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Assessing the impact of measurement error in household consumption on estimates of catastrophic health expenditure in India

The National Sample Survey (NSS) collects reliable data on morbidity, health care, and health spending through its annual multi-subject and multi-round health surveys. Evidences from these surveys have been extensively used for research and policy. While these surveys collect comprehensive information on morbidity, hospitalisation, health expenditure, information on household consumption expenditure (which is used to explain the economic gradient in health outcomes) is collected through a single question. Literature suggests that having a single question on consumption expenditure results in measurement errors. In this paper, we examine the effect of measurement errors of household consumption expenditure on estimates of catastrophic health expenditure (CHE) in India using data from the 68th round of the consumption survey (2011-12) and the 71st round of the health survey (2014), carried out by the National Sample Survey (NSS). The consumption survey canvassed a detailed schedule on consumption and interviewed 101,651 households, whereas the health survey interviewed 65,932 households from across the country. Descriptive statistics, estimates of CHE, and logistic regression models were used in the analysis. We used both the budget share approach and the capacity-to-pay approach for estimating CHE. The NSS health survey was found to have underestimated monthly per capita consumption expenditure (MPCE) in India by 32%, with the level of underestimation being significant across the states. Using the budget share approach, the CHE of India in 2014-15 was estimated at 23.4% without adjusting for the underestimation of consumption and 21.1% after adjusting for it. Similarly, using the capacity-to-pay approach, CHE was estimated to be 13.4% without adjustment and 10.4% with adjustment. The estimates differed considerably across the states. In general, it was observed that the use of a single question on consumption overestimated CHE in India. The pattern was similar regarding the intensity of CHE. The predictors of CHE were similar using both the methods, but the unadjusted estimates of CHE showed significantly higher predicted probabilities of incurring CHE across household characteristics. It is recommended to include disaggregated questions on household consumption in the future rounds of the NSS-based health surveys. Researchers using NSS data need to be aware of the effect of measurement errors of consumption expenditure on estimates of catastrophic expenditure. Adjusting for the underestimation of MPCE may improve the estimation of CHE in India.

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Introduction

In developing countries, the monthly per capita consumption expenditure (MPCE), is a direct measure of standard of living, and is used to explain economic differentials in health outcomes in many population-based surveys. Most of the developing countries estimate the distribution of living standard, poverty, and inequality using standard consumption surveys carried out at regular intervals. These population-based consumption surveys often collect a number of questions on consumption. On the contrary, in population-based health surveys, the number of questions on household consumption varies from a single aggregated question to a small set of questions to a number of disaggregated questions (Heijink et al. 2011; Lu et al. 2009; Micklewright, 2010; NSSO, 1996, 2006, 2014, 2016; Xu et al. 2009). The use of a single aggregated question on consumption may be misleading and have a considerable effect on the health expenditure estimates, specifically on important Sustainable Development Goal (SDG) indicators like catastrophic health expenditure (CHE) and impoverishment.

The structure of the survey instrument, including the number of questions, their wording, and the reference period, has a direct bearing on the measurement error in the consumption and the health surveys. Longer modules on household consumption have been found to generate higher estimates than shorter modules, with the estimates varying in the range of 10–67% (Deaton and Gross, 2000; Jolliffe and Scott, 1995; Lanjouw and Lanjouw, 2001).

The risk of measurement error arising from the use of a single question on household consumption is large and, therefore, the practice is not recommended in the literature (Lu et al. 2009). Studies have suggested that the measurement error is more pronounced among the socioeconomically marginal households and large families. The magnitude and the direction of errors of consumption expenditure depend upon the expenditure category examined, the respondents' characteristics, the survey protocol, and the method used to assess the errors (Fricker et al. 2015). The World Health Survey (WHS) integrated a number of disaggregated questions across 50 countries and found lower estimates of food expenditure than those derived from the other surveys in the respective countries (Xu et al. 2009).

Cross-country studies suggest that multi-item questions produce higher aggregate estimates of health expenditure than a single-item question (Browning et al. 2003; Heijink et al. 2011; Lu et al. 2009). While some studies have found that CHE occurs more frequently in the poorer households, others have reported it to be more common in the affluent households (Li et al. 2012; Somkotra and Lagrada, 2009; van Doorslaer et al. 2007). The variations in CHE between surveys are attributed to variations in out-of-pocket payments (OOP) for health care, household expenditure, and methods used to estimate CHE (Mohanty and Dwivedi, 2021; Pandey et al. 2018a, 2018b).

India has made pioneering efforts for collecting high-quality household consumption data through the official statistical system—the National Sample Survey Organisation (NSSO)—since independence. The consumption schedule of NSSO has also undergone changes in content, coverage, and size over time. Besides having a regular, detailed consumption schedule, it also has an abridged version, which has been integrated into the employment and unemployment survey (NSS 68th round, schedule 10.0, 2011–12). The abridged version of the consumption schedule, developed by NSSO, has also been integrated with other population-based surveys such as the Longitudinal Ageing Survey of India (LASI) and the India Human Development Survey (IHDS) (Desai et al. 2011–2012; IIPS et al. 2020). In the last two rounds of the NSS survey, that is, in 2014 and 2018, only a single question of consumption expenditure was canvassed.

Now, many household surveys have abandoned the practice of using a single aggregated question on household consumption in

population-based surveys. However, the NSS-based health surveys continue to use a single question, which results in the underestimation of the denominator and has implications for the estimates of CHE. No Indian study has addressed this issue so far.

In this context, the main objective of this paper is to estimate the effect of measurement error due to the use of a single question on consumption expenditure on the estimates of catastrophic health expenditure in India. The following are the three contributions of this paper: First, this is the first study to provide the estimates of CHE adjusted to the measurement error of consumption expenditure in India. Second, the study shows that the adjusted estimates of CHE are lower than the unadjusted estimates using two alternative methods, namely the budget share approach and the capacity-to-pay approach. Third, our results indicate that the NSS-based health surveys in India underestimate the consumption expenditure. This necessitates adjusting the estimates of consumption expenditure to make reliable estimates of CHE for research and policy.

Literature review

A growing body of research has been conducted to estimate CHE by analysing health expenditure surveys (Joe, 2015; Karan et al. 2014; Mohanty et al. 2018; Pandey et al. 2018a, 2018b). While the estimates of CHE vary across the studies, the inferences are similar. These studies have found high CHE among the poor, in the poorer regions, in rural areas, and in large households. However, few studies have examined the quality of data used for estimating CHE in India. According to a recent study conducted by Mohanty et al. (2018), the consumption expenditure derived from the health survey of 2014 was underestimated by a minimum of 20%, which had implications for the estimates of CHE.

These CHE estimates from consumption survey collected data on hospitalisation, outpatient services, maternal care, and specific diseases. The estimates of CHE incurred on health services varied from 4 to 15% in the year 2004 and from 15 to 25% between the years 2011 and 2014 (Ghosh, 2011; Pandey et al. 2018a). Two articles published in the WHO bulletin have brought attention to significant differences in the measurement of CHE due to the utilisation of different methodologies and data sources. These papers, authored by Raban et al. in 2013 and Pandey et al. in 2018, have proposed the need for standardising the estimation of CHE. Many studies conducted on CHE in India have employed the budget share (BS) approach. These studies have often cited the lack of available data on food expenditure as a primary reason for not utilising the capacity-to-pay (CTP) approach. There is a lack of consistency in the estimates of CHE obtained from the BS and CTP methods when utilising the same data source (Raban et al. 2013; Bonu et al. 2009; Mohanty et al. 2018).

The estimates of consumption expenditure differ as a result of variations in survey designs and survey priorities such as whether a survey is a consumption survey, a living standard survey, or a health survey. Numerous surveys are more likely to underestimate their actual spending when asked a single question on consumption expenditure (Browning, Crossley, & Weber, 2003). On the other hand, when a comprehensive list of expenditure items is used, it has been found to generate more accurate and reliable data on consumption. The number of inquiries conducted to assess consumption expenditure can range from a solitary question to more than 400 questions, contingent upon the nature of the surveys and the specific context in which they are administered. It is important to note that the accuracy of consumption data is also influenced by factors such as the length of recall periods and the design of consumption questions (Lu et al. 2009; Battistin et al. 2003). For instance, collecting food consumption

data for a shorter reference period (say 7 days) minimise recall bias and gives higher consumption estimates than a reference period of a month/year (Heijink et al. 2011; Lavado et al. 2013).

Materials and methods

Data. Unit data from the consumption survey of 2011–12 and the health survey of 2014, carried out by the National Sample Survey (NSS), was used in the analysis. The NSS was set up by the Government of India in 1950 and since then has been conducting multi-round and multi-subject surveys annually. The rationale behind choosing these two rounds of the survey was the nature of the questions canvassed on consumption expenditure and the proximity of the time period.

The 68th round of the consumption survey, 2011–12 (henceforth referred to as 68(1.0)), was a quinquennial consumption survey that aimed at providing reliable estimates of per capita consumption expenditure, poverty, and inequality in the country. Data from this survey was used for deriving poverty estimates in the country (Rangarajan & Dev, 2015). The survey covered a total of 101,651 households across the states and union territories of India using a detailed version of the consumption schedule that had 346 questions. The questions on consumption were extensive and covered consumption of households elaborately in a given reference period. Various recall periods were used to collect the data: 7 days for food expenditure; 30 days for non-food items such as fuel, light, health expenditure of outpatient visit, rents, and taxes; and 365 days for clothing, footwear, education, institutional medical care, and durable goods.

The 25th schedule of the 71st round of the health survey, 2014 (henceforth referred to as 71(25.0)), covered a sample of 65,932 households. The primary focus of the health survey was to provide comprehensive information on health expenditure, hospitalisation, outpatient visits, type of ailment, nature of ailment, total duration of ailment, expenses on pre- and post-natal care, and economic independence of individuals aged 60 years and above. The question on health expenditure was systematically canvassed for each episode of hospitalisation/outpatient visit, along with the type of ailment, level of care, source of meeting health care expenditure, etc. However, the health survey canvassed only a single question on household consumption under the head, “Household’s usual consumer expenditure (Rupees) in a month,” to estimate the household consumption expenditure.

Unit data from both the surveys has been extensively used by researchers (Kastor and Mohanty, 2018; Mohanty and Dwivedi, 2021; Mohanty and Kastor, 2017; Pandey et al. 2018a, 2018b). Both the surveys used a stratified multistage cluster sampling design. The primary sampling units (PSUs) were the 2011 census villages for the rural areas and urban frame survey blocks for the urban areas.

Variables

Outcome variables. MPCE and CHE of a household were the two outcome variables in the analysis. MPCE is defined as the household consumption expenditure divided by household size and standardised on a monthly basis. CHE is defined as a household’s out-of-pocket payment exceeding a predefined budget share (BS)/capacity to pay (CTP) of the household. MPCE was estimated from both the consumption and the health surveys, while CHE was estimated from the health survey.

Independent variables. Age of head of household, education of head of household, household size, religion and caste of head of

household, place of residence, region, and states were the independent variables used in the analysis.

Methods. Our analytical strategy was primarily to compare the CHE estimates obtained from the consumption and the health surveys. In doing so, we considered the consumption estimates from the consumption survey as the gold standard. Since the health survey was conducted 2 years after the consumption survey, we adjusted the estimates of 2014 for underestimation as well as price levels. Our objective was to estimate the extent of underestimation/overestimation of CHE in the health surveys in India. This was done under the assumption that the NSS consumption survey of 2011–12 was the gold standard for consumption estimates and that the NSS health survey of 2014 was the gold standard for deriving estimates of out-of-pocket (OOP) expenditure as the survey systematically collected detailed data on health expenditure.

Descriptive statistics, price index, CHE estimates using the budget share approach and the capacity-to-pay approach, and logistic regression were used in the analysis. Mean and 95% CI (confidence intervals) were used to compare the variations in consumption expenditure in the two surveys. We standardised MPCE and plotted the cumulative distribution function (CDF) to understand the distribution of household consumption. For the CDF plot, MPCE was truncated at the 1st percentile and the 99th percentile and standardised in both the surveys using the following formula:

$$\frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Adjusted and unadjusted MPCE. The MPCE derived from the 2011 to 12 consumption survey was taken as the standard, while the MPCE derived from the 2014 health survey was adjusted to it. The MPCE from both the surveys was referred to as unadjusted MPCE. The adjustments were made to account for two factors: (a) underestimation in health survey and (b) inflation. The 2014 health survey was conducted 2 years after the 2011–12 consumption survey and hence the estimates were adjusted to the 2014 prices. The MPCE derived from the consumption survey was adjusted to the 2014 prices using the consumer price index and referred to as the adjusted MPCE from the consumption survey for 2014. The state specific price index of agricultural labourers for rural areas and industrial workers for urban areas was used to adjust the prices (Mohanty et al. 2022; Mohanty et al. 2019).

Estimation of catastrophic health expenditure. We estimated the incidence and intensity of CHE using two of the commonly used approaches: the budget share approach (BS) and the capacity-to-pay approach (CTP). Both the approaches differ conceptually. The BS approach is simpler and is often used in the NSS-based health surveys (Mohanty et al. 2018; Somkotra and Lagrada, 2009; van Doorslaer et al. 2007). The budget share approach defines a household as having incurred CHE if the household’s OOP expenditure exceeded 10% of its consumption expenditure (HCE).

$$\text{Mathematically, } CHE_i = \frac{OOP_i}{HCE_i} \geq 0.1 \tag{2}$$

$$\text{Incidence of } CHE_{BS} = \frac{1}{N} \sum CHE_i \tag{3}$$

Where CHE_i is the catastrophic health expenditure of the i^{th} household, OOP_i is the out-of-pocket expenditure of the i^{th} household, and N is the total number of households.

$$\text{Intensity of CHE} = \frac{1}{U} \sum \left(\frac{OOP_i}{HCE_i} - 0.1 \right) \quad (4)$$

Where U is the number of households incurring catastrophic health expenditure.

The intensity of CHE was computed for households that incurred catastrophic health spending.

We also estimated the incidence and intensity of CHE using the capacity-to-pay (CTP) approach. The CTP approach defines a household facing catastrophe if:

$$E_i = \frac{OOP_i}{(HCE_i - SE)} \geq 0.4 \quad (5)$$

Where SE is the subsistence expenditure of the household.

The share of median food expenditure of the 2011–12 consumption survey was used (as constant) for the 2014 health survey to derive subsistence expenditure as used in a recent study (Mohanty and Dwivedi, 2021).

$$\text{Incidence of CHE}_{\text{ctp}} = \frac{1}{N} \sum E_i \quad (6)$$

$$\text{Intensity of CHE}_{\text{ctp}} = \frac{1}{U} \sum \left(\frac{OOP_i}{(HCE_i - SE)} - 0.4 \right) \quad (7)$$

Where U is the number of households incurring CHE.

Two sets of logistic regression model were used to understand the predictors of adjusted and unadjusted estimates of CHE. The basic form of the logistic regression model, which yields the probability of occurring of an event, can be depicted as:

$$\log_e [P(Y_i = 1|X_i)/1 - P(Y_i = 1|X_i)] = \log_e [\pi/1 - \pi] \quad (8)$$

$$= \alpha + \beta_1 X_{i1} + \dots + \beta_k X_{ik}$$

Where Y_i is the binary response variable, X_i is the set of explanatory variables such as sociodemographic characteristics like age, sex, education, place of residence, caste, household size, and states, and $\beta_1, \beta_2, \dots, \beta_k$ are the coefficients of the X_i variables. The results of the logistic regression analysis were presented as predicted probabilities of incurring adjusted and unadjusted CHE by sociodemographic characteristics.

Results

The key indicators, such as median age, proportion urban, household size, and proportion of scheduled caste and scheduled tribe population, were similar in both the surveys. The estimates of MPCE in the consumption survey of 2011–12 were higher (₹1772 vs ₹1625) than those in the health survey of 2014 (Table 1).

Table 2 presents the distribution of the unadjusted and price adjusted estimates of MPCE obtained from the 2011 to 12 consumption survey and the 2014 health survey at 2014 prices according to some selected sociodemographic characteristics. Overall, the estimates of MPCE obtained from the health survey (₹1625) were lower by 8.3% than those obtained from the consumption survey (₹1772). The estimates were 24.5% lower when the MPCE from the consumption survey was adjusted to the 2014 prices (₹2153). The estimates of MPCE from the health survey were lower at each level of distribution compared to the consumption survey. For instance, at the 95th percentile, they were 24% lower. The pattern was similar at the 5th, 25th, and 75th percentiles. The ratio of the unadjusted MPCE in 2014 to the adjusted MPCE in 2011–12 at the 2014 prices showed the extent of underestimation of the consumption expenditure in the health survey. The underestimation was relatively higher in the case of female-headed households, households headed by a person having secondary level of education, rural households, and households belonging to SC/ST and OBC castes.

Table 1 Summary statistics from consumption survey, 2011-12 and health survey, 2014.

Variable	Consumption Survey, 2011-12	Health Survey, 2014
Number of households	101,651	65,932
Average Households size	4.42	4.51
%Urban	31.25	32.56
%SC/ST	27.95	27.83
%Hindus	83.04	82.35
Median Age	25	26
Sex Ratio	935	942
Number of questions on consumption	346	1
MPCE (₹) [95% CI]	1772 [1762-1784]	1625 [1615-1635]
Adjusted MPCE at 2014 prices [95%CI]	2153 [2139-2166]	1625 [1615-1635]

Figure 1 shows the cumulative distribution function (CDF) of the estimates of MPCE obtained from the 68th round of the consumption survey (2011–12) and the 71st round of the health survey (2014) by rural and urban areas. In general, the CDF curves of MPCE from the consumption and the health surveys for rural and urban areas show a similar pattern across the standardised MPCE. The CDF curve of MPCE for urban areas lies below the curve for the rural areas in both the surveys, suggesting that the probability of having a low MPCE score was higher in rural areas compared to urban areas. The CDF curve of MPCE derived from the consumption survey is smoother than that derived from the health survey.

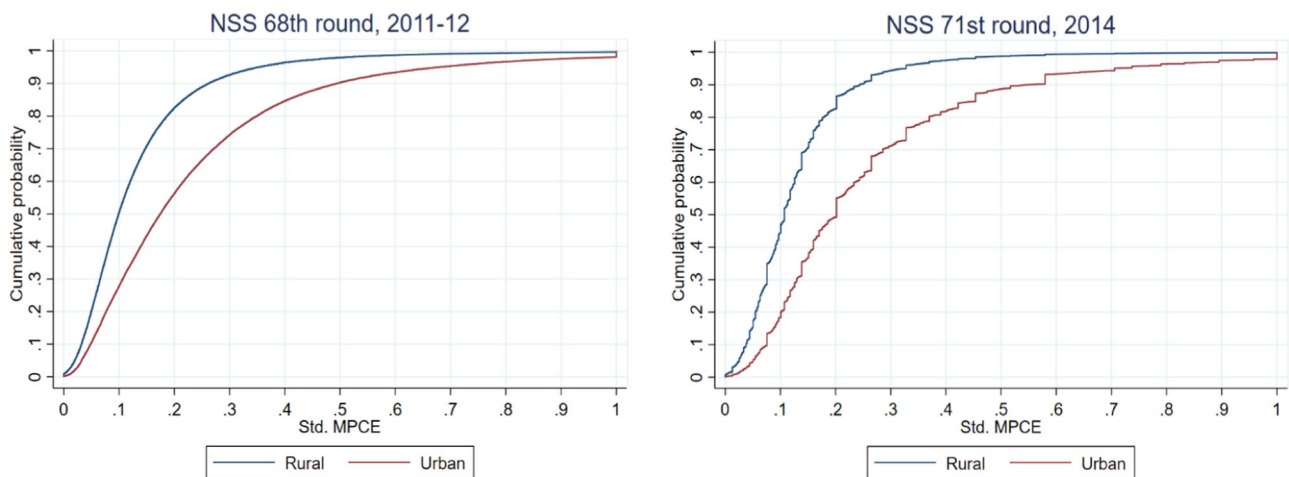
Figure 2 presents the variations in the estimates of MPCE derived from the consumption survey, 2011–12, adjusted to the 2014 prices and the estimates of MPCE derived from the health survey, 2014, by states of India. In India, the MPCE derived from the health survey (₹1625) was lower than that derived from the consumption survey (₹2153) (at 2014 prices); the pattern was consistent across the states except Delhi. In the case of the consumption survey adjusted to the 2014 prices, MPCE was the highest in Kerala (₹3614), followed by Delhi (₹3377) and Haryana (₹3160). It was the lowest in Odisha (₹1421), followed by Bihar (₹1426) and Chhattisgarh (₹1474). In the case of the health survey, MPCE was the highest in Delhi (₹3747), followed by Kerala (₹2552) and Punjab (₹2368) and the lowest in Chhattisgarh (₹1124), followed by Odisha (₹1091) and Bihar (₹1065). A large variation was observed in the ratio of MPCE of the consumption survey and health survey. The ratio was the highest in Uttarakhand (1.57), followed by Karnataka (1.57) and Haryana (1.47), while it was the lowest in Assam (1.17), followed by Gujarat (1.23) and Punjab (1.27) (Supplementary Table S1).

