Health Shocks and Vulnerability to Poverty in India: Evidence from the National Sample Surveys, 1995-2018

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The majority of studies on out-of-pocket healthcare payments have focused on current welfare losses to households, reflected in their impact on poverty, while largely neglecting possible future welfare losses. Using consecutive rounds of household-level health survey data and a three-step Feasible Generalised Least Squares method, we examine whether health shocks make households vulnerable to poverty, estimate vulnerability across different population subgroups, and examine its transition in India. We find that the mean household vulnerability has remained above 0.7 from 1995 to 2018, indicating a high probability that a household will fall into poverty due to health shocks. In addition, female-headed households, households in rural areas, households with poor hygiene practices, households with low-educated heads, and households without insured members have a higher incidence of poverty vulnerability. Contrary to expectations, households with members covered by government-sponsored insurance are found to be more vulnerable than others. The results suggest that the determinants of health shocks need to be taken into account when designing poverty-reduction strategies. The paper recommends expanding a pre-designed health insurance, sanitation, and basic education drive that could effectively normalise the effects of health shocks on vulnerable households in India.

Keywords: vulnerability to poverty, feasible generalised least squares method, health shocks, health status, NSS, India

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For supplementary materials such as appendices, datasets, and author disclosure statements, see the article page at https://healthempirics.org/

A sudden medical crisis often places an immense and multifaceted strain on a family's economic well-being. Health shocks may lead to hospitalisation or death of a family member, triggering high out-of-pocket (OOP) health expenditure or loss of a breadwinner's income. These crises result in temporary or permanent disabilities that diminish a household's long-term earning capacity (Atake, 2018; Mitra et al., 2016). While droughts and floods are collective disasters, a serious illness is an idiosyncratic shock that is just as destabilising but far less predictable. A household's vulnerability to a health shock is determined by two primary factors- its financial capacity and its access to effective insurance. So, for the poor, the intersection of high treatment costs and a lack of coverage, coupled with any illness or injury, is a health shock (Dhanaraj, 2016). Faced with such a shock, vulnerable households resort to distress sales of productive capital in the short run. By selling livestock or land and draining savings, they trade long-term stability for covering the current treatment expenses (Somi et al., 2009). In the long run, the effect of a health shock shifts towards greater reliance on structural austerity, as it reduces budgets earmarked for education, housing, and productive capital (Panikkassery, 2020; Somi et al., 2009). Such a health shock arising from a disparity between rising medical costs and household payment capacity is a major concern for policymakers.

Indian households face a substantial financial burden, as OOP health expenditure accounts for around 62.7% of total health expenditure (WHO, 2021). In fact, during 1993-2012, the growth rate of household health spending was much higher than household consumption expenditure (Mohanty et al., 2016). In addition, a high share of households is pushed below the poverty line annually due to high OOP health expenses (Hooda, 2017). From the point of view of framing public policies aimed at reducing poverty, it is more sensible to forecast the probability that a household will fall below the poverty line in the future (ex ante measurement) than to estimate whether the household was below the poverty line in the past (ex post measurement). This implies that estimating a household's vulnerability to poverty due to a sudden health shock provides a more predictive dimension for policy-making, enabling a transition from relief-oriented measures to risk-management measures. In the context of health shocks, vulnerability to poverty can be defined as the probability that high OOP health expenses in the current period will drive a household's net consumption expenditure below the poverty line in subsequent periods. Unlike ex-post poverty measures, which document past welfare, vulnerability to poverty is a forward-looking, ex-ante construct. It encapsulates households at risk of falling into poverty due to health shocks, not just those already residing in poverty.

Review of Literature

The major reasons for OOP expenses and consequential income losses among households are multiple events of repeated and serious illness and injuries. In these circumstances, the lack of accessible health insurance coverage leaves households facing significant financial instability and economic hardship. (Hoogeveen et al., 2004). Empirical evidence further suggests that households are also unable to stabilise earnings or sustain basic consumption due to serious illness and injuries. Evidence from rural Ethiopia suggests that poorer households lack the mechanisms to stabilise consumption over time; furthermore, the impact of adverse shocks is borne disproportionately by women within households (Dercon & Krishnan, 2000). Utilising similar data, Asfaw and von Braun (2004) found that informal risk-sharing networks in rural Ethiopia are insufficient to stabilise non-food consumption following the illness of a household head.

The impact of illness shocks on household heads, affecting a household's income and consumption pattern, has also been studied in multiple studies. Evidence from China suggests that the illness of a household head correlates with diminished labour supply and income, as well as higher OOP health expenditures, which are significantly higher in insured populations than in the uninsured (Wagstaff & Lindelow, 2005). Wagstaff (2007) found evidence that urban Vietnamese households face higher vulnerability in income following the death or illness or drop in body mass index of a working-age adult, regardless of insurance status. Meanwhile, Nguyet and Mangyo (2010) observed that illness or injury to Indonesian household heads leads to significant reductions in both labour hours and aggregate consumption expenses. Similar evidence from Laos suggests that poor households face more shocks in terms of illness, injury and death, and these are more prominent among the poor households. Many households also reported that consumption expenditures had to be reduced after an illness or injury in the household, which affected their welfare as well (Wagstaff & Lindelow, 2014).

Empirical research also shows that, while medical expenses are a source of economic risk due to illness in Indonesian households, this is largely confined to poor households, rural dwellers, and informal-sector workers who lack formal protection (Sparrow et al., 2014). Investigating the longitudinal effects of injury on a household's welfare and health expenditure levels in Zambia, it has been found that injury significantly reduced earned income and household welfare—measured by consumption—both before and after the 2002 structural adjustment period (Hangoma et al., 2018). Conversely, there is no evidence of income stabilisation among households facing illness, injury, or death-related shocks without a loss in household welfare (Mitra et al., 2016).

A plethora of literature on illness- or injury-related shocks has sought to estimate the level of consumption smoothing by households when they faced such shocks and the myriad ways these strategies helped mitigate their impact. However, there is less evidence on how these shocks might drive households into future poverty. The fact that high OOP health expenses can push households below the poverty line is well-documented (Hooda, 2017). It is also known that when OOP health expenses rise, this necessitates budget shifting, in which essential spending on education, fuel, and housing is reduced to offset medical costs (Panikkassery, 2020). So, health shocks, measured either by high OOP health expenses relative to a household's capacity to pay or by reduced household income due to illness or injury, can be significant predictors of future poverty.

