Heliyon 9 (2023) e18902

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Equity and extent of financial risk protection indicators during COVID-19 pandemic in rural part of Tamil Nadu, India

Yuvaraj Krishnamoorthy *, Sathish Rajaa, Isha Sinha, Murali Krishnan, Gerald Samuel, Krishna Kanth

Department of Community Medicine, ESIC Medical College and PGIMSR, K.K. Nagar, Chennai, India

ARTICLE INFO

Keywords:
Health expenditures
Impoverishment
India
Rural health

ABSTRACT

Catastrophic health expenditure [CHE] in India is on a rise. This situation would worsen even further when resources are disproportionately distributed across various socioeconomic classes. Hence, we conducted this study to determine the equity and extent of out-of-pocket [OOP] payments, Catastrophic health expenditure and impoverishment among rural households during COVID-19 pandemic in Tamil Nadu, India. A cross-sectional survey covering 2409 households was conducted during November 2021 across six districts in rural part of Tamil Nadu. Information on out-of-pocket payments, Catastrophic health expenditure (based on 40% capacity-to-pay [CTP] method) and impoverishment was obtained through World Health Organization standard criteria. Point estimates were reported as proportions with 95% Confidence Interval [CI]. Our results showed that the proportion of households with out-of-pocket payments on health and Catastrophic health expenditure in the month preceding the survey was 82.8% (95%CI: 81.2%–84.3%) and 26.9% (95%CI: 25.1%–28.7%) respectively. Nuclear (couple with dependent children only) and joint family type (extended family), presence of under-five children and lower socioeconomic status were significant determinants of Catastrophic health expenditure. The prevalence of impoverishment was 6.4% (95%CI: 5.4%–7.5%). To conclude, more than three fourth of the rural households in Tamil Nadu has out-of-pocket payments for health with one-fourth having Catastrophic health expenditure. Almost one in fourteen non-poor households faced impoverishment during the COVID-19 pandemic. This shows the disproportionate distribution of health expenses especially in the rural areas. Hence, appropriate financial risk protection measures should be taken in order to progress towards universal healthcare in our country.

1. Introduction

The United Nations member states have embraced the Sustainable Development Goals (SDGs) with the aim of achieving universal health coverage (UHC) by 2030. UHC encompasses equitable access to healthcare, the delivery of quality health services, and the safeguarding of households from financial distress [1,2]. Financial risk protection plays a pivotal role in accelerating progress towards UHC [3]. Furthermore, it contributes to the attainment of other health-related targets under the SDGs by 2030. Metrics such as catastrophic health expenditure (CHE) and impoverishment serve as valuable tools in evaluating the performance of a health system

* Corresponding author.
E-mail addresses: yuvi.1130@gmail.com (Y. Krishnamoorthy), psrajaa2410@gmail.com (S. Rajaa), simplyisha9@gmail.com (I. Sinha), physiomuralikrishna@gmail.com (M. Krishnan), sgerald94@gmail.com (G. Samuel), mkrishnakanth1998@gmail.com (K. Kanth).

https://doi.org/10.1016/j.heliyon.2023.e18902
Received 2 January 2023; Received in revised form 30 July 2023; Accepted 2 August 2023
Available online 3 August 2023

with regard to financial risk protection. These indicators facilitate the monitoring of a country's progress towards UHC [4].

Healthcare financing in India amounts to over $34 billion (approximately 6% of GDP per capita). A mere 15% of this financing is publicly funded, with 4% coming from social insurance, 1% from private insurance, and a staggering 80% from out-of-pocket expenses incurred by the general population [5]. The majority of public healthcare financing in the country stems from state government budgets (around 80%), followed by the Central government (12%) and local governments (8%). The healthcare financing mechanisms employed by various governments, however, are not consistent across countries and significantly influence their progress towards UHC. This is particularly relevant for lower-middle-income countries like India, where public health expenditure is limited [6]. Although out-of-pocket (OOP) expenses by the general population have been decreasing, the OOP expenditure as a proportion of income has not shown a decline [6].

The prevalence of CHE has been on the rise globally over the past decade. Around the world, 800 million people allocate more than 10% of their total household expenditure to healthcare. This results in nearly 100 million individuals falling into poverty each year due to out-of-pocket spending on health [4]. India is no exception, experiencing a rate of increase in CHE that is twice the global average annual percentage point change [7]. Consequently, it is crucial to understand the burden and determinants of OOP, CHE, and impoverishment in each state/UT within the country to develop tailored strategies.

The contribution of this study is twofold. Firstly, it aims to investigate the equity, burden, and determinants of financial risk protection indicators (out-of-pocket payments, catastrophic health expenditure (CHE), and impoverishment) among rural households in Tamil Nadu, India. By employing the capacity-to-pay (CTP) approach, which takes into account the impact of health expenses on the poor, this study provides a more equitable assessment of CHE and financial hardship indicators. It is worth noting that previous studies in India have primarily utilized the budget share (BS) approach [8], which is more straightforward for computational purposes and does not consider the specific needs of the poor. The reason why, World Health Organization has recommended an alternative called the capacity-to-pay (CTP) approach. This method defines health expenditure as "catastrophic" if out-of-pocket health payments exceed 40% of capacity-to-pay [9–11]. Thus, our study addresses the scarcity of research that has applied the CTP method to estimate financial risk protection indicators in India. Additionally, estimating the equity and burden of financial risk protection indicators in a state like Tamil Nadu, which has made significant strides in the health sector, and implemented various healthcare policies and programs over the years, helps us to gain valuable insights into the effectiveness of these policies.

Secondly, our study fills the research gap on the impact of the COVID-19 pandemic on the financial struggles of households in India. Recent studies have demonstrated that the COVID-19 pandemic has adversely affected health equity across various socioeconomic classes, resulting in job losses, homelessness, reduced access to health insurance, and increased physical and mental morbidity and mortality [12]. Additionally, social movement restrictions and isolation have further impacted health [13]. However, there is a lack of existing literature capturing the equity and extent of financial risk protection indicators during the COVID-19 pandemic specifically in Tamil Nadu.

