Applied Health Economics and Health Policy
https://doi.org/10.1007/s40258-026-01051-5

ORIGINAL RESEARCH ARTICLE

Causal Impact of Primary Care and Publicly Funded Health Insurance on Catastrophic Health Spending From Climate-Sensitive Diseases in India

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Received: 26 December 2025 / Accepted: 18 May 2026

Abstract

Background Universal health coverage has become central to health policy debates, particularly as a strategy to protect households from financial hardship and impoverishment related to out-of-pocket (OOP) spending. Many low- and middle-income countries (LMICs), including India, have relied predominantly on publicly funded health insurance (PFHI) to improve financial protection against OOP spending. PFHI generally covers low-frequency, high-cost hospitalization expenses, even though non-hospitalization expenses are the main contributors to OOP. Global evidence suggests that stronger primary health care (PHC) provision is crucial for reducing catastrophic health expenditure (CHE). This issue becomes particularly important in the context of climate-sensitive diseases (CSDs), whose incidence is increasing due to more frequent and extreme weather events, which may increase the risk of CHE.

Objective This study estimates the causal impact of publicly provided PHC and PFHI on CHE arising from CSDs.

Methods Using district-level data for all 640 Census districts in India, we applied propensity score matching and inverse probability weighting to compare the effects of PHC and PFHI on CHE associated with CSDs.

Results The findings show that strengthened PHC substantially reduces OOP spending and CHE associated with CSDs, whereas PFHI shows no statistically significant effect.

Conclusion These results highlight the need to prioritize climate-resilient PHC systems to address the escalating health impacts of climate change and advance equitable progress toward universal health coverage in LMICs.

1 Background

Climate change is now widely acknowledged as one of the most significant threats facing humankind. Among its many consequences, climate change has resulted in increased global average temperatures, changes in precipitation patterns, rising sea levels, and an increase in the frequency and intensity of extreme weather events (EWEs) [1]. In addition to the physical damages associated with natural disasters and climate extremes, the human health

Key Points for Decision Makers

Strengthening primary health care may be more effective in reducing financial hardship from climate-sensitive diseases than expanding publicly funded health insurance alone.

As climate-sensitive diseases increase with more frequent extreme weather events, climate-resilient primary health care systems are essential to ensure timely, equitable, and affordable access to care.

Progress toward universal health coverage in India may require greater public investment in comprehensive primary health care, with less reliance on insurance-led approaches focused mainly on tertiary care.

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Published online: 01 June 2026

impact of climate change has been significant and has received widespread recognition in political and scientific forums [2].

According to the World Health Organization (WHO), the mortality burden caused by climate-induced emergencies like heat stress, malnutrition, and malaria is projected to increase by 250,000 deaths annually between 2030 and 2050 [3]. While climate-related health impacts are expected to affect all regions worldwide, people living in countries with weaker health systems are anticipated to be at greater risk. Given the extent of human health risks posed by the climate crisis, *climate resilient* health systems are being tasked with meeting the healthcare needs of the population during disasters. Despite the uncertainties associated with a rapidly changing climate, climate-resilient health systems have the capacity to predict, address, cope with, and recover from the damages caused by external stressors [4].

Resilience of health systems is measured by their ability to handle health risks, without disrupting the continuity of vital health care functions. Resilient health systems are typically those that have improved their adaptive capacities, which is the ability to withstand shocks and recover from their damaging impact, by taking certain timely measures [5]. Some of these measures include strengthening primary health care (PHC), addressing shortages of human resources and infrastructure, building climate-resilient healthcare facilities, identifying barriers to healthcare access, assessing efficacy of healthcare functions and interventions so that they remain functional and responsive during disasters, and strengthening surveillance capacities to track population health and environmental risks [6]. Furthermore, resilient health systems are able to reorganize services to respond effectively to adversities and the changing needs of people, which is why they are also adaptable [7].

In addition to ensuring that healthcare is provided uninterrupted during crises, resilient health systems are recognized for delivering good health outcomes during times of normalcy [7, 8]. Such systems possess certain important characteristics that merit attention. First, resilient health systems encourage individuals to seek regular and timely healthcare, which increases the likelihood of timely detection of potential health threats [9]. Second, resilient health systems when underpinned by strong PHC, are well equipped to diagnose and manage both emerging and existing health threats [10]. This strength stems from the potential of primary care to coordinate care across various levels of the health system and treatment specializations [11]. Third, health systems that are resilient have the ability to adapt and use lessons learned from crises to improve healthcare delivery during normal times [8].

The concept of universal health coverage (UHC) provides the foundation for resilient health systems. Formally emphasized in the World Health Assembly (WHA) Resolution 58.33 in 2005, UHC encourages member states to expand financial coverage to ensure adequate and equitable distribution of health care, and to prevent catastrophic health expenditure (CHE) and impoverishment caused by seeking medical care [12]. As UHC recognizes some critical market failures in healthcare, espouses a greater role for public financing in augmenting demand, and promotes equitable, affordable, adequate, and continuous access to care, resilience is an integral component of health systems [8]. A UHC-driven approach is crucial for achieving resilience in health systems in the following ways. First, UHC is grounded in the principle of equity, emphasizing improved healthcare access for all, regardless of socioeconomic status. Similarly, resilient health systems prioritize health care for the most vulnerable, who are most affected during crises. Second, UHC highlights financial protection against CHE, especially vital in times of crisis when communities face heightened economic strain. Third, UHC stresses the need for access to consistent, high-quality care, while resilient health systems ensure essential services continue even during disasters.

In 1978, the Alma-Ata Declaration highlighted the importance of an integrated and well-functioning PHC to ensure that everyone achieved the highest attainable level of health by the year 2000 [13]. PHC essentially includes three interlinked components: meeting the preventive, promotive, curative, rehabilitative, and palliative healthcare needs of individuals in primary care and providing core public health functions at the population level; adopting multi-sectoral measures to address the determinants of health; and empowering people and communities to participate in healthcare decision making and developing health services [14]. The principles of the Alma-Ata Declaration were reaffirmed in 2018 by the Astana Declaration, which stressed that PHC is the foundation for countries to attain UHC [13].

Several studies have demonstrated that robust PHC has been instrumental for health systems in achieving UHC in many countries. For instance, Kruk et al. [15] asserted that between 1978 and 2008, low- and middle-income countries (LMICs) that enhanced PHC initiatives facilitated better access to healthcare for the poor in cost-effective ways. This phenomenon improved healthcare access among rural populations and resulted in better health outcomes, especially in Latin American countries like Haiti [15]. Perry et al. [16] showed that community-based PHC projects that had been operational in Bangladesh, Haiti, and India led to improvements in child survival outcomes. Reductions in child mortality were achieved through the engagement of community-level workers who maintained regular contact

with communities and served as the first point of contact for healthcare [16]. Despite the fact that well-functioning primary health systems can aid countries in achieving UHC in cost-effective ways, they have not been prioritized in many countries, including India.