While the policy implications of health shocks are immense, there is a significant gap in understanding the nexus between health shocks and households' likelihood to fall below the poverty line, especially in the Indian context. There is also a dearth of research on how household- and community-level determinants modulate future poverty risks arising from health shocks. To address this, the study utilises multiple rounds of National Sample Survey (NSS) data to quantify vulnerability to poverty specifically induced by health shocks. To this end, it employs a three-step Feasible Generalised Least Squares (FGLS) framework to identify the key correlates of vulnerability and examine its change over the years.

Empirical Approach, data and variables

The empirical literature identifies three primary approaches for estimating vulnerability: Vulnerability as Expected Poverty (VEP), Vulnerability as Low Expected Utility (VEU), and Vulnerability as Uninsured Exposure to Risk (VER). The VEP approach defines vulnerability as the probability that a household's projected consumption expenditure will fall below a predefined poverty threshold within a future time horizon (Novignon et al., 2012; Chaudhuri, 2003. The VEU approach defines vulnerability as the gap between the utility of a given consumption level and the expected utility associated with that level. Conversely, the VER approach quantifies vulnerability as the net welfare loss resulting from a household's inability to access efficient risk-mitigation or consumption-smoothing mechanisms.

To analyse vulnerability to health shocks, the study uses the VEP, drawing on methodologies established by Chaudhuri (2003) and Novignon et al. (2012). The selection of VEP over alternative frameworks VEU and VER is justified by two reasons. First, unlike the VEU approach, which often requires panel data, the VEP framework is applicable to cross-sectional datasets. This allows for a comprehensive estimation of vulnerability using large-scale surveys where longitudinal data is unavailable (Atake, 2018; Novignon et al., 2012; Chaudhuri, 2003). The VER approach, on the other hand, is ex post in nature as it measures the impact of shocks after they have occurred, while the VEP approach facilitates an ex ante assessment.

Using the VEP approach

Following Chaudhuri (2003), the welfare level of a household is measured in terms of the value of consumption and vulnerability of household *h* at time $t(V_{\_ht})$ is defined as the probability that the consumption level of a household in time *t+k* ($C_{h,t+k}$) will lie below the consumption poverty line *z.* In other words,

$$V_{ht} = Pr\ (lnC_{h,t+k} < lnz) \tag{1}$$

It is assumed that the household h's consumption level is determined by the stochastic process given as:

$$lnC_h = X_h\beta + \epsilon_h \tag{2}$$

Where C_h is the consumption expenditure of household *h,* X_h is the vector of household characteristics, such as the household's location, the household head's education and gender, etc. β is a vector of parameters to be estimated, and ϵ_h is the zero-mean disturbance term.

It must be noted that, when using cross-sectional data, certain assumptions are made. First, the random disturbance term ϵ_h is log normally distributed, implying that C_h is also log-normally distributed. This assumption is made to enable the estimation of the probability that a household with a given set of characteristics. X_h will be consumption poor. Second, the economy is assumed to be stable over the analysis period, thereby excluding the possibility of aggregate shocks or abrupt structural changes.

Thus, a household with characteristics X_h The probability of being vulnerable to poverty at period *t+k* can be estimated using the coefficients from equation 2.

$$\widehat{V_h} = pr\ (lnC_{h,t+k} < ln\ z|X_h) = \emptyset(ln\ z - X_h\hat{\beta}\widehat{\sigma} \tag{3}$$

Where $\widehat{V_h}$ is the estimated vulnerability to poverty of household h (the probability that the consumption level of household h will be below the poverty line, conditional on household characteristics, ∅(.) is the cumulative density of the standard normal distribution and $\widehat{\sigma}$ is the standard error from equation (2).

- **Presence of heteroscedasticity**

To address the problem of heterogeneous variance of the disturbance term, the variance of ϵ_h

$$(\text{i.e., } \sigma^2_{\epsilon,h})$$

is assumed to be related to household characteristics in some parametric way as:

$$\sigma^2_{\epsilon,h} = X_h\theta + \mu_h \tag{4}$$

To estimate θ , a three-stage Feasible Generalized Least Squares (FGLS) method is used. The FGLS method provides a consistent estimate of the actual variance of consumption even in the presence of measurement errors (Amemiya, 1977).

At the first stage, equation (2) is estimated using the Ordinary Least Squares (OLS) method. The estimated residuals are used to estimate equation (5) by OLS:

$$\hat{\sigma}^2_{OLS,h} = X_h\hat{\theta} + \hat{\mu}_h \tag{5}$$

At the second stage, predicted values from equation (5) are used to transform equation (5) as given below

$$\frac{\sigma^2_{OLS,h}}{X_h\hat{\theta}} = \frac{X_h}{X_h\hat{\theta}}\theta + \frac{\mu_h}{X_h\hat{\theta}} \tag{6}$$

Now, estimation of equation (6) by OLS gives us an asymptotically efficient FGLS estimate,

$$\hat{\theta}_{FGLS}$$

It should be noted that,

$$X_h\hat{\theta}_{FGLS}$$

is a consistent estimate of

$$\sigma^2_{\epsilon,h}$$

Moreover, it is also the variance of the idiosyncratic component of household consumption. The standard error of

$$\hat{\theta}_{FGLS}$$

is now used to transform equation (2):

$$\hat{\sigma}_{\epsilon,h} = \sqrt{X_h\hat{\theta}_{FGLS}} \tag{7}$$

$$\frac{lnC_h}{\hat{\sigma}_{\epsilon,h}} = \frac{X_h}{\hat{\sigma}_{\epsilon,h}}\beta + \frac{\epsilon_h}{\hat{\sigma}_{\epsilon,h}} \tag{8}$$

Estimating equation (8) using OLS gives us $\hat{\beta}$. The estimated parameters

$$\hat{\beta}_{FGLS} \quad \text{and} \quad \hat{\theta}_{FGLS}$$

enable us to estimate the expected log consumption (denoted by equation 9) and the expected variance of log consumption (denoted by equation 10).

