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Do publicly funded health insurance schemes reduce out-of-pocket expenditure?: Evidence from India

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Abstract

Background Globally, there is an evident policy emphasis to achieve the longstanding objective of universal health coverage (UHC). Publicly funded health insurance schemes (PFHIs) are increasingly becoming one of the prominent ways of financing healthcare, especially in low and middle-income countries (LMICs) like India. These schemes are envisioned to achieve the SDG 3.8 - "ensuring financial protection against catastrophic health expenditure (CHE) and access to affordable and quality healthcare for all." It becomes imperative to investigate their effectiveness on their primary objective i.e. in providing financial risk protection.

Methods This study uses pan-India secondary data on household social consumption on health from three NSS rounds- 60 (2004), 71(2014) and 75(2017-18). Through an instrumental variable (IV) analysis, to address any possible endogeneity, we aim to determine the relationship between PFHI enrolment and out-of-pocket expenditure (OOPE) for hospitalization care.

Results We find that despite being covered by PFHIs, there is significant OOPE incurred and CHE incidence, more so in private hospitals. Further, the CHE incidence between the 'PFHI covered' and 'not insured' households is not statistically significant. Finally, IV regression finds no evidence of a statistical relationship between PFHI enrolment and OOPE incurred per hospitalization case in 2017-18.

Conclusion Our study finds no evidence of a statistically significant impact of these schemes in ensuring financial protection. Existing studies show that PFHIs tend to be concentrated in private sector and do not ensure equity in access or financial protection. Through PFHIs, the role of private sector in public policy has become more apparent. Our analysis suggests limited effectiveness of insurance-based models in solving the UHC problem of the country and questions their concerted expansion.

Keywords Publicly Funded Health Insurance Schemes (PFHIs), Universal Health Coverage, Health insurance, OOPE, Financial protection, RSBY

JEL classification I13, I18, I38, C26

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Introduction

In the case of India, as in other nations globally, there is an evident policy emphasis to achieve the longstanding objective of universal health coverage (UHC). The World Health Organization (WHO) defines UHC as "all people having access to the health care they need without suffering financial hardship." [24]. In recent times, India's commitment to the sustainable development goals (SDGs) to be achieved by 2030 provides another impetus to realize the goal of UHC [25]. To ensure financial protection from hospitalisation expenses, Publicly Funded Health Insurance schemes (PFHIs) are increasingly becoming one of the leading ways of financing healthcare, especially in low- and middle-income countries (LMICs).

There has been a wave of such schemes in the country, starting with the Rajiv Arogyashri scheme (RAS) in Andhra Pradesh in 2007 followed by similar schemes in other states like Tamil Nadu, Kerala, Karnataka to name a few. In 2008, the Union government launched Rashtriya Swasthya Bima Yojana (RSBY) for Below Poverty Line (BPL) workers in the informal sector to provide respite from hospitalisation expenses (mainly secondary care) for up to INR 30,000 annually per family. In 2018, Pradhan Mantri Jan Aarogya Yojna (PMJAY) was launched by the Union government with an annual cover of INR 5 lakh. With the launch of PMJAY and its rapid expansion, PFHIs have become dominant in the approach of government's policy to achieve UHC.

The central objective of PFHIs is to ensure financial protection from costly inpatient care. The schemes do not provide comprehensive care by design and focus on the more expensive secondary and tertiary care. From 2008, when the first national health insurance scheme RSBY was launched, to 2017-18 (the latest year for which data is available) a decade has passed. Some of the state-specific health insurance schemes have been operational for more than a decade. An empirical evaluation of these schemes is crucial to ascertain their impact on Out-of-pocket expenditure (OOPE). OOPE is the cost incurred at the point of use and exposes households to extreme vulnerability [42]. OOPE is considered one of the most regressive forms of health financing as access to medical care is determined by the financial condition of the household.

Recent studies have highlighted limited financial protection with these insurance schemes in different LMICs. Erlangga [12] has argued that the National Health Insurance in Indonesia had no significant impact on OOPE or catastrophic health expenditure (CHE). Thuong et al. [49] found no statistically significant impact of PFHI in Vietnam on the probability of having inpatient OOPE. In a similar vein, Liu and Zhao [33] have found that Urban Resident Basic Insurance does not reduce OOP spending in China. Another study by Wagstaff and Lindelow [52] points out that health insurance increases the risk of high and catastrophic spending in China. Bredenkamp and Buisman [6] have pointed out rising CHE and OOPE in Philippines despite a rise in insurance enrolment.

Similarly, in case of India, several studies have examined the impact on PFHIs on financial protection and provided evidence of limited or no impact of such schemes [16, 18, 28, 40, 41]. Prinja et al. [39] have provided a systematic review of impact evaluation studies focusing on PFHIs and financial protection in India. Of the seven studies with strong methodological design, five studies reported an increase in OOPE, while two studies-Fan et al. [13] and Sood et al. [48] showed a decline in OOPE. However, these two studies suffered from limitations owing to methodological problems in observational studies due to data constraints. The studies used indirect identification strategy like program rollout [13] and hospital admissions and deaths of conditions that are covered in these schemes [48] where PFHI beneficiaries were not directly observable in the data. Further, the short period of analysis makes it difficult to draw conclusive effects about the impact of the scheme. The use of OLS regression in Sood et al. [48] in the presence of endogeneity cannot yield rigorous impact evaluation results, also pointed out by Garg et al. [18]. Further, a distinction between OOPE at public and private hospitals has not been made. Recent evaluations of PMJAY [7, 16, 17] highlight that OOPE and CHE persist despite insurance.