The theoretical underpinning of our empirical modelling is influenced by the fundamental understanding in health economics and public health that socio-economic determinants often play a pivotal role in shaping a household's financial risk due to health expenditure. Research has shown that factors such as family type, presence of under-five children, and socioeconomic status significantly influence the financial burden households bear due to healthcare costs [6–11,14]. This understanding serves as the basis for the selection of our independent variables. Our empirical model, therefore, is a reflection of these theoretical insights. Through our model, we map the theoretical relationship between household characteristics and their likelihood of incurring catastrophic health expenditure and being impoverished due to healthcare costs.

The empirical model does not only present the factual data derived from our survey but also contextualizes these within the wider theoretical framework of health economics and public health. By doing so, we hope to contribute to the growing body of evidence that stresses the importance of understanding the social determinants of health in order to effectively design policies aimed at ensuring financial risk protection and advancing towards universal healthcare.

Thus, we decided to undertake this study by employing the CTP approach to investigate the equity, burden, and determinants of financial risk protection indicators (out-of-pocket payments, CHE, and impoverishment) among rural households in Tamil Nadu, India.

2. Methods

2.1. Study setting

This community-based cross-sectional study was carried out over a one-month period in November 2021 in Tamil Nadu, a southern state in India. The state has a total population of 72,147,030, with 37,229,590, or 51.6% of the population, residing in rural areas [15]. The per capita income in Tamil Nadu is INR 130,197 [16]. Approximately 12% of the population falls below the poverty line, with 16% in rural areas and 7% in urban areas [17]. Tamil Nadu is recognized as one of India's top performers in healthcare delivery. The state's per capita health expenditure is INR 1,235, which exceeds the combined average of major (non-empowered action group) states [18].

2.2. Sample size calculation

The sample size was calculated using OpenEpi (v3.01 updated in 2013, USA), based on a proportion of CHE (24.6%) among households in Tamil Nadu according to National Sample Survey data, with a relative precision of 10% and a 95% confidence interval. The minimum sample size required was 1177. After accounting for a design effect of 2 and a non-response rate of 10%, the final sample size was 2588. To divide the sample across six districts, we arrived at a final sample size of 2592 (432 participants from each district)

[19].

2.3. Sampling strategy

A multi-stage stratified random sampling process was employed to select districts, villages, and households (Figure-1).

Stage 1: In the initial stage, all districts were categorized into low, medium, and high strata based on their human development index (HDI) scores [20]. HDI was chosen for stratification because its indicators represent crucial demand-side characteristics that explain health status, healthcare-seeking behavior, service utilization, and healthcare expenditure. From each stratum, two districts were randomly chosen to ensure representation of people belonging to high, low, and middle HDI groups The final districts that were chosen are Trichy, Tirunelveli, Salem, Pudukkottai, Villupuram, and Theni.

Stage 2: Villages served as the primary sampling unit (PSU). A list of villages in the selected districts, along with their total population details, was obtained. From each selected district, seven villages were chosen using probability proportional to size (PPS) sampling. The sampling interval was calculated by dividing the cumulative sum of the population across all villages in each district by the total number of villages selected for the survey. From each selected village, 62 households were selected.

Stage 3: In the final stage, systematic random sampling was used to choose households from each village. We excluded households that remained locked even after three consecutive visits.

2.4. Study procedure

Before initiating the data collection process, approval was obtained from the Institutional Ethics Committee. Data was collected

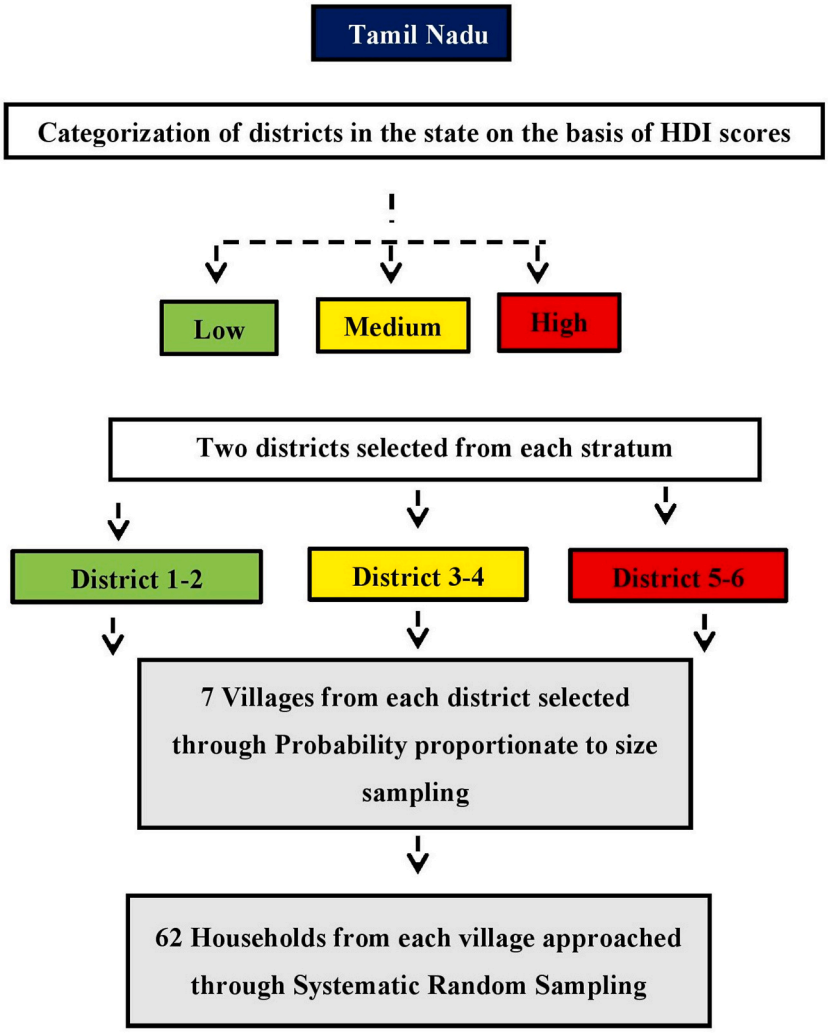

Fig. 1. Sampling flowchart.

between the second and third waves of the COVID-19 pandemic in the country. The head of the household or an available member in the selected households was approached, and data collection began after acquiring informed written consent. A pretested semi-structured questionnaire was used for data collection, which was divided into two sections: the first section included information on sociodemographic details of the respondents, such as age and gender, as well as household details like the number of family members, working members, elderly and under-five children in the household, family type, religion, and total household monthly income. The second section collected expenditure details, including total household expenditure, food and non-food expenditures, and total health expenditure over the past month. Interviews were conducted at the respondents' households and took approximately 15–20 min to complete.