Table 3 presents the incidence and intensity of CHE with and without adjusting for the underestimation of the consumption expenditure in India. The unadjusted intensity of CHE for India was 39.5% and the adjusted estimate was 31.5%. The extent of overestimation of CHE was similar across MPCE quintiles, place of residence, age of head of household, and caste and religion of head of household. With reference to educational attainment of head of household, the level of overestimation was higher for those with higher secondary and above levels of education compared to those with no education.

Figure 3 shows the incidence of CHE using the budget share approach and the CTP approach with and without adjusting for consumption expenditure. The incidence of CHE without adjusting for the consumption expenditure using the budget share approach was 24.4%, while it was 21.1% after adjusting for it. In

Table 2 Distribution of MPCE, 95% CI by sociodemographic characteristics of consumption and health survey in India.

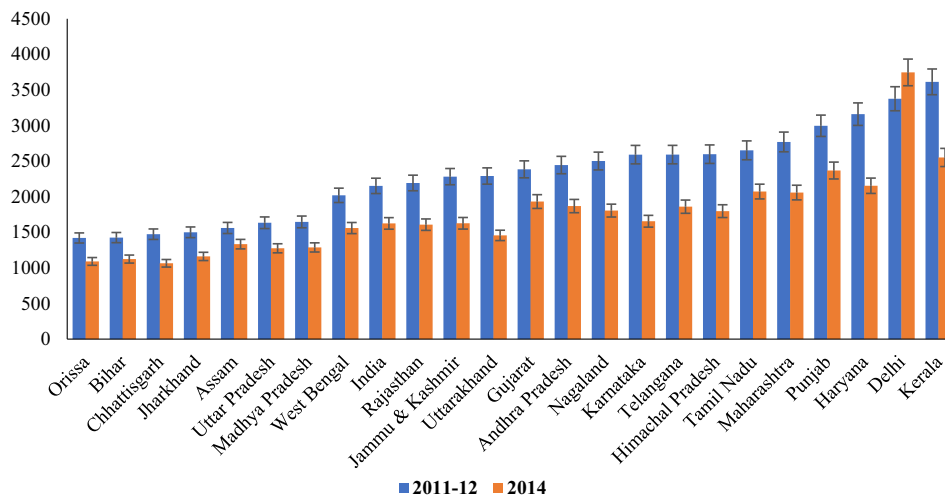
Variable	Consumption Survey, 2011-12	Consumption Survey, 2011-12 adjusted to 2014 prices	Health Survey, 2014	Ratio of unadjusted MPCE 2014 to MPCE 2011-12 at 2014 prices
	Mean (₹) [95% CI]	Mean (₹) [95% CI]	Mean (₹) [95% CI]	
<i>Percentile</i>				
5%	646 (638-654)	789 (780-799)	600 (592-608)	0.760
10%	754 (748-761)	920 (911-929)	700 (689-711)	0.761
25%	975 (967-983)	1189 (1178-1199)	900 (892-908)	0.757
50%	1345 (1333-1357)	1639 (1624-1655)	1286 (1261-1310)	0.784
75%	2003 (1986-2020)	2433 (2411-2454)	1845 (1808-1882)	0.758
90%	3071 (3033-3109)	3721 (3676-3766)	2900 (2818-2982)	0.779
95%	4071 (4007-4135)	4928 (4845-5012)	3750 (3726-3775)	0.761
<i>Age of head of HHs</i>				
Below 35	1836 (1807-1864)	2225 (2192-2259)	1593 (1568-1618)	0.716
35-44	1699 (1681-1717)	2061 (2039-2084)	1522 (1504-1541)	0.739
45 and above	1791 (1776-1807)	2177 (2158-2196)	1683 (1670-1697)	0.773
<i>Sex of the head of households</i>				
Male	(1749-1772)	2137 (2123-2151)	1618 (1607-1629)	0.757
Female	1899 (1859-1939)	2319 (2270-2368)	1695 (1664-1725)	0.731
<i>Education of head of household</i>				
No education	1276 (1265-1288)	1558 (1544-1573)	1189 (1180-1198)	0.763
Primary	1471 (1459-1484)	1796 (1780-1811)	1408 (1394-1421)	0.784
Middle/Secondary	1884 (1864-1904)	2289 (2264-2314)	1690 (1673-1706)	0.738
Higher secondary and above	3167 (3128-3207)	3809 (3762-3857)	2835 (2794-2876)	0.744
<i>Household Size</i>				
1-4	2302 (2282-2322)	2798 (2773-2822)	2078 (2058-2097)	0.743
5-7	1504 (1492-1517)	1825 (1810-1840)	1422 (1410-1433)	0.779
8+	1313 (1295-1331)	1593 (1572-1615)	1189 (1174-1204)	0.746
<i>Place of residence</i>				
Rural	1430 (1420-1440)	1753 (1740-1766)	1287 (1280-1295)	0.734
Urban	2630 (2606-2653)	3152 (3123-3181)	2414 (2392-2436)	0.766
<i>Caste</i>				
SC/ST	1364 (1353-1375)	1658 (1645-1672)	1247 (1236-1257)	0.752
OBC	1664 (1649-1680)	2037 (2018-2056)	1533 (1520-1546)	0.753
Others	2343 (2316-2370)	2819 (2787-2852)	2157 (2131-2182)	0.765
<i>Religion</i>				
Hindu	1759 (1747-1771)	2136 (2122-2150)	1622 (1611-1633)	0.759
Muslim	1596 (1563-1628)	1942 (1902-1982)	1420 (1399-1440)	0.731
Others	2479 (2427-2531)	2998 (2935-3062)	2325 (2265-2384)	0.776
Total	1772 [1762-1784]	2153 [2139-2166]	1625 [1615-1635]	0.755



(a) 68th round of consumption survey 2011-12

(b) 71st round of health survey, 2014

Fig. 1 Cumulative distribution function of standardised MPCE by residence from 68th round of consumption survey 2011-2012 and 71st round of health survey, 2014. The figure shows the CDF of estimates of MPCE for the two survey rounds for urban and rural areas.



Note: Estimates of union territories and smaller states were not shown due to low sample size; Refer to Table S1 for the actual values

Fig. 2 State variation in MPCE of 2011-2012 (consumption survey) adjusted to 2014 price and MPCE of 2014 (health survey) with 95% CI by states of India. The figure illustrates the variations in MPCE from the two surveys across states of India.