In that regard, empirical evaluation of these schemes that improve methodological lacuna in the existing literature is crucial to engage with the larger debates on health systems, financing and achieving UHC. A study on PFHIs at a pan-India scale which understands their effectiveness on financial protection becomes imperative. Our study looks at the cause-and-effect relationship between PFHI enrolment and size of OOPE in India in 2017-18. We use instrumental variable analysis to address endogeneity to provide direct evidence about the schemes' impact. The evaluative studies on these schemes have mostly been small primary level studies, descriptive studies, or focused on a few states and most of the studies have not utilised the latest unit level data on household social consumption in health in 2017-18. This article is an intervention in this regard. Along with pan-India nationally representative results, the analysis also sheds light on different groups of states categorised based on proportion of their state's population covered by the schemes to understand if the effect of schemes varies for states with more population covered by the schemes or not. Such a study may provide us crucial insights in the functioning of existing PFHI schemes in the country and provide lessons towards informed policy decision-making.

This article is structured as follows. After discussing the 'materials and methods' in Sect 2, Sect 3 broadly studies the descriptive trends in OOPE and CHE incidence in India. Sections 4 and 5 aim to analyse causal inference between PFHIs and OOPE in India in 2017-18. Through rigorous empirical analysis, it is tested whether PFHIs have an impact in reducing OOPE. Section 6 delineates the discussion of findings before the limitations and conclusions of the study are laid out in Sects 7 and 8 respectively.

Materials and methods

This article is based on analysis of anonymised data from nationally representative large-scale surveys conducted by the office of National Sample Survey Organisation (NSSO), under the Ministry of Statistics and Programme Implementation (MoSPI), Government of India. We use the cross-sectional data from Household Social Consumption: health from NSS rounds – 60 (2004), 71 (2014) and 75 (2017-18). The latest round (75th) of NSS survey on health and morbidity was conducted from July 2017 to June 2018 and surveyed a total of 5,55,114 individuals. The 1,13,823 sample households comprised 64,552 rural households and 49,271 urban households.

We calculate OOPE per hospitalisation case as total expenditure incurred per hospitalisation case minus the amount reimbursed (by government, employer or insurance company) at 2017-18 prices. We use Consumer Price Index (CPI) data to adjust the expenditure figures. Further, a household is considered to have incurred CHE if the household OOPE is greater than 10 per cent (CHE-10), 25 per cent (CHE-25) or 40 per cent (CHE-40) threshold of the total household annual consumption expenditure [51]. We look at only inpatient expenditures for OOPE and CHE incidence as these schemes are targeted for hospitalisation expenses only.

We focus on the impact of PFHIs on financial protection and attempt to establish *causal inference* between the two. In the prevalent literature, health insurance has been identified as a potentially endogenous variable [13, 15, 26]. That is, households with relatively high health expenditures have a higher probability of being enrolled in a PFHI and the other way round, that the households with insurance coverage are seeking more healthcare [41]. In addition, poverty is a likely determinant of health insurance enrolment for financial protection [3, 15]. Selection-bias in insurance is problematic because an observable association between insurance and financial protection (say OOPE) may not be due to the insurance but due to other underlying unobservable characteristics such as socio-economic parameters like class, caste, religion among others. Ignoring endogeneity tends to exaggerate effects of insurance and price, creating a bias in the results [53]. According to [53], the essential selection bias problem is one wherein individual who self-select into the insurance programme have unobservable characteristics – related to preferences or health status – that make them more likely than others to join the programme and influence their decision to use health services. In our analysis, this may also influence the out-of-pocket expenditure observed.

We test the association between OOPE and PFHI enrolment by employing the causal inference technique of instrumental variable (IV) analysis (Sects. 4 and 5). A suitable IV instrumental variable should satisfy two conditions. "First, according to the *relevance criterion*, the instrumental variable is correlated with the causal variable of interest [PFHI enrolment in our case]. Second, according to the *exclusion restriction*, the instrumental variable is uncorrelated with the dependent variable [OOPE in our case]. That is, the only reason for the relationship between the outcome variable [OOPE] and the instrument is the causal variable of interest [PFHI enrolment]" ([2], p. 85). Further, a "good" instrument is one that comes from "institutional knowledge and one's ideas about the processes determining the variable of interest" (ibid. p. 170). For all model specifications, the IV regression results are generated using STATA 19 with the ivreg2 command.

Literature points out that the use of instrumental variable analysis can help address the issue of endogeneity in cross-sectional datasets [3, 32, 36, 43, 52]. This helps in eliminating some of the biases of observational studies to provide a rigorous impact evaluation of the PFHIs.

Since the NSS data on social consumption on health round 75 (2017-18) provides a neat separation of insurance categories of PFHIs from those of government employer schemes like the Central Government Health scheme (CGHS), (that was not the case in the previous round- NSS 71st round (2014)), we use the 75th round to carry our analysis.

Results: PFHIs and the desired financial protection- a descriptive enquiry

The PFHIs launched in the country have an exclusive focus to provide respite from costly inpatient treatment. This section will descriptively assess the financial protection provided by these schemes from 2004 to 2017-18. Two indicators of financial protection will be looked at- namely, average OOPE per hospitalisation case and incidence of CHE by the households.