$$E\left[\left(\widehat{lnC_h}|X_h\right)\right] = X_h\hat{\beta} \tag{9}$$

$$Var\left[\left(ln\hat{C}_h|X_h\right)\right] = \hat{\sigma}^2_h = X_h\hat{\theta} \tag{10}$$

Finally, vulnerability to poverty can be estimated as

$$\hat{V}_h = \varphi\left(\frac{\ln z - X_h\hat{\beta}_{FGLS}}{\sqrt{X_h\hat{\theta}_{FGLS}}}\right) \tag{11}$$

- **'Vulnerability to poverty' threshold**

Since the estimated vulnerability to poverty $\hat{V}_h$ for a household, h can be any value between 0 and 1 (0 meaning no vulnerability at all and 1 meaning complete vulnerability). It is reasonable to assume 0.5 as a threshold for vulnerability to poverty (Novignon et al., 2012). Any household with an estimated vulnerability of 0.5 or higher is considered vulnerable to poverty; otherwise, it is not. To present our results, we express vulnerability to poverty as the percentage of vulnerable households and the mean vulnerability. A higher mean vulnerability implies a higher probability of being vulnerable to poverty due to health shocks (Atake, 2018). All analyses are conducted using Stata (version 14), with sample weights applied.

- **Time horizon**

The literature does not suggest any specific time horizon for assessing a household's vulnerability. Assessed at time point t, vulnerability can be estimated for any future time point *(t+k)* where *k* is usually ≥ 1 (Atake, 2018; Novignon et al., 2012).

- **Data**

We use data from four NSS health rounds: 52nd (1995-96), 60th (2004), 71st (2014), and 75th (2017-18), with nationally representative samples of 120942, 73868, 65932, and 113816 households, respectively.1 In addition to detailed household and individual-level data, the surveys collected a rich set of information on reported morbidity, healthcare utilisation and healthcare expenditure from the sample households. The recall period for hospitalisation and outpatient (OP) care is 1 year and 15 days, respectively, preceding the survey.

To maintain temporal consistency in the absence of official poverty thresholds for specific survey years, this study employs a deflation-and-inflation indexing strategy to align available poverty lines with the corresponding National Sample Survey (NSS) rounds. For the NSS 52nd Round (1995–96), state-specific thresholds were derived by deflating the official 2004–05 poverty lines. Conversely, for the NSS 71st (2014) and NSS 75th (2017–18) Rounds, the 2011–12 poverty lines were adjusted upward. In all instances, poverty lines for urban households were adjusted using the Consumer Price Index for Industrial Workers (CPI-IW), while poverty lines for rural households were adjusted using the Consumer Price Index for Agricultural Labourers (CPI-AL). For the 60th Round (2004), the proximate 2004–05 state-specific poverty lines were applied directly.

- **Dependent Variable**

The dependent variable utilised to estimate vulnerability to poverty is net monthly household consumption expenditure, defined as total monthly household consumption expenditure minus out-of-pocket (OOP) health expenditure. Since data on household OOP health expenditure were collected using recall periods of varying lengths (15 days for outpatient care and 365 days for inpatient care), they were standardised into monthly equivalents through appropriate scaling factors. In the next stage, we subtracted OOP health expenditure from total household consumption to arrive at net household consumption expenditure. Furthermore, following Asfaw & von Braun (2004), this exercise treats health expenditures as an exogenous component, mitigating endogeneity bias within the consumption function.

- **Independent Variables**

To measure a household's health status, we use a standardised proxy variable. This variable is constructed by calculating the ratio of household members who reported any event of illness or injury (15 days prior to the survey) or hospitalisation in the last year, to the total household size (Atake, 2018; Novignon et al., 2012).

Environmental determinants, such as access to potable water and improved sanitation, serve as indicators of hygiene-related living conditions. It is hypothesised that households with better living conditions exhibit lower morbidity rates and, consequently, have enhanced health outcomes. Demographic factors such as the presence of vulnerable cohorts, specifically children (0–14 years), the elderly (60 and above years), and women of reproductive age (15–49 years), can significantly affect household healthcare demand and expenditure (Atake, 2018; Novignon et al., 2012). Other household-level covariates included in the model are geographic and social indicators (sector, region, and caste), occupational category, household size, and the socio-demographic characteristics of the household head (gender and educational attainment). Additionally, the presence and type of health insurance coverage are important variables in financial protection (Atake, 2018; Mitra et al., 2016). Given the paucity of *ex ante* literature, this study draws on ex post empirical findings to corroborate and contextualise the results.

Results and Discussions

Selected descriptive statistics for the periods 1995–96, 2004, 2014, and 2017–18 are summarised in Table 1. Analysis of household-level morbidity reveals that the proportion of households with at least one ailing member rose from 21.82% in 1995–96 to a peak of 32.84% in 2014, then declined to 25.18% in 2017–18. There has also been a substantial improvement in hygiene indicators, as the share of households with unhygienic latrine facilities plummeted from 74.20% in 1995–96 to 22.59%

in 2017–18. Significant shifts in household demographics have also been observed. The share of female-headed households increased from 10.03% to 12.18% over the study period. The educational profile of household heads improved markedly, as the proportion of uneducated heads decreased from 43.63% in 1995–96 to 28.36% by 2017–18. The descriptive analytics also indicate a transformative expansion in health insurance among households. Household insurance coverage, which was negligible at less than 1% in 1995–96, reached 18.74% by 2017–18. This growth was largely driven by government-sponsored health insurance (GSHI) schemes, which saw coverage increase from 15.39% in 2014 to 18.74% in 2017–18.