Publicly funded health insurance (PFHI) has been promoted as an effective strategy to address crucial market failures in delivering UHC [17]. However, the efficacy of health insurance in boosting utilization of inpatient department (IPD) care and reducing out-of-pocket (OOP) expenditure has been disputed both in international and national settings. For instance, Wagstaff and Lindelow [18] used three household surveys in China from 1994 to 2004 to show that health insurance contributed to an increase in OOP spending and aggravated the risk of sizable CHE. Wagstaff and Lindelow [18] highlight that the government's schedules for physicians' fees and medicine prices encourage the provision of high-tech sophisticated health care in China. Providers typically offer expensive care beyond what is considered medically necessary for their personal gain [18]. In situations like these, those with insurance are likely to receive more than necessary medical care and incur higher OOP expenses than those without insurance coverage.

Findings from India mirror these concerns. Based on their analysis of the National Sample Survey (NSS) consumer expenditure data from 1999 to 2012, Karan et al. [19] observed that while inpatient OOP spending declined for the poorest households, total OOP increased due to increased utilization of outpatient services. Similarly, Selvaraj and Karan [20] analysed two rounds of the Consumer Expenditure Survey (CES) (2004–2005 and 2009–2010) to examine the pre- and post-impact of health insurance schemes such as the RSBY, the Rajiv Aarogyasri scheme in Andhra Pradesh, and the Tamil Nadu Health Insurance Scheme. They concluded that rather than providing financial protection, these schemes were associated with increased real per-capita health expenditure and a higher incidence of CHE in the districts where they were implemented [20]. Using data from the 71st Round of the NSS, Ranjan et al. [21] found that PFHI schemes could reduce CHE by only about 1% for the bottom three income quintiles. Consistent with the broader evidence, Garg et al. [22] used data from the National Family Health Survey (NFHS-5, 2019-21) and found that neither Ayushman Bharat-Pradhan Mantri Jan Arogya Yojana (AB-PMJAY) nor other PFHI schemes significantly reduced OOP expenditure or distress financing for institutional births.

As observed in the paragraphs above, both PHC and PFHI are considered important strategies to attain UHC, which is central to health system resilience. While there have been studies that have estimated the impact of health insurance or PFHI on outcomes linked with healthcare utilization and OOP, there is no study that evaluates and compares the impact of PFHI and PHC on CHE linked with climate-sensitive diseases (CSDs) in the Indian context. In this paper, we attempt to address this gap by evaluating and comparing the impact of two treatment variables, PHC and PFHI, on an outcome variable measuring CHE due to CSDs. In this study, healthcare expenditures associated with CSDs are considered catastrophic when they exceed 10% of a household's monthly consumption expenditure. This analysis examines the relative effectiveness of PFHI and PHC in mitigating CHE. The focus on CSDs is particularly relevant because their incidence is expected to rise with ongoing climate change, posing a growing challenge to UHC and health system resilience.

Since observational studies are likely to experience selection bias, we used two contemporary econometric approaches—propensity score matching (PSM) and inverse probability weighting (IPW)—to estimate causal impacts in the absence of randomized treatment assignment. While PSM is usually used to analyse data at the individual or household level, our analysis utilizes data aggregated at the district level. This approach offers several advantages. First, district-level indicators have a greater ability to capture the social determinants of health, such as public health infrastructure and climate change-induced weather risks, that influence CHE outcomes, particularly in the context of CSDs. Second, aggregating data from multiple nationally representative sources reduces noise and measurement error, particularly those arising from self-reported household surveys [23, 24]. Finally, the use of district-level analysis can reduce overfitting in matching models, leading to treatment effect estimates that are more stable and generalizable [25].

In order to ensure comparability across districts, which is essential for matching, and reduce the likelihood of confounding, this study draws on the vulnerability framework outlined in the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [26]. According to this framework, vulnerability is a function of exposure, sensitivity, and adaptive capacity. In the context of CSDs, exposure refers to a district's environmental risks (e.g., temperature extremes, pollution), sensitivity reflects the population's underlying health status and socio-demographic risks (e.g., poverty, disease prevalence), and adaptive capacity captures the ability of health system and population to respond effectively to crises (e.g., healthcare infrastructure, household characteristics). The application of this framework enables this study to match districts with similar profiles of climate-related health vulnerability, leading to improved comparability and validation of the study's matching estimates. Furthermore, matching treatment and control districts on known vulnerability dimensions reduces the risk of confounding in the estimated treatment effect [27].

The contribution of this study lies in its specific focus on CSDs, where evidence remains limited, especially in the context of developing countries, including India. Second,

the study provides a comparative assessment of primary care and PFHI coverage in reducing CHE, which has not been investigated in the context of climate-induced health risks. Third, the indicators used in the present study are aggregated at the district level for all 640 Census 2011 districts from seven data sources, three of which are unit-level records. Finally, the study draws on the IPCC framework of exposure, sensitivity, and adaptive capacity for its empirical design, which enables us to account for climate vulnerability in a systematic way.

2 Methods

2.1 Methodological Approach: Propensity Score Matching and Inverse Probability Weighting

Randomized controlled trials (RCTs) are widely considered the gold standard for estimating causal effects because random assignment eliminates selection bias. However, in observational studies, treatment assignment is not random, raising the risk of bias due to systematic differences between treated and control groups. To address this, this study employed two quasi-experimental methods—PSM and IPW.

Given that this study used cross-sectional data aggregated at the district level, where treatment status was not randomly assigned, PSM allowed us to construct a valid counterfactual by balancing observed covariates between treated and control districts. Unlike household-level analyses commonly found in the literature, our use of district-level PSM offers a broader policy perspective by accounting for contextual factors such as environmental exposure, health status, household characteristics, and healthcare infrastructure.

PSM uses a logit model, appropriate for binary treatment variables, to estimate the propensity score, which is the probability of receiving treatment based on a set of observed covariates. The selection of covariates is based on their theoretical relevance to both treatment assignment and health outcomes. We estimated propensity scores using the 'common support' option to ensure overlap between treatment and control districts. We performed several iterations with different combinations of matching variables or refined the covariate set to satisfy the balancing property, which ensured that matched observations were similar with respect to observable characteristics [28].

For matching, we used kernel-based PSM. This method creates the counterfactual outcome by assigning weights to all control group observations based on their proximity in propensity scores to each treated observation. This method improves precision and reduces variance compared with one-to-one matching. As a robustness check, we also used nearest-neighbour matching with a calliper to ensure covariate balance and mitigate potential selection bias. After the propensity scores were generated, we used the 'psmatch2' command for matching treatment and control group observations.

While PSM can effectively reduce bias caused by observable confounders, unobserved factors could still bias the treatment effect. To strengthen our causal inference results, we used the statistical technique of IPW. In this method, the inverse of the estimated propensity score was used to reweight observations. IPW creates a pseudo-population group that balances the distribution of matching variables [29]. By combining PSM and IPW, this study provides a robust framework for evaluating the causal effects of PHC and PFHI on CHE caused by CSDs.

2.2 Variables and Data Sources

Sections 2.2.1 and 2.2.2 describe the treatment and outcome variables, and the matching variables respectively. A summary of all variables, along with their data sources and reference years, is presented in Table 1.

2.2.1 Treatment and Outcome Variables

Drawing on WHO's [3] conceptualization, we define climate-sensitive diseases (CSDs) as a broad category of health conditions whose incidence or severity is influenced by climatic factors such as temperature, precipitation, and EWEs. These include both infectious diseases (e.g., vector- and water-borne illnesses) and non-communicable conditions (e.g., cardio-metabolic and respiratory diseases). These conditions may be affected directly or indirectly through changes in environmental and social determinants of health.

As stated earlier, we used PSM to evaluate and compare the impact of two treatment variables on an outcome variable. The outcome variable is a continuous measure of households facing CHE due to CSDs. When healthcare expenditures associated with CSDs exceed 10% of the monthly household consumption expenditure, we consider them to be catastrophic. To estimate CHE due to CSDs, we identified 18 CSDs and vector-borne diseases (VBDs) from the 75th Round of the National Sample Survey, focussing on health consumption [30]. This identification followed a careful process of mapping ailments listed in the NSS to the Tenth Revision of International Classification of Diseases (ICD-10) and International Classification of Primary Care (ICPC-3). Existing literature shows that climate-sensitive factors such as extreme heat, air pollution, and changing rainfall worsen cardiovascular, respiratory, metabolic, neurological, and infectious diseases [31, 32]. This highlights the relevance of the selected CSDs and VBDs in the context of climate change. A more detailed discussion of the literature review and the mapping process is provided in the electronic supplementary material (ESM; Table S1).

Table 1 Summary of outcome, treatment, and matching variables, with data sources and reference years. Source: Authors' compilation based on data from NSS 75th Round, NFHS-4, Rural Health Statistics, Census of India 2011, India Meteorological Department, and IIT Delhi

Variable type	Variable	Brief description	Data source	Year
Outcome	CHE due to CSDs	Catastrophic health expenditure defined as OOP health spending exceeding 10% of monthly household consumption expenditure	NSS, 75th Round (health spending and MPCE)	2017–2018
Treatment	Primary care coverage	Population-to-facility ratio based on sub-centres and health and wellness centres	Rural Health Statistics; Census (adjusted using NSS)	2018–2019 (facilities); 2011 (population, adjusted to 2017–2018)
Treatment	PFHI coverage	Share of population covered under any public/employer-supported health insurance	NSS 75th Round	2017–2018
Matching	Disastrous heat waves	District exposure to extreme heat events	India Meteorological Department (Climate Hazard Atlas)	1969–2019 (cumulative)
Matching	BPL population	District-level poverty estimates based on revised Tendulkar methodology using MPCE and price indices	Authors' calculation using NSS and price indices	2017–2018 (constructed)
Matching	$PM_{2.5}$ concentration	Fine particulate matter concentration (particles ≤ 2.5 µm in diameter)	IIT Delhi, Centre for Atmospheric Sciences	2015
Matching	Maximum temperature	District-level temperature exposure	NFHS-4 (GPS-linked data)	2015–2016
Matching	Built-up population	Proxy for urbanization	NFHS-4 (GPS-linked data)	2015–2016
Matching	Diarrhoea prevalence	Child health indicator	NFHS-4	2015–2016
Matching	Stunting prevalence	Nutritional status	NFHS-4	2015–2016
Matching	Skilled births (%)	Healthcare access	NFHS-4	2015–2016
Matching	NLST	Nighttime thermal exposure reflecting heat stress	NFHS-4 (GPS-linked data)	2015–2016
Matching	Clean fuel (%)	Household living conditions	NFHS-4	2015–2016
Matching	Chronic ailments prevalence	Population health status	NSS 75th Round	2017–2018

Note 1: Population data from Census 2011 is adjusted using NSS-based growth to approximate 2017–2018 levels. Differences in reference years reflect data availability constraints

BPL below poverty line, *CHE* catastrophic health expenditure, *CSDs* climate-sensitive diseases, *GPS* Global Positioning System, *IIT* Indian Institute of Technology, *MPCE* monthly per-capita consumption expenditure, *NFHS* National Family Health Survey, *NLST* night land surface temperature, *NSS* National Sample Survey, *OOP* out-of-pocket, *PFHI* publicly funded health insurance, $PM_{2.5}$ particulate matter with aerodynamic diameter ≤ 2.5 µm

The two treatment variables in our analysis include (i) the population served by each primary care facility, and (ii) households covered by PFHI. For simplicity, we refer to these as 'primary care coverage' and 'PFHI coverage' respectively. Primary care coverage was measured using the population-to-health-system ratio at the district level, which serves as a proxy for service availability. The variable was computed by adding the number of district-wise sub-centres and health and wellness centres at the sub-centre level from Rural Health Statistics [33]. These facilities serve as the most decentralized tier of the public health system in India and are the primary point of contact for communities. The ratio was then used to derive the number of health facilities per capita (explained in the ESM). A higher ratio indicates relatively more constrained access to primary care. However, it is important to highlight that this measure does not capture variation in facility size or quality of services across districts.

PFHI coverage is based on the NSS and measured using district-level information on whether individuals are covered under any scheme for health expenditure support [30]. This includes government-sponsored schemes, government or public sector employer-supported schemes, and other employer-supported health insurance schemes. Individuals not covered under any such scheme were classified as uninsured. The district-level PFHI variable was constructed by aggregating individual responses to obtain the share of the population covered by any form of publicly supported health insurance. However, it is important to note that PFHI schemes vary across states in terms of design, coverage, and

implementation. Therefore, this variable captures overall insurance coverage instead of differences across schemes. We conducted two independent PSM exercises, one for primary care coverage and one for PFHI coverage.

According to the World Bank Handbook of Impact Evaluation, PSM performs best when the treatment and control groups have a large and nearly equal number of observations [34]. An equal-sized treatment and control group was not feasible because it did not satisfy the balancing property of propensity scores. Therefore, we used a 40:60 ratio between the treatment and control groups as advised in the literature [35]. Treatment variables were dichotomously coded as follows:

1. The primary care coverage variable is stratified into two groups. The series is arranged in increasing order. The bottom 40% of districts ($n = 256$), representing areas with lower levels of primary care coverage (i.e., facilities catering to larger populations), are coded as the treatment group (1), while the remaining 60% ($n = 384$) are coded as the control group (0). Thus, the treatment captures exposure to lower primary care coverage. The variable has a mean of 10,804 and ranges from 523 to 409,716, which reflects substantial variation in the population served per facility across districts (ESM, Table S2).
2. The PFHI variable is constructed as the share of households without insurance. The series is arranged in decreasing order, such that higher values correspond to lower levels of insurance coverage. The top 40% of districts ($n = 256$), representing areas with the lowest insurance coverage, are coded as the treatment group (1), while the remaining 60% ($n = 384$) are coded as the control group (0). Thus, the treatment captures exposure to lower levels of PFHI coverage. The variable has a mean of 0.86 and ranges from 0.02 to 1, which indicates high levels of uninsurance across districts (ESM, Table S2).