Out-of-pocket expenditure in India- 2004 to 2017-18

The average OOPE incurred by Indians from 2004 to 2017-18 (at 2017-18prices) by quintile class of MPCE in rural and urban India showed an interesting picture. While average OOPE for all quintile classes showed a decline from 2004 to 2017-18 in rural India (see Table 1), in urban India, there was a steady rise during the same period (Table 2). This trend is statistically significant for

Table 1 Average OOPE in Rural India in INR (at 2017-18 prices), by quintile class: 2004 to 2017-18 (Hospitalisation case level)

Rural Quintiles	2004 (A)	2014 (B)	2017-18 (C)	Difference(C-A)
1st	10,851	9,054	8,964	-1,888***
2nd	11,762	11,430	11,076	-687
3rd	13,421	11,279	11,667	-1,754**
4th	15,249	14,753	13,588	-1,660**
5th	21,468	24,577	19,337	-2,131*
Total	16,112	15,433	13,602	-2,510***
Observations	20,066	29,844	51,724	

Source: Author's estimates using NSS unit-level records, Various rounds

Significance level: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

Table 2 Average OOPE in Urban India in INR (at 2017-18 prices), by quintile class: 2004 to 2017-18 (Hospitalisation case level)

Urban Quintiles	2004 (A)	2014 (B)	2017-18 (C)	Difference (C-A)
1st	11,732	11,142	12,356	624
2nd	12,303	15,361	15,634	3,331***
3rd	18,844	18,954	21,988	3,144
4th	22,010	25,354	22,468	458
5th	36,297	37,752	32,468	-3,830
Total	21,235	22,697	20,872	-363
Observations	11,849	25,182	39,725	

Source: Author's estimates using NSS unit-level records, Various rounds

Significance level: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

rural India but is only significant for the second quintile class in urban India. To get a better picture, the OOPE figures were disaggregated by the type of provider. There was a rise in the average OOPE incurred at private hospitals from 2004 to 2017-18 and a fall in the average OOPE incurred at public hospitals during the same period for rural and urban India. The fall (rise) in average OOPE for public (private) hospitals from 2004 to 2017-18 is evident for all the quintile classes (Table 3). The differences are statistically significant. The fall in average OOPE figures for rural areas and in public hospitals of the country warrants some explanation.

The falling OOPE in public hospitals is indicative of the role of public health intervention in the form of National Health Mission 2005. The period under study also corresponds to increased public health provisioning through the National Health Mission (NHM) that promoted public health system strengthening. The supply side financing scheme was launched by the Union government to support the state health systems. From its inception in 2005 to 2012, the focus was on rural areas. In 2013, the scheme was remodeled as NHM where urban areas were also included.

One of the objectives of NHM is to reduce OOPE (and not just explicit user fees). The NHM focused on reducing OOPE on drugs and diagnostics, where most expenditure was made. "The most cost-effective way of providing social protection against the rising costs of health care is by making a major part of health services available through public health facilities on cashless basis" [20]. Further, the provision of free drugs and diagnostics, free transport, and the removal of user fees under Janani Shishu Suraksha Karyakaram (JSSK), has brought down OOPE. To that effect, NHM-Free Drugs Service and NHM-Free Diagnostics Service Initiative were launched in 2015.

PFHIs are another government health intervention during the period of analysis. The policy rationale for introducing the schemes was to reduce OOPE with a Public Private Partnership (PPP) model for healthcare service delivery. However, the average OOPE in private

Table 3 Average OOPE in India in INR (at 2017-18 prices), by quintile class and Hospital Type (Hospitalisation case level)

	Public Hospitals				Private Hospitals			
Rural Quintile	**2004 (A)**	**2014 (B)**	**2017-18 (C)**	**Diff (C – A)**	**2004 (D)**	**2014 (E)**	**2017-18 (F)**	**Diff (F – D)**
1st	7385	4127	3052	-4332***	15,564	20,264	22,275	6711***
2nd	7848	5548	3672	-4176***	15,487	21,344	24,986	9499**
3rd	7654	4802	3602	-4052***	18,690	19,069	24,585	5895***
4th	10,204	5659	3839	-6365***	18,896	23,344	24,883	5987***
5th	13,462	8429	5144	-8318***	24,903	31,838	29,901	4998***
Observations	9542	15,989	30,766		10,490	13,855	20,958	
Urban Quintile	**2004 (A)**	**2014 (B)**	**2017-18 (C)**	**Diff (C – A)**	**2004 (D)**	**2014 (E)**	**2017-18 (F)**	**Diff (F – D)**
1st	6651	3960	3908	-2743***	17,897	19,705	23,316	5419***
2nd	7358	6221	4327	-3031***	16,205	22,974	25,966	9762***
3rd	8071	5760	4745	-3326***	25,941	26,231	33,989	8048***
4th	10,737	8469	5831	-4906***	27,579	32,152	30,017	2437
5th	17,971	19,435	7008	-10,963***	41,318	41,844	38,289	-3028
Observations	5115	10,277	16,735		6725	14,905	22,990	

Source: Author's estimates using NSS unit-level records, Various rounds

Significance level: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

hospitals did not fall from 2004 (pre-insurance) to 2017-18 (post-insurance) as seen in Table 3. There was no fall in the average OOPE per hospitalisation case for the first two quintile classes (that these schemes targeted at) during this period when care was sought in private hospitals. We will now evaluate the OOPE burden during this period among the *PFHI insured* and those not covered under any insurance (*uninsured*).

Insurance and OOPE in India

Table 4 shows the average OOPE for the PFHI insured population, other types of insured, and uninsured in public and private hospitals for rural and urban areas. While the high difference between the public and private OOPE is notable for the insured as well as uninsured (public hospitals provide subsidised care), being covered by a health insurance programme does not lead to zero OOPE. For an uninsured individual taking treatment in a public hospital, the average OOPE is less than that for all types of insured in rural areas (except PFHI covered where the OOPE falls further) and for all cases where care is sought in private hospitals (Table 4). Mean test of differences in OOPE for PFHI covered and not covered is statistically significant in private hospitals. That is, there is some reduction in OOPE, however, average OOPE for PFHI covered private hospitalisations is INR 22,293 in rural areas and INR 26,185 in urban areas. This questions the effectiveness of insurance in providing financial protection especially when treatment is sought at a private healthcare facility. However, there might be some effect arising out of the fact that public and private hospitals are treating different types of diseases.