Table 2 exhibits the shifts in mean vulnerability estimates and the prevalence of vulnerable households from 1995 to 2018. The data reveal a marginal but consistent contraction in mean household vulnerability, falling from 0.464 in 1995–96 to 0.435 by 2017–18. This downward trajectory is also portrayed in the proportion of vulnerable households, which diminished from 45.08% to 40.97% over the same period. These findings align with ex post estimates from the Ministry of Statistics and Programme Implementation (MOSPI), which report a significant decline in observed poverty incidence—from 45.3% in 1993–94 to 21.9% in 2011–12 (see Table A1 in Appendix). However, a critical finding of this analysis is the widening gap between ex post poverty and ex ante vulnerability estimates. Furthermore, the intensity of risk remains high for those categorised as vulnerable households, i.e. those with a mean vulnerability higher than 0.5. For this sub-group, mean vulnerability scores remained persistently above the 0.7 threshold throughout the study period (0.746 in 1995–96, 0.752 in 2004, 0.737 in 2014, and 0.736 in 2017–18). This lack of substantial improvement indicates that, while fewer households are entering the vulnerability bracket, the degree of vulnerability, or the risk of falling below the poverty line, has remained largely stagnant over the past two decades.

Comparative analysis of mean vulnerability and the prevalence of vulnerable households across various demographic characteristics reveals that rural households consistently exhibited higher levels of vulnerability than their urban counterparts throughout the 1995–2018 period (Table 3). The mean vulnerability index for rural households increased from 0.551 in 1995–96 to 0.579 by 2017–18. During this interval, the proportion of rural vulnerable households increased, rising from 56.68% in 2004 to 60.00% in 2014, and further to 61.73% in 2017–18. These trends suggest a limited capacity among rural populations to ensure earned income and consumption expenditures from the deleterious effects of health shocks (Mitra et al., 2016).

Disaggregation by occupational category indicates that households with members engaged as casual labour have the highest risk of falling below the poverty line. This is evidenced by a higher mean vulnerability and a larger share of vulnerable households across all four data waves than among self-employed or regular wage-

Table 1: Select descriptive statistics

Variables	52nd round	60th round	71st round	75th round
Survey month- year	**July 1995- June 1996**	**January - June 2004**	**January - June 2014**	**July 2017- June 2018**
Sample households	120942	73868	65932	113816
Average household size (SE)	4.92 (0.01)	4.82 (2.47)	4.51 (2.16)	4.35 (2.09)
Households with at least one ailing member (%)	20.82	30.29	32.84	25.18
Households with at least one child (%)	44.36	40.96	33	24.92
Households with at least one elderly (%)	21.29	26.47	26.87	22.63
Households with at least one female in the reproductive group (%)	86.78	92.74	92.08	92.11
Households with unhygienic sanitation facilities (%)	74.20	62.62	42.07	22.59
Households without access to safe drinking water (%)	4.56	13.75	8.21	6.43
Female Headed Household (%)	10.03	11.08	12.00	12.18
Households with illiterate head (%)	43.63	39.14	32.38	28.36
Households with primary level educated head (%)	38.57	40.48	38.73	37.38
Households with secondary level educated head (%)	12.12	13.79	19.66	23.34
Households with above secondary level educated head (%)	5.54	6.58	9.23	10.92
Households with any member having health insurance coverage (%)	0.38	1.86	18.60	18.74
Household with any member having GSHI (%)	-	-	15.39	18.74
Households having any member having employer provided health insurance (%)	-	-	1.62	15.31
Households with any member having household arranged health insurance (%)	-	-	1.73	1.72
Households with any member having other types of health insurance (%)	-	-	0.17	1.71

Source: NSS 52nd (1995-96), 60th (2004), 71st (2014), 75th (2017-18) round unit-record data

Note: Data on type of insurance coverage not available for NSS 52nd (1995-96) and 60th (2004) rounds.

Table 2: Estimated vulnerability to poverty for the years 1995-96, 2004, 2014 and 2017-18

Variables	**1995-96**	**2004**	**2014**	**2017-18**
Mean vulnerability score	0.464	0.458	0.441	0.435
Vulnerable households (%)	45.08	43.54	41.28	40.97
Mean vulnerability of vulnerable households	0.746	0.752	0.737	0.736

Source: NSS 52nd (1995-96), 60th (2004), 71st (2014), 75th (2017-18) round unit-record data

earning households. These findings align with ex post empirical literature, which finds limited asset ownership, income volatility, and diminished earning capacity as being the primary drivers of vulnerability to poverty among these specific cohorts (Thorat et al., 2017).

The analysis found that households utilising unhygienic sanitation facilities exhibit higher vulnerability than their counterparts, with mean vulnerability scores rising from 0.568 in 1995–96 to 0.585, 0.647, and 0.668 across the survey waves (2004, 2014, and 2017–18, respectively). The prevalence of vulnerable households for this cohort also rose from 60.03% in 1995–96 to 77.12% by 2017–18. Similar disparities are observed regarding water security, where households lacking safe drinking water consistently displayed higher vulnerability during the study period 1995-96, 2004 and 2017-18. These findings support the hypothesis that improved sanitation and safe drinking water facilities are important for mitigating morbidity and subsequent healthcare expenditures among households. These facilities enhance household welfare and productivity, thereby attenuating vulnerability to poverty in the long term. (Atake, 2018; Novignon et al., 2012).

The gendered dimensions of poverty are also evident from the analysis as female-headed households have both higher mean vulnerability and a larger share of vulnerable households throughout the 1995–2018 period, despite a marginal decline between 1995 and 2014. This aligns with global ex post evidence suggesting that female-headed households face a higher probability of chronic poverty (Kossoudji & Mueller, 1983; Atake, 2018). This might be primarily due to a gendered allocation of material resources such as land and employment opportunities. Coupled with cultural constraints that inhibit the accumulation of social capital and labour productivity among women, this increases the vulnerability of female-headed households to poverty. It is also found that households with uneducated household heads and those with primary-level education exhibit higher vulnerability to poverty compared to those with more educated heads. Households headed by individuals with primary education experienced a deterioration in future welfare,

Table 3: Vulnerability to poverty profile across sample household characteristics for the years 1995-96, 2004, 2014 and 2017-18

