observations were lost.

3.6 Balance of covariates across treatment and control groups

The balance of covariates in the raw and matched samples is assessed using standardised differences in mean and variance ratio tests as suggested by Zhang *et al.* (2019). Table 2 compares the standardised mean difference and variance ratio between raw and matched samples for the treated and control groups. The standardised difference compares the difference in means in units of the pooled standard deviation (Zhang *et al.*, 2019). An indicator of a good balance in a matched sample is when the standardised mean difference for all the study covariates across treatment and

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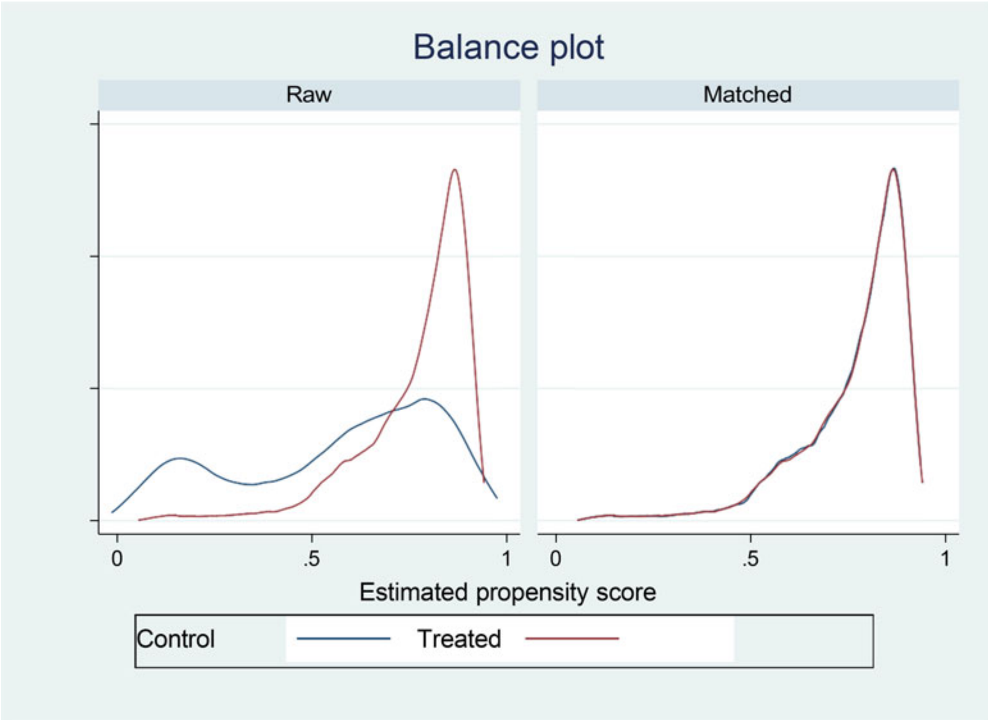

Figure 1. Balance plot for the PS.

control groups is not more than 0.1, and the variance ratio approaches 1 (Garrido *et al.*, 2014; Zhang *et al.*, 2019). Studies have empirically shown that in data, balanced enough for randomisation, PS use may actually produce imbalance (King and Nielsen, 2019), thus, we compare the balance in raw as well as matched samples. Comparing the mean differences in the raw and matched samples (in Table 1) we have achieved a good balance with the PSM method.

Table 1. Standardised mean difference and variance ratio in raw versus matched sample

	Standardised mean difference		Variance ratio	
Variables	Raw	Matched	Raw	Matched
Age	0.42	0.07	0.74	0.87
Education	−0.62	0.04	0.70	0.96
Parity	0.31	0.09	1.01	0.97
Wealth index	−0.34	0.02	0.65	0.74
Social category = SC/ST	0.10	−0.02	1.08	1.09
Reported tubectomy	0.31	0.05	NA	NA
Religion = Hindus	0.05	0.02	0.02	1.75
Rural residence	0.45	−0.02	NA	NA
Bad obstetric history	0.09	0.06	NA	NA
Reported any NCD	0.07	0.02	NA	NA

NA, variance ratio not available for binary variables.