Catastrophic health spending in India

To get a deeper insight into the effectiveness of these schemes, it is important to look at catastrophic incidence among households. This is because the schemes cover procedures that have a debilitating financial effect on the households. While RSBY covered secondary care, the newer generation of insurance schemes provide cover against tertiary care, in particular surgical care [31]. The prime objective of these schemes is to offer financial protection against CHE, defined in terms of hospitalisation care (ibid.). The most recent national-level PFHI-PMJAY, "envisions to help mitigate CHE on medical treatment which pushes nearly 6 crore Indians into poverty each year [23].

Through a descriptive evaluation, we wish to assess the role played by the PFHIs in reducing the incidence of CHE by the households. We look at the CHE incidence among the households in the country by their insurance coverage in 2017-18 (Table 5). Despite PFHI coverage, 32.3 per cent, 14.5 per cent and 8.3 per cent of households incurred CHE at 10, 25 and 40 per cent of their annual consumption spending, respectively. When testing if the difference in CHE incidence at the three levels of threshold is statistically different from those without insurance (uninsured), our result became insignificant. That is, the CHE incidence between the PFHI covered and uncovered households was not statistically different from each other. However, this was not the case with government employer insurance, wherein CHE incidence among those covered by government employer schemes like CGHS and private employer schemes like ESI have lower CHE incidence than the uninsured and the difference is statistically significant.

In Table 6, we look at the provider type and type of insurance of households, while computing the CHE

Table 4 Average OOPE in India in 2017-18 in INR - By Insurance Type and Hospital type, (Hospitalisation case level)

Insurance type	PFHI (A)	Government Employer (e.g. CGHS)	Private employer (e.g. ESIS)	PVHI	Not insured (B)	Difference(C) (A – B)
Rural						
Private hospitals	22,293	26,984	22,997	17,795	27,313	-5020***
Public hospitals	3,627	7,018	4,181	5,913	3,887	-260
Observations	8,653	645	284	231	41,374	
Urban						
Private hospitals	26,185	29,069	20,637	29,232	33,037	-6852***
Public hospitals	4,590	4,065	3,473	6,601	4,879	-289
Observations	4,049	1,807	1,171	1,657	30,552	
Total						
Private hospitals	23,361	28,515	21,219	27,702	29,478	-6,117***
Public hospitals	3,846	5,085	3,677	6,364	4,122	-276
Observations	12,702	2,452	1,455	1,888	71,926	

Source: Author's estimates using NSS unit-level records, Various rounds

Significance level: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Note: PVHI is abbreviated for Private Voluntary Health Insurance, CGHS is abbreviated for Central Government Health Scheme and ESIS is abbreviated for Employees' State Insurance scheme

Table 5 CHE incidence in India, by Insurance type: 2017-18 (Per cent Households)

CHE	PFHI (A)	Govt. Employer (e.g. CGHS)	Private Employer (e.g. ESIS)	PVHI	Uninsured (B)	Difference(C) (A – B)	T statistic
CHE-10	32.3	26.5	29.9	31.8	32.7	-0.4 (0.010)	-0.15
CHE-25	14.5	9.9	11.0	12.2	13.7	0.8 (0.007)	0.96
CHE-40	8.3	5.6	6.7	7.8	7.8	0.5 (0.005)	0.62

Source: Author's estimates using NSS unit records, Various rounds

Note the difference is in percentage points

Significance level: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

Robust standard errors are indicated in parentheses

Table 6 CHE Incidence in India: 2017-18, By insurance type and provider type (Per cent Households)

Insurance type	CHE-10			CHE-25			CHE-40		
Provider type	Public	Private	Difference	Public	Private	Difference	Public	Private	Difference
PFHI	17.3	64	46.7***	7.6	32.2	24.6***	1.1	19.5	18.4***
Govt. Employer	5.0	42.6	37.6***	2.8	16.4	13.6***	0.9	8.6	7.7***
Pvt. Employer	11.4	46.8	35.4***	4.5	12.1	7.6	1.1	8.9	7.8
PVHI	11.4	37.6	26.2***	6.1	18	11.9*	0.9	12	11.1***
Not insured	12.6	63.2	50.6***	4.9	28.7	23.8***	1.2	17.5	16.3***

Source: Author's estimates using NSS unit-level records, Various rounds

Note the difference is in percentage points

Significance level: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

incidence for the households in 2017-18. For each type of insured and the uninsured, the per cent of households incurring CHE at 10, 25 and 40 per cent thresholds is higher for private hospitals than public hospitals. These differences are statistically significant. Notably, despite PFHI coverage, there was considerable CHE incidence especially in the private hospitals. These figures are approximately similar to the uninsured households.

This section looked at the descriptive statistics of inpatient OOPE in the country from 2004 to 2017-18. There is a statistically significant rise in private inpatient OOPE in both rural and urban India for all quintile classes of MPCE. For public hospitalisations, there is a statistically significant decline in average OOPE in both rural and urban areas and for all quintile classes of MPCE during the same period. Despite PFHI coverage, the private inpatient OOPE is high and suggests limited effectiveness of insurance schemes in securing financial protection. In the following sections, we test the effectiveness of insurance schemes in India by employing a causal inference channel to be able to draw robust conclusions.

Results: Instrumental variable regression – based on programme coverage

Our descriptive study pointed out little respite from OOPE and CHE with PFHIs in India even though providing financial protection from costly inpatient care is one of the main aims of these schemes. Here, we test the association between insurance and OOPE further. Through the following econometric exercise, we aim to assess the *impact* of PFHIs on financial protection, mainly OOPE on health. This can help in making a more detailed comment on their effectiveness and impact.