Variables	**Mean Vulnerability**				**Vulnerable households (%)**			
	1995-96	2004	2014	2017-18	1995-96	2004	2014	2017-18
Sector								
Rural	0.551	0.548	0.568	0.579	57.36	56.68	60	61.73
Urban	0.354	0.376	0.359	0.339	42.64	32.8	29.3	25.94
Occupation type of household								
Self-employed	0.433	0.424	0.458	0.457	39.76	37.59	43.63	43.4
Regular wage and salaried	0.279	0.297	0.347	0.336	18.16	22.56	28.17	26.03
Casual labour	0.659	0.632	0.639	0.612	74.37	71.16	71.51	68.04
Others	0.588	0.644	0.697	0.753	60.77	69.04	74.46	83.87
Type of sanitation and drinking water facilities								
Hygienic sanitation facilities	0.304	0.358	0.393	0.451	21.15	28.81	32.99	42.1
Non-Hygienic sanitation facilities	0.568	0.585	0.647	0.668	60.03	62.66	73.42	77.12
Availability of safe drinking water	0.497	0.494	0.501	0.494	49.53	49.16	50.21	49.12
Non-availability of safe drinking water	0.559	0.54	0.495	0.586	59.86	55.31	47.67	62.91
Gender of household head								
Female	0.728	0.698	0.652	0.692	80.14	77.07	70.08	75.15
Male	0.475	0.475	0.479	0.473	46.64	46.63	47.27	46.52
Education of household head								
No education	0.615	0.607	0.613	0.597	66.89	65.98	66.29	64.13
Up to Primary	0.474	0.502	0.535	0.541	45.65	49.3	55.19	56.5
Up to Secondary	0.319	0.349	0.387	0.437	23.35	27.09	31.03	38.86
Above secondary	0.164	0.166	0.198	0.242	5.11	7.24	11.47	14.95

Source: Estimated from NSS 52nd (1995-96), 60th (2004), 71st (2014), 75th (2017-18) round unit-record data

Table 4: Vulnerability to poverty profile across demographic characteristics for the years 1995-96, 2004, 2014 and 2017-18

Variables	**Mean Vulnerability**				**Percentage of vulnerable households**			
	1995-96	2004	2014	2017-18	1995-96	2004	2014	2017-18
Household with at least one child	0.446	0.443	0.464	0.421	43.19	42.82	45.55	40.44
Household without any child	0.543	0.539	0.518	0.526	55.43	54.99	52.20	53.19
Household with elderly member	0.466	0.501	0.520	0.511	43.80	48.56	52.00	50.56
Household without elderly member	0.509	0.499	0.493	0.497	51.68	50.52	49.27	49.85
Household with woman of reproductive age group	0.458	0.472	0.475	0.471	44.46	46.49	46.81	46.4
Household without woman of reproductive age group	0.774	0.853	0.794	0.838	86.40	94.90	87.11	92.19

Source: Estimated from NSS 52nd (1995-96), 60th (2004), 71st (2014), 75th (2017-18) round unit-record data with mean vulnerability and the proportion of vulnerable households rising from 0.474 (45.65%) in 1995–96 to 0.541 (56.50%) in 2017–18 (Turčínková & Stávková, 2012). These results support the notion that higher education facilitates access to higher wages, which acts as a buffer against future consumption shocks arising from health shocks (Dhanaraj, 2016).

Table 4 presents the impact of household demographic composition and insurance coverage on estimates of vulnerability to poverty. The mean vulnerability to poverty among households with elderly members is higher than that of households without elderly members, and the estimates have risen from 0.466 in 1995–96 to 0.520 in 2014. Additionally, households with women of reproductive age also share a similar trend of rising mean vulnerability to poverty during the study period. Given that the elderly often suffer from chronic comorbidities that require frequent outpatient visits and hospitalisations, this necessitates higher healthcare allocations and reduced net consumption expenditure, thereby exacerbating overall household vulnerability (Mahumud et al., 2017).

As a household's vulnerability to poverty is a non-linear function of its future consumption trajectory, it is theoretically expected to maintain a positive relationship with expected consumption levels and a negative relationship with the volatility (variance) of the consumption levels. To examine these dynamics, Table 5 presents the estimated coefficients for the determinants of ex ante mean and variance of future consumption. The results reveal a significant negative relationship between health status and vulnerability to poverty, as well as greater variance in consumption patterns during the 1995–2018 period. This suggests that a household's current health status is a significant determinant of vulnerability to poverty, as an increase in the proportion of members with any illness or injury raises vulnerability to poverty (Atake, 2018; Novignon et al., 2012).

The study further finds that larger households exhibit lower mean vulnerability to poverty and less variance in future consumption compared to smaller households. This phenomenon can be attributed to economies of household size, in which members achieve greater efficiency through cooperative consumption, including shared housing costs, utility expenses, and bulk purchases of essential commodities (Thorat et al., 2017).

The analysis also suggests other structural factors that significantly exacerbate vulnerability to poverty by simultaneously reducing expected mean consumption and inflating consumption volatility across all four survey waves (1995–96, 2004, 2014, and 2017–18). These risk factors include rural location, belonging to the Scheduled Tribe (ST) or Scheduled Caste (SC) groups, casual labour, and female household headship. The presence of high-dependency groups, such as children and the elderly, in the household also consistently increases the risk of falling below the poverty line in future. It has also been observed that the presence of insured

Table 5: Determinants of vulnerability to poverty for the years 1995–96, 2004, 2014 and 2017–18