Table 2. Details of overall sample and matched sample

Sample	PFHI = 0	PFHI = 1
All	800	1,968
CEM matched	405	819
PSM with caliper (0.047)	798	1,968

Another balance diagnostic for covariate balance is standardised percentage bias which considers both mean differences and variances (Rosenbaum and Rubin, 1983; Austin, 2011). The standardised percentage bias is 'the percentage difference of the sample means in the treatment and control groups as a percentage of the square root of the average of sample variances in the treated and control groups' (Rosenbaum and Rubin, 1985). We compare the standardised percentage bias in the raw and matched samples in Figure 2. The proposed maximum standardised difference for covariates lies in the range of 10–25 per cent (Garrido *et al.*, 2014). We have achieved a good matching as evident (in Figure 2) with standardised differences less than 10 per cent for all the study covariates.

3.7 Estimating average treatment effect on the treated

We aim to estimate the average effect of treatment (having Aarogyasri scheme coverage) on treated (ATT) on the probability of 'visit to a doctor'; 'preventive health checks'; and the probability of surgical intervention.

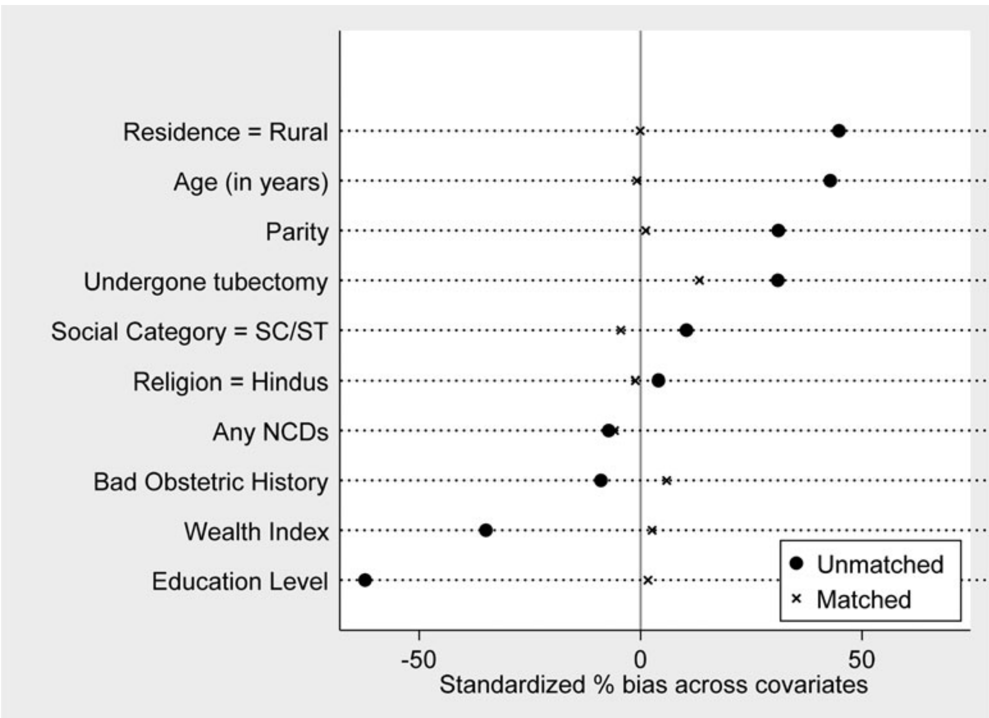

Figure 2. Standardised bias in raw and matched samples.

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Considering Rosenbaum and Rubin (1985) potential-outcome framework:

$Y_i(0)$ is the outcome for individual i when treatment $T = 0$, and
$Y_i(1)$ is the outcome for individual i when treatment $T = 1$

As we observe either $Y_i(0)$ or $Y_i(1)$ for an individual, there is a need to estimate the unobserved outcome. Using the estimated PS we first match each of our observation in the treatment group to our control group. Then, in the matched sample, the observed outcome (data) for each subject in the control group serves as a potential outcome for the matched subject in the treatment group. For example, for a person (i) belonging to a treatment group with covariates X_i, the unobserved potential outcome $Y_i(0)$ is based on the average outcome of some similar individuals (similar on covariates) from the control group.