Table 3 Incidence and intensity of catastrophic health expenditure (using budget share approach) with and without adjusting consumption expenditure in India, 2014.

Variables	Incidence of CHE (%)		Ratio of unadjusted to adjusted estimates	Intensity of CHE (%)		Ratio of unadjusted to adjusted estimates
	Unadjusted	Adjusted		Unadjusted	Adjusted	
<i>MPCE quintile</i>						
Poorest	25.0	21.9	1.14	50.0	40.4	1.24
Poorer	23.8	20.6	1.16	39.8	31.7	1.26
Middle	24.3	21.1	1.15	34.8	27.1	1.28
Richer	25.8	22.0	1.17	35.3	28.4	1.24
Richest	22.6	19.7	1.15	34.9	27.5	1.27
<i>Place of residence</i>						
Rural	24.7	21.4	1.15	40.8	32.4	1.26
Urban	23.8	20.6	1.16	36.7	29.6	1.24
<i>Age of the head of household</i>						
Below 35	20.5	17.7	1.16	33.2	26.6	1.25
35-44	20.3	17.6	1.15	36.5	29.0	1.26
45 and above	27.8	24.1	1.15	42.0	33.5	1.25
<i>Sex of the head of household</i>						
Male	24.1	20.8	1.16	38.5	30.8	1.25
Female	26.6	23.6	1.13	46.0	36.0	1.28
<i>Education of the head of household</i>						
No education	23.5	20.7	1.13	43.4	34.1	1.27
Primary	26.66	23.1	1.15	35.8	28.1	1.27
Middle/Secondary	25.2	21.6	1.17	40.7	33.3	1.22
Higher secondary and above	21.6	18.5	1.16	35.7	28.8	1.24
<i>Household Size</i>						
1-4	21.9	19.2	1.14	44.5	35.1	1.27
5-7	26.5	22.6	1.17	35.4	28.6	1.24
8+	31.7	27.4	1.16	32.0	25.4	1.26
<i>Religion</i>						
Hindu	23.6	20.4	1.16	39.8	31.9	1.25
Muslim	27.5	24.4	1.13	38.9	30.5	1.28
Others	31.1	27.0	1.15	37.1	28.4	1.30
<i>Caste</i>						
SC/ST	21.6	18.6	1.16	40.7	32.5	1.25
OBC	24.7	21.3	1.16	40.4	32.3	1.25
Others	26.6	23.3	1.14	37.4	29.6	1.26
Total	24.4	21.1	1.15	39.5	31.5	1.25

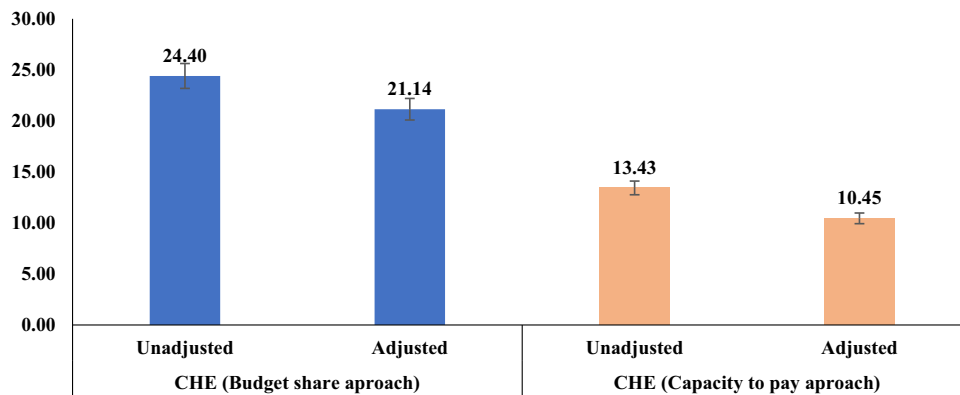


Fig. 3 Incidence of catastrophic health expenditure (%) using budget share approach and capacity to pay approach with and without adjusting consumption expenditure in India, 2014. The figure demonstrates the adjusted and unadjusted CHE using the BS approach and the CTP approach.

Table 4 Incidence and intensity of catastrophic health expenditure (using budget share approach) with and without adjusting consumption expenditure in states of India, 2014 (see Fig S1).

States	Incidence of CHE (%)		Ratio of unadjusted to adjusted estimates	Intensity of CHE (%)		Ratio of unadjusted to adjusted estimates
	Unadjusted	Adjusted		Unadjusted	Adjusted	
<i>India</i>	24.4	21.1	1.15	39.5	31.5	1.25
Delhi	9.2	10.2	0.90	28.8	30.2	0.95
Assam	13.4	12.7	1.06	32.9	28.6	1.15
Gujarat	18.4	15.9	1.15	25.8	21.9	1.18
Bihar	19.2	17.2	1.12	53.8	44.9	1.20
Jharkhand	18.0	14.8	1.22	28.7	23.7	1.21
Uttarakhand	23.9	17.0	1.41	39.2	32.0	1.23
West Bengal	33.7	29.2	1.15	37.8	30.8	1.23
Uttar Pradesh	24.6	22.0	1.11	43.4	35.1	1.24
Madhya Pradesh	20.3	18.6	1.09	46.7	37.8	1.24
Tamil Nadu	24.0	21.1	1.14	35.6	28.5	1.25
Punjab	32.2	28.8	1.12	30.9	24.7	1.25
Orissa	32.8	28.7	1.14	56.0	44.6	1.25
Maharashtra	22.6	19.8	1.14	36.9	29.4	1.26
Jammu & Kashmir	25.0	20.1	1.24	34.9	27.5	1.27
Chhattisgarh	12.8	11.7	1.09	100.4	78.8	1.27
Himachal Pradesh	21.5	17.7	1.21	45.8	35.1	1.31
Andhra Pradesh	29.6	26.1	1.13	32.5	24.9	1.31
Rajasthan	17.8	14.9	1.19	32.0	24.4	1.31
Kerala	43.0	33.6	1.28	27.9	20.7	1.35
Telangana	29.6	27.1	1.09	47.3	34.1	1.39
Karnataka	26.9	20.3	1.33	35.5	25.3	1.41
Haryana	21.2	17.7	1.19	34.5	23.2	1.49

Estimates of union territories and smaller states were not shown due to low sample size.

contrast, the incidence of CHE using the capacity-to-pay approach without adjustment was 13.43%, whereas it was 10.45% when adjustment was made. Therefore, the overestimation of CHE in the health survey was revealed to be 3% using both the approaches.