Outcome measures for this study were OOP for health, CHE and impoverishment. Determination of outcome variables is described as follows:

1) OOP health payments:

Information on OOP health payments was obtained via following questions:

> "Whether you or anyone in the household had any health-related expenses or spent any amount for seeking healthcare in the past one month?"

If any household answered "yes", then they were classified as having OOP health payments and the following question was asked: "*How much was spent on household health spending?*"

2) CHE calculation:

We have computed CHE and reported results based on CTP method [21–28]. The most commonly accepted cut off or threshold to define health expenditure to be catastrophic is $\geq$ 40% CTP [20].

WHO has given a detailed methodology on the calculation of CHE based on the CTP of a household [29].

WHO standard method for calculating CHE:

Following are the steps involved in computing catastrophic health expenditure:

Step 1. Generation of food expenditure share of the household (FES):

FES=Food expenditure of the household/Total household expenditure (FEH/THE)

Step 2. Generation of household equivalent size (HES):

HES = hhsize^{β};Whereas hhsize is the size of the household and β is the coefficient value of the equivalence scale. We made use of β value 0.56 which is the most commonly used household scale multiplier and estimated from regression equation based on 69 countries.

Step 3. *Generation of equivalent food expenditure (EFE):*

EFE = FEH/HES

Step 4. Identification of 45th and 55th percentile of FES in the sample

Step 5. Calculation of average of EFE of households within the 45th and 55th percentile of FES and that value is used to define poverty line (PL)

Step 6. Calculation of subsistence expenditure for each of the households in the sample (SEH):

SEH=PL * HES

A household is considered poor when the total household expenditure is less than the subsistence expenditure;

Poor = 1 (yes) if THE < SEH

Poor = 0 (no) if THE $\geq$ SEH

Step 7. *Calculation of household's capacity to pay (CTP):*

The household's capacity to pay (ctp_h) is defined as the non-subsistence effective income of the household. However, some households may report food expenditure that is lower than subsistence spending (seh > foodh). This indicates that the household's food expenditure is less than the estimated poverty standard for that country. If the household's food expenditure is less than the subsistence expenditure, non-food expenditure is considered as non-subsistence spending.

CTP = THE-SEH if FEH $\geq$ SEH

CTP = THE-FEH if FEH < SHE

Step 8. Calculation of catastrophic health expenditure (CHE):

Catastrophic heath expenditure occurs when a household's total out-of-pocket health payments equal or exceed 40% of household's capacity to pay or non-subsistence spending. The threshold of 40% could be changed according to countries' specific situation.

CHE = 1 (yes) if OOPHE/CTP $\geq$40%

CHE = 0 (no) if OOPHE/CTP <40%

3) Impoverishment calculation:

Non-poor household is considered impoverished by health expenditure if the difference between total household expenditure and out-of-pocket health expenditure is less than the subsistence expenditure required for a household.

Impoverishment = 1 (yes) if THE $\geq$ SEH & THE-OOPHE $<$ SEH, otherwise

Impoverishment = 0 (no)

2.5. Statistical analysis

All analyses were conducted using STATA 14.2 (StataCorp, College Station, TX, USA). Continuous variables were summarized as mean and standard deviation (SD), while cost data were presented as median with interquartile range (IQR) due to their non-normal distribution. Cost data were reported in US dollars ($1 = 73.936 INR, according to the 2021 yearly average exchange rate reported by the Internal Revenue Service). Categorical variables were summarized as proportions. Outcome variables (OOP health payments, CHE, and impoverishment) were reported with 95% Confidence Intervals (CIs).

We considered the heterogeneity of the sample size across different districts, which does not reflect the actual population proportion. To control for this bias and ensure that the survey data accurately represents the population distribution across the districts, we implemented a data reweighting procedure.

Our reweighting approach was premised on adjusting the raw data to match the population structure of the districts as per the most recent census. This process ensures that the results are not unduly influenced by over- or under-represented districts in the survey data.

The weights were computed by dividing the actual population ratio by the survey population ratio for each district. The derived weights were then applied to each survey response from the corresponding district. The computation was performed as follows:

$$Weight\ (i) = Actual\ Population\ Ratio\ (i)\ /\ Survey\ Population\ Ratio\ (i)$$

where 'i' refers to the respective district.

Logistic regression was utilized to assess the determinants of health expenditure outcomes. Factors with p-values less than 0.20 in univariable analysis were included in multivariable analysis. Multilevel modelling was performed to account for the multiple levels

Table 1
Sociodemographic details of the study participants (N = 2409).

Sociodemographic characteristics	Frequency, n (%)	Weighted proportion
Mean (SD) Age of the respondents = 42.7 (14.1) years		
Gender of the respondents		
Male	1083 (45.0)	41.5
Female	1326 (55.0)	58.5
Socioeconomic status[#]		
Upper (INR 7770 and above)	72 (3.0)	2.6
Upper middle (INR 3808 to 7769)	577 (23.9)	21.6
Middle (INR 2253 to 3807)	783 (32.5)	30.2
Lower middle (INR 1166 to 2252)	861 (35.8)	39.9
Lower (<1166)	116 (4.8)	5.7
Family type		
Nuclear	1905 (79.1)	80.0
Joint	343 (14.2)	12.2
Three-generation	161 (6.7)	7.8
Religion		
Hindu	1984 (82.3)	80.5
Muslim	320 (13.3)	16.1
Christianity	105 (4.4)	3.4
Districts		
Tiruchirappalli	422 (17.5)	25.3
Tirunelveli	420 (17.4)	21.5
Salem	420 (17.4)	20.5
Pudukkottai	419 (17.4)	9.8
Theni	420 (17.4)	8.2
Villupuram	308 (12.8)	14.6
Households with at least one under-five child		
No	1253 (52.0)	53.5
Yes	1156 (48.0)	46.5
Households with at least one elderly		
No	835 (34.7)	36.1
Yes	1574 (65.3)	63.9
Households with a family member affected with COVID-19 in the last year		
No	1964 (81.5)	78.9
Yes	445 (18.5)	21.1

[#]Modified BG Prasad classification 2021; INR = Indian Rupees.

involved in the sampling strategy. The impact of clustering at village and district levels on all health expenditure outcomes was evaluated using a random-intercept model [30]. A likelihood ratio test (LR test) was conducted to compare this model with the naïve model (final model in logistic regression). Multivariable logistic regression analysis based on the random-intercept model was performed for outcomes with significant LR tests. The effect size was reported as adjusted Odds Ratio (aOR) with 95% CIs. Variables with p-values less than 0.05 were considered statistically significant.