ATT is estimated by taking average of the difference between the observed and potential outcomes for each subject in the treatment group. The ATT is given as (Abadie and Imbens, 2006, 2016)

$$ATT(p) = E[Y_i(1) - Y_i(0)]|T = 1 \tag{1}$$

3.8 Robustness checks

For robustness checks, we use different matching specifications and PS trimming as suggested (Caliendo and Kopeinig, 2008; Austin, 2011; Garrido *et al.*, 2014). The sensitivity of results was checked with caliper variations. The caliper variations were selected based on the rule of 0.2–0.25 of the standard deviation of the PS (Austin, 2011). The standard deviation of PS for our study sample was 0.19; accordingly, the caliper width ranged from 0.038 to 0.047. Stratified matching helps us to achieve better matching (Austin, 2011). In this, we first divide the whole sample into strata based on PSs and then estimate treatment effect in each of the strata. Bootstrapped repetitions ($n = 500$) were used to get robust estimates. Additionally, we perform CEM as a robustness check for our estimates. CEM consists of temporarily coarsening (grouping) covariates/determinants of treatment assignment (PFHI coverage in our case) by recoding such that similar values are grouped and assigned the same numerical value. Then, via an 'exact matching' algorithm, observations with the same values for all the coarsened covariates form one stratum. Observations in strata with at least one treatment and one control observation are retained (Blackwell *et al.*, 2009). After obtaining the CEM-matched sample and CEM weights, the difference in means of the outcome variable is considered as the treatment effect. CEM is considered superior in terms of ensuring exact matching and adjusting imbalance in one variable has no effect on maximum imbalance on any other (Iacus *et al.*, 2012). A recent study on utility of CEM and other matching methods notes that CEM results in best balance of covariates but at a cost of increased bias and lower precision due to loss of study sample (Ripollone *et al.*, 2020). We use CEM as it allows us to use sampling weights and ensures better balance of covariates. As evident in Table 2, there was a significant loss of sample in the case of CEM while in the case of PSM only two observations had to be dropped with a caliper of 0.047.

3.9 Sensitivity analysis

As a robustness check, we did sensitivity analysis using bounded approach as proposed by Rosenbaum (Becker and Caliendo, 2007). We checked the sensitivity of our estimates with respect to deviations from the identifying assumption, i.e. confoundedness, of the matching approach. For a binary outcome, Mantel and Haenszel bounds are proposed (Becker and Caliendo, 2007). Our estimates remain insensitive even when the odds of selection into the treatment are doubled or tripled (see Appendix supplementary table).

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4. Results and discussion

4.1 Descriptive results

Table 3 presents the differences in the mean/proportion of the study covariates among the treated and comparison groups in the matched pool and unmatched sample. The mean age in our comparison group is significantly lower (34.5 years) as compared to the treated group (38.6 years). Women in the non-PFHI (comparison) group have higher levels of education with a mean of 5.76 years of completed education while PFHI beneficiaries have lower level of education (mean: 2.77). The treated and comparison groups are similar in religious affinity with more than 85 per cent of study participants belonging to Hindu religion. The treated group has a lower mean factor score of wealth index (11,776) which is well expected as the Aarogyasri scheme targets poor families. As the scheme targets poor people concentrated in rural areas we observe that 80 per cent of our treated group resides in rural areas. In total, 15 per cent of our comparison group and 13 per cent of our treatment group reported having NCDs. In total, 13 per cent of comparison group and 11 per cent of treatment group reported having had miscarriage or still-birth (bad obstetric history).

For treatment effect analysis using matching estimators it is critical to understand the factors determining assignment into the treatment group. In total, 71 per cent of our sample reported

Table 3. Mean differences between treatment and comparison groups in unmatched and matched samples

Variable	Sample [unmatched (U)/matched (M)]	Mean in treatment group $N_U = 1{,}968$ $N_M = 1{,}968$	Mean in control group $N_U = 800$ $N_M = 1{,}968$	p-value for *t*-test/proportion test
Age (in years)	U	38.7	34.51	0.00
	M	38.7	38.12	0.07
Education	U	2.77	5.77	0.00
	M	2.77	2.82	0.74
Wealth index	U	11,777	38,035	0.00
	M	11,777	12,041	0.91
Residence = rural	U	0.8	0.6	0.00
	M	0.8	0.82	0.20
Parity	U	2.58	2.2	0.00
	M	2.58	2.51	0.06
Belongs to SC/ST	U	0.31	0.26	0.02
	M	0.31	0.29	0.16
Undergone tubectomy	U	0.64	0.49	0.00
	M	0.64	0.63	0.49
Religion = Hindus	U	0.87	0.85	0.33
	M	0.87	0.92	0.00
Bad obstetric history	U	0.11	0.14	0.03
	M	0.11	0.09	0.13
Any NCD[a]	U	0.13	0.16	0.08
	M	0.13	0.12	0.25

N_U, sample size in unmatched; N_M, sample size in matched.
[a]NCDs include asthma, thyroid, hypertension, diabetes, and cancer.

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Table 4. Average effects of treatment on treated

Estimator	Doctor's visit	Health check-up	Surgical intervention
Nearest neighbour 1:1	−0.014 (0.028)	0.004 (0.017)	0.107 (0.029)***
PS trimming	0.019 (0.025)	0.012 (0.022)	0.114 (0.029)***
Nearest neighbour 1:3	−0.008 (0.024)	0.003 (0.017)	0.081 (0.022)***
Stratified matching	0.017 (0.023)	0.018 (0.015)	0.086 (0.025)
CEM matching	0.021 (0.028)	0.025 (0.018)	0.067 (0.028)***

having PFHI (Aarogyasri) coverage. In Table 4 we present the odds ratio of having PFHI coverage in our sample. Women in the age group of 35–39 years have 2.2 times higher odds of having PFHI coverage and the odds ratio decreases with increasing age. The richest quintile is associated with a reduction in the odds of PFHI coverage by 67 per cent. The middle quintile has significantly higher odds (1.3) of having PFHI coverage. Studies have found that most often poorest quintiles are migrants from other states who lack access to BPL cards, an eligibility criterion to get enrolled in state-specific PFHI schemes (Nandi *et al.*, 2015; Ghosh and Gupta, 2017). Perhaps this could explain the higher odds of having PFHI coverage among middle-income quintiles in comparison to the poorest quintile. There is no significant association of PFHI coverage with religion and social category. The morbidity factors like the presence of NCDs or having had bad obstetric history are not associated with PFHI coverage in our sample. This is indicative of limited selection bias in schemes offering coverage to poor people without screening and universal coverage of poor families, identified through an income cut-off as a BPL card in the Indian context. Women who have opted for permanent sterilisation (tubectomy) are 1.29 times more likely to have PFHI coverage. This could be explained as PFHI covers poor families and studies from low- and middle-income countries have identified lower socioeconomic status as a significant factor for the higher prevalence of permanent contraceptive measures (tubectomy) among poor women (de Oliveira *et al.*, 2014).

4.2 Effect of PFHI coverage on health service use

Table 5 presents estimates of the ATT of PFHI coverage. Our ATT estimates suggest that PFHI coverage has no significant effect on the probability of a doctor's visit (effect size: 0.019) and

Table 5. Sub-sample analysis

Sub-sample	Sample size	ATT (S.E.)
By age group		
15–30 years	789	0.10 (0.036)***
31–40 years	664	0.045 (0.063)
>40 years	1,314	0.051 (0.054)
By parity		
Parity ≤1	507	0.072 (0.057)
Parity ≥2	2,261	0.079 (0.033)**
By education level		
Up to primary level	1,900	0.068 (0.034)**
Secondary and above	868	0.058 (0.047)

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health check-up (effect size: 0.003) while it significantly increases the probability of hysterectomy among women of the reproductive age group (15–49 years) by 11 percentage points in our study sample. We use different matching specifications, namely nearest-neighbour 1:1 and nearest-neighbour 1:3, and PS trimming for robustness checks as suggested (Caliendo and Kopeinig, 2008; Austin, 2011; Garrido *et al.*, 2014). With different matching specifications, the effect of PFHI coverage on 'doctor's visit' and 'preventive health check-up' remained insignificant. While our estimates for our main outcome variable 'whether undergone hysterectomy' remained significant even with different specifications. When we used PS trimming, the estimated effect of PFHI on differential probability of hysterectomy between the treatment and control groups was 11.4 (p-value: 0.00), and when we used stratification and nearest-neighbour 1:1 matching it became 8.4. The mean difference in a CEM-matched sample and using CEM weights is 6.7 (p-value: 0.018). Overall, with different estimators the effect size for 'probability of hysterectomy' ranged from 6.7 to 11.4 percentage points (see Table 5).

4.3 Results of sub-sample analysis

We performed sub-sample analysis by age categories, parity, and education level (Table 6). The youngest age cohort (15–30 years) shows significant ATT estimate followed by older-adult age cohort (above 40 years) while ATT estimate is insignificant for middle-age cohort (31–40 years). In terms of parity, those with two and more children have the highest and significant ATT estimate. The results suggest that having PFHI coverage increases the chances of hysterectomy at a younger age, though in medical literature higher age is a risk factor for hysterectomy. The lower age at hysterectomy has health implications in long term, as early menopause causes associated cardiac and osteoporotic morbidities (Singh and Sivakami, 2014). Our estimates by education level suggest that the impact of PFHI remains significant for women with lower education status. This finding is contrary to the existing empirical evidence which suggests that adults with higher educational attainment are more likely to use health services (Cutler and Lleras-Muney, 2012; Fletcher and Frisvold, 2009). The higher rates of hysterectomy among younger women belonging to low-income families having lower education status and poor job security has been consistently linked to their health insurance status (Desai, 2016; Desai *et al.*, 2017). Studies trying to understand the factors related to normalisation of hysterectomy at a younger age in India using qualitative research methods found that the poor or deficient sexual and reproductive health services, lack of awareness about the side-effects of hysterectomy, and promotion of invasive procedure by private providers due to profit motives contributes to unacceptably higher rate of hysterectomy in women at a younger age in Indian context (Desai, 2016; Desai *et al.*, 2017).

Table 6. Reasons for hysterectomy as reported in the sample

	Public		Private		
	N	%	*N*	%	Total
Total surgeries	141	14	830	86	971
Reason: 'excessive bleeding'	83	15	466	85	549
Reason: 'uterine fibroid'	35	13	237	87	272
Reason: 'uterine rupture'	22	11	178	89	200
Reason: 'uterine cancer'	5	17	24	83	29
Reason 'uterine prolapse'	7	22	25	78	32
Reason: 'post-partum haemorrhage'	4	29	10	71	14

Table 7. ATT estimate for sub-sample (excluding malignant conditions)

Estimator	Coef.	Std. Err.	*z*	*p* > *z*
NN (1)	0.09	0.03	3.31	0
NN (3)	0.1	0.02	4.28	0

Sample size: 2,503 (after excluding malignant conditions).

4.4 Reasons for hysterectomy as reported in our sample

We analysed the profile of hysterectomies performed in our sample. Bivariate analysis (Table 7) reveals that 86 per cent of the total hysterectomies were performed in private hospitals under PFHI. Studies from India report that profit motives under PFHI schemes drive unnecessary procedures being done in private hospitals empanelled under these schemes (Nandi *et al.*, 2015, 2017; Ghosh and Gupta, 2017). Desai *et al.* (2017) report similar findings from the state of Gujarat. Using the population-level data from the NFHS-4 survey, the authors report that two-thirds of hysterectomies were performed in the private sector. In terms of reasons for hysterectomy, the most common self-reported reason is 'excessive bleeding'. Out of the total reported hysterectomies (971) in our sample, 549 (57 per cent) reported 'excessive bleeding' as the reason for undergoing hysterectomy. As per medical literature, hysterectomy for benign conditions is not recommended unless alternatives are exhausted especially at a younger age (Scialli, 1998). This finding is indicative of substituting primary and preventive care with surgical intervention for conditions that could be managed conservatively. This finding has significant policy implications in terms of the need for an effective utilisation management system and affordable alternative treatments for poor women. No doubt that PFHI schemes have ensured improved access to specialised care for poor women (La Forgia and Nagpal, 2012; Garg *et al.*, 2020; Reshmi *et al.*, 2021) but, given the cost-effectiveness of preventive and primary care PFHI schemes be designed so as not to replace primary care with secondary care. This study finds that there is an increased demand for hysterectomies due to PFHI coverage. Given, hysterectomy at a younger age has long-term health implications for women, women with poor education levels and from lower income quintiles must be educated about this and alternative affordable treatment options must be explored before opting for surgical intervention.

