Health Empirics

HEALTH EMPIRICS

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IHEPA
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About IHEPA

The Indian Health Economics and Policy Association (IHEPA) is a registered society under the Society's Registration Act 1960. The secretariat is located at the International Institute for Population Sciences, Mumbai. IHEPA welcomes all those interested in issues relating to health economics and policy to be a part of this association. IHEPA welcomes young scholars and researchers, grassroots practitioners, the private sector and community - based organizations to participate actively so that all views and experiences can be heard, debated, understood and absorbed.

Aims and Scope

Health Empirics welcomes original research contributions across a broad spectrum of topics related to health economics, healthcare delivery, and health policy assessment. The journal serves as a critical forum for academic researchers, policy analysts, and healthcare leaders, aiming to bridge the gap between rigorous empirical evidence and actionable health policy.

We are committed to publishing original research that demonstrates analytical depth, addressing complex health challenges through robust methodological frameworks.

Key Areas of Inquiry: The scope of the journal encompasses, but is not limited to:

1. **Applications of Health Econometrics:** Advanced statistical methods, causal inference, and quantitative evaluation.
2. **Assessment of Health Policies:** Impact evaluation, cost-effectiveness analysis, and policy design methodologies.
3. **Determinants of Health:** Social, economic, and environmental factors, including risk factor quantification.
4. **Healthcare Management & Financing:** Insurance systems, provider incentives, efficiency analysis, and financial protection.
5. **Inequalities in Health:** Measurement of disparities, equity in access, and distributional analysis.
6. **Methodological Innovations:** Novel data collection, mixed-methods frameworks, and Big Data applications.

Audience: The journal addresses a diverse audience including academic researchers, health policy analysts, healthcare administrators, and international development practitioners.

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Information for Authors

Health Empirics invites submissions of Original Research, Methodological Papers, Policy Analyses, and Systematic Reviews. We particularly encourage submissions from doctoral researchers and practitioners working at the intersection of research and policy.

Submission Quick Guide:

- Manuscript Length: Recommended length is 4,000–8,000 words, including references and appendices.
- File Format: Microsoft Word (.doc, .docx) only.
- Formatting:
  - ◊ Use APA 7th Edition style for citations and references.
  - ◊ Font: Times New Roman, 12-point, 1.5 line spacing.
  - ◊ Margins: 2.5 cm (1 inch) on all sides.
  - ◊ Abstract: Structured (Background, Methods, Results, Conclusion); 200–250 words.
- Review Process: All submissions undergo an initial desk review (1 week). Manuscripts passing screening advance to double-blind peer review (approx. 6 weeks).
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Editorial Note

Udaya Shankar Mishra*
Editor-in-Chief, Health Empirics

It is with distinct privilege that we introduce the inaugural issue of Health Empirics. This publication is realized through an overwhelming response from the research community, characterized notably by the robust submissions of emerging scholars dedicated to the rigorous inquiry on health-related topics.

The nomenclature of this journal, Health Empirics, is deliberate. In the contemporary landscape of public policy, the demand for meaningful, actionable research has shifted decisively toward the empirical. While theoretical frameworks remain foundational, the complexity of modern health challenges necessitates evidence-based governance. We posit that the most effective bridge between observation and intervention is constructed upon rigorous data analysis. Thus, this journal is established to prioritize empirical scrutiny as the bedrock of policy formulation.

Distinguished from publications that operate within the siloes of clinical science, population health, or pure economics, Health Empirics adopts a multidisciplinary mandate. We recognize that health is multifaceted, existing simultaneously as a biological reