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# The links between catastrophic health expenditures and multidimensional poverty: An instrumental variable analysis in India

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**Abstract**

The relationship between multidimensional poverty and catastrophic health expenditures has not been studied in detail, specifically how dependent such a connection is according to the specific context. This study aims to determine whether households who face catastrophic health expenditures in India have a higher probability of living in multidimensional poverty, given their socio-economic background and the protection provided by access to health insurance. We explore such a relationship in the case of India, exploiting variation in the development level of its regions and the socio-economic conditions faced conditional on caste. Using data from the

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Indian Human Development Survey, we exploit longitudinal variation at the household level using a linear probability model. We complement this analysis with an instrumental variable analysis, using a health shock to analyse the causal relationship between facing a shock which increases catastrophic health expenditures and living in multidimensional poverty. The results revealed that households facing catastrophic health expenditures in India have a higher probability of being multidimensionally poor. Such a relationship was only partially mitigated if the household was protected by health insurance, and there were almost no differences according to the caste of the household. Moreover, the relationship was stronger outside South India, especially on the role of health insurance. and place of residence. In the case of the instrumental variable analysis, the results show the same pattern as in the longitudinal model; however, the results are not significant.

**JEL Codes:** D14, I3, I15

**Keywords:** Catastrophic Health Expenditures;Multidimensional Poverty; India; Instrumental Variables

# 1 Introduction

Since the World Health Assembly in 2005, many countries have made commitments to ensure that their health systems provide financial protection against the risks of catastrophic health expenditures (CHE) or impoverishment due to out-of-pocket health-care payments (OOP) (World Health Organization, 2005). Recently, as a result of the call for universal health-care coverage without creating financial risks, which was enshrined in the Sustainable Development Goal 3.8 (SGD 3.8), many countries have renewed their commitment to achieve universal health-care coverage by 2030, as a means of preventing financial hardship and ensuring equitable health outcomes, based on the principle that access to health care is a human right (Inter-Agency and Expert Group, 2016).

van Doorslaer et al. (2006) ranked India among the top five countries with the highest percentage of households incurring CHE, along with Bangladesh, Vietnam, China, and Nepal. In India, 16.5 per cent of households suffered CHE, with an incidence of 44 per cent of CHE incurred by households who used private hospitals (Sriram and Albadrani, 2022). This high level of CHE is the result of a context where 82.2 per cent of health expenditure is financed by OOP.

The incidence of CHE in India could be higher in households with at least one child younger than 5 years, one elderly person, and one female member educated to secondary level, and if at least one member of the household used a private health-care facility for treatment (Sriram and Albadrani, 2022). Studies have examined the impact of using private and public health facilities on OOP payments for health care (Sriram and Khan, 2020; Prinja et al., 2019; Harish et al., 2020).

The appearance of community health-insurance schemes in India is linked to the reduction in the incidence of CHE, but these programs are not sufficient, due to their lack of coverage and to the exclusion of some key services from the benefit package (Devadasan et al., 2007). As Sriram and Albadrani (2022) conclude, expanding health-insurance coverage, increasing coverage limits, and including coverage for outpatient and preventative services are vital in order to protect households in India.

The reduction of poverty proposed in Sustainable Development Goal 1 (SGD 1) can be analysed by means of a multidimensional approach and not only as a measurement in terms of income levels. Although it is essential to consider income and consumption factors, there are other elements associated with poverty, such as lag in access to education, health factors such as malnutrition, and living conditions such as access to electricity, clean drinking water, and sanitation services, among others (Channell et al., 2022). ThThese indicators of poverty are incorporated in the Multidimensional Poverty Index (MPI) as a more accurate measure of poverty conditions (World Bank Group, 2020).

The national Multidimensional Poverty Index (MPI) in India revealed that 25.0 per cent of the population were multidimensionally poor, with an intensity of 47.1 per cent and a national MPI of 0.118. In addition, there are important regional and social differences between the levels of multidimensional poverty. For example, Bihar is the State with the largest percentage of people living in multidimensional poverty (51.9 per cent), and Kerala has the lowest rate (0.7 per cent) (NITI Aayog - National Institution for Transforming India, 2021). Although the number of multidimensionally poor individuals has reduced over time, India is still one of the countries with the largest number of people living in multidimensional poverty (UNDP and OPHI, 2019).

The probability of facing CHE and impoverishment could increase when households experience a health shock such as the presence of chronically ill or disabled members, some event of hospitalisation, or the death of the household head or earner. To cope with the high health-care expenses caused by these events, households resort to a range of different strategies, for instance, using savings, selling assets, getting into debt, reducing consumption, using health insurance, or sending children out to work (Kruk et al., 2009; Joe, 2015; Sangar et al., 2018; Mishra and Mohanty, 2019; Kumar et al., 2020; Balla et al., 2022). Longitudinal studies in Indian states showed a greater likelihood of experiencing CHE in households with a member who has a chronic illness (Swetha et al., 2020) aand in households in which an earning member experiences a health shock (Daivadanam et al., 2012; Dhanaraj, 2014), and those studies examined the adoption of different mechanisms to deal with these situations.

CHE in India might trigger multidimensional poverty (MP) because of the high level of OOP. Prevalence of CHE in India is associated with variables often related to multidimensional poverty, such as economic and social status, educational level of the household head, annual household income, proximity to a health-care facility, occupation of the household head, age of household members, caste, and district of residency (Loganathan et al., 2017; Pal, 2012; Sriram and Albadrani, 2022; Swetha et al., 2020).

The link between MP and CHE is not clear, and it has not been analysed in the context of India. The aim of this study is to estimate how the onset of CHE might affect the lev- els of multidimensional poverty in households in India, and to analyse the factors that might be underpinning it. To do so, we used two-way fixed-effects panel regressions, employing longitudinal household-level data, following an empirical strategy similar to that adopted by Pinilla-Roncancio et al. (2022). The main purpose was to verify whether CHE was positively associated with an increase in multidimensional poverty, and which factors might be associated with this change. And also to analyse if, when using an instrumental variable (IV) (diagnosis of chronic conditions), there was a causal effect between CHE and

MP.

# 2 Methods

## 2.1 Data

The India Human Development Survey (IHDS) is a collaborative project of the University of Maryland -College Park, the National Council of Applied Economic Research (NCAER)- in Delhi, Indiana University, and the University of Michigan. The IHDS is a multi-thematic, nationally representative panel and its objective is to document demographic, social and economic changes in India (Desai et al., 2005; Desai and Vanneman, 2012). The first round of data collection was conducted between 2004 and 2005, and the second round between 2011 and 2012.

For the first round of the IHDS, 41,554 households were selected, and in the second round 15.2 per cent of those households were not included. The second round included a refreshment sample of 2,134 households in order to maintain the representativity of the survey. For this research we used a balanced sample, which included only households with information in both waves. Therefore, the final sample was 28,418 households (see Table 1).

**Table 1:** Sample size

| Year | Interviewed sample | Interviewed Households | Final Sample (%) |
|---|---|---|---|
| (1) | (2) | (3) | (4) |
| 2004 - 2005 | 215,754 | 41,554 | - |
| 2011 - 2012 | 204,560 | 39,119 | 84.8% |

## 2.2 Household Expenditures

The IHDS collects information on household expenditures. However, some modules of consumption were collected using different reference periods, for example, food consumptiondata were collected for the last seven days, and education expenditures for the last 12 months. Therefore to harmonise the reference period of household expenditures, we used the methodology developed by ILO (2006) and OECD (2013). WWe included in the analysis expenditures related to housing, education, and food . Note that Desai et al. (2005) and Desai and Vanneman (2012) sstate that the vast majority of households produce their own food, and therefore, to avoid bias in this variable, we chose to record the amount of consumption of each item and then convert it to the commercial value for each area where the households reside. We also computed health expenses, including information on in-patient and out-patient services and other expenses (personal hygiene items, transportation, leisure, and other personal purchases).

## 2.3 Multidimensional Poverty Measure

We created a multidimensional poverty (MP) measure using the Alkire and Foster (AF) method (Alkire and Foster, 2008). The AF method is currently one of the most widely used methods to calculate multidimensional poverty. The AF method uses a counting approach to identify deprivation in different indicators, and then defines who is or is not multidimensionally poor. The AF method computes three sub-indicators: the incidence of poverty or the percentage of people who are multidimensionally poor ($H$), the intensity of poverty ($A$), or the average number of deprivations that multidimensionally poor people face; and finally ($M_0$) or the adjusted headcount ratio.

We compute a MP measure that includes some of the indicators of the national MPI for India (NITI Aayog - National Institution for Transforming India, 2021) and other indicators related to coping mechanisms that households use to mitigate the potential impact of CHE on their levels of poverty. It was not possible to replicate the national MPI for India, given data limitations (for example, IHDS does not include information on nutrition or child mortality). The final MP measure includes five dimensions and 13 indicators. We used nested weights (equal weight for each of the dimensions and equal relative weight for each indicator in the dimension) and a poverty line of 40 per cent. Table 2 presents the dimensions, indicators, deprivation cut-offs and weights included in the MP measure.

**Table 2:** Dimensions, indicators, deprivation cutoffs and weights of the MP measure.

| Dimensions | Indicator | Deprivation Cutoff |
|---|---|---|
| Health (1/5) | Access to a clean source of water (1/10) | A household is deprived if the source of drinking water is an open well, river, canal, stream, pond, tanker truck, bottled water or others. |
| | Improved Sanitation (1/10) | A household is deprived if it has an unconnected toilet, latrine, low tide, or no sanitation. |
| Education (1/5) | School Attendance (1/15) | A household is deprived if at least one school-age child is not attending school. |
| | School Lag (1/15) | A household is deprived if at least one school-age child (8 to 14 years old) is two or more years behind the grade expected for his or her age. |
| | Years of Schooling (1/15) | A household is deprived if at least one household member aged 14 or older has not completed 6 years of education. |
| Employment and Social Protection (1/5) | Health Insurance (1/10) | A household is deprived if at least one member does not have health insurance. |
| | Job diversity (1/10) | A household is deprived if all members between the ages of 15 and 64 work in agriculture . |
| Living Standards (1/5) | Asset Ownership (1/15) | A household is deprived if it does not have at least 2 of the following assets: TV, refrigerator, bicycle, stove, radio OR a car. |
| | Land Ownership (1/15) | A household is deprived if it does not own land for its economic activity. If the main economic activity of the household is not agriculture, it is not considered deprived. |
| | Livestock (1/15) | A household is deprived if it does not own livestock. If the main economic activity of the household is not farming, it is considered non deprived. |
| Housing (1/5) | Electricity (1/15) | A household is deprived if it does not have electricity. |
| | Housing Materials (1/15) | A household is deprived if the floors, walls, or ceilings are made of natural or unsuitable materials. |
| | Cooking Fuel (1/15) | A household is deprived if the main cooking fuel is charcoal or firewood. |

## 2.4 Catastrophic Health Expenditures (CHE)

For the construction of CHE, we used the Xu (2004) definition. According to this definition, a household presents CHE when it spends 40 per cent of its income on health-care expenditures after paying for food. To study the robustness of the results, we compute all the analysis using different cutoffs to define CHE (between 10 per cent and 30 per cent).

## 2.5 Empirical Strategy

### 2.5.1 Main Estimates

The aim of the empirical strategy is to analyse the association between CHE and MP. A simple regression analysis between the two variables is likely to be biased, due to endogeneity: the onset of poverty might result in CHE for households that were subject to regular OOP expenditures (reverse causality); or a non-health shock such as a local economic downturn might result in both CHE and MP simultaneously (omitted variable bias). To obtain causal estimates, we consider two main alternatives. First, we estimate linear probability regression models with a two-way fixed effects (TWFE) model. Second, we estimate the same models but using an instrumental variable (IV) model. We instrument the onset of CHE using the diagnosis of health conditions. All analyses were performed using the Stata 17 package, and the function *reghdfe* (Correia, 2016).

First, the linear probability TWFE, can be written as:

$$y_{it} = X_{it}\beta + \gamma h_{it} + \delta_t + \alpha_i + u_{it} \tag{1}$$

where $y_{it}$ is the incidence of MP, a variable that takes the value of 1 if household $i$ was multidimensionally poor in wave $t$ and zero otherwise. $h_{it}$ corresponds to the existence of CHE, in this case, a dummy variable indicating the onset of catastrophic payments. $X_{it}$ includes household-level control variables, such as age, sex, education level of the household head, and region and area of residence in wave $t$. $\delta_t$ is a wave-specific fixed effect, which captures aggregate shocks that affect the overall probability of facing MP due to macroeconomic conditions, political scenarios, among others. $\alpha_i$ are the household fixed effects that capture the time-invariant characteristics. Finally, $u_{it}$ is an error term that includes idiosyncratic time-varying unobservable characteristics. Under this specification, identification comes from the observed variation in MP onset with variation in CHE onset.

In this setup, $\hat{\gamma}$ is identified as the difference of the time variation on MP status for households with a change in CHE status compared to those that did not face such a change. Thus, the estimated parameter $\hat{\gamma}$ would identify the impact of the CHE on MP onset as long as there were no unobserved time-invariant variables related to both variables. In other words, if in addition to the occurrence (or disappearance) of the health shocks that trigger the CHE and, as a result, the coping mechanism, MP is triggered, other reasons affect both variables that are not common to the entire country or region.

We can add a second equation that aims to identify the reason for the onset of CHE. Another linear probability model is considered,

$$h_{it} = X_{it}\iota + \eta S_{it} + \omega_t + v_i + \epsilon_{it} \tag{2}$$

where the probability of CHE is explained in terms of the same controls and fixed effects described above, plus the report of any major morbidity for any household member $S_{it}$.[1] The error term $\epsilon_{it}$ includes other reasons, different from health shocks, that would drive the onset of CHE (for example income, other acute health shocks such as accidents, or another type of shock). This equation is effectively the first stage of the IV regression (under the two-stage least squares, 2SLS), where the main equation is still 1, but in which $h_{it}$ corresponds to a version where only the variation coming from health shocks

[1] Major morbidities in IHDS correspond to the self-reported diagnosis of cataract, tuberculosis, high blood pressure, heart disease, diabetes, leprosy, cancer, asthma, polio, paralysis, epilepsy, mental illness, sexually transmitted diseases, and AIDS. Households can even report other long-term conditions without specifying them.

is exploited. In this setup, $\hat{\gamma}$ is identified as discussed for the TWFE estimator, but considering only variations in CHE and MP that are the result of variations on the onset of health shocks. To assess the relevance of the instruments and then whether results might be biased due to weak instruments, we compute the Cragg-Donald's F-statistic for each specification.