4.5 Alternate explanations

As a robustness check for our arguments, we explore alternate explanations for our significant ATT estimates. One may argue that the surgical intervention followed an emergency and, in such cases, PFHI coverage might have helped women access timely care. To test this hypothesis, we exclude women who reported malignant conditions as the reason for hysterectomy (Scialli, 1998), including cancer (29), post-partum haemorrhage (14), uterine rupture (191), and uterine prolapse (32) and repeated our analysis (see Table 6). The ATT estimates remained significant even when we exclude malignant indications for hysterectomy from our sample. These results support our arguments that in the case of elective surgeries, the PFHI coverage creates perverse incentives and results in unnecessary procedures being performed affecting the efficiency of health spending. A recent review of the literature (Atlas *et al.*, 2019) regarding patients' decision-making for elective surgery and their sources of information finds that patients mainly rely on doctors' information which could be biased in their interests. We argue that women with poor education levels have less access to other sources and thus as compared to women with higher education levels they are more likely to give in to the demands of doctors for undergoing hysterectomy instead of alternative therapies. The results are suggestive of increased demand for surgical intervention; however, due to data limitations, we could not ascertain whether it is the supply side or demand side. Existing factors that could promote demand-side moral hazard

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are cashless treatment with no co-payments and the absence of alternative treatment options for poor women (Desai *et al*., 2017). Our study results also indicate towards a possible supplier-induced demand given significant asymmetries of information exist in cases of complex medical procedures like hysterectomy. Moreover, bivariate analysis in our study sample reveals that 86 per cent of the total hysterectomies were performed in private hospitals. Studies from India report that the profit motives under PFHI schemes drive unnecessary procedures being performed in private hospitals empanelled under these schemes (Nandi *et al*., 2015, 2017; Ghosh and Gupta, 2017). Desai *et al*. (2017) using population-level data from the state of Gujarat report similar findings wherein they found that two-thirds of the hysterectomies were performed in the private sector for women enrolled in the PFHI scheme. Within the limitations of data, we can only speculate that the increased demand could be supplier-induced, but, it is also possible that the treated group had lower care to start with and thus the need for surgical intervention. Further, studies are required to understand the nature of the moral hazard, whether patient-driven or supplier-induced.

5. Limitations of the study

Although our study is among the few studies that have analysed health insurance and the issue of moral hazard in the Indian context, some limitations need acknowledgement. Firstly, causal inference best be estimated using random assignments and with the use of matching methods we could only balance our treatment and control groups on observable covariates. Thus, bias from unobserved covariates affecting treatment or outcome cannot be ruled out. Secondly, this study has analysed the effect of PFHI coverage on surgical intervention using a single outcome measure (hysterectomy) due to data limitations. Moreover, the data on 'whether hysterectomy was done or not', and confounding variables, like the presence of NCDs are self-reported, thus, effect of reporting biases on our results could not be ruled out. The sample size is small, though representative of the state. There may be a role of contextual factors explaining higher rates of hysterectomy in the study setting which could better be explored using qualitative in-depth studies. Future research may benefit from the analysis of multiple outcome variables and random assignment into treatment and comparison groups.

6. Conclusion

This study estimated the effect of PFHI (Aarogyasri) coverage on the probability of hysterectomy among women of the reproductive age group in our study sample. We find that on average, having a PFHI coverage significantly increases the probability of hysterectomy in our study sample and the estimates remain significant for women in lower age categories, women having lower education levels, and higher order parity. Further studies are required to understand the nature of moral hazard, demand side, or supply side. The study contributes to the scant literature on moral hazard and PFHI schemes, especially in the Indian context. The study findings indicate towards the need for critical appraisal of the design and delivery of PFHI schemes in India given Indian government is increasingly relying on PFHI schemes to serve their indigent population and a huge amount is spent to run insurance-based models of care. Currently, the incentive alignment under PFHI schemes is biased towards surgical care, for both patients and providers. PFHI schemes adopt prospective payment methods that shift cost-control policy away from demand-side interventions (such as deductibles and coinsurance) to the supply-side. For inpatient surgery care, the physician is the dominant decision-maker, so demand-side incentives may be less effective than supply-side controls. Further, PFHI schemes target poor families thus demand-side incentives to reduce moral hazard are not suggested on equity grounds. The cost-effectiveness of a PPS depends on the behaviour of providers. Stringent policy measures may be explored for ensuring cost-effectiveness in resource-constraint settings like India.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S174413312400001X.

Competing interests. None.

Ethical approval. Not applicable as this study is based on publicly available anonymised data.

Availability of data and materials. Data are publicly available. Data reference: we downloaded our study data from the following link, after registering for the DHS programme: http://www.dhsprogram.com/data/dataset_admin/login_main.cfm.

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