Variables	1995–96		2004		2014		2017–18	
	Ex ante mean Consumption (SE)	Ex ante variance Consumption (SE)	Ex ante mean Consumption (SE)	Ex ante variance Consumption (SE)	Ex ante mean Consumption (SE)	Ex ante variance Consumption (SE)	Ex ante mean Consumption (SE)	Ex ante variance Consumption (SE)
Health Status	−1.059* (0.014)	0.526* (0.005)	−1.356* (0.021)	3.042* (0.030)	−1.605* (0.026)	0.820* (0.009)	−1.293* (0.018)	0.688* (0.007)
Household size	0.136* (0.001	−0.048* (0.001)	0.130* (0.003)	−0.288* (0.003)	0.127* (0.005)	−0.047* (0.002)	0.163* (0.003)	−0.059* (0.002)
Rural household	−0.101* (0.007)	0.041* (0.003)	−0.249* (0.013)	0.560* (0.006)	−0.272* (0.013)	0.100* (0.006)	−0.462* (0.008)	0.167* (0.004)
ST household	−0.135* (0.008)	0.047* (0.004)	−0.110* (0.016)	0.230* (0.007)	−0.118* (0.019)	0.053* (0.008)	−0.137* (0.012)	0.070* (0.005)
SC household	−0.065* (0.005)	0.016* (0.003)	−0.031* (0.011)	0.071* (0.005)	−0.023 (0.014)	0.020 (0.006)	−0.066* (0.009)	0.031* (0.004)
Consumption level category								
Poor household	−0.491* (0.005)	−0.038* (0.002)	−0.620* (0.010)	−0.014* (0.005)	−0.708* (0.012)	0.019* (0.005)	−0.789* (0.008)	0.126* (0.004)
Regular wage/ salaried household	0.046* (0.008)	0.018* (0.005)	0.049* (0.017)	−0.051* (0.009)	0.008 (0.015)	0.006 (0.007)	0.062* (0.010)	0.003 (0.005)
Casual labour household	−0.121* (0.005)	0.011* (0.002)	−0.129* (0.010)	0.240* (0.005)	−0.130* (0.013)	0.016* (0.006)	−0.071* (0.008)	0.004 (0.004)
Other occupation household	−0.090* (0.008)	0.033* (0.004)	−0.202* (0.014)	0.467* (0.007)	−0.151* (0.023)	0.047* (0.009)	−0.117* (0.014)	0.029* (0.006)
Household with hygienic sanitation facilities	0.217* (0.006)	−0.063* (0.004)	0.280* (0.011)	−0.632* (0.008)	0.285* (0.013)	−0.103* (0.006)	0.203* (0.009)	−0.072* (0.004)
Household with safe drinking water	−0.036* (0.010)	0.020* (0.005)	−0.025* (0.012)	0.068* (0.006)	−0.150* (0.019)	0.056* (0.008)	−0.009 (0.014)	0.031* (0.006)

Variables	1995–96		2004		2014		2017–18	
	Ex ante mean Consumption (SE)	Ex ante variance Consumption (SE)	Ex ante mean Consumption (SE)	Ex ante variance Consumption (SE)	Ex ante mean Consumption (SE)	Ex ante variance Consumption (SE)	Ex ante mean Consumption (SE)	Ex ante variance Consumption (SE)
Female head household	−0.109* (0.007)	0.031* (0.003)	−0.048* (0.014)	0.116* (0.006)	−0.077* (0.017)	0.090* (0.007)	0.127* (0.011)	−0.112* (0.005)
Household head's education: Primary	0.112* (0.005)	−0.034* (0.002)	0.089* (0.010)	−0.198* (0.005)	0.058* (0.013)	−0.066* (0.006)	0.054* (0.009)	−0.050* (0.004)
Household head's education: Secondary	0.264* (0.007)	−0.072* (0.004)	0.269* (0.014)	−0.585* (0.009)	0.193* (0.016)	−0.082* (0.008)	0.147* (0.010)	−0.071* (0.005)
Household head's education: above secondary	0.514* (0.010)	−0.107* (0.006)	0.590* (0.020)	-1.270* (0.016)	0.557* (0.022)	−0.166* (0.011)	0.409* (0.014)	−0.138* (0.007)
Number of children in household	−0.075* (0.003)	0.014* (0.001)	−0.054* (0.006)	0.105* (0.003)	−0.044* (0.008	0.005 (0.004)	−0.035* (0.006)	0.005 (0.003)
Number of elderly members in household	−0.023* (0.004)	0.003 (0.002)	−0.006 (0.008)	0.003 (0.004)	−0.056* (0.009)	0.018* (0.004)	−0.044* (0.006)	−0.044* (0.006)
Number of reproductive age women in household	0.066* (0.004)	−0.036* (0.002)	0.032* (0.005)	−0.081* (0.003)	0.015* (0.006)	−0.005 (0.003)	0.004 (0.004)	−0.009* (0.002)
Household having any member having health insurance coverage	0.133* (0.033)	−0.042* (0.019)	0.271* (0.031)	−0.648* (0.019)	0.210* (0.014)	−0.097* (0.006)	0.131* (0.009)	−0.069* (0.004)

Source: Estimated from NSS 52nd (1995–96), 60th (2004), 71st (2014), 75th (2017–18) round unit-record data.

Note: Dependent variables are ex-ante mean of consumption and ex ante variance of consumption.

Standard errors (SE) are given in parentheses.

* Indicates 5% level of significance

members significantly influences the consumption levels in future. While insurance may marginally lower the expected future mean consumption, it substantially reduces the variability in consumption patterns. By smoothing consumption and protecting against OOP health payments, insurance coverage effectively lowers the probability of ex ante vulnerability to poverty.

An analysis of mean vulnerability across social and income strata reveals that households from marginalised groups, specifically Scheduled Tribes (ST) and Scheduled Castes (SC), are more vulnerable to poverty than non-SC/ST cohorts. Throughout the 1995–2018 period, ST households consistently exhibited the highest mean vulnerability among all other caste categories, with scores escalating from 0.615 in 2004 to 0.631 in 2017–18 (Figure 1; Appendix Tables A2, A3). These findings also align with ex post empirical research (Thorat et al., 2017).

The study also illustrates a diverging trajectory across income categories: for poor households, mean vulnerability to poverty and the prevalence of vulnerable households both rise, from 0.510 (51.85%) in 1995–96 to 0.671 (76.07%) by 2017–18. Conversely, a reciprocal downward trend was observed among non-poor households (Figure 2; Appendix Tables A2, A3). This indicates the existence of a medical poverty trap, as diversion of limited resources toward health expenditures subsequently compromises the household's ability to procure nutritional sustenance, preventive and curative health care, and educational opportunities. These findings reinforce the theoretical consensus that poverty is both a primary driver and a consequence of ill health (Atake, 2018).