Table 4 presents the state patterns of incidence and intensity of CHE derived from the health survey using the budget share approach with and without adjusting for consumption expenditure. Barring Delhi, the incidence of unadjusted CHE was higher than that of adjusted CHE across the states of India. The incidence of adjusted CHE varied from 12% in Chhattisgarh to 34% in Kerala (Supplementary Fig. S1). The extent of overestimation was higher than the national average in the states of Kerala, Karnataka, Uttarakhand, Rajasthan, Haryana, Himachal Pradesh, and Jharkhand. The pattern of overestimation of the intensity of CHE was like that of the incidence of CHE. The intensity of adjusted CHE varied considerably, from 21% in

Kerala to 79% in Chhattisgarh. The corresponding overestimation of the intensity of CHE was the highest in Haryana, followed by Karnataka, Telangana, and Kerala.

Table 5 presents the incidence and intensity of CHE with and without adjusting for consumption expenditure using the CTP approach. The unadjusted CHE was estimated at 13.43%, whereas the adjusted CHE was estimated at 10.45%. In other words, CHE was overestimated by 3% without adjusting for underestimation of the consumption expenditure. The incidence of unadjusted CHE was higher than that of adjusted CHE across socio-demographic characteristics. For example, the extent of overestimation was higher in the case of middle MPCE quintile, urban residence, male-dominated households, primary level of education, and other religions. For example, the unadjusted estimates of CHE were higher in the richer MPCE quintile compared to the poorer MPCE quintile, higher in urban than rural areas and did not show any pattern with the educational attainment of head of

Table 5 Incidence and intensity of catastrophic health expenditure (using capacity to pay approach) with and without adjusting consumption expenditure in India, 2014.

Variables	Incidence of CHE (%)		Ratio of unadjusted to adjusted estimates	Intensity of CHE (%)		Ratio of unadjusted to adjusted estimates
	Unadjusted	Adjusted		Unadjusted	Adjusted	
<i>MPCE quintile</i>						
Poorest	19.73	16.92	1.17	377.1	341.5	1.10
Poorer	13.91	10.50	1.32	91.2	79.0	1.15
Middle	11.79	8.38	1.41	67.7	59.5	1.14
Richer	11.18	8.26	1.35	66.2	56.1	1.18
Richest	8.75	6.49	1.35	57.3	47.1	1.22
<i>Place of residence</i>						
Rural	14.98	11.78	1.27	192.0	181.6	1.06
Urban	10.22	7.69	1.33	108.3	98.3	1.10
<i>Age of the head of household</i>						
Below 35	11.55	9.10	1.27	109.3	95.8	1.14
35-44	10.79	8.60	1.26	178.7	161.7	1.10
45 and above	15.49	11.9	1.30	178.1	172.2	1.03
<i>Sex of the head of household</i>						
Male	13.19	10.25	1.29	147.5	136.5	1.08
Female	15.2	11.93	1.27	319.8	316.6	1.01
<i>Education of the head of household</i>						
No education	15.06	12.03	1.25	244.4	236.1	1.04
Primary	14.46	10.86	1.33	142.9	133.7	1.07
Middle/Secondary	13.2	10.27	1.29	123.8	111.0	1.12
Higher secondary and above	9.24	7.15	1.29	115.2	99.5	1.16
<i>Household Size</i>						
1-4	12.05	9.52	1.27	211.7	199.6	1.06
5-7	14.67	11.12	1.32	138.8	131.3	1.06
8+	17.2	13.67	1.26	96.3	83.3	1.16
<i>Religion</i>						
Hindu	13.15	10.23	1.29	176.0	167.0	1.05
Muslim	14.91	11.98	1.24	152.1	142.7	1.07
Others	15.01	10.64	1.41	90.5	79.7	1.14
<i>Caste</i>						
SC/ST	12.77	10.26	1.24	248.9	229.9	1.08
OBC	13.74	10.59	1.30	168.7	163.2	1.03
Others	13.59	10.42	1.30	106.7	96.4	1.11
Total	13.43	10.45	1.29	170.8	161.1	1.06

household. The unadjusted and adjusted estimates of CHE were lower than those revealed by the budget share approach.

Table 6 presents the state variations in the adjusted and unadjusted estimates of the incidence and intensity of CHE using the CTP approach in India. The incidence of unadjusted CHE was higher than the incidence of adjusted CHE across the states of India except Delhi. The incidence of adjusted CHE varied from 5% in Gujarat to 17% in Odisha (Supplementary Fig. S2). Among the states, the level of overestimation in the incidence of CHE was the highest in Rajasthan, followed by Haryana, Kerala, and Uttarakhand. In many states of the country, the incidence and intensity of CHE were overestimated if the consumption expenditure was not adjusted. The intensity of the adjusted CHE varied from 41% in Haryana to 55% in Madhya Pradesh. The intensity of CHE was overestimated to the extent of 39% in Karnataka, 38% in Haryana, and 28% each in Himachal Pradesh and Uttarakhand.

Table 7 presents the results of the logistic regression analysis of CHE (using the budget share approach) with and without adjusting for consumption expenditure in India. The predictors of incurring CHE both with and without adjusting for consumption expenditure were almost similar. The predicted probabilities of incurring CHE were overestimated by 13-18% after adjusting CHE across the selected sociodemographic characteristics. Evidently, the predicted probabilities of incurring CHE without adjusting (0.432) were significantly higher than with adjusting (0.201) among the richest MPCE quintile (overestimated by

15.4%). The likelihood of incurring CHE with and without adjusting was lower in the urban areas than in the rural areas.

However, the predicted probabilities of unadjusted CHE were significantly overestimated by 14.9% than after adjusting CHE in the urban areas. Older adults (45+) were more likely to incur CHE without adjusting [AOR = 1.33; 95%CI: 1.339-1.34] as well as with adjusting [AOR = 1.34; 95%CI: 1.34-1.35] than their other counterparts; however, the predicted probabilities of unadjusted CHE were overestimated by 15.1% when the adjustment was made in CHE. Households headed by women were significantly more likely to incur CHE with and without adjusting than households headed by males, whereas the predicted probabilities of CHE were significantly higher (0.272) before adjusting than after adjusting CHE (0.0.240). The likelihood of incurring CHE with and without adjusting was higher in Muslim and 'Other religion' households than Hindu households. However, the predicted probabilities of unadjusted CHE were significantly overestimated by 13% in the case of Muslim households and 15% in the case of 'Other religion' households when the adjustment was made in CHE. Similarly, the predicted probabilities of unadjusted CHE in the case of OBC and 'Other caste' groups were overestimated by 16% and 13% when the adjustment was made in CHE.

Table 8 presents the results of the logistic regression analysis of CHE (using the CTP approach) with and without adjusting for consumption expenditure in India. Though the predictors of CHE remained similar with and without adjustment using the CTP

Table 6 Incidence and intensity of catastrophic health expenditure (capacity to pay approach) with and without adjusting consumption expenditure in India, 2014.