2.6. Equity analysis

Inequities in OOP payments, CHE, and impoverishment based on wealth were assessed using the concentration curve and concentration index. Firstly, the concentration curve was derived by plotting the cumulative proportion of health expenditure against the cumulative proportion of the population ranked by socioeconomic status [31]. If the concentration curve is situated below the line of equality (i.e., a 45° line), it indicates that health expenditure is more concentrated among those with higher incomes, and vice versa. The "Lorenz" package was utilized to obtain concentration curves. Subsequently, the concentration index was calculated using the "conindex" package [32]. Inequity was deemed statistically significant if the p-value was less than 0.05.

3. Results

3.1. Sociodemographic and expenditure details

Socio-demographic details of the households are detailed in Table-1. In total, 2480 households were approached and 2409 households responded completely (97.1% response rate). Mean (SD) age of the respondents was 42.7 (14.1) years. Median number of family members in each household was 4 (IQR = 3–5). Almost half of the households had at least one under-five child, while nearly two-thirds of the households had at least one elderly. The median total monthly household expenditure was $108 (IQR = $68-$135); median monthly household food expenditure was $54 (IQR = $41-$81); median monthly household expenditure on health was $14 (IQR = $3-$27). Around 18.5% of the interviewed households had at least on member who was affected with COVID-19 during the last one year. Weighted proportion of each of these indicators were reported as per the sociodemographic indicators of Tamil Nadu [33, 34].

3.2. Burden of OOP health payments, CHE and impoverishment

The unweighted and weighted proportion of financial risk protection indicators are provided in Table-2. The unweighted proportion of households with OOP health payments in the month preceding the survey was 82.8% (95%CI: 81.2%–84.3%). The weighted proportion was 78% (95%CI: 66.9%–86.1%).

For the calculation of CHE based on CTP criteria, first average of the household food expenditure within the 45th and 55th percentile was found out to define the poverty line (value = $25). Then, subsistence expenditure was found out by multiplying with equivalent household size, which in turn was used to calculate the CTP. The unweighted proportion of households spending ≥40% CTP on health was 26.9% (95%CI: 25.1%–28.7%). The weighted proportion was 27.2% (95%CI: 21.1%–34.2%). The unweighted and weighted proportion of non-poor households pushed below poverty line because of OOP spending on health (impoverishment) was 6.4% (95%CI: 5.4%–7.5%) and 7.8% (95%CI: 4.8%–12.3%).

3.3. Determinants of OOP health payments

Table-3 shows the determinants of OOP health payments among the surveyed households. First, we checked the clustering at district level and found a significant LR test ($p < 0.001$), depicting a significant effect of clustering. Then, another level was added to check the clustering effect at villages. We found a significant reduction in the log-likelihood value compared to the previous model (712–627) indicating a significant clustering effect at villages and districts. Hence, the logistic regression was run with a random intercept model including both district and village levels.

Households living as joint family has 2.20 times higher odds of having OOP expenditure on health when compared to nuclear family households (aOR = 2.20; 95%CI: 1.11–4.32). Households belonging to upper class (aOR = 13.55; 95%CI: 2.79–65.91), upper middle class (aOR = 3.78; 95%CI: 1.84–7.80), and middle class (aOR = 2.64; 95%CI: 1.39–5.00) has significantly higher odds of having OOP payments on health when compared to lower-class households. Households having at least one under-five children had 4.13 times higher odds of having OOP payments on health (aOR = 2.20; 95%CI: 2.82–6.06) when compared to households without under-five children and this association was statistically significant.

Table 2
Weighted and Unweighted Prevalence of Financial Risk Protection Indicators in rural Tamil Nadu, N = 2409.

Financial Risk Protection Indicators	Unweighted proportion (95% CI)	Weighted proportion (95% CI)
Catastrophic health expenditure	26.9 (25.1–28.7)	27.2 (21.1–34.2)
Out of pocket expenditure	82.8 (81.2–84.3)	78.0 (66.9–86.2)
Impoverishment	6.4 (5.4–7.5)	7.8 (4.8–12.3)

Table 3
Determinants of OOP expenditure on health among rural households in Tamil Nadu (N = 2409).

Characteristics	Total, N	OOP health expenses, n (%)	Adjusted Odds Ratio[#] (95%CI)	*P*-value
Family Type				
Nuclear	1905	1516 (79.6)	Ref	–
Joint	343	320 (93.3)	2.20 (1.11–4.32)	0.02*
Three generation	161	159 (98.8)	1.20 (0.21–6.82)	0.84
Religion				
Hindu	1984	1579 (79.6)	Ref	–
Muslim	320	313 (97.8)	0.38 (0.11–1.36)	0.14
Christianity	105	103 (98.1)	0.66 (0.10–4.28)	0.66
Socioeconomic Status				
Upper	72	70 (97.2)	13.55 (2.79–65.91)	0.001*
Upper middle	577	536 (92.9)	3.78 (1.84–7.80)	<0.001*
Middle	783	668 (85.3)	2.64 (1.39–5.00)	0.003*
Lower middle	861	648 (75.3)	1.67 (0.90–3.09)	0.10
Lower	116	73 (62.9)	Ref	–
Households with at least one elderly				
Absent	835	640 (76.6)	Ref	–
Present	1574	1355 (86.1)	0.68 (0.40–1.15)	0.15
Households with at least one under-five child				
Absent	1253	989 (78.9)	Ref	–
Present	1156	1006 (87.0)	4.13 (2.82–6.06)	<0.001*

Ref - Reference value.
*p value statistically significant.
[#]Clustering at the level of districts and villages was adjusted using random-intercept model.