As the CHE and MP are defined using a specific cut-off (in the case of CHE the cut-off reflects the percentage of health expenditures related to the level of income; and in the case of MP, the cut-off is the percentage of deprivation that a household needs to face if it is to be considered multidimensionally poor). Therefore, it is crucial to understand whether the results are driven by a specific selection of these values; thus, we tested our main estimates using alternative cut-offs for CHE and MP.

### 2.5.2 Heterogeneity

India provides an opportunity to understand how the relationship between CHE and MP differs according to the institutional setting. First, we explore results for South India (Andhra Pradesh, Karnataka, Kerala, Tamil Nadu, and Pondicherry in the IHDS classification) independently, as these territories have experienced sustained growth, lower fertility levels, and the largest reduction in multidimensional poverty in recent years in comparison with the rest of the country (Alkire and Seth, 2015a). Second, we explore the scenario in which the household head belongs to a Scheduled Caste (SC) or Scheduled Tribe (ST), as these households typically face marginalisation when accessing health care (Maity, 2017).

We also consider the heterogeneity of impacts based on household characteristics set at their previous wave value ($t-1$): (i) household expenditure in quartiles, (ii) place of residence (living in a rural area), and (iii) access to health insurance. The main specification in equation 1 is modified as follows:

$$y_{it} = X_{it}\beta + \sum_{k=1}^{K} \gamma_k [h_{it} \times 1\{E_{i,t-1} = k\}] + \delta_t + \alpha_i + u_{it} \quad (3)$$

where $E_{i,t-1}$ represents the lag of the variables used for the heterogeneous effect. $E$ is a discrete variable that takes $K$ values depending on the specific exercise. For example, for the presence of the CHE in the previous wave, there are two parameters of interest: one indicating that effect for households that had faced CHE ($\gamma_1$) in the past, and another for the case of households that did not experience CHE ($\gamma_2$). $E_{i,t-1}$ represents the lagged variables used for the heterogeneous effect.

# 3 Results

The descriptive statistics reveal that, on average, in the first round household heads were aged 46 years old, and they had on average 5.3 years of education. Household size was 4.1, and households had on average two children aged 12 years or younger. Also, 75 per cent of the households were living in rural areas. For the second round, as expected, the average age of the head of the household was 53 years, there were no changes in household size in comparison with year 1, and there was a reduction in the average number of children per household see Table 3.

**Table 3:** Descriptive statistics of households by wave

| Variables (1) | Round 1 (2) | Round 2 (3) |
|---|---|---|
| Head of household age | 46.00 | 53.00 |
| | (12.34) | (12.45) |
| Household size | 4.10 | 4.10 |
| | (1.82) | (1.82) |
| Children per household | 2.00 | 1.50 |
| | (1.10) | (0.71) |
| Number of seniors per household | 1.20 | 1.30 |
| | (0.37) | (0.45) |
| Years of schooling of the household head | 5.30 | 5.50 |
| | (4.80) | (4.85) |
| Urban | 0.25 | 0.25 |
| | (0.46) | (0.46) |
| Rural | 0.75 | 0.75 |
| | (0.46) | (0.46) |

*Notes*: Standard deviations in parentheses. The second column refers to the averages of the variables for 2004-2005. The third column refers to the averages of the variables for 2011-2012. Own calculations using IHDS.

## 3.1 Multidimensional Poverty Measure

In 2004, the indicators with the largest deprivation were health insurance (68.23 per cent), years of schooling (63.71 per cent), and access to improved sanitation (57.70 per cent). For 2011, years of schooling (53.75 per cent) and health insurance (51.91 per cent) continue being the two indicators with the largest deprivations. When comparing the variation of the censored headcount ratios over time (the percentage of people who are multidimensionally poor and deprived in each indicator), it is observed that all indicators presented a reduction in the levels of deprivation, and the differences between years are statistically significant. In fact, asset ownership (-25.04 per cent), health insurance (-16.32 per cent), and electricity (-13.84 per cent) are the indicators that presented the greatest reductions between years see Figure 1.

**Figure 1:** Absolute change of the censored headcount ratios by indicator.

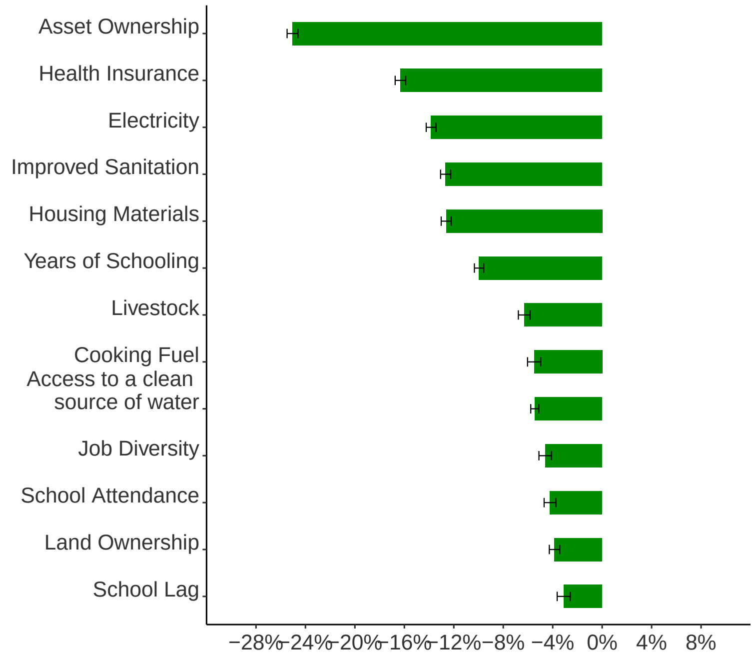



Table 4 shows the results for multidimensional poverty. For the first round, 63.41 per cent of households were multidimensionally poor with an intensity of 57.17 per cent, meaning that on average multidimensionally poor households faced more than half of the weighted deprivations included in the index, and the adjusted headcount ($M0$) was 0.362. In addition, over time poverty presented a significant reduction where the incidence decreased by 11.59 percentage points (p.p.), the intensity of multidimensional poverty reduced by 4.16 p.p. and the $M_O$ had a reduction of 0.08 points. These differences are statistically significant. In addition, on scrutinising the results of the robustness analysis presented in Annex A3, we found similar results, when we used different poverty lines ($k$).

Table 4: Incidence, intensity and Multidimensional Poverty Measure

| | (2004 - 2005) (2) | (2011 - 2012) (3) | Absolute Difference (4) |
|---|---|---|---|
| $H$ (incidence) (%) | 63.41 | 51.82 | -11.59*** |
| $A$ (intensity) (%) | 57.17 | 53.01 | -4.16*** |
| $M_0$ (Multidimensional Poverty Measure) | 0.362 | 0.274 | -0.088*** |

*Notes*: * p<0.10, ** p<0.05, *** p<0.01. Authors calculations using IHDS's .