Figure 1: Change in mean vulnerability and percentage of vulnerable households across caste from 1995 to 2018

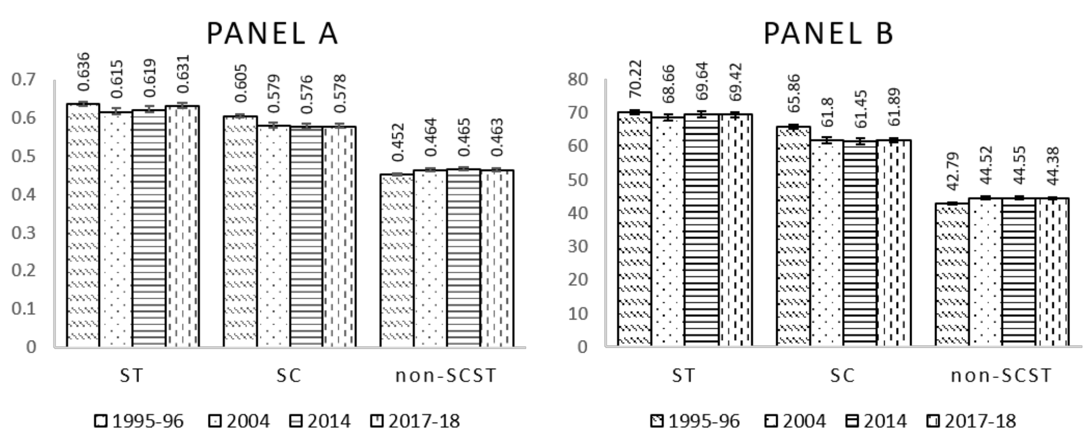
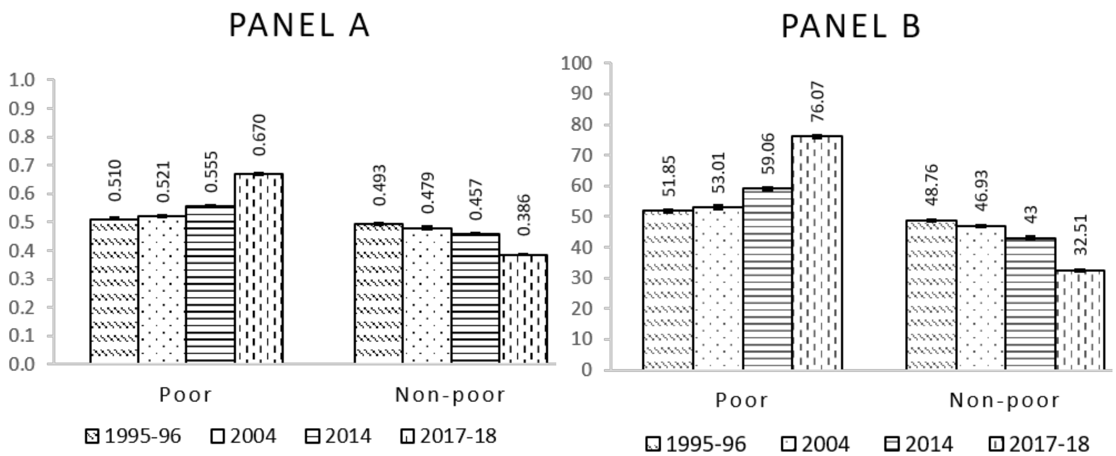


Figure 2: Change in mean vulnerability and percentage of vulnerable households across income categories from 1995 to 2018

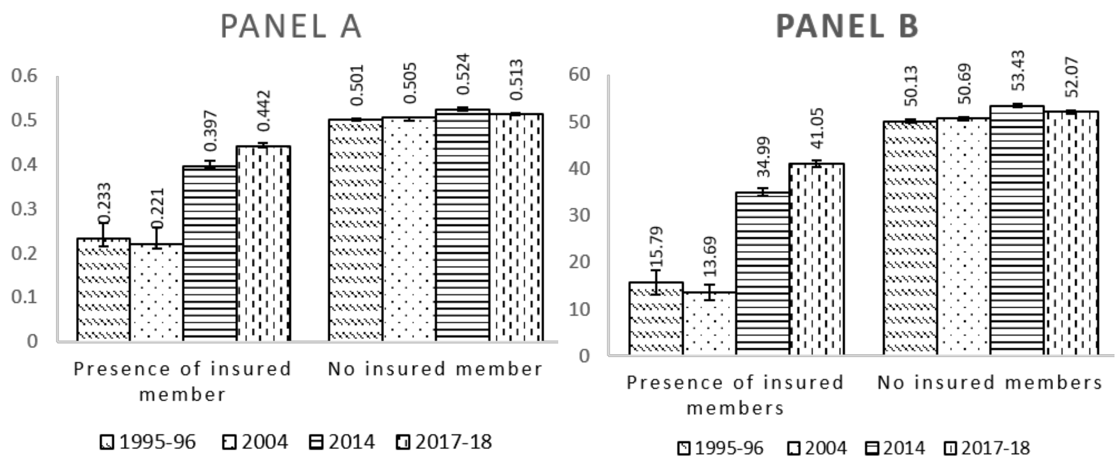


The study also examined the role of health insurance coverage in reducing households' vulnerability to poverty. Comparative analysis between insured and uninsured households reveals that the latter consistently maintained a higher mean vulnerability to poverty than the former. In fact, uninsured households experienced an increase in both mean vulnerability and the prevalence of vulnerable households, rising from 0.501 (50.13%) in 1995–96 to 0.524 (53.43%) by 2014 (Figure 3; Appendix Tables A2, A3). These findings align with existing research suggesting that households with insurance coverage have lower OOP health expenditures (Sepheri et al., 2006).

With the introduction of the Rashtriya Swasthya Bima Yojana (RSBY) in 2008, granular data on types of insurance coverage are available only for the 71st (2014) and 75th (2017–18) survey rounds. Quite surprisingly, households with at least one member enrolled in GSHI schemes have significantly higher mean vulnerability and a higher share of vulnerable households than those covered by alternative insurance schemes. For the GSHI-covered households, mean vulnerability surged from 0.426 in 2014 to 0.667 in 2017–18, while the proportion of vulnerable households nearly doubled from 38.26% to 69.18% during the same period (Figure 4; Appendix Tables A2, A3).