3.4. Determinants of CHE

Table-4 shows the determinants of CHE among the surveyed households. The model for CHE also showed a significant clustering effect at both village and district levels with a significant LR test ($p < 0.001$) and a significant reduction in the log-likelihood (1370–1208). Hence, a random intercept model adjusting for village and district levels were performed.

Households living as nuclear type (aOR = 3.15; 95%CI: 1.90–5.22) and joint type of family (aOR = 3.11; 95%CI: 1.78–5.42) had significantly higher odds of having CHE when compared to those households living as a three-generation family. When compared to households in the middle socioeconomic class, households in the lower socioeconomic class had significantly higher odds (aOR = 1.94; 95%CI: 1.18–3.20) of having CHE. Households having at least one under-five children had 1.90 times higher odds of having CHE (aOR = 1.90; 95%CI: 1.49–2.42) when compared to households without under-five children and this association was statistically significant.

Table 4
Determinants of CHE among rural households in Tamil Nadu (N = 2409).

Characteristics	Total, N	CHE n (%)	Adjusted Odds Ratio (95%CI)	*P*-value
Family type				
Nuclear	1905	506 (26.6)	3.15 (1.90–5.22)	<0.001*
Joint	343	108 (31.5)	3.11 (1.78–5.41)	<0.001*
Three generation	161	34 (21.1)	Ref	–
Religion				
Hindu	1984	524 (26.4)	1.79 (0.76–4.20)	0.18
Muslim	320	107 (33.4)	1.76 (0.70–4.45)	0.23
Christianity	105	17 (16.2)	Ref	–
Socioeconomic status				
Upper	72	27 (37.5)	1.39 (0.78–2.48)	0.27
Upper middle	577	163 (28.2)	0.80 (0.59–1.08)	0.15
Middle	783	206 (26.3)	Ref	–
Lower middle	861	210 (24.4)	0.89 (0.68–1.17)	0.39
Lower	116	42 (36.2)	1.94 (1.18–3.20)	0.009*
Households with at least one elderly				
Absent	835	178 (21.3)	Ref	–
Present	1574	470 (29.9)	1.21 (0.88–1.66)	0.25
Households with at least one under-five child				
Absent	1253	246 (19.6)	Ref	–
Present	1156	402 (34.8)	1.90 (1.49–2.42)	<0.001*

Ref - Reference value.
*p value statistically significant.
[#]Clustering at the level of districts and villages was adjusted using random-intercept model.

3.5. Determinants of impoverishment

Table-5 shows the determinants of impoverishment among the surveyed non-poor households. The model for impoverishment also showed a significant clustering effect at both village and district levels with a significant LR test ($p < 0.001$) and a significant reduction in the log-likelihood (465–435). Hence, a random intercept model adjusting for village and district levels were performed. In multivariable model, non-poor households with under-five children had 1.63 times higher odds of having impoverishment (aOR = 1.63; 95%CI: 1.07–2.48) when compared to non-poor households without under-five children.

3.6. Equity analysis

The concentration curve and index for the health expenditure outcomes are depicted in Figs. 2–4. The highest inequity was found in impoverishment as evident by a concentration index of −0.67 (Fig. 4). OOP health expenses distribution was inequitable with concentration indices 0.11 (Fig. 2). All these inequities were statistically significant ($p < 0.001$). Least inequity was seen for CHE by households with concentration index of −0.01 ($p = 0.69$) which indicates that there is no significant inequity in the CHE among the households in rural Tamil Nadu (Fig. 3).

4. Discussion

This study presents an in-depth analysis of equity, extent, and determinants of financial risk protection indicators, such as OOP payments for health, CHE, and impoverishment, offering valuable insights for policy makers and practitioners. We utilized data from a community-based survey among rural households across six districts in Tamil Nadu. We have found that nearly 80% of rural households in Tamil Nadu has OOP payments for health in the past month preceding the survey. Although the findings were substantially higher when compared to similar studies conducted in other low middle income settings [25–28], our finding were in line with the previous studies conducted in the South Indian states [6,19,22,35]. We also found that households belonging to upper and upper-middle class had significantly higher odds of having OOP expenditure on health when compared to lower-class households. This can be attributed to the fact that people who are economically well off, seek private healthcare facilities for any health-related complaints. The reason being, the private sector is believed to be of higher quality compared to public sector facilities. Nevertheless, there is a need to find out which section of society has the maximum impact due to these expenditures.

We found that more than one-fourth of the households experienced CHE based on the capacity-to-pay (CTP) model. While wide variations in CHE across countries can be observed, depending on the method used to determine CHE [24–28], our findings align with previous studies comparing different methods for determining CHE [36]. In our study, the CHE was higher than in other regions of the country [19]. Over the past two decades, disease epidemiology in India has undergone significant changes, with a transition towards non-communicable diseases [37]. These diseases and injuries now dominate the disease burden in most states. Prior studies have demonstrated that CHE tends to be higher in states with higher epidemiological transition levels (ETL), as this directly affects the amount and types of healthcare services needed [19,38–40]. Consequently, this impacts the overall health expenditure of households. Tamil Nadu, being one of the states with higher ETL, experiences higher CHE than most other states in the country, which could explain our findings [19].

We found that nearly one in fourteen non-poor households fell below the poverty line due to their OOP health expenditures. The high burden of OOP payments, CHE, and impoverishment might be attributed to the ongoing COVID-19 pandemic, which could have a substantial financial impact on households, particularly in rural areas. Our analysis also assessed the socioeconomic inequalities of OOP health payments, CHE, and impoverishment to pinpoint high-risk groups with greater health expenditure distribution. This

Table 5
Determinants of Impoverishment among rural non-poor households in Tamil Nadu (N = 2191).

Characteristics	Total, N	Impoverishment n (%)	Adjusted Odds Ratio (95%CI)	*P*-value
Family type				
Nuclear	1716	111 (6.5)	0.55 (0.17–1.82)	0.33
Joint	314	24 (7.6)	1.61 (0.49–5.34)	0.43
Three generation	161	5 (3.1)	Ref	–
Religion				
Hindu	1774	134 (7.5)	2.39 (0.71–8.05)	0.16
Muslim	316	4 (1.3)	Ref	–
Christianity	101	2 (2.0)	1.63 (0.22–12.24)	0.63
Households with at least one elderly				
Absent	723	50 (6.9)	[Not included in the model]	
Present	1468	90 (6.1)		
Households with at least one under-five child				
Absent	1131	53 (4.7)	Ref	–
Present	1060	87 (8.2)	1.63 (1.07–2.48)	0.02*

Ref - Reference value.
*p value statistically significant.
#Clustering at the level of districts and villages was adjusted using random-intercept model.