## 3.2 Catastrophic Health Expenditures

For the first round, 40.46 per cent of households incurred CHE; for the second round, there was a significant reduction to 17.85 per cent. Households that faced CHE in the first round spent around three times more on health care than households that did not face CHE; for the second round the difference was about seven times. This high spending was concentrated in outpatient medical expenses in both rounds. In addition, it is observed that households that faced CHE reduced their expenditures on housing, food, and education. The size of the households that faced CHE was larger compared with the size of households without CHE. In addition, households that faced CHE had on average a household head with a lower level of education compared with those that did not face CHE (Table 5).

**Table 5:** Descriptive statistics of households with and without CHE

| Variables | Complete Sample | | CHE: Yes | | CHE: No | | Differences |
|---|---|---|---|---|---|---|---|
| | Round 1 | Round 2 | Round 1 | Round 2 | Round 1 | Round 2 | |
| | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Age of the head of the household | 45.87 | 52.46 | 45.64 | 54.31 | 46.02 | 51.92 | $\omega\ \rho\ \tau$ |
| Average household size | 4.08 | 4.08 | 4.09 | 3.86 | 4.07 | 4.15 | $\omega\ \rho\ \tau$ |
| Average number of children per household | 2.02 | 1.54 | 2.09 | 1.56 | 1.97 | 1.54 | $\phi\ \rho\ \tau$ |
| Number of members older than 65 | 1.15 | 1.26 | 1.15 | 1.28 | 1.16 | 1.25 | $\phi\ \omega\ \rho\ \tau$ |
| Years of schooling of the head of the household | 5.06 | 5.16 | 4.42 | 3.96 | 5.51 | 5.52 | $\phi\ \omega\ \rho\ \tau$ |
| Urban households | 0.25 | 0.25 | 0.17 | 0.14 | 0.30 | 0.28 | $\phi\ \omega\ \rho\ \tau$ |
| Rural households | 0.75 | 0.75 | 0.83 | 0.86 | 0.70 | 0.72 | $\phi\ \omega\ \rho\ \tau$ |
| Expenditures ($ USD) | 199.78 | 445.90 | 111.68 | 249 | 88.10 | 196.90 | $\phi\ \omega\ \rho\ \tau$ |
| Educaction Expenditures (%) | 2.48 | 7.38 | 1.53 | 3.61 | 3.70 | 12.15 | $\phi\ \omega\ \rho\ \tau$ |
| Health Expenditures (%) | 19.90 | 29.14 | 32.89 | 45.96 | 3.43 | 7.87 | $\phi\ \omega\ \rho\ \tau$ |
| Health Expenditures (%): Medical out-patient | 68.71 | 61.37 | 64.93 | 44.46 | 71.68 | 64.60 | $\phi\ \omega\ \rho\ \tau$ |
| Health Expenditures (%): Medical in-patient | 29.12 | 33.25 | 30.82 | 55.06 | 26.43 | 29.08 | $\phi\ \omega\ \rho\ \tau$ |
| Health Expenditures (%): Therapeutic app | 0.93 | 5.39 | 0.28 | 0.50 | 1.96 | 6.32 | $\phi\ \omega\ \rho\ \tau$ |

*Notes*: The eighth column shows the statistically significant differences. $\phi$ means that the difference between columns 4 and 6 is statistically significant. $\omega$ means that the difference between columns 5 and 7 is statistically significant. $\rho$ means that the difference between columns 4 and 5 is statistically significant. $\tau$ means that the difference between columns 6 and 7 is statistically significant. Expenditures are presented in USD in real terms as a baseline using the first round of the survey as a baseline.

## 3.3 Catastrophic Health Expenditures and Multidimensional Poverty

### 3.3.1 Correlation

Table 6 presents the incidence H, intensity A, and M0 disaggregated by households that did and did not incur CHE. Of households that faced catastrophic expenditures in the first round, 72.52 per cent were multidimensionally poor, a percentage that was higher than the proportion of households that did not face CHE (64.19 per cent). For the second round, both groups (households with and without CHE) presented lower levels of multidimensional poverty. However, as in round one, a larger proportion of households that faced CHE were multidimensionally poor, in comparison with households that did not face CHE (53.21 per cent vs. 48.81 per cent).

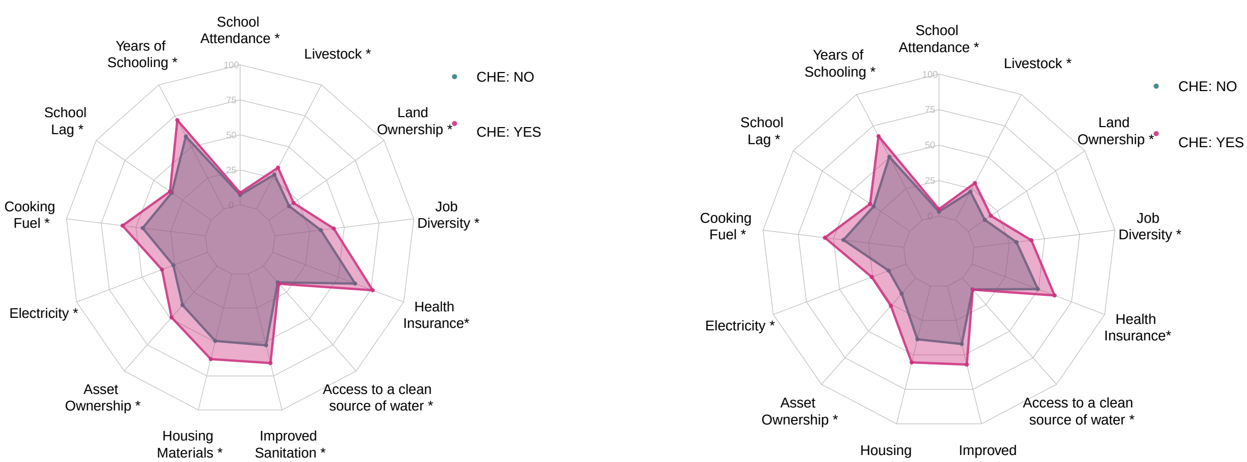
**Table 6:** Incidence, intensity and $M_0$ by wave and CHE.

| Variables | CHE: Yes | | CHE: No | | Differences |
|---|---|---|---|---|---|
| | Round 1 | Round 2 | Round 1 | Round 2 | |
| | (2) | (3) | (4) | (5) | (6) |
| $H$ (incidence) (%) | 72.52 | 53.21 | 64.19 | 48.81 | $\phi\ \omega\ \rho\ \tau$ |
| $A$ (intensity) (%) | 57.82 | 54.03 | 56.66 | 52.68 | $\phi\ \omega\ \rho\ \tau$ |
| $M_0$ (Multidimensional Poverty Measure) | 0.419 | 0.346 | 0.327 | 0.257 | $\phi\ \omega\ \rho\ \tau$ |

*Notes*: The sixth column shows the statistically significant differences. $\phi$ means that the difference between columns 2 and 4 is statistically significant. $\omega$ means that the difference between columns 3 and 5 is statistically significant. $\rho$ means that the difference between columns 3 and 5 is statistically significant. 2 and 3. $\tau$ means that the difference in column 4 and 5 is statistically significant.