2.2.2 Matching Variables

The selection of covariates was guided by their potential to influence both treatment assignment and health expenditure outcomes. We included variables that represent environmental exposure, socioeconomic conditions, health status, and healthcare access because these factors affect both the distribution of PHC/PFHI coverage and the likelihood of incurring CHE. This selection is further informed by the IPCC framework on climate vulnerability. The Fourth Assessment Report (AR4) of the IPCC defines vulnerability as a function of exposure, sensitivity, and adaptive capacity. Exposure refers to the level of a system's contact with disasters or EWEs, sensitivity is the degree to which the system is affected by EWEs, and adaptive capacity is the ability to cope and recover. Adaptive capacity reduces vulnerability, whereas exposure and sensitivity increase it (IPCC, 2007) [26].

In this study, these factors determine the health vulnerability of districts to climate change and EWEs. To assess treatment effects, we matched districts with similar indicators affecting health vulnerability due to climate change, ensuring comparable groups across observable characteristics [35].

Exposure indicators include maximum temperature (2015), night land surface temperature (NLST, 2015), potential evapotranspiration (2015), and built-up population (2014), derived from geospatial covariates of NFHS-4 [36]. District-level data on disastrous heat waves was sourced from India Meteorological Department hazard maps, focusing on districts experiencing more than 200 deadly heat waves between 1969 and 2019 [37]. Fine particulate matter ($PM_{2.5}$, 2015) data came from the Centre for Atmospheric Sciences, IIT Delhi.

Adaptive capacity indicators include district-wise monthly per-capita consumption expenditure (MPCE) from the NSS 75th Round [30] (ESM), monthly household income and the ratio of working population from the Periodic Labour Force Survey (PLFS) [38], percentage of births attended by skilled healthcare personnel (proxy for skilled health personnel) from NFHS-4 [39], and household characteristics such as use of clean fuel, electricity, and improved sanitation from NFHS-4 [39].

Sensitivity indicators include below poverty line (BPL) population estimates (ESM), stunting prevalence, diarrhoea prevalence, and chronic ailment prevalence, sourced from the NSS 75th Round [30] and NFHS-4 [39].

Treatment variables should not affect matching variables to avoid obscuring treatment effects [28]. While many matching variables were tested in initial iterations, only those satisfying the balancing property of PSM were retained.

1. When primary care coverage is the treatment variable, matching variables are disastrous heat waves, BPL population, $PM_{2.5}$, maximum temperature, built-up population, diarrhoea prevalence, and stunting prevalence.
2. When PFHI is the treatment variable, matching variables are percentage of skilled births, NLST, percentage of households using clean fuel, prevalence of chronic ailments, maximum temperature, and stunting prevalence.

Variables that did not satisfy the balancing property or common support conditions were excluded from the final specification. This approach helps reduce bias arising from observable confounders and ensures comparability between treated and control districts.

3 Results

3.1 Distribution of Out-of-Pocket Expenditure Across Disease Categories and Descriptive Associations Between Primary Health Care, Publicly Funded Health Insurance, and Catastrophic Health Expenditure

A breakdown of household OOP expenses based on disease categories, including vector-borne, water-borne, respiratory, heat-related (cardiometabolic), and other non-communicable/general medical conditions is provided in Table 2. These estimates are derived from combined inpatient and outpatient net OOP expenditures. The results indicate that heat-related cardio-metabolic conditions and other non-communicable/general medical conditions account for the largest share of household medical expenditures (approximately 36% each). Vector-borne diseases account for roughly 17–18% of expenditures, while respiratory and water-borne illnesses contribute smaller shares (around 5% and 4–5%, respectively). This breakdown is useful in capturing the relative contribution of different CSD categories to household medical expenditures.

Figure 1 shows that districts where each primary care facility serves a larger population size report higher levels of CHE, which is suggested by the upward-sloping fitted line. This relationship suggests that in districts where primary care infrastructure is under greater population pressure, the chances of households facing CHE due to CSDs are also very high. On the other hand, the box plots in Fig. 2 show that median CHE is marginally higher in districts where higher percentages of households are covered by PFHIs compared with those with lower insurance coverage (movement from right to left boxes), barring the top-right category of districts. It is important to note that the data represented in Figs. 1 and 2 are derived from raw district-level aggregates. The subsequent analysis examines these relationships in more detail while accounting for potential confounding factors.

Table 2 Distribution of net out-of-pocket (OOP) medical expenditure across disease categories. Source: Authors' calculations based on National Sample Survey (NSS), 2017–2018

Disease category	Share of total OOP expenditure (%)
Vector-borne	17.5
Water-borne	4.5
Respiratory	5.2
Heat/cardio-metabolic	36.1
Non-communicable diseases (NCDs)/general medical conditions	36.6

3.2 Preliminary Matching Diagnostics

As mentioned earlier, the presence of a sufficient range of overlapping propensity scores is required to ensure quality of matching in PSM. Table S3 (see ESM) displays the distribution of treated and untreated units based on their inclusion within the common support region when primary care coverage is the treatment variable. This analysis was conducted on 634 out of 640 observations, accounting for 99% of the sample, indicating a strong overlap in propensity scores between treated and untreated groups. Out of the 256 treated units, 253 (98.8%) fell within the region of common support. This means that almost all treated units could be appropriately matched with untreated units. Of the 384 untreated units, 381 (99.2%) were within the region of common support. The matching process thus achieved strong overlap and comparability, with only a small number of observations excluded due to lack of common support. Thus, the matched sample provides a more credible basis for estimating treatment effects.

The analysis that uses PFHI as the treatment variable appears to have a strong matching quality, as evidenced by the high percentage of observations that fall within the region of common support (ESM, Table S4). Out of a total of 640 observations, 621 (97% of the sample) were retained for analysis, indicating substantial overlap in propensity scores between treated and untreated groups. The number of treated units on support was 239 out of 256 (93.4%), indicating that most treated individuals had comparable untreated counterparts. Among the untreated group, 99.5% of the 384 units (382 units) were on support, further confirming the adequacy of the common support region for reliable matching. The minimal number of off-support observations suggests that the matching process effectively addressed the issue of comparability. As a result, the treatment effect estimates derived from the matched sample are more credible.