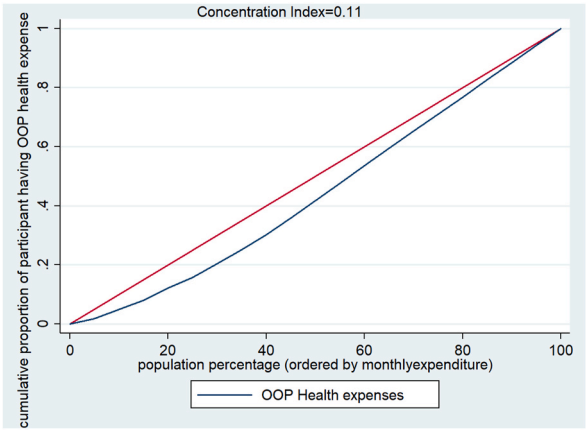

Fig. 2. Concentrative curve for OOP health expenses against monthly household expenditure.

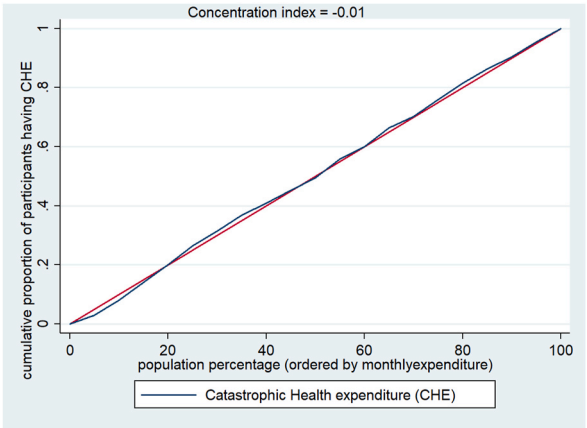

Fig. 3. Concentrative curve for CHE against monthly household expenditure.

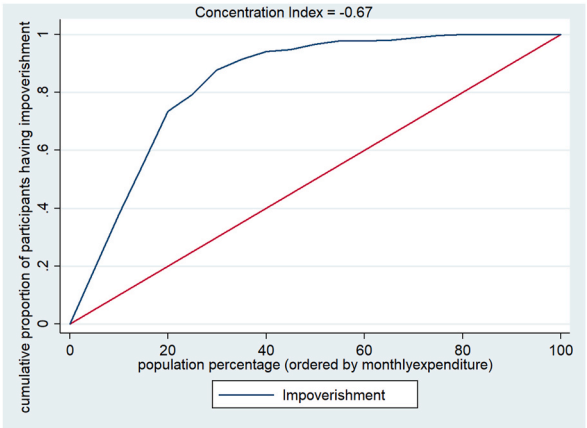

Fig. 4. Concentrative curve for impoverishment health expenses against monthly household expenditure.

revealed a concerning finding: impoverishment was more concentrated among households from lower socioeconomic classes, even though upper and upper-middle-class households had a higher concentration of OOP health expenses. This indicates that the poorest households face a disproportionate burden compared to upper-class households. Potential reasons for this troubling finding may include increased usage of NCD care services, a preference for private healthcare facilities over government health centers or hospitals,

and a lack of financial risk protection measures for high-end procedures in secondary or tertiary care facilities [22].

In households structured as nuclear families, the likelihood of encountering OOP payments for healthcare was reduced; however, these families faced a significantly greater risk of catastrophic health expenditure (CHE) when compared to families spanning three generations. This could be attributed to the likelihood of having fewer health expenses due to the smaller family size. However, when such expenses arise, these households may need to spend beyond their capacity-to-pay, given the fewer working members in the family. In contrast, in a three-generation family, additional earners can share the expenses among themselves, making health expenditures less catastrophic.

We found a significant association between the presence of at least one under-five child in the household and higher odds of OOP health payments, CHE, and impoverishment. This finding is consistent with previous studies which have also identified the presence of under-five children as a significant determinant of health expenditures [41–43]. This could be due to the increased need for health services among under-five children, dietary supplements, and frequent visits to health facilities for acute respiratory infections (ARI) or diarrheal episodes. The higher health expenditures for under-five children may lead to a higher financial burden on households, especially those with limited financial resources.

Our study has the following strengths. To begin with, this study contributes to the limited research available on evaluating out-of-pocket (OOP) health payments, catastrophic health expenditure (CHE), and impoverishment in India, especially in rural areas, during the COVID-19 pandemic. The use of a representative sample and high response rate increases the generalizability of the study findings. Furthermore, this study employs WHO standard criteria for measuring CHE and impoverishment, which has been used in only a few studies conducted in India. The study also utilized equity analysis to identify socioeconomic inequalities in the distribution of health expenditure outcomes. Additionally, advanced statistical techniques were utilized to account for the complex multi-stage sampling strategy and clustering effects at the district and village levels.

Despite these strengths, our study has certain limitations. First, the expenditure data was self-reported by the participants and it was not verified by any other sources. Hence, there is a possibility of recall bias in the expenditure data obtained. Second, we obtained data only on the direct costs and did not enquire about the indirect costs involved. Inclusion of indirect costs can further escalate the proportion of households facing CHE and impoverishment. Third, the cross-sectional nature of the survey makes it difficult to infer causal relationship between the exposure and outcome.

This study has several programmatic implications. The country's programmatic and policy reforms including the National health policy 2017 focus on improving the quality of healthcare services provided at public facilities and achieve financial risk protection [44]. Government of India has already taken a massive step towards achieving universal health coverage by introducing the Ayushman Bharat scheme which is supposed to have a greater impact on reducing these inequities and achieve financial risk protection throughout the country [45]. However, future studies need to focus on the utilization and impact of these programmes on achieving financial risk protection even across the poorest sections of society.

Similar to our study, state-specific studies are required to identify the equity and extent of OOP health payments, CHE and impoverishment, so that schemes can be customized to meet the needs of each of the states in our country. Though, there has been multiple calls for increasing the share of GDP per capita spent on the health sector, it cannot be the only factor sufficient to reduce the CHE in a country. Increasing the share of prepaid total health expenditure in the form of taxation or mandatory contributions might help in making significant progress towards achieving the sustainable development goal on universal health coverage throughout India.