Figure 2 shows the censored headcount ratios(percentage of households who are deprived in a specific indicator and are also multidimensionally poor) of each of the indicators included in the MP measure, disaggregated by households that did and did not face CHE. On average, households that faced CHE presented higher levels of deprivation in all indicators, compared with those that did not face CHE, with the exception of school attendance, access to a clean source of water, and school lag.

**Figure 2:** Censored headcount per indicator 2004-2005 and 2011-2012




(a) 2004-2005 (b) 2011-2012

*Notes*: $*$ significant differences between the incidence of deprivations using a level of significance equal to 5 per cent .

hen we analysed the cross-sectional data, we found a significant and positive association between being multidimensionally poor and facing CHE. Thus, a household that faces CHE has a higher probability of living in multidimensional poverty (13 p.p.), compared with those that do not face CHE (see Table 7). Results are more precise for the fourth expenditure quartile, a finding similar for other countries as discussed in the literature (Pinilla-Roncancio et al., 2022). There is no difference for those living in rural and urban areas in terms of this association. In addition, we analysed whether having or not having health insurance changed the probability of being multidimensionally poor. The results revealed that households that did not have health insurance in $t-1$ and faced CHE had higher chances of being multidimensionally poor in comparison with those that had health insurance in $t-1$ and did face CHE (4 p.p. vs. 3 p.p.).

Columns 2 and 3 explore the case of South India vs other regions of the country. The main coefficient is larger for households located outside South India. In particular for individuals living in rural areas, and for those of the first expenditure quartile.

Columns 4 and 5 consider the case of caste. There is no difference according this variable but on the fourth expenditure quartile, where the effect is larger for individuals who are not SCT/SST. A similar difference is find for those living in urban areas.

**Table 7:** Catastrophic health expenditure and health shock

| Regression Model | (1) India | (2) Not South India | (3) South India | (4) SCT/SST Caste | (5) Other Caste |
|---|---|---|---|---|---|
| 1. Catastrophic Health-care Expenditures (CHE) 40% - Cross-Section | 0.13*** | 0.13*** | 0.13*** | 0.13*** | 0.12*** |
| | (0.00) | (0.01) | (0.00) | (0.00) | (0.01) |
| 2. Catastrophic Health-care Payments (CHE) 40% - Longitudinal | 0.03** | 0.06* | 0.02* | 0.03** | 0.03*** |
| | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) |
| | | F=20.19 [p-value=0.00] | | F=0.03 [p-value=0.86] | |
| 3. First Quartile [t-1] × CHE =Yes [t] | 0.01 | 0.03* | 0.00 | 0.01 | -0.00 |
| | (0.02) | (0.03) | (0.02) | (0.02) | (0.03) |
| | | F=6.05 [p-value=0.01] | | F=1.60 [p-value=0.21] | |
| 4. Second Quartile [t-1] × CHE =Yes [t] | 0.03 | 0.05 | 0.02 | 0.03 | 0.02 |
| | (0.02) | (0.04) | (0.02) | (0.02) | (0.04) |
| | | F=1.19 [p-value=0.27] | | F=0.00 [p-value=0.97] | |
| 5. Third Quartile [t-1] × CHE =Yes [t] | 0.02 | 0.03 | 0.02 | 0.04* | -0.03 |
| | (0.02) | (0.04) | (0.02) | (0.02) | (0.04) |
| | | F=0.00 [p-value=0.95] | | F=2.29 [p-value=0.13] | |
| 6. Fourth Quartile [t-1] × CHE =Yes [t] | 0.05*** | 0.09** | 0.04 | 0.03** | 0.11*** |
| | (0.01) | (0.02) | (0.01) | (0.01) | (0.02) |
| | | F=2.04 [p-value=0.15] | | F=5.26 [p-value=0.02] | |
| 7. Living in Urban areas [t-1] × CHE =Yes [t] | 0.03*** | 0.03 | 0.03 | 0.02 | 0.05*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| | | F=0.42 [p-value=0.52] | | F=3.28 [p-value=0.07] | |
| 7. Living in Rural areas [t-1] × CHE =Yes [t] | 0.03*** | 0.06*** | 0.01 | 0.03*** | 0.02*** |
| | (0.02) | (0.03) | (0.02) | (0.02) | (0.03) |
| | | F=21.86 [p-value=0.00] | | F=0.63 [p-value=0.43] | |
| 8. Health Insurance =No[t-1] × CHE =Yes [t] | 0.04** | 0.10*** | 0.01 | 0.05** | 0.04* |
| | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) |
| | | F=9.38 [p-value=0.00] | | F=0.15 [p-value=0.70] | |
| 9. Health Insurance =Yes[t-1] × CHE =Yes [t] | 0.03*** | 0.05*** | 0.02* | 0.02*** | 0.03*** |
| | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) |
| | | F=11.04 [p-value=0.00] | | F=0.00 [p-value=0.99] | |
| Mean of MP Incidence | 57.441 | 50.579 | 73.875 | 59.147 | 51.865 |
| Mean of CHE Incidence | 28.362 | 27.974 | 29.307 | 27.295 | 31.849 |

Note: Each number in the rows represents the results of a separate regression, e.g., "3." refers to the four estimated parameters from the heterogeneity TWFE regression between incidence of multidimensional poverty and CHE at 40% level interacted with the fourth quartile dummies. All regressions include household and wave fixed effects, and control variables such as age and sex of the head of the household, the number of children under 5 in the household, the number of adults over 65, region and area of residence (rural/urban) in wave *t*). Robust standard errors are presented in parentheses. Significance levels: * 0.1 ** 0.05 *** 0.01.

### 3.3.2 Instrumental Variables

In this section, we consider a variation in the CHE and MP relationship, which is driven only by the onset (or end) of an underlying health condition that might be responsible for the change in health expenditures.

We start by documenting the relationship between health shocks represented by the diagnosis of a chronic condition and CHE. Table 8 presents estimates for equation (2). It shows that for all subsets of the dataset, the relationship between a health shock and CHE is positive and significant, even in the presence of health insurance. Table 9 reproduces Table 7, but under this alternative estimator.[2]. On top of the coefficient, it presents Cragg-Donald's F-Statistic for the first stage. First, using the cross-sectional variance, we observe a negative relationship between CHE and MP. This is exactly the opposite of what is expected, and the oppositte to what we obtained in 7. These results probably reflect selection in terms of who reports the onset of certain conditions: wealthier households are able to get a diagnosis of certain health conditions. For our specific measure of health shocks, a similar pattern is observed: Figure 3 shows that wealthier households are more likely to report a diagnosis of a health shock. The implication is that the results of this section should be treated as local average treatment effects (LATE): results correspond to those individuals whose CHE was triggered by a diagnosis of health conditions; in other words, those who demand health services that result in diagnostics procedures. They do not represent individuals who face CHE due to the onset of acute events -which might be secondary to undiagnosed chronic conditions-.