We use the district-wise and state-wise coverage of PFHIs in the country as an Instrumental variable (IV) in capturing the effect of insurance on financial protection. The level of diffusion or penetration of insurance at a possible granular level with the existing data is assumed to have a direct impact on the behavior choice of households in enrolling into the scheme but is not related to OOPE except through the insurance choice. A continuous variable is used that ranges from 0 to 100 per cent and is calculated by looking at the PFHI covered individuals (district-wise and state-wise) as a proportion of the total population (district-wise and state-wise). To avoid mechanical correlation, we calculate the proportion of PFHI enrolled in the district excluding the person herself. The leave-one-out instrument is widely used in impact evaluation analyses [2, 11, 14, 34, 53]. Similar identification strategy that uses level of program diffusion as an instrumental variable was used for an impact-evaluation study of health insurance for the poor on OOPE in Mexico [15] and as a correction for selection bias in health insurance in Ecuador [53]. Galárraga et al. [15] used program penetration variable by taking the "ratio of insured households over eligible (uninsured households) at the locality level" (p. 442). They used this variable as an aggregate continuous proxy for program participation at the household level. Waters [53] has used the average GHI insurance affiliation rate in the community as an instrumental variable for insurance. It is calculated using all the values in the community other than the value for the individual in the question. The use of community controls in regression has also been suggested by [29].

The main explanatory variable to be analysed here is enrolment into the PFHIs. Since PFHI enrolment is endogenous, we instrument this by using district wise PFHI coverage (continuous variable- 0 to 100 per cent).

Outcome variable

Out-of-pocket expenditure (OOPE) is the dependent variable in our analysis. The OOPE is calculated per hospitalisation case as the difference between the total expenditure and total reimbursement (if any). Note that for inpatient care, the total expenditure includes medical expenditure as well as non-medical expenditure (loss of income, food and stay of the attendant etc.).

Covariate vector

The covariates used in the regression analysis include religion, sector (rural or urban), gender, household size, monthly per-capita consumption expenditure (MPCE), type of hospital (public or private), social group (ST/SC/OBC/Others) to control for the socio-economic characteristics of households. In addition, we use a categorical variable that categorizes the states of the country in four groups- (i) Group 1 states (high coverage states): where more than 50 per cent of the state's population is covered by a PFHI scheme, (ii) Group 2 states (medium coverage states): where 20 to 50 per cent of state's population is covered by a PFHI scheme, (iii) Group 3 states (low coverage states): where 5 to 20 per cent of state's population is PFHI covered, and (iv) Group 4 states (very low coverage states): where less than 5 per cent of state's population is PFHI covered. Two district level covariates are included, district-wise hospitalization rate and log mean monthly per capita expenditure of the district to control for the health demand and economic condition at the district level. Please refer to table A2 of the annexure for summary statistics of the key hospitalization variables.

The software uses the traditional two-stage least squares approach as follows.

$\mathrm{Y}_j = \mathrm{X}_j \ + \ \mathrm{T}_j \ + \ \mathrm{e}_j$

$\mathrm{T}_j = \mathrm{Z}_j \ \gamma + \mu_j$

here Y is OOPE per hospitalisation case (at 2017-18 prices), X is the covariate vector, T is PFHI enrolment (where PFHI enrolment is a binary variable with 0 signifying not enrolled in any insurance scheme and 1 signifying enrolled in PFHI) and Z is the instrumental variable.

Table 7 looks at the IV regression results for all states of the country with and without state FE. In addition, we added a regression specification (columns 3 and 4) where we used the categorical variable of states according to their population coverage as a control variable. We find that there is no statistically significant impact of PFHIs on average OOPE per hospitalisation case in the country in 2017-18. The public OOPE per hospitalisation case was substantially less than the private OOPE for all the regression specifications run. From tables A2 to A5, an expected gradient in terms of increased financial protection in states categorized according to PFHI coverage. Thus, no statistical relationship between PFHI coverage and OOPE questions the role of these schemes in effectively securing financial protection for inpatient care.

We run the IV regressions for the four distinct groups of states based on their insurance coverage separately. Here, we argue that using this as a control variable in a single regression run for all the states is not enough as there are wide state-wise differences in insurance coverage. For example, Andhra Pradesh and Bihar have a huge difference in proportion of the state's population covered by a PFHI scheme. To make the comparisons better and to get robust estimates for the impact of these schemes on OOPE, we argue in favor of running the regression specifications for each group of states separately. Refer to Tables A3 to A6 for detailed regression results for high coverage states, medium coverage states, low coverage states and very low coverage states respectively for the year 2017-18. The summary results are presented in Table 8.

Results: Robustness checks for IV regression

We argue that a continuous variable depicting the level of penetration or diffusion of PFHIs district-wise in each state of the country may help deal with the issue of possible endogeneity. We argue that this IV is not correlated with the error term as district-wise PFHI coverage is correlated with some supply side characteristics like the number of hospitals available, administrative outreach and community-level effects of programme participation across districts within the same state. We use state fixed effects, district controls (mean MPCE and hospitalization rate) and other socio-demographic and hospitalization related controls. Given the set of covariates, we argue that the leave-one-out instrument is not correlated with the demand side observable characteristics like income, social group among others, that may also be correlated with OOPE (dependent variable). This identification strategy by using a geographical indicator to proxy for program diffusion should give us more robust results as it is not related to the health expenditures of the individuals directly. Through falsification and sensitivity checks, the instrument predicts outcome for a subsample of eligible households and does not affect outcomes not related to insurance. This consolidates the choice of the IV further. In the next section, we perform the necessary

Table 7 IV Regression results: All States

VARIABLES	(1)	(2)	(3)	(4)
	OOPE	Log OOPE	OOPE	Log OOPE
PFHI (Instrumented)	-5,238	-0.0461	-6,279	-0.00139
	(3,783)	(0.117)	(4,102)	(0.135)
Monthly per capita consumption expenditure	3.315***	0.0001***	3.294***	0.0001***
	(0.487)	(7.70e-06)	(0.482)	(7.97e-06)
Sector: Urban	-713.3	-0.0195	-533.3	-0.0307
(Base: Rural)	(694.7)	(0.0239)	(665.8)	(0.0250)
Household Size	577.1***	0.0268***	549.8***	0.0198***
	(106.4)	(0.00380)	(108.5)	(0.00405)
Gender: Female	-3,921***	-0.0940***	-3,884***	-0.0871***
(Base: Male)	(793.7)	(0.0241)	(805.7)	(0.0244)
Hospital Type: Public hospitals	-21,473***	-2.097***	-20,702***	-2.034***
(Base: Private hospitals)	(735.4)	(0.0317)	(682.6)	(0.0313)
Mean Hospitalisation rate (district-wise)	-20,161	-2.766***	-1,426	-0.462
	(17,679)	(0.719)	(10,928)	(0.651)
Log (Mean MPCE (district-wise))	452.8	0.293***	-1,577	0.119*
	(1,728)	(0.0579)	(1,324)	(0.0668)
High coverage states			3,563	-0.126
(Base: Very low coverage states)			(3,617)	(0.107)
Medium Coverage states			-200.0	-0.0114
			(1,977)	(0.0597)
Low coverage states			932.1	0.0503
			(1,303)	(0.0549)
Religion FE	Yes	Yes	Yes	Yes
Social Group FE	Yes	Yes	Yes	Yes
Disease FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	No	No
Constant	11,562	7.566***	22,687**	7.869***
	(13,833)	(0.434)	(9,966)	(0.465)
Observations	84,628	84,628	84,628	84,628
R-squared	0.168	0.520	0.163	0.498

Source: Author's estimates using NSS 75th round

Standard errors in parenthesis (clustered at district level). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 8 Summary results for IV regression

State group	Log (OOPE)	Under-identification test (*p* value)	Weak IV (F -statistic)	Observations
High coverage states	0.014 (0.283)	0	146.427	9,348
Medium Coverage states	0.046 (0.128)	0	727.041	9,370
Low coverage states	-0.41** (0.204)	0	255.263	19,059
Very low coverage states	1.554* (0.902)	0	428.814	46,851
All states	-0.046 (0.117)	0	1136.173	84,628

Source: Author's estimates using NSS 75th round

Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Standard errors in parentheses (clustered at district level)

post-estimation tests for robustness for the IV regressions done.

This section discusses the post-estimation tests run for the regression specifications for the IV regression. (see Table 8). 'Weak identification' arises when the excluded instruments are correlated with the endogenous regressors, but only weakly. Therefore, when instruments are weak, estimators can perform poorly [4]. The weak IV test statistic for high coverage states, medium coverage states, low coverage states and very low coverage states, is much higher than the Stock Yogo critical values. Hence, we reject the null hypothesis that the instrument is weak. That is, for all India as well as all state groups (according to coverage) pass the weak IV test.

"The underidentification test is an LM [Lagrange-multiplier] test of whether the equation is identified, i.e., that the excluded instruments are "relevant" or correlated with the endogenous regressors. Under the null, the statistic is distributed as chi-squared with degrees of freedom=(L1-K1 + 1). A rejection of the null indicates that the matrix is full column rank, i.e., the model is identified" [5]. Here, the null hypothesis is rejected, and the model is identified for all the groups of states and regressions for all India (Table 8). The test of underidentification further consolidates the model.

"For overidentifying restrictions, Sargan Hansen test is used with the joint null hypothesis that the 'instruments are valid instruments', i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. If the null hypothesis is rejected, it may raise doubt on the validity of the instruments" [5]. However, the test cannot be applied as only one continuous variable is used as an IV. In that case, the validity of the instrument through this test cannot be tested.

The summary results are presented in Table 8. We find no significant effect of PFHI enrolment on OOPE for high coverage and medium coverage states. In low coverage states, we find a statistically significant reduction in OOPE at 5 per cent level of significance. However, when the same analysis is done by excluding Tamil Nadu, the significant effect disappears. We argue that the reduction in OOPE as seen in the low coverage states, was due to TN characterized by the strong public health system of the state. For very low coverage states, a significant but positive relationship between log OOPE and PFHI enrolment emerges (where PFHI enrolment leads to a significant increase in the OOPE). The post-estimation tests validate our findings that the instrumental variable is not weakly identified and that the model is not underidentified. The results did not differ when the regression analysis was done for alternate specification where the explanatory variable was PFHI covered versus non-PFHI covered (including all other types of insured). That is, the coefficient for PFHI covered continued to have no significant effect on OOPE reduction except for low coverage states.

Discussion

In this article, we investigate the effectiveness of PFHIs in India in achieving its primary objective, ensuring financial risk protection from hospitalisation expenses. Our descriptive findings indicate that despite being covered by PFHIs, there is OOPE incurred per hospitalisation case and households incurred CHE. The level of OOPE and CHE incidence is significantly higher in private hospitals. Notably, the CHE incidence between PFHI covered and 'not covered' is *not* statistically different from each other.

It is important to test the association between PFHIs and OOPE to determine if the schemes had any impact in reducing OOPE. We use an instrumental variable analysis to address the issue of endogeneity in data relating to health insurance. Our analysis provides evidence that PFHI enrolment and OOPE burden per hospitalisation case are not statistically related i.e., the scheme has no significant impact on OOPE in 2017-18. That is, it does not lead to a significant reduction in OOPE relative to individuals not covered under any insurance scheme. In addition, we find no evidence of significant impact of PFHIs on OOPE per hospitalisation case, for high coverage states and medium coverage states. For low coverage stages, we find that the reduction in OOPE is primarily driven by Tamil Nadu. For very low coverage states, there is a rise in OOPE associated with PFHI coverage. However, the difference in the public and private OOPE per hospitalisation case, even for the insured population, is statistically significant. Finally, sub-group analyses exploring the distributional and equity effects of PFHIs in India show no significant impact of the schemes for the bottom two quintiles, casual labour households and rural areas. A small positive effect is seen on males and third quintile class of MPCE.

Our findings are consistent with the more recent literature on these schemes. Karan et al. [28] used a DID framework to show that neither the likelihood of inpatient spending nor the amount spent on inpatient care or CHE reduced. Garg et al. [18] argue that even for states with a greater financial cover (Tamil Nadu, Karnataka and Andhra Pradesh) than the national-level PFHI, i.e. RSBY, enrolment under these schemes is not associated with a reduction in the size of OOPE. Garg et al. [16] used IV regression with Propensity Score Matching (PSM), provided evidence that there was no impact of PMJAY or other insurance schemes on OOPE and incidence of CHE in Chhattisgarh. Ranjan et al. [40] used the PSM technique and found there is no statistically significant association between PFHI enrolled and CHE for the bottom three quintiles.

Some of the reasons for the limited effectiveness of these schemes include the continued spending on drugs and diagnostics despite insurance – non-availability of drugs and diagnostics or not covered under RSBY [1, 18, 28], the provider behavior and lack of regulation of private providers [18] due to mechanisms at play including provider capture and double billing [16, 40], "the lack of an appropriate regulatory regime and poor monitoring and governance leading to different forms of co-payment and manipulation, commonly referred to as 'gaming the system' ([40], p. 10).

Another reason for OOPE being incurred could be due to the low utilization of the PFHIs when hospitalized due to several demand and supply side factors. Our analysis focuses on coverage alone, but recent studies have highlighted that despite being covered and hospitalised, there are issues with scheme usage [7, 17]. Some of those who are covered and did not use the scheme will incur more OOPE. Furthermore, those who are covered and used the scheme, also incur OOPE when providers ask for payments for diagnostic tests done before admission in the fear that the case might not ultimately lead to hospitalization under the scheme or even pay for the difference in the cost paid by the government and the providers' preferred treatment [17, 44, 50]. With the expanded PFHI-PMJAY, the public policy moves ahead with its continued focus on these schemes as a strategy to achieve UHC. It becomes imperative to assess its value at large.

The emergence of PFHIs in the forefront of public policy pronouncements demonstrates a major change in the health-financing paradigm in the LMICs. There is a shift from supply side financing to demand side financing with these insurance schemes. With PFHIs, the role of the private sector in public policy has become more apparent. Strategic purchasing and purchaser-provider split are the key elements of these schemes [18, 31, 46]. In PFHIs, there is a clear separation between the financing and provisioning function, wherein the funding comes from public resources while treatment can be provided by a public or a private provider. These changes are indicative of a move away from input-oriented approach to output-based models [45].

However, there are certain issues associated with an ever-increasing role of the private sector. Other studies have highlighted the equity considerations while accessing private care, where the most vulnerable groups are not able to use it as well as the better off do [10]. Other studies have highlighted that the public sector is less expensive and catered to the more vulnerable groups [38]. Nandi and Schneider [37] argue that utilisation in the private sector was disproportionately higher in areas with least social and health need thereby exhibiting the Inverse Care law [21]. Choudhury and Datta [8] provided evidence that the empanelment of private hospitals by insurance companies is relatively low in states with low per capita incomes, where a substantial proportion of PMJAY beneficiaries are concentrated. Therefore, the private sector leading to inequity in access, availability and affordability needs to be highlighted out more to question the focus on privatisation in public policy.

Limitations

NSS household social consumption on health in India in 2017-18 is based on household-reported OOPE. This has limitations arising out of the longer recall period of 365 days, as well as estimates of expenditures on pre-hospitalisation and post-hospitalisation is not captured. Further, the paper has used an instrumental variable analysis. Given the nature of the method, the problem of endogeneity remains anomalous and cannot be dealt with entirely, especially with the limitation of using cross-sectional survey data. We argue that the IV regression with district controls capturing the economic development and hospitalization rates, state fixed effects and household socioeconomic control variables, plausibly satisfies the exclusion restriction as supported by sensitivity and consistency checks. Finally, the availability of the upcoming NSS 80th round can help in assessing the effect of the expanded PFHI-PMJAY in ensuring reduction in OOPE at the national level.

Apart from the methodological limitations, it is important to state the limitations of the use of the UHC framework. It is seen that universal health coverage is a relatively restrictive notion compared to the idea of universal health care, with the former primarily focusing on financial protection irrespective of the nature of the health system overall. Universal health care, on the other hand, is a more inclusive concept that brings an emphasis on building a comprehensive health care system that addresses curative as well as preventive and promotional aspects. While acknowledging this limitation of the universal health coverage concept, this article continues to use UHC in the sense of coverage as the main aim here is to assess the PFHI schemes, which in turn are primarily focused on financial protection. The larger critique of how such a focus does not address many of the gaps in the health system remains relevant.

Conclusion

In this article, we raise our concerns regarding the insurance-based model of healthcare solving the OOPE problem of the country. There are wide state-wise differences in population coverage [22, 47], however, for financial coverage, no evidence of significant impact of these schemes is seen across different categorization of states based on their population coverage. This is telling since no statistically significant relationship between PFHI coverage and OOPE is seen even for the high and medium coverage states. The evidence from the literature and our analysis till now (2017-18 to be precise) given the most recent pan-India data available bring out the limited effectiveness of insurance schemes in India in terms of its central argument of ensuring financial risk protection.