5. Conclusion

Our study shows that more than three fourth of the rural households in Tamil Nadu has OOP payments for health during COVID-19 pandemic. More than one-fourth of the households had CHE and almost one in fourteen non-poor households was pushed below the poverty line due to OOP heath expenses. The most worrying finding is that the impoverishment is more concentrated in the lower socioeconomic classes. This shows the disproportionate distribution of health expenses especially in the rural areas. Hence, appropriate financial risk protection measures targeting the poor sections of the society should be taken in order to reduce the CHE and impoverishment during pandemic period and progress towards universal healthcare in our country.

Author contribution statement

Yuvaraj Krishnamoorthy: Conceived and designed the analysis, Analyzed and interpreted the data, Contributed analysis tools and data and Wrote the paper.

Sathish Rajaa: Designed the analysis, Analyzed and interpreted the data, Contributed analysis tools and data and Wrote the paper.

Isha Sinha: Designed the analysis, Contributed analysis tools and data and Wrote the paper.

Murali Krishnan: Designed the analysis, Contributed analysis tools and data and Wrote the paper.

Gerald Samuel: Designed the analysis, Contributed analysis tools and data and Wrote the paper.

Krishna Kanth: Designed the analysis, Contributed analysis tools and data and Wrote the paper.

Data availability statement

Data will be made available on request.

Funding or sources of support in the form of grants, equipment, drugs

None.

A statement confirming compliance with animal/human ethics guidelines, including the name of ethics approval committee and date of approval

This study was approved by Institutional Ethics Committee of ESIC Medical College & PGIMSR, Chennai dated November 01, 2021 with IEC No. IEC/2021/1/26.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yuvaraj Krishnamoorthy is Associate Editor and Sathish Rajaa is Advisory Board Member in Heliyon Journal.

Acknowledgments

Nil.

References

[1] [cited 2022 Feb 13]. Available from:, Resolution A/RES/70/1. Transforming Our World: the 2030 Agenda for Sustainable Development New York: Seventieth United Nations General Assembly, 2015 http://www.un.org/ga/search/view_doc.asp?symbol=A/RES/70/1&Lang=E.
[2] United Nations, Sustainable development goals [cited 2022 feb 13], Available from: http://www.un.org/sustainabledevelopment/sustainable-development-goals/.
[3] World Health Organisation, Health in 2015: from MDGs, Millennium Development Goals to SDGs, Sustainable Development Goals [cited 2022 Feb 13]. Available from:, 2015 http://apps.who.int/iris/bitstream/handle/10665/200009/9789241565110_eng.pdf?sequence=1.
[4] Tracking Universal Health Coverage: 2017 Global Monitoring Report, World Health Organisation and International Bank for Reconstruction and Development/ The World Bank; Licence: CC BY-NC-SA 3.0 IGO, 2017.
[5] Ravi Duggal, Financing Healthcare in India - Prospects for Health Insurance, Center for Inquiry into Health and Allied Themes, 2015.
[6] A. Wagstaff, G. Flores, J. Hsu, M.-F. Smitz, K. Chepynoga, L.R. Buisman, et al., Progress on catastrophic health spending in 133 countries: a retrospective observational study, Lancet Global Health 6 (2) (2018) e169–e179.
[7] A. Pandey, G.B. Ploubidis, L. Clarke, L. Dandona, Trends in catastrophic health expenditure in India: 1993 to 2014, Bull. World Health Organ. 96 (1) (2018) 18–28.
[8] J. Cylus, S. Thomson, T. Evetovits, Catastrophic health spending in Europe: equity and policy implications of different calculation methods, Bull. World Health Organ. 96 (9) (2018) 599.
[9] K. Xu, D.B. Evans, K. Kawabata, R. Zeramdini, J. Klavus, C.J. Murray, Household catastrophic health expenditure: a multicountry analysis, Lancet 362 (9378) (2003) 111–117.
[10] J. Arsenijevic, M. Pavlova, W. Groot, Measuring the catastrophic and impoverishing effect of household health care spending in Serbia, Soc. Sci. Med. 78 (2013) 17–25.
[11] A. Wagstaff, Measuring catastrophic medical expenditures: reflections on three issues, Health Econ. 28 (6) (2019) 765–781.
[12] WHO, Addressing human Rights as key to the COVID-19 response. https://apps.who.int/iris/bitstream/handle/10665/331811/WHO-2019-nCoV-SRH- Rights-2020.1-eng.pdf?sequence=1&isAllowed=y. (Accessed 10 May 2020).
[13] D.N. Poole, D.J. Escudero, L.O. Gostin, D. Leblang, E.A. Talbot, Responding to the COVID-19 pandemic in complex humanitarian crises, Int. J. Equity Health 19 (1) (2020) 41, https://doi.org/10.1186/s12939-020-01162-y.
[14] S.E. Berki, A look at catastrophic medical expenses and the poor, Health Aff. 5 (4) (1986) 138–145.
[15] Census, Tamil Nadu Population 2011 [Internet] [cited 2022 Feb 13]. Available from:, 2011 https://www.census2011.co.in/census/state/tamil+nadu.html#:~:text=As%20per%20details%20from%20Census,are%2036%2C137%2C975%20and%2036%2C009%2C055%20respectively.
[16] Press Information Bureau, Ministry of statistics and programme implementation. Per capita income [cited 2022 Feb 13]. Available from: https://pib.gov.in/newsite/printrelease.aspx?relid=169546.
[17] World Bank, Tamil Nadu – poverty, growth & inequality [Internet] [cited 2022 Feb 13]. Available from: https://documents1.worldbank.org/curated/en/380971504177733539/pdf/119267-BRI-P157572-Tamil-Nadu-Poverty.pdf.
[18] Central Bureau of Health Intelligence, Ministry of Health and Family Welfare. National Health Profile [cited 2019 Nov 7]. Available from:, 2019 https://www.cbhidghs.nic.in/showfile.php?lid=1147.
[19] A. Pandey, G.A. Kumar, R. Dandona, L. Dandona, Variations in catastrophic health expenditure across the states of India: 2004 to 2014, PLoS One 13 (10) (2018), e0205510.
[20] State Planning Commission, Government of Tamil Nadu, Tamil Nadu human development report 2017 – status of human development, Available from: http://www.spc.tn.gov.in/TNHDR2017/chapter2.pdf.
[21] S. Bonu, I. Bhushan, M. Rani, I. Anderson, Incidence and correlates of 'catastrophic' maternal health care expenditure in India, Health Pol. Plann. 24 (6) (2009) 445–456.
[22] M.Z. Raban, R. Dandona, L. Dandona, Variations in catastrophic health expenditure estimates from household surveys in India, Bull. World Health Organ. 91 (10) (2013) 726–735.
[23] E. Van Doorslaer, O. O'Donnell, R.P. Rannan-Eliya, A. Somanathan, S.R. Adhikari, C.C. Garg, et al., Catastrophic payments for health care in Asia, Health Econ. 16 (11) (2007) 1159–1184.
[24] T. Somkotra, L.P. Lagrada, Which households are at risk of catastrophic health spending: experience in Thailand after universal coverage, Health Aff. 28 (3) (2009) w467–w478.
[25] S. Rezaei, A. Woldemichael, M. Ebrahimi, S. Ahmadi, Trend and status of out-of-pocket payments for healthcare in Iran: equity and catastrophic effect, J. Egypt. Publ. Health Assoc. 95 (1) (2020 Nov 3) 29.
[26] S. Rezaei, M. Hajizadeh, Measuring and decomposing socioeconomic inequality in catastrophic healthcare expenditures in Iran, J. Prev. Med. Pub. Health 52 (4) (2019 Jul) 214–223, https://doi.org/10.3961/jpmph.19.046.
[27] B. Piroozi, A. Mohamadi-Bolbanabad, G. Moradi, H. Safari, S. Ghafoori, Y. Zarezade, F. Bidarpour, S. Rezaei, Incidence and intensity of catastrophic health-care expenditure for type 2 diabetes mellitus care in Iran: determinants and inequality, Diab. Metab. Syndr. Obes. 13 (2020) 2865–2876.