Once the longitudinal dimension is incorporated, the estimates are positive but not significant. For both general results (rows 1 and 2 in Table 9), under the different partitions of the sample (the five columns), the first stage is strong, meaning that the lack of significance is not the result of weak instruments. The estimated coefficients for the instrumented longitudinal case are larger than for the pure longitudinal case presented

[2] In both Tables 8 and 9, instead of using the interactions presented in Table 7, the regressions are performed on the specific data subset. For this reason, there is a Cragg-Donald's F-Statistic for each row.

in Table 7 but more imprecise. Larger standard errors are expected as less variation is exploited with the IV estimator, but nevertheless, the imprecision highlights that there might be substantial heterogeneity in the MP response to the onset of CHE driven exclusively by the onset of health events.

**Table 8:** Catastrophic health expenditures and health shock: first stage of the instrumental variables strategy

| Regression Model | (1) India | (2) Not South India | (3) South India | (4) SCT/SST Caste | (5) Other Caste |
|---|---|---|---|---|---|
| 1. Healthshock - Cross-Section | 0.11*** | 0.11*** | 0.11*** | 0.10*** | 0.10*** |
| | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) |
| 2. Healthshock - Longitudinal | 0.12*** | 0.11*** | 0.11*** | 0.12*** | 0.12*** |
| | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) |
| 3. First Quartile [t-1] × Healthshock =Yes [t] | 0.14*** | 0.14*** | 0.14*** | 0.13*** | 0.16*** |
| | (0.02) | (0.03) | (0.03) | (0.02) | (0.04) |
| 4. Second Quartile [t-1] × Healthshock =Yes [t] | 0.09*** | 0.10*** | 0.04 | 0.08*** | 0.10* |
| | (0.03) | (0.03) | (0.05) | (0.03) | (0.05) |
| 5. Third Quartile [t-1] × Healthshock =Yes [t] | 0.13*** | 0.13*** | 0.04 | 0.12*** | 0.14*** |
| | (0.02) | (0.03) | (0.06) | (0.03) | (0.05) |
| 6. Fourth Quartile [t-1] × Healthshock =Yes [t] | 0.11*** | 0.10*** | 0.10* | 0.10*** | 0.12*** |
| | (0.02) | (0.02) | (0.06) | (0.02) | (0.05) |
| 7. Living in Urban areas [t-1] × Healthshock =Yes [t] | 0.12*** | 0.10*** | 0.12*** | 0.12*** | 0.10*** |
| | (0.01) | (0.01) | (0.03) | (0.01) | (0.02) |
| 7. Living in Rural areas [t-1] × Healthshock =Yes [t] | 0.13*** | 0.14*** | 0.11*** | 0.12*** | 0.16*** |
| | (0.01) | (0.01) | (0.02) | (0.01) | (0.02) |
| 8. Health Insurance =No[t-1] × Healthshock =Yes [t] | 0.16*** | 0.18*** | 0.04 | 0.15*** | 0.17*** |
| | (0.02) | (0.03) | (0.06) | (0.03) | (0.04) |
| 9. Health Insurance =Yes[t-1] × Healthshock =Yes [t] | 0.12*** | 0.12*** | 0.12*** | 0.12*** | 0.14*** |
| | (0.01) | (0.01) | (0.02) | (0.01) | (0.02) |

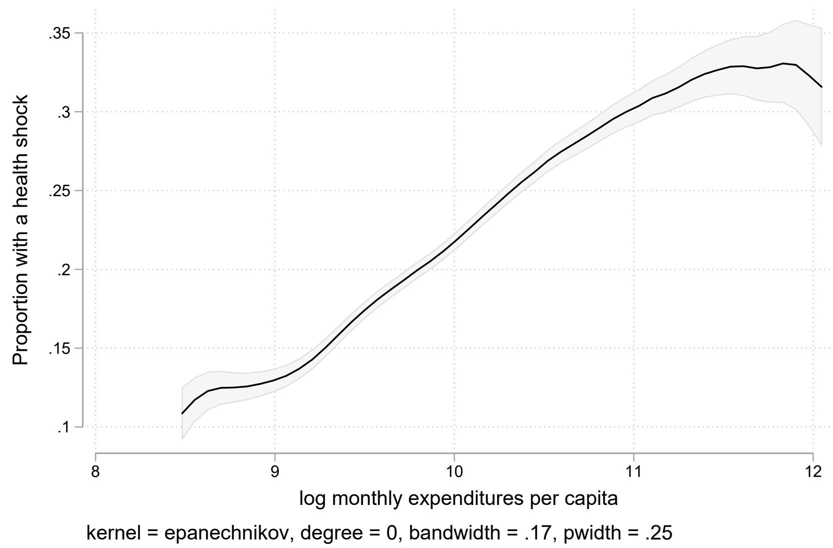
Note: Each coefficient represents the results of a separate regression, for the specified sample combination between the conditions in the rows and the columns. Regressions are TWFE regression between CHE at 40% and report of the diagnosis of a chronic condition: cataract, tuberculosis, high blood pressure, heart disease, diabetes, leprosy, cancer, asthma, polio, paralysis, epilepsy, mental illness, sexually transmitted diseases, and AIDS. All regressions include household and wave fixed effects, and control variables (age and sex of the head of the household, the number of children under 5, and the number of adults over 65, region dummies, and a dummy of area of residence (rural/urban) in wave $t$). Robust standard errors are presented in parentheses. Significance levels: * 0.1 ** 0.05 *** 0.01.

**Table 9:** Catastrophic health expenditures and incidence of multidimensional poverty, instrumental variables estimates

| l | (1) India | | (2) Not South India | | (3) South India | | (4) SCT/SST Caste | | (5) Other Caste | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. | F-Stat | Coef. | F-Stat | Coef. | F-Stat | Coef. | F-Stat | Coef. | F-Stat |
| Iealth-care Expenditures (CHE) 40% - Cross-Section | -0.49*** | 573.56 | -0.48*** | 429.39 | -0.35*** | 145.46 | -0.37*** | 406.05 | -0.75*** | 124.80 |
| | (0.05) | | (0.06) | | (0.09) | | (0.05) | | (0.12) | |
| Iealth-care Expenditures (CHE) 40% - Longitudinal | 0.05 | 279.85 | 0.06 | 196.71 | 0.04 | 49.73 | 0.08 | 207.96 | -0.03 | 70.92 |
| | (0.05) | | (0.06) | | (0.10) | | (0.05) | | (0.10) | |
| t-1] × CHE =Yes [t] | -0.15* | 49.38 | -0.03 | 28.27 | -0.22* | 19.44 | -0.05 | 33.23 | -0.33 | 16.06 |
| | (0.09) | | (0.13) | | (0.12) | | (0.10) | | (0.21) | |
| e [t-1] × CHE =Yes [t] | -0.02 | 12.01 | -0.33 | 10.36 | 0.99 | 0.59 | -0.07 | 8.49 | 0.10 | 3.66 |
| | (0.25) | | (0.29) | | (1.62) | | (0.29) | | (0.47) | |
| [t-1] × CHE =Yes [t] | 0.35** | 29.75 | 0.33* | 25.49 | 0.84 | 0.40 | 0.35* | 21.07 | 0.33 | 7.53 |
| | (0.17) | | (0.18) | | (1.96) | | (0.20) | | (0.35) | |
| e [t-1] × CHE =Yes [t] | 0.17 | 30.14 | 0.16 | 23.31 | 0.17 | 2.94 | 0.21 | 23.00 | 0.00 | 7.00 |
| | (0.15) | | (0.17) | | (0.50) | | (0.17) | | (0.29) | |
| n areas [t-1] × CHE =Yes [t] | 0.20 | 60.69 | 0.34** | 35.25 | -0.27 | 15.55 | 0.26** | 54.68 | -0.24 | 5.41 |
| | (0.13) | | (0.17) | | (0.25) | | (0.12) | | (0.46) | |
| l areas [t-1] × CHE =Yes [t] | 0.04 | 60.69 | 0.00 | 35.25 | 0.21 | 15.55 | 0.05 | 54.68 | 0.10 | 5.41 |
| | (0.07) | | (0.09) | | (0.14) | | (0.08) | | (0.16) | |
| ce =No[t-1] × CHE =Yes [t] | 0.06 | 40.93 | 0.06 | 41.73 | 0.14 | 0.47 | -0.04 | 25.41 | 0.21 | 15.46 |
| | (0.13) | | (0.13) | | (1.26) | | (0.16) | | (0.23) | |
| nce =Yes[t-1] × CHE =Yes [t] | 0.03 | 287.78 | 0.04 | 195.80 | 0.04 | 54.55 | 0.08 | 204.57 | -0.09 | 84.02 |
| | (0.05) | | (0.06) | | (0.09) | | (0.05) | | (0.09) | |
| dence | 57.441 | | 50.579 | | 73.875 | | 59.147 | | 51.865 | |
| idence | 28.362 | | 27.974 | | 29.307 | | 27.295 | | 31.849 | |