3.3 Estimated Treatment Effects

3.3.1 Treatment Effects When Primary Care Coverage is the Treatment Variable

Table 3 presents the estimated average treatment effect on the treated (ATET) of primary care coverage using kernel matching, nearest-neighbour matching with a 0.05 calliper, and IPW. The ATET estimate represents the estimated effect of district-level primary care coverage on CHE due to 18 CSDs. Using kernel matching, the estimated incidence of CHE is 4.5% in the treated group and 2.6% in the control group, which results in an ATET of 1.87%. This indicates that households in districts with higher population-to-primary-health-system ratios (i.e., lower effective coverage) are more likely to experience CHE by 1.87 percentage points. Using nearest-neighbour matching with a calliper of 0.05,

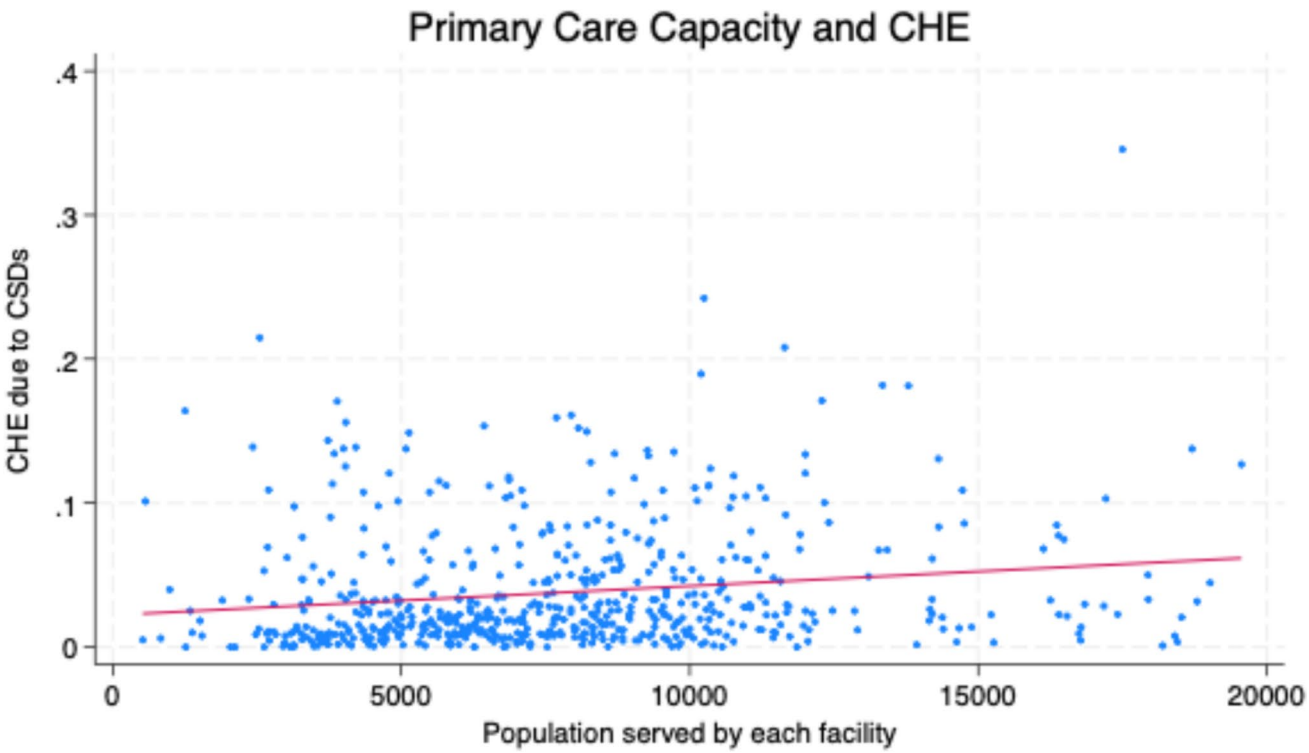

Fig. 1 District-level association between primary care capacity and catastrophic health expenditure (CHE) due to climate-sensitive diseases (CSDs). Source: Authors' calculations based on National Sample Survey (NSS) 75th Round, Rural Health Statistics, and Census 2011

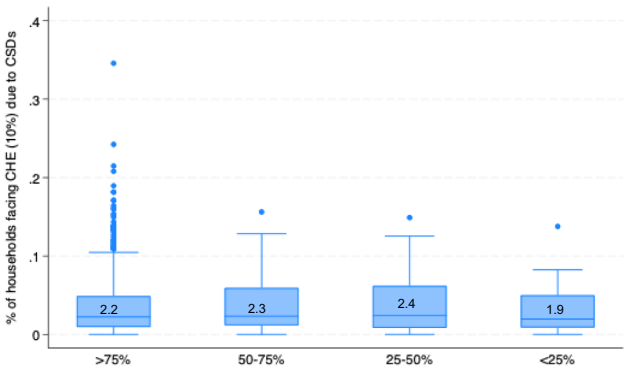

Fig. 2 Box plot of catastrophic health expenditure (CHE) at the 10% threshold due to climate-sensitive diseases (CSDs), by categories of households without publicly funded health insurance (PFHI) coverage (%). Source: Authors' calculations based on National Sample Survey (NSS) 75th Round

the estimated ATET is 1.50%. This suggests that households in districts with relatively lower primary care coverage are 1.50 percentage points more likely to experience CHE due to CSDs. Using IPW, the estimated ATET coefficient is 2.97%, which implies a similar finding: households in districts with higher population-to-primary-health-system ratios are more likely to suffer from CHE due to CSDs. It is also important to note that since the *p*-values of the ATET estimates from all matching methods are below 0.05, and the corresponding confidence intervals (CIs) do not include zero, the estimates are statistically significant. These results should be interpreted as reflecting capacity constraints rather than a negative causal effect of PHC per se.

Table 4 presents the balance of covariates between treated and control groups before and after matching, with primary care coverage as the treatment. All covariates were found to

Table 3 Average treatment effects of primary care coverage by using different matching methods. Source: Authors' estimates

Matching method	Treated	Control	Average treatment effect on the treated (ATET)	Std error	*t*-stat	*p*-Value	95% CI (lower)	95% CI (upper)
Kernel matching	0.04557	0.02685	0.01872	0.00546	3.43	0.0006	0.00799	0.02945
Nearest neighbour (0.05 calliper)	0.04557	0.03064	0.01493	0.00600	2.49	0.0128	0.00317	0.02669
Inverse probability weighting (IPW)			0.02966	0.01146	2.59	0.010	0.00719	0.05212

have significant imbalances between the treated and control groups prior to matching, which was reflected in high standardized bias values. For instance, the standardized bias for $PM_{2.5}$ was 91.6%, for built-up population was 56.2%, and for diarrhoea prevalence was 46.2%. The presence of this degree of standardized bias indicated a need for statistical adjustment to decrease confounding and ensure comparability between groups. As a result of PSM implementation, both kernel and nearest-neighbour methods (with a 0.05 calliper) improved the covariate balance significantly. With kernel matching, the bias for disastrous heatwaves was decreased to 0.7%, 0.1% for built-up population, and 1.7% for $PM_{2.5}$. Similarly, nearest-neighbour matching (with 0.05 calliper) resulted in reduced biases for covariates, such as 1.4% for stunting prevalence, 1.6% for disastrous heatwaves, and 2.5% for BPL population. Post-matching comparisons across all covariates showed *p*-values exceeding the 0.05 threshold, indicating that there were no statistically significant differences between the treated and control groups after matching. The results indicate that both matching methods are effective in achieving adequate covariate balance and minimizing selection bias.