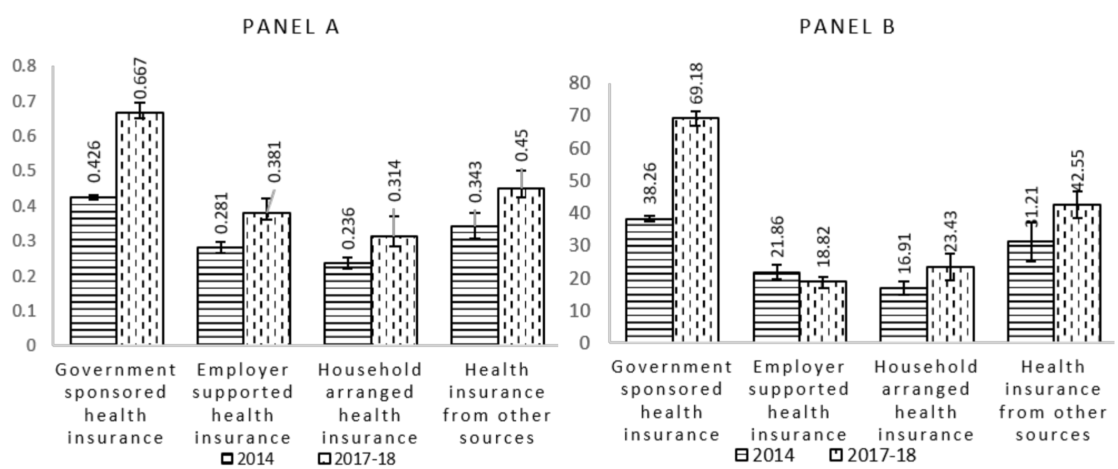
These results indicate that GSHI schemes have largely failed to provide the requisite financial protection necessary to smooth consumption levels in future. This inadequacy is supported by empirical evidence showing an increase in average hospitalisation costs even among GSHI-enrolled households (Selvaraj & Karan, 2012). The ineffectiveness of schemes like RSBY is frequently attributed

Figure 3: Change in mean vulnerability and percentage of vulnerable households across presence of insured and uninsured members in household from 1995 to 2018



to continued OOP spending on pharmaceuticals and diagnostics that are either unavailable at empanelled facilities or excluded from scheme protocols (Karan et al., 2017). Furthermore, limited coverage caps and administrative frictions, such as hospitals' reluctance to admit patients due to lengthened reimbursement cycles, further render the GSHI schemes ineffective (Ghosh, 2014).

Figure 4: Change in mean vulnerability and percentage of vulnerable households across type of insurance coverage among household members from 2014 to 2017-18



Conclusion and Policy Suggestions

The analysis demonstrates that health shocks exert a statistically significant but negative impact on future expected consumption expenditures while simultaneously increasing consumption expenditure volatility. These will make households more vulnerable to poverty. Although there has been a decline in absolute poverty rates and in the percentage of vulnerable households, the widening gap between these two metrics warrants serious concern. This gap suggests that the proportion of households currently at risk of falling into poverty exceeds those currently categorised as poor. This implies that the rate at which households are expected to descend into poverty due to health-related shocks in subsequent periods exceeds the rate at which households successfully exit poverty. Such findings necessitate a strategic shift toward policy interventions that are operationally distinct from traditional poverty alleviation, specifically targeting the mitigation of household vulnerability.

Estimates further reveal that the mean vulnerability of at-risk households has remained persistently above 0.7 across the 1995–96, 2004, 2014, and 2017–18 periods, indicating stagnation for these households. The disproportionate share of vulnerable households falls largely on rural households, ST and SC communities, and households with members engaged as casual labour. These groups exhibit both a higher mean vulnerability to health shocks and constitute a larger share of the vulnerable households relative to their counterparts. For these historically marginalised social groups, the implementation of income-stabilising policy mechanisms, complemented by robust government health insurance schemes, is necessary to reduce future descents into poverty.

Furthermore, the data indicate that households with poor sanitation facilities have experienced increases in both the mean vulnerability to poverty and the percentage of the population that is vulnerable from 1995 to 2018. Enhancing access to improved sanitation facilities is a critical public health intervention that can improve household resilience by preventing specific morbidities and premature mortality. Similarly, female-headed households exhibit a significantly higher risk profile and represent a larger share of the vulnerable population compared to male-headed households. Mitigating these risks requires gender-sensitive, targeted interventions, including expanding income-generating opportunities, providing childcare support, and implementing institutional policies to eliminate market and resource discrimination. Additionally, ensuring equitable access to healthcare and conducting aggressive educational campaigns can minimise welfare losses from health shocks. The results further underscore that households with illiterate or primary-level education heads demonstrate higher mean vulnerability to poverty and an increasing share of vulnerable households over the study period. This calls for a universal basic education program to augment human capital and mitigate the adverse effects of health shocks on future poverty.

Finally, the study attempts to assess the role of GSHI schemes in reducing economic vulnerability. Paradoxically, the results suggest that the presence of an insured household member increases mean vulnerability and the share of vulnerable households from 2014 to 2018. A comparative assessment of vulnerability metrics across the pre- and post-GSHI (e.g., RSBY) phases indicates that vulnerability to poverty increased for households with at least one GSHI-covered member. These counterintuitive findings highlight the limited success of the current pan-India health insurance framework. Therefore, a fundamental redesign and expansion of health insurance programs are required, focusing on substantially reducing OOP health expenditures to stabilise household consumption in the wake of medical contingencies.

Endnotes

1. NSS is conducted by the Statistics Wing, called the National Statistical Office (NSO) of the Ministry of Statistics and Programme Implementation (MOSPI) in India. The data is available in the public domain and can be downloaded from the MOSPI website (http://mospi.nic.in/).
2. The study has used the Tendulkar committee poverty line, i.e., the minimum consumption expenditure/income required to identify households as poor.
3. The study has categorised households into three strata: Scheduled Castes (SC), Scheduled Tribes (ST), and non-SC/ST (comprising Other Backwards Classes and General Castes). Historically, SC and ST populations have faced systemic socio-economic marginalisation and discrimination owing to their low positions within the traditional Hindu caste hierarchy. Thereby, the Constitution of India have accorded them with special status.

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