in the rows represents the results of a separate regression, for the specified country in the columns, e.g, "3." refers to the four estimated parameters from VFE regression between incidence of multidimensional poverty and CHE at 40% level interacted with the fourth quartile dummies. All regressions include e fixed effects, and control variables (age and sex of the head of the household, the number of children under 5, and the number of adults over 65, region nmy of area of residence (rural/urban) in wave *t*). Robust standard errors are presented in parentheses. Significance levels: * 0.1 ** 0.05 *** 0.01.

**Figure 3:** Non-linear regression between health shocks (diagnosis of chronic conditions) and expenditures



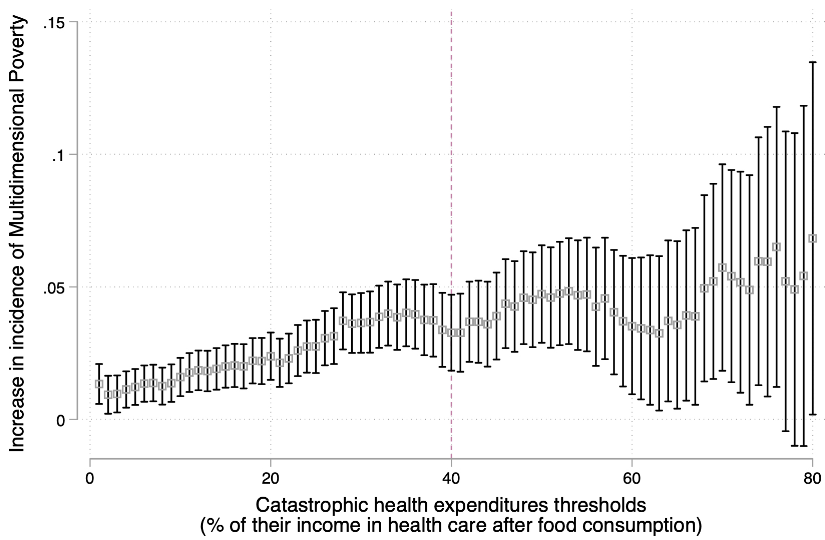

Note: local linear polynomial excluding the lower percentile (1%) and upper percentile (100%) from the analysis. Chronic conditions are: cataract, tuberculosis, high blood pressure, heart disease, diabetes, leprosy, cancer, asthma, polio, paralysis, epilepsy, mental illness, sexually transmitted diseases, and AIDS.

#### 3.3.3 Sensitivity to Different Cutoffs

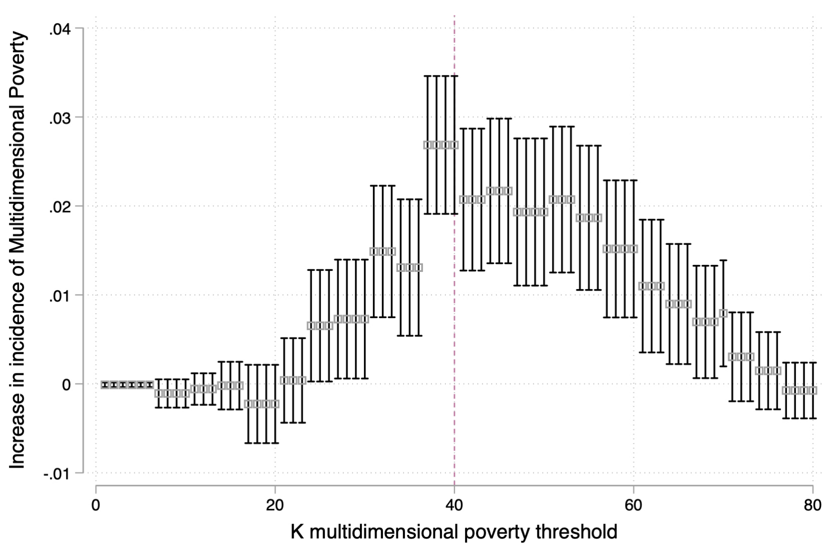
As both MP and CHE are defined on the basis of cut-offs of underlying continuous variables, we analysed how sensitive the main result was to such values. Panel a of Figure 4 shows the main longitudinal estimate changing the CHE cutoff value. The vertical line represents the cutoff used in the main estimates (40), where we find the value of 2.7 p.p. (Column 1 of Row 2 of Table 1) with its respective 95 per cent confidence interval. Such a coefficient would be almost the same for cut-offs between 30 and 70. Panel b of Figure 4 shows the estimated coefficient for alternative MP cut-offs, where 40 was the poverty cut-off that was used for the analysis. In this case, we observe that the coefficient would be slightly smaller if we considered any other cut-off. Yet, for most of the poverty cut-offs between 30 and 60, the estimate is above 1 p.p.. Hence, we can conclude that the estimated relationship is stable, and we can assert that the onset of CHE results in higher levels of MP.

**Figure 4:** Sensitivity of the estimates to MP and CHE cut-offs

(a) Catastrophic health expenditures cut-off




(b) Poverty cut-off (k)



# 4 Discussion

This article has analysed the relationship between multidimensional poverty and catastrophic health expenditure in India. The primary purpose was to identify if CHE was positively associated with an increase in multidimensional poverty, and which factors could be associated with this change. Also, to analyse if, when using an IV (diagnosis of chronic conditions), there was a causal effect between CHE and MP. The analysis revealed that when we analyse the association between CHE and MP using cross-sectional data, there is a positive association between both conditions. A similar result is found when we analyse longitudinal data. In addition, as expected, when a household has health insurance in $t-1$ and faces CHE, the probability of becoming multidimensionally poor is lower than for households without health insurance. We also analysed whether living in the South of India was a factor that might have a potential effect on the increase (or not) of the probability of being multidimensionally poor for households who faced CHE. We found that living in the South of India – the region with one of the largest reductions of multidimensional poverty over the years (Alkire and Seth, 2015b) – was a protective factor. Finally, in the case of caste, the only important difference arises for the households with larger expenditures per capita, where being of Other Caste (different from SCT/SST) and facing CHE positively correlates strongly with being multidimensionally poor.

In addition to the longitudinal analysis, we explore the causal relationship between CHE and MP, using an instrumental variable (diagnosis of a chronic condition). In the first stage of the analysis, we found a strong relationship between the health shock and being multidimensionally poor. In the second stage, we found that in a cross-sectional analysis using an instrumental variable analysis, households that faced CHE associated with the health shock analysed had a lower probability of being multidimensionally poor.

AAlthough contrary to what was expected, this finding is consistent with the literature, where it has been verified in India (and other middle-income countries) that there is a positive wealth gradient on the detection of hypertension (García et al., 2022).Therefore, in India, wealthier households might have higher chances than poorer households of accessing health-care services and being diagnosed with a chronic disease. Thus, those households also have higher chances of facing CHE associated with that diagnosis.

In the longitudinal analysis with instrumental variables, we found that households that face a health shock and CHE have a higher probability of being multidimensionally poor, although these results are not significant. The only statistically significant result was when the household was in the highest quartile of expenditures in $t_1$ and faced CHE in $t$; in this case, households faced a higher probability of being multidimensionally poor than households that were in the third and fourth quartiles and did not face CHE in $t_1$. Also, when we used the instrumental variable, we did not find differences between the place of residence (south of India or other regions) or caste or health insurance.

Given that the instrument that we have chosen selects a specific sample, in this case households with at least one member who has been diagnosed with chronic illness, we cannot analyse the potential effect of CHE on MP for households that have not faced CHE as a result of this shock. In addition, in India 21 per cent of the households that have a member who has been diagnosed with a chronic disease belong to the richest segment of the population; therefore the effect of CHE on their levels of poverty is lower compared with the effect on households who are poorer.

Finally, it is important to highlight that in the case of India MP and CHE are two related conditions. Therefore, households that face CHE are more likely to become multidimensionally poor, and their levels of deprivation might increase. In addition, it is important to understand that households can implement multiple strategies to reduce the impact of a health shock, and those can create higher levels of deprivation in the indicators included in the MP measure presented in the article, but others might be associated with using their savings or borrowing money. For lack of data, these strategies have not been included in the measure that we proposed, but they have been identified as some of the main strategies that households use to mitigate a shock (Joe, 2015; Sangar et al., 2018; Balla et al., 2022).

## 4.1 Limitations

The results presented in this article reveal that in India, facing CHE results in a risk of increasing MP. Although these results are essential, there are some limitations to be considered. First, limitations related to the instrument that was used. Although the F-stat reveals that the instrument is strong, and in the first stage of the analysis there is a correlation between the instrument and the dependent variable, the instrument only captures CHE related to chronic conditions and for a specific subgroup of the population. Therefore, it is recommended to explore additional instruments that can capture the potential effect of acute health shocks (for example, accident, or death of a household member).

# 5 Conclusions

The results of this study reveal that in India households that face catastrophic health-care expenditures have a higher probability of becoming multidimensionally poor, compared with households that do not face CHE. As expected, having health insurance is a protective factor which reduces the chances of a household becoming multidimensionally poor.

Also, living in the south of India is a protective factor, and few differences were found according to caste. When we analysed this relationship using instrumental variables, we found that in the case of cross-sectional data, households that face a health shock have a lower probability of becoming multidimensionally poor, compared with households that do not face a health shock. Although this finding is contrary to what was expected, it is associated with the fact that a higher percentage of wealthier households have members who have been diagnosed with a chronic condition. Finally, when we used the instrument in a longitudinal setting, we found a positive but insignificant association between a health shock and MP.

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# A Supplementary Materials

**Table A1:** Standardization of Household Expenditure

| Reference Period | Frequency |
|---|---|
| 1 day | The month is 30 times the day. |
| 7 days | The month is 4.28 times the week. |
| 15 days | The month is 2 times the 15 days. |
| 30 days | No change needed |
| 60 days | The month is 1/2 of the total |
| 90 days | The month is 1/3 of the total |
| 180 days | The month is 1/6 of the total |
| 365 days | The month is 1/12 of the total |

**Table A2:** Incidence of CHE using thresholds from 10% to 40%.

| | Round 1<br>(1) | Round 2<br>(2) | Difference<br>(3) |
|---|---|---|---|
| Catastrophic health expenditures at 10% | 65.33 | 61.55 | -3.78*** |
| Catastrophic health expenditures at 20% | 57.43 | 43.79 | -13.64*** |
| Catastrophic health expenditures at 30% | 48.89 | 31.90 | -16.99*** |
| Catastrophic health expenditures at 40% | 40.46 | 22.61 | -17.85*** |

*Notas*: The first column refers to the percentage of households that incurred catastrophic health expenditures depending on the thresholds for the year 2004 - 2005. The second column refers to the percentage of households that incurred catastrophic health expenditures depending on the thresholds year 2011 - 2012. The third column is the difference between columns 2 and 3, and whether their differences are statistically significant. * p<0.10, ** p<0.05, *** p<0.01. IHDS calculation.

**Table A3:** Incidence, Intensity and $M_0$ according to different poverty cutoffs.

| | Round 1 (2) | Round 2 (3) | Difference (4) |
|---|---|---|---|
| K=10% | | | |
| H (%) | 99.62 | 99.21 | -0.42*** |
| A (%) | 48.68 | 42.36 | -6.32*** |
| $M_0$ | 0.48 | 0.42 | -0.06*** |
| K=20% | | | |
| H (%) | 94.80 | 92.63 | -2.17*** |
| A (%) | 50.33 | 44.25 | -6.08*** |
| $M_0$ | 0.48 | 0.41 | -0.07*** |
| K=30% | | | |
| H (%) | 84.73 | 78.83 | -5.91*** |
| A (%) | 53.48 | 47.84 | -5.64*** |
| $M_0$ | 0.45 | 0.38 | -0.08*** |
| K=40% | | | |
| H (%) | 68.58 | 56.78 | -11.80*** |
| A (%) | 58.34 | 53.67 | -4.67*** |
| $M_0$ | 0.40 | 0.30 | -0.10*** |
| K=50% | | | |
| H (%) | 50.67 | 35.50 | -15.17*** |
| A (%) | 63.64 | 59.94 | -3.71*** |
| $M_0$ | 0.32 | 0.21 | -0.11*** |
| K=60% | | | |
| H (%) | 33.24 | 17.51 | -15.73*** |
| A (%) | 68.96 | 66.62 | -2.34*** |
| $M_0$ | 0.23 | 0.12 | -0.11*** |

*Notes*: The second column refers to the estimates for the year 2004 - 2005. The third column refers to the estimates for the year 2011 - 2012. The fourth column is the difference of columns 2 and 3. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. IHDS calculation.