[28] S. Rezaei, M. Hajizadeh, S. Ahmadi, S. Sedghi, B. Piroozi, A. Mohamadi-Bolbanabad, E. Homaie Rad, Socioeconomic inequality in catastrophic healthcare expenditures in Western Iran: a decomposition analysis, 2019, Int. J. Soc. Econ. 46 (9) (2019) 1049–1060.
[29] World Health Organization, Distribution of Health Payments and Catastrophic Expenditures Methodology, World Health Organization, Geneva, 2005.
[30] W. Bouwmeester, J.W. Twisk, T.H. Kappen, W.A. van Klei, K.G. Moons, Y. Vergouwe, Prediction models for clustered data: comparison of a random intercept and standard regression model, BMC Med. Res. Methodol. 13 (1) (2013) 19.
[31] O. O'donnell, E. Van Doorslaer, A. Wagstaff, M. Lindelow, Analyzing Health Equity Using Household Survey Data: a Guide to Techniques and Their Implementation, World Bank, 2007.
[32] O. O'Donnell, S. O'Neill, T. Van Ourti, B. Walsh, Conindex: estimation of concentration indices, 2016, STATA J. 16 (2016) 112–138.
[33] [Internet]. [cited 2023 May 31]. Available from:, Socio Economic Indicators, 2021 https://www.tn.gov.in/deptst/ecoindicator.htm.
[34] Tamil Nadu Population, Sex Ratio & Literacy Rate 2023 [Internet]. [cited 2023 May 31]. Available from:, 2022 https://www.census2011.co.in/census/state/tamil+nadu.html.
[35] U. Vasudevan, S. Akkilagunta, S.S. Kar, Household out-of-pocket expenditure on health care - a cross-sectional study among urban and rural households, Puducherry, J. Family Med. Prim. Care 8 (2019) 2278–2282.
[36] S. Buigut, R. Ettarh, D.D. Amendah, Catastrophic health expenditure and its determinants in Kenya slum communities, Int. J. Equity Health 14 (1) (2015) 46.
[37] Indian Council of Medical Research, Public Health Foundation of India, and Institute for Health Metrics and Evaluation. India: Health of the Nation's States- the India State-Level Disease Burden Initiative, ICMR, PHFI, and IHME, New Delhi, 2017.
[38] X. Kea, P. Saksenaa, A. Hollyb, The Determinants of Health Expenditure: a Country-Level Panel Data Analysis, World Health Organisation, Geneva, 2011.
[39] V.D. Kien, H. Van Minh, K.B. Giang, A. Dao, L.T. Tuan, N. Ng, Socioeconomic inequalities in catastrophic health expenditure and impoverishment associated with non-communicable diseases in urban Hanoi, Vietnam, Int. J. Equity Health 15 (1) (2016) 169.
[40] A. Kastor, S.K. Mohanty, Disease-specific out-of-pocket and catastrophic health expenditure on hospitalization in India: do Indian households face distress health financing? PLoS One 13 (5) (2018), e0196106.
[41] R. Ravangard, S. Jalali, M. Bayati, et al., Household catastrophic health expenditure and its effective factors: a case of Iran, Cost Eff. Resour. Allocation 19 (2021) 59, https://doi.org/10.1186/s12962-021-00315-2.
[42] F.M. Knaul, R. Wong, H. Arreola-Ornelas, O. Méndez, R. Bitran, A.C. Campino, C.E. Flórez Nieto, U. Giedion, D. Maceira, M. Rathe, M. Valdivia, Household catastrophic health expenditures: a comparative analysis of twelve Latin American and Caribbean Countries, salud pública de méxico 53 (2011) s85–s95.
[43] Y. Mohammadzadeh, K. Hasanzadeh, Determinants of health and the cost of catastrophic health expenses in households, J. Knowl. Health 11 (3) (2016) 8–16.
[44] Ministry of Health and Family Welfare, National Health Policy 2017, Government of India, New Delhi, 2017.
[45] Press Information Bureau, Ministry of Finance, Government of India, National Health Protection Scheme to Provide Hospitalisation Cover to over 10 Crore Poor and Vulnerable Families [cited 2019 Nov 7]. Available from:, Feb 1, 2018 http://pib.nic.in/newsite/PrintRelease.aspx?relid=176049.