States	Incidence of CHE (%)		Ratio of unadjusted to adjusted estimates	Intensity of CHE (%)		Ratio of unadjusted to adjusted estimates
	Unadjusted	Adjusted		Unadjusted	Adjusted	
<i>India</i>	13.43	10.45	1.29	170.85	161.09	1.06
Jharkhand	11.03	8.37	1.32	242.47	281.71	0.86
Delhi	2.4	2.62	0.92	93.24	100.12	0.93
Madhya Pradesh	13.76	11.8	1.17	527.02	555.22	0.95
Rajasthan	9.97	5.99	1.66	66.54	65.35	1.02
Uttar Pradesh	16.25	13.35	1.22	260.44	234.80	1.11
Orissa	21.6	17.22	1.25	271.15	239.71	1.13
Maharashtra	11.12	8.72	1.28	101.72	89.04	1.14
West Bengal	18.45	14.85	1.24	123.91	108.45	1.14
Assam	9.05	8.26	1.10	90.40	78.66	1.15
Telangana	15.77	11.48	1.37	108.41	93.16	1.16
Gujarat	5.97	5.05	1.18	84.54	72.32	1.17
Tamil Nadu	10.97	8.54	1.28	80.16	68.25	1.17
Punjab	15.6	11.57	1.35	60.83	51.62	1.18
Bihar	13.93	12.04	1.16	155.54	131.96	1.18
Chhattisgarh	8.75	7.21	1.21	571.44	483.42	1.18
Jammu & Kashmir	12.17	8.88	1.37	99.04	83.33	1.19
Andhra Pradesh	15.9	11.22	1.42	56.14	46.30	1.21
Kerala	16.37	10.57	1.55	61.38	49.86	1.23
Uttarakhand	12.51	8.32	1.50	83.47	65.32	1.28
Himachal Pradesh	12.44	9.23	1.35	93.84	73.08	1.28
Haryana	10.22	6.45	1.58	56.79	41.10	1.38
Karnataka	13.08	8.89	1.47	88.31	63.63	1.39

Estimates of union territories and smaller states were not shown due to low sample size; See Supplementary Fig. S1.

Table 7 Result of logistic regression analyses showing significant predictors of catastrophic health expenditure using budget share approach with and without adjusting consumption expenditure in India.

Variables	Unadjusted	Predicted probabilities	Adjusted	Predicted probabilities	Percentage change
<i>MPCE quintile</i>					
Poorest [®]		0.250		0.220	13.4
Poorer	0.923*** (0.92, 0.92)	0.235	0.905*** (0.9, 0.91)	0.204	15.3
Middle	0.949*** (0.95, 0.95)	0.240	0.935*** (0.93, 0.94)	0.209	14.8
Richer	1.06*** (1.06, 1.06)	0.261	1.005*** (1, 1.01)	0.221	17.8
Richest	0.906*** (0.9, 0.91)	0.232	0.89*** (0.89, 0.89)	0.201	15.4
<i>Place of residence</i>					
Rural [®]		0.247		0.214	15.4
Urban	0.952*** (0.95, 0.95)	0.238	0.96*** (0.96, 0.96)	0.207	14.9
<i>Age of the head of household</i>					
Below 35 [®]		0.221		0.189	16.9
35-44	0.898*** (0.9, 0.9)	0.203	0.92*** (0.92, 0.92)	0.177	15.1
45 and above	1.335*** (1.33, 1.34)	0.274	1.344*** (1.34, 1.35)	0.238	15.1
<i>Sex of the head of household</i>					
Male [®]		0.240		0.208	15.6
Female	1.187*** (1.19, 1.19)	0.272	1.21*** (1.21, 1.21)	0.240	13.2
<i>Education of the head of house-hold</i>					
No education [®]		0.224		0.197	13.7
Primary	1.251*** (1.25, 1.25)	0.265	1.219*** (1.22, 1.22)	0.230	15.2
Middle/Secondary	1.219*** (1.22, 1.22)	0.260	1.175*** (1.17, 1.18)	0.224	16.3
Higher secondary and above	1.024*** (1.02, 1.03)	0.228	0.99*** (0.99, 0.99)	0.196	16.8
<i>Household Size</i>					
1-4 [®]		0.221		0.195	13.3
5-7	1.281*** (1.28, 1.28)	0.266	1.209*** (1.21, 1.21)	0.226	17.5
8+	1.534*** (1.53, 1.54)	0.302	1.443*** (1.44, 1.45)	0.258	16.9
<i>Religion</i>					
Hindu [®]		0.238		0.206	15.6
Muslim	1.139*** (1.14, 1.14)	0.262	1.163*** (1.16, 1.16)	0.231	13.3
Others	1.416*** (1.41, 1.42)	0.305	1.402*** (1.4, 1.4)	0.266	15.0
<i>Caste</i>					
SC/ST [®]		0.218		0.188	16.0
OBC	1.17*** (1.17, 1.17)	0.246	1.163*** (1.16, 1.16)	0.212	15.9
Others	1.303*** (1.3, 1.3)	0.266	1.321*** (1.32, 1.32)	0.234	13.8
Constant	0.19*** (0.19, 0.19)		0.166*** (0.17, 0.17)		

AOR adjusted odds ratio, 95% CI 95% confidence interval.
[®]Reference category *p < 0.05; **p < 0.01; ***p < 0.001.

Table 8 Result of logistic regression analyses showing significant predictors of catastrophic health spending using capacity to pay approach with and without adjusting consumption expenditure in India.

Variables	Unadjusted	Predicted probabilities	Adjusted	Predicted probabilities	Percentage change
<i>MPCE quintile</i>					
Poorest*		0.200		0.174	15.0
Poorer	0.629*** (0.63, 0.63)	0.137	0.545*** (0.54, 0.55)	0.104	32.0
Middle	0.516*** (0.52, 0.52)	0.115	0.421*** (0.42, 0.42)	0.082	40.5
Richer	0.495*** (0.49, 0.5)	0.111	0.418*** (0.42, 0.42)	0.082	36.1
Richest	0.396*** (0.4, 0.4)	0.091	0.332*** (0.33, 0.33)	0.066	37.9
<i>Place of residence</i>					
Rural*		0.141		0.109	28.5
Urban	0.824*** (0.82, 0.82)	0.119	0.824*** (0.82, 0.82)	0.092	29.2
<i>Age of the head of household</i>					
Below 35*		0.121		0.093	30.0
35–44	0.85*** (0.85, 0.85)	0.105	0.881*** (0.88, 0.88)	0.083	26.4
45 and above	1.341*** (1.34, 1.34)	0.156	1.342*** (1.34, 1.34)	0.121	28.9
<i>Sex of the head of household</i>					
Male*		0.132		0.103	28.7
Female	1.194*** (1.19, 1.2)	0.153	1.202*** (1.2, 1.2)	0.120	27.2
<i>Education of the head of house-hold</i>					
No education*		0.130		0.102	28.3
Primary	1.101*** (1.1, 1.1)	0.141	1.053*** (1.05, 1.05)	0.106	33.1
Middle/Secondary	1.114*** (1.11, 1.12)	0.143	1.126*** (1.12, 1.13)	0.113	26.7
Higher secondary and above	0.891*** (0.89, 0.89)	0.118	0.93*** (0.93, 0.93)	0.095	23.9
<i>Household Size</i>					
1–4*		0.132		0.107	23.9
5–7	1.044*** (1.04, 1.04)	0.137	0.952*** (0.95, 0.95)	0.102	34.2
8+	1.044*** (1.04, 1.05)	0.137	0.982*** (0.98, 0.98)	0.105	30.6
<i>Religion</i>					
Hindu*		0.133		0.103	28.9
Muslim	1.043*** (1.04, 1.04)	0.137	1.093*** (1.09, 1.09)	0.111	23.6
Others	1.322*** (1.32, 1.32)	0.167	1.221*** (1.22, 1.22)	0.122	36.7
<i>Caste</i>					
SC/ST*		0.115		0.092	25.7
OBC	1.226*** (1.22, 1.23)	0.137	1.175*** (1.17, 1.18)	0.106	29.8
Others	1.384*** (1.38, 1.39)	0.152	1.334*** (1.33, 1.34)	0.118	28.6
Constant	0.179*** (0.18, 0.18)		0.159*** (0.16, 0.16)		