Post-matching and post-weighting diagnostics (Tables S5–S6, ESM) indicate that covariate balance was successfully achieved. Both matching methods (kernel and nearest neighbour) and IPW substantially reduced standardized biases to acceptable levels. Likelihood ratio test and Rubin's B/R statistics also show no remaining systematic imbalance between treated and control groups.

3.3.2 Treatment Effects When Publicly Funded Health Insurance Coverage is the Treatment Variable

Table 5 shows the effect of PFHI on CHE due to 18 CSDs, based on ATET estimates. Using kernel matching, the treated group has an estimated CHE incidence of 3.81%, while the control group has 3.84%. The resulting ATET is − 0.04 percentage points, which indicates a negligible difference in CHE between districts with higher and lower PFHI coverage. Nearest-neighbour matching with a calliper of 0.05 produces an ATET of − 0.23 percentage points, which shows a small and statistically non-significant difference. The IPW method produces an ATET of 0.078 percentage points, which suggests a small positive difference in CHE in districts with lower PFHI coverage, but this estimate is also not statistically significant. All three *p*-values are above 0.05, and the corresponding confidence intervals include zero. These statistics show that PFHI coverage does not have a significant effect on CHE in this sample. In other words, the evidence suggests that PFHI does not have a statistically significant effect on the likelihood of CHE in treated districts. The estimates differ slightly in direction across methods, but none are statistically significant.

Table 4 Covariate balance before and after matching when primary care coverage is the treatment variable. Source: Authors' estimates

Covariates	Sample	Treated mean	Control mean	% Bias	% Reduction	*t*-stat	*p*-Value
Disastrous heatwaves	Unmatched	28.27	111.53	− 43.2		− 5.04	0
	Kernel	28.605	30.013	− 0.7	98.3	− 0.13	0.896
	NN (0.05 calliper)	28.605	25.466	1.6	96.2	0.31	0.76
BPL population	Unmatched	0.28071	0.36799	− 18.3		− 2.22	0.027
	Kernel	0.28403	0.27343	2.2	87.9	0.28	0.78
	NN (0.05 calliper)	0.28403	0.27209	2.5	86.3	0.3	0.762
Particulate matter ($PM_{2.5}$)	Unmatched	71.735	57.205	91.6		11.23	0
	Kernel	71.503	71.78	− 1.7	98.1	− 0.2	0.838
	NN (0.05 calliper)	71.503	73.125	− 10.2	88.8	− 1.22	0.223
Built-up population	Unmatched	0.14013	0.05462	56.2		7.44	0
	Kernel	0.13172	0.13187	− 0.1	99.8	− 0.01	0.993
	NN (0.05 calliper)	0.13172	0.11703	9.7	82.8	0.92	0.357
Diarrhoea prevalence	Unmatched	9.7828	7.4708	46.2		5.76	0
	Kernel	9.7964	9.4662	6.6	85.7	0.67	0.502
	NN (0.05 calliper)	9.7964	10.015	− 4.4	90.5	− 0.42	0.678
Stunting prevalence	Unmatched	38.602	34.214	44.9		5.61	0
	Kernel	38.713	39.121	− 4.2	90.7	− 0.48	0.634
	NN (0.05 calliper)	38.713	38.85	− 1.4	96.9	− 0.16	0.872
Maximum temperature	Unmatched	31.148	29.533	38.2		4.46	0
	Kernel	31.15	31.215	− 1.5	96	− 0.25	0.802
	NN (0.05 calliper)	31.15	30.929	5.2	86.3	0.9	0.367

Table 5 Average treatment effects of publicly funded health insurance (PFHI) by using different matching methods. Source: Authors' estimates

Matching method	Treated	Control	Average treatment effect on the treated)	Std error	*t*-stat	*p*-Value	95% CI (lower)	95% CI (upper)
Kernel	0.0381	0.0384	− 0.00040	0.00450	− 0.0889	0.9292	− 0.00922	0.00842
Nearest neighbour (0.05 calliper)	0.0381	0.0404	− 0.00230	0.00580	− 0.3966	0.6917	− 0.01367	0.00907
Inverse probability weighting (IPW)			0.00078	0.00351	0.2210	0.8251	− 0.00611	0.00766

Table 6 displays the balance of covariates between treated and control groups before and after matching, with PFHI as the treatment variable. All covariates showed significant imbalances between the treated and control groups before matching. Before matching, standardized biases were 69.9% for chronic ailments, 64.8% for stunting, and 56.7% for skilled births. These differences indicate the presence of substantial differences between the treatment and control groups. The balance improved considerably after using PSM, with both kernel and nearest-neighbour matching. Kernel matching resulted in a reduction in bias to 1.2% for skilled births, 1.5% for NLST, 0.6% for clean fuel, 5.0% for chronic ailments, and 5.1% for stunting. Comparable reductions in bias were observed in matching using nearest neighbour (with 0.05 calliper), with chronic ailments seeing a reduction of 2.3% and stunting seeing a reduction of 3.4%. The effectiveness of both PSM methods was confirmed by the absence of statistically significant covariate differences after matching, with all *p*-values above 0.05.

Covariate balance diagnostics (Tables S7–S8, ESM) show that both PSM and IPW were effective in reducing pre-treatment differences. After matching and weighting, standardized mean biases fell below conventional thresholds. Rubin's *B* and *R* statistics were within acceptable ranges. Likelihood ratio tests also indicated no remaining imbalance between groups.

3.4 Sensitivity Analysis

Following the methodology proposed by Altonji et al. [40], we formally assessed the sensitivity of the estimated associations to selection on unobservables. We calculated the delta statistic by comparing the treatment coefficients obtained from the unadjusted and adjusted specifications. To be

Table 6 Covariate balance before and after matching when publicly funded health insurance (PFHI) is the treatment variable. Source: Authors' estimates