We highlight some important considerations for policy focused on PFHIs in realizing the goal of UHC. Firstly, despite insurance, private sector hospitalisations are associated with higher OOPE and CHE incidence. Other studies have pointed out issues of double billing associated with provider behaviour leading to different forms of copayments by the beneficiaries to the private hospitals. This entails stricter governance and monitoring by the government in ensuring provider compliance with the contract between the provider and the government within the scheme. Secondly, our descriptive findings showed a reduction in OOPE seen in public hospitals and rural hospitals from 2004 to 2017-18. Thirdly, our empirical analysis finds evidence that there is reduction in OOPE in low coverage states, that is driven primarily by Tamil Nadu. With TN's strong public health system and primary healthcare system in place [35, 9, 27], OOPE can be reduced. Within PFHIs, there needs to be a focus on prioritization of public hospitals. Necessary gate-keeping system can be put in place that allows treatment in a private hospital conditional on referral from a public facility. Finally, efforts made in strengthening the public health system has the dual advantage of ensuring financial protection as well as equity. This can reduce the dependence on the private sector.

The schemes are recent and the lack of data in the public domain makes it difficult to conclusively say that insurance-based financing models can solve the universal health coverage problem of the country. This article is significant in exploiting the available dataset and questions the PFHI strategy in the form of scaling up of the previous national PFHI – RSBY into the more recent PMJAY and understand its possible future trajectories. While these surveys do not yet capture the effects of the expanded national PFHI, PMJAY, the state schemes have a similar design, that is, they are targeted schemes for a few households and only cover inpatient care. The article encourages further research into these schemes and analyses of the impact of the expanded PFHI-PMJAY.

Kutzin [30] correctly suggests that to attain UHC, policy and policy analysis need a shift from schemes to system. George [19] argues that giving mere assurance to every individual (demand side) without ensuring necessary healthcare services to the population (supply side) is a severe miscalculation that will cost the health of the population. The continued reliance on the private sector within a public programme for health insurance needs to be cautioned. The equity concerns raised in the literature regarding the involvement of the private sector cannot be ruled out. The results from our analysis highlight a need to re-evaluate the policy focus on PFHIs as a channel for reducing OOPE burden and, therefore, in solving the UHC problem of the country. Finally, there is a need to emphasise the alternative healthcare financing model that is publicly financed and publicly provided that needs to be strengthened.

Abbreviations

BPL	Below Poverty Line
CGHS	Central Government Health Scheme
CHE	Catastrophic Health Expenditure
CHE-10	Catastrophic Health Expenditure calculated using the threshold of 10 per cent of usual annual consumption spending
CHE-25	Catastrophic Health Expenditure calculated using the threshold of 25 per cent of usual annual consumption spending
CHE-40	Catastrophic Health Expenditure calculated using the threshold of 40 per cent of usual annual consumption spending
CPI	Consumer Price Index
ESIS	Employees' State Insurance Scheme
FE	Fixed Effects
HLEG	High Level Expert Group
IV	Instrumental Variable
JSSK	Janani Shishu Suraksha Karyakaram
LMICs	Low and Middle Income Countries
MoSPI	Ministry of Statistics and Programme Implementation
MPCE	Monthly Per capita consumption expenditure
NHM	National Health Mission
NSS	National Sample Survey
NSSO	National Sample Survey Office
OBC	Other Backward Castes
OLS	Ordinary Least Squares
OOPE	Out of pocket expenditure
PFHIs	Publicly Funded Health Insurance schemes
PVHI	Private Voluntary Health Insurance
PMJAY	Pradhan Mantri Jan Arogya Yojana
RAS	Rajiv Arogyasri scheme
RSBY	Rashtriya Swasthya Bima Yojana
SC	Scheduled Castes
SDGs	Sustainable Development Goals
ST	Scheduled Tribes
UHC	Universal Health Coverage
WB	World Bank
WHO	World Health Organization

Supplementary Information

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Supplementary Material 1

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Author contributions
AS has contributed to the study design, data analysis, interpretation and writing of the manuscript.

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Data availability
The data is derived from datasets available in public domain. NSS 75th round on Household Social Consumption: Health can be accessed from [https://microdata.gov.in/nada43/index.php/catalog/152] (https://microdata.gov.in/NADA/index.php/home). NSS 71st round: Social Consumption: Health, can be accessed at [https://microdata.gov.in/nada43/index.php/catalog/135]. (https:/microdata.gov.in/nada43/index.php/catalog/135). NSS 60th round: Survey on Morbidity and healthcare, can be accessed at [https://microdata.gov.in/nada43/index.php/catalog/107] (https:/microdata.gov.in/nada43/index.php/catalog/107).

Declarations

Ethics approval and consent to participate
Ethical approval for this study was not needed. This article is based on anonymized data from secondary source (cross-sectional data), National Sample Survey (NSS) 75th round Household Social Consumption: Health available in public domain. It can be accessed upon registration at https://m

icrodata.gov.in/nada43/index.php/catalog/152. The Ministry of Statistics and Programme Implementation (MoSPI), Government of India suppresses or anonymises the identification details of individuals/establishments. The author did not have access to any identifiable information related to the households. The survey is conducted by the National Sample Survey Office (NSSO) of the Ministry of Statistics and Programme Implementation of the Government of India. Data available in the public domain are approved for research purposes by Ministry of Statistics and Programme Implementation, Government of India. Refer to https://mospi.gov.in/sites/default/files/data_disemination/Data_Dissemination_Guidelines%20_feb19.pdf for data dissemination guidelines.

Consent for publication
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