AOR adjusted odds ratio, 95% CI 95% confidence interval.
 *Reference category *p < 0.05; **p < 0.01; ***p < 0.001.

approach, the predicted probabilities of incurring CHE were significantly higher before adjusting than after adjusting CHE for the selected sociodemographic characteristics. The predicted probabilities of incurring unadjusted CHE were overestimated by 15–40% after adjusting CHE across the selected sociodemographic characteristics. It was found that using the CTP approach, the probability of incurring CHE with and without adjusting decreased significantly from the poorer MPCE quintile to the richest one. The likelihood of incurring CHE with and without adjusting was lower in urban areas than in rural areas, while the predicted probabilities of incurring unadjusted CHE were significantly overestimated by 29.2% after adjusting CHE in urban areas. Older adults (45+) were more likely to incur CHE with and without adjusting [AOR = 1.341; 95%CI: 1.34–1.34] compared to their counterparts. Female-headed households were significantly more likely to incur CHE with and without adjusting than male-headed households, whereas the predicted probabilities of CHE were significantly higher (0.153) before adjusting than after adjusting CHE (0.120) (overestimated by 27.2%). Similarly, OBC and ‘other caste’ groups were significantly more likely to incur CHE with and without adjusting CHE than other caste groups; however, the

predicted probabilities of unadjusted CHE were overestimated by 29.8 and 28.6% after adjusting CHE.

Discussion

Data on household consumption is an integral part of health surveys and key to explaining the economic gradient of health outcomes and health care utilisation. Consumption data is also used for estimating catastrophic health expenditure. While health surveys collect detailed data on health expenditure, ailments, and health care, they include only a limited number of questions on household consumption expenditure. A detailed consumption schedule is not recommended due to time and resource constraints and on the grounds of the purpose of the survey. However, data on household consumption adequately measures the economic gradient and helps draw reliable inferences. The National Sample Survey, the official statistical system of India, has been a pioneer in devising various modules of the consumption schedule but uses only a single question on consumption expenditure in the health surveys. A large number of studies have used the NSS-based health survey data and estimated CHE for different states across India (Joe, 2015; Karan et al. 2014; Mohanty et al. 2018; Pandey et al. 2018a, 2018b). However, none of them have examined the

effect of the measurement error on the estimates of CHE in India. This is the first ever study that examined the sensitivity of estimates to measurement error in consumption expenditure in India. The following are the salient findings of the study.

First, in the NSS-based health survey in India, the consumption expenditure was underestimated to the extent of 32%. The level of underestimation was robust across the states of India and across sociodemographic characteristics. This is primarily due to the survey having only a single aggregative question on consumption expenditure. Our finding is consistent with the literature. Numerous studies, elsewhere in the world, have suggested that having only a single question on consumption expenditure underestimates the standard consumption estimates (Browning et al. 2003; Heijink et al. 2011; Lu et al. 2009).

Second, the incidence of catastrophic health expenditure, derived using the budget share from the health survey without adjusting for the measurement error, was overestimated by at least 15%. Overestimation was observed across the socio-demographic characteristics. The intensity of CHE was also overestimated by about 25% in the country. The level of overestimation in both the incidence and intensity of CHE varied across the states of India. In the states of Haryana, Karnataka, Telangana, and Kerala, the overestimation in the intensity of CHE was over 25%.

Third, the level of overestimation in the incidence and the intensity of CHE was found to be high even with the capacity-to-pay approach. The level of overestimation in the incidence of CHE using the CTP approach was 29% and varied considerably across the household characteristics. A wide variation in the incidence and intensity of CHE was observed across the states of India. The overestimation in the intensity of CHE using the CTP approach was higher in the states of Karnataka, Haryana, Himachal Pradesh, and Uttarakhand.

Finally, the predictors of the adjusted and unadjusted CHE remained similar. However, using both the approaches of estimating CHE, the predicted probabilities of incurring CHE were significantly higher before adjusting than after adjusting CHE across the selected sociodemographic characteristics.

Our results demonstrate that the NSS-based health surveys in India underestimate the consumption expenditure, which means that the estimates require adjusting to accurately estimate CHE. If the underestimation is not adjusted, it leads to overestimation of CHE. The use of both the budget share and the CTP approaches yielded similar inferences. In this context, many earlier estimates are possibly overestimated as, to our knowledge, none of the previous studies have addressed this issue.

Conclusion

Our analysis is illustrative and suggests the need to understand the data gap in the health surveys. While adjusting for underestimation is a temporary fix, it is suggested that the disaggregated version of the consumption schedule be integrated in the health surveys. The abridged consumption schedule of NSS has already been integrated into the IHDS and the LASI surveys—two of the nationally representative large-scale surveys in India (Desai et al. 2011–2012; IIPS et al. 2020). Unfortunately, NSS's own health survey does not integrate the consumption schedule. Canvassing a small set of disaggregated questions on household consumption will likely take no more than 10 min, and this practice is already in place in many other population-based surveys. Doing so will also help us estimate the food expenditure, a necessity to estimate CHE using the CTP approach. At present, there is no data on food expenditure, and researchers often cite non-availability of data as a limitation to compute CHE using the CTP approach in health surveys. We conclude that researchers need to be aware that the

estimates of CHE derived from the health survey data conducted by the NSS need to be adjusted for underestimation of consumption expenditure to provide reliable estimates of CHE in India. Furthermore, the NSS health surveys should include disaggregated questions on consumption expenditure to help provide better CHE estimates for policy formulation.

Data availability

Data are publicly available and can be downloaded by registering at <http://microdata.gov.in/nada43/index.php/home>. The datasets analysed during the current study are available in the figshare repository, <https://doi.org/10.6084/m9.figshare.24216405.v2>.

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Competing interests

The authors declare no competing interests.

Ethical approval

This data used in this paper is based on secondary data, which is available in public domain for research purpose. Therefore, no ethical approval was required from any institutional review board.

Informed consent

This paper does not involve any human participants. The data is from secondary source.

Additional information

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