Variable	Sample	Treated mean	Control mean	% Bias	% Bias reduction	*t*-stat	*p*-Value
Skilled births	Unmatched	86.278	77.862	56.7		6.96	0
	Kernel	85.368	85.183	1.2	97.8	0.14	0.886
	Nearest neighbour (0.05 calliper)	85.368	84.629	5	91.2	0.58	0.565
Night land surface temperature	Unmatched	20.164	18.693	35.7		4.42	0
	Kernel	19.986	19.925	1.5	95.8	0.17	0.868
	Nearest neighbour (0.05 calliper)	19.986	19.807	4.3	87.8	0.47	0.636
Clean fuel	Unmatched	42.963	34.388	37.1		4.63	0
	Kernel	42.055	42.203	− 0.6	98.3	− 0.07	0.947
	Nearest neighbour (0.05 calliper)	42.055	40.649	6.1	83.6	0.62	0.533
Chronic ailments	Unmatched	0.04306	0.01571	69.9		9.34	0
	Kernel	0.03418	0.03221	5	92.8	0.62	0.538
	Nearest neighbour (0.05 calliper)	0.03418	0.03327	2.3	96.7	0.28	0.776
Maximum temperature	Unmatched	30.636	29.874	17.1		2.08	0.038
	Kernel	30.606	30.44	3.7	78.2	0.44	0.662
	Nearest neighbour (0.05 calliper)	30.606	30.303	6.8	60.2	0.79	0.43
Stunting prevalence	Unmatched	32.313	38.407	− 64.8		− 7.98	0
	Kernel	33.15	32.673	5.1	92.2	0.57	0.568
	Nearest neighbour (0.05 calliper)	33.15	32.826	3.4	94.7	0.39	0.697

specific, the delta value was computed as the ratio of the adjusted coefficient to the difference between the unadjusted and adjusted coefficients. This ratio estimates the relative strength of selection on unobserved factors, compared with observed factors, that would be required to fully explain away the estimated association.

In the primary care specification, the estimated coefficient increases from 0.0128 in the unadjusted specification to 0.0140 after controlling for district-level characteristics. This indicates that the unadjusted estimate is likely to underestimate the association between limited primary care access and CHE. The estimated delta value is − 11.8. This implies that unobserved factors would need to be approximately 11.8 times stronger than observed factors and operate in the opposite direction to nullify the estimated association. Given the inclusion of a rich set of district-level socioeconomic, environmental, and health controls in our model, this appears unlikely. Therefore, the estimated association between limited primary care access and CHE appears relatively robust to omitted variable bias.

In the PFHI-based specification, the estimated coefficient on lack of insurance coverage decreases in magnitude from − 0.0073 in the unadjusted specification to − 0.0035 after controlling for district-level characteristics. This suggests that the unadjusted estimates overstate the magnitude of the association between lack of insurance and CHE. The estimated delta value is 0.89. This implies that selection on unobserved factors of approximately similar magnitude to observed factors would be sufficient to eliminate the estimated association. Once we include observable district-level socioeconomic and environmental characteristics in the specification, the estimated relationship also becomes statistically insignificant. These findings suggest that the estimated association between lack of insurance and CHE is sensitive to omitted variable bias. At the same time, this result is consistent with the broader empirical findings of the study, including the descriptive patterns and matching-based estimates, which indicate a relatively weak relationship between insurance coverage and CHE.

4 Discussion

Our results suggest that the impact of PFHI on households facing CHE is not statistically significant. On the other hand, the link between strengthening PHC and the reduction of CHE is straightforward and devoid of ambiguities. It is important to note that our estimates reflect average district-level effects and do not capture within-district heterogeneity in access to care.

The notion of health systems' resilience came to the forefront in the aftermath of the 2013–2016 Ebola outbreak and, more recently, during the COVID-19 pandemic [41]. Strong PHC is widely recognized as the frontline of health systems and plays a vital role in enhancing their resilience during crises. Since robust PHC systems are in close contact with communities, they provide comprehensive and integrated care before, during, and after crises. This helps prevent health systems from becoming overwhelmed during crises. Due to their constant engagement with communities, health systems with strong PHC are able to detect and respond to crises in a timely manner [42].

A growing body of evidence suggests that countries with strong PHC could respond more effectively to the COVID-19 pandemic than those with weak PHC. For instance, Thailand's ability to tackle the pandemic can be traced back to its robust PHC network, which involves village health volunteers to connect with every household. This PHC network takes a proactive approach in delivering essential health interventions, such as early disease detection, vaccination, and health education directly to the public [43]. In Austria, PHC centres assumed an important role by setting up multidisciplinary teams that helped maintain continuity of care for non-COVID patients, while also providing care to those with COVID-19. The PHC centres contributed significantly to limiting the spread of the pandemic by expanding screening and testing capacity and providing patient education [44].

In addition to building health system resilience during crises, strong PHC contributes to the strengthening of health systems in stable settings. By facilitating early diagnosis of underlying risk factors and health vulnerabilities, health systems with strong PHC can detect the onset of diseases in their early stages and reduce the chances of disease progression, tertiary care, and high curative spending [45]. PHC facilities can be utilized as hubs for integrated care, aiding in the early detection, treatment, and management of multiple chronic conditions [46]. Moreover, through effective referral systems and gatekeeping, PHC can reduce the overuse and dependence on secondary and tertiary care [47].

Government spending on PHC is associated with more equitable health outcomes compared with spending on tertiary care. This is because strengthening PHC ensures the provision of continuous, comprehensive, and coordinated health services to all who need them, primarily by enhancing health promotion, preventive care, and public health initiatives [13]. Health systems with strong PHC discourage excessive reliance on specialized services and instead focus on positioning PHC as the first point of contact for addressing the majority of health needs [42]. PHC professionals often have comprehensive access to patients' medical histories and socioeconomic backgrounds [44].

By making care more accessible, foregrounding PHC in health systems contributes to improved health outcomes across the population, irrespective of socioeconomic status [48]. On the other hand, health systems that prioritize

tertiary care are often associated with regressive financing outcomes. This is because a significant proportion of low-income households spend a larger share of their income on tertiary care compared with higher-income households, often resulting in CHE [49]. There is also broad consensus that systems emphasizing workforce specialization and tertiary care services tend to disrupt the continuity of care, leading to inefficiencies and inequitable health outcomes [50]. Furthermore, health systems that do not provide comprehensive PHC coverage often leave populations more vulnerable to the adverse impacts of disease outbreaks and conflicts.

In addition to being cost effective, PHC has the potential to support more climate-resilient and environmentally sustainable health systems. It is important to highlight that the healthcare sector accounts for approximately 4.6% of global carbon emissions [51]. The potential of PHC to reduce emissions from the healthcare sector is being discussed at a peripheral level in academic circles. However, given that advances in the health sector have primarily focused on tertiary-level biomedical approaches that are carbon intensive, the expansion of PHC is gradually being recognized as a means of decarbonizing the health sector [52].

Therefore, it is appropriate to infer that investments in specialized, tertiary care services are likely to lead to inequities in healthcare access and deepen economic inequalities for households with lower incomes and inadequate financial protection against CHE [50]. In contrast, approaches that prioritize primary care, improve the social, political, and environmental determinants of health, and strengthen the engagement of individuals and communities in health policymaking result in enhanced healthcare access and reduced financial vulnerability among disadvantaged sections of the population [53]. Thus, investments in PHC are essential to advancing progress toward UHC in LMICs. Due to the possibility that climate change will increase the frequency and severity of EWEs and the incidence of CSDs, it is essential to have climate-resilient health systems that are anchored in strong PHC. Even if crises cause temporary disruptions to healthcare services, these systems can detect threats early, ensure continued access to care, promote equitable health outcomes, and maintain progress towards UHC.

To situate these findings within India's health system, it is important to consider the historical and policy context shaping PHC and insurance coverage in the country. Even though India was a signatory to the Alma Ata Declaration, uneven industrialization, sluggish economic growth, and rampant levels of impoverishment forced it to withdraw from the idea of a welfare state and subscribe to Selective Primary Healthcare (SPHC) [54]. Consequently, India has witnessed increasing privatization of health care services since the 1970s [55]. India launched the National Rural Health Mission (NRHM) in 2005 to improve the provision of PHC in rural areas.

NRHM, or the present-day National Health Mission (NHM), is the only PHC-oriented effort primarily responsible for providing reproductive and child health and family welfare services, with a secondary responsibility for disease control programs [55]. Despite the fact that the Government of India's Ayushman Bharat Programme encompasses both primary and curative care components to expand UHC, insurance-backed tertiary care remains the dominant UHC approach in India. Therefore, while UHC is aimed at providing financial protection against healthcare payments and may include subsidized and tax-financed free health care services, it may be considered equivalent to the provision of privately driven health insurance in the Indian context [21]. One may reasonably infer that in its endeavour to expand UHC, India has systematically diverted away from strengthening PHC.

The rapid growth of corporate hospitals, situated mainly in urban areas, has increased the demand for high-end curative procedures and has pushed the PHC agenda to the margins [56]. Our results are consistent with existing literature that presents mixed evidence of the impact of health insurance and PFHI on CHE due to CSDs. This is because in the absence of adequate regulation, PFHI schemes have been associated with unethical and profit-maximizing practices of the private healthcare sector, such as double billing, oversupply of medical services, and denial of admission to patients [57, 58]. Instead of providing financial protection against OOP payments, such practices increase treatment costs and render households vulnerable to CHE and impoverishment. Therefore, despite an increase in PFHI coverage, such malpractices on the part of private providers have led to an increase in OOP and CHE for patients.

Our findings suggest that the impact of PFHI on households facing CHE is inconclusive. In contrast, the link between strengthening PHC and reducing CHE is more straightforward and unambiguous. The ongoing push for UHC in India, particularly through Ayushman Bharat, offers an opportunity to rethink the health system's priorities. Rather than focusing primarily on insurance-driven tertiary care, India should strengthen its PHC systems, which would not only provide better health outcomes but also contribute to equitable and climate-resilient healthcare for all populations.

5 Study Limitations

Our study has a few important limitations. First, the analysis is based on district-level data. This may mask heterogeneity across households within districts. District-level averages

may not fully reflect differences in healthcare access and spending at the household level. Factors such as distance to facilities and quality of services may vary within districts. Therefore, the estimated effects should be interpreted as average district-level effects. Second, while PSM and IPW reduce bias from observable confounders, unobserved factors such as district-specific political will, local cultural attitudes toward formal medicine, and health-seeking behaviour cannot be fully ruled out. This is partly because comparable district-level data on these dimensions are not available. In order to address this concern, we conducted an additional sensitivity analysis following Altonji et al. [40], which assessed how strong selection of unobservables would need to be to overturn the results. The findings suggest that the main estimates are reasonably robust, even though this does not fully eliminate concerns related to omitted variable bias. Third, the study uses quantitative indicators such as the population-to-facility ratio and PFHI coverage. These capture availability and coverage but do not reflect the quality or functionality of healthcare services, which are important for reducing CHE. In addition, PFHI schemes vary across states in terms of design, coverage, and implementation, which is not fully captured in the aggregate coverage measure used in this study. Fourth, the analysis relies on cross-sectional data drawn from multiple sources and years. Although we use the closest available years to maintain consistency, some temporal mismatch remains and may introduce noise into the estimates.

Fifth, primary care coverage is measured using sub-centres and health and wellness centres at the sub-centre level. While this measure represents the most decentralized tier of the public health system, higher-level facilities such as PHCs, CHCs, and district hospitals could not be included in the analysis. Sixth, while PHC coverage and PFHI are used as proxies for health system resilience, these indicators primarily capture service availability and financial coverage. They do not reflect broader dimensions of resilience such as comprehensiveness, quality and continuity of services, governance capacity, and community participation. Seventh, although the IPCC framework is used to guide the selection of covariates, the analysis does not examine interaction effects between climate vulnerability and health system capacity. Exploring such heterogeneity in future work could provide additional insights. Eighth, the primary care coverage variable reflects a population-to-facility ratio and combines both supply and demand factors. This limits our ability to understand whether higher CHE is driven by inadequate service capacity or higher underlying demand for care, especially when data for district-level primary care workforce is unavailable. Finally, district-level mortality data is limited in developing country contexts, which restricts our ability to assess whether higher PHC or PFHI coverage translates into improved health outcomes beyond financial protection.

6 Concluding Observations

While India's pursuit of UHC has largely focused on expanding health insurance coverage, robust PHC systems remain essential to achieving true universal health coverage. Our results using PSM and IPW support the potential of strengthening PHC to reduce the financial burden caused by CSDs.

Despite initiatives like NRHM, PHC continues to be underprioritized in India. Fragmented public health systems, financing shortfalls, and disproportionate growth of tertiary care and private providers have weakened integrated, people-centred care. The current reliance on publicly financed but privately delivered insurance schemes has often led to rising treatment costs and limited reductions in OOP spending.

Strengthening public provisioning of healthcare through PHC should be prioritized over private sector-led insurance models. Public health systems are more efficient in delivering essential services and better positioned to reduce costs through strategic procurement and comprehensive care. Subsidized, tax-financed PHC improves access and supports equitable health outcomes, which insurance schemes alone have struggled to achieve.

Our district-level analysis using PSM and IPW indicates that stronger PHC systems are associated with reduced CHE due to CSDs. In contrast, the impact of PFHI on CHE remains inconclusive.

These findings highlight the need for policymakers to focus on strengthening PHC. Redirecting public investment from insurance-based models to expanding and improving PHC can better protect households from economic shocks and advance progress towards equitable and resilient UHC.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s40258-026-01051-5.

Funding The authors did not receive financial support from any organization for this study.

Declarations

Conflict of Interest The authors declare no competing interests.

Ethics Approval Not applicable.

Consent to Participate Not applicable.

Consent for Publication (from Patients/Participants) Not applicable.

Data Accessibility Statement The results presented in this manuscript are supported by multiple datasets, all of which are openly available at the locations cited in the References.

Code Availability The code used for the analysis is available from the corresponding author upon reasonable request.

Author Contributions Divya Chaudhary: conceptualization, methodology, data curation, formal analysis, investigation, writing—original draft, writing—review and editing. Indranil Mukhopadhyay: concep-

tualization, methodology, validation, supervision, writing—review and editing. Both authors were involved in the conception and design, analysis and interpretation of the data, drafting and revising the manuscript critically for important intellectual content, and approved the final version to be published. Both authors agree to be accountable for all aspects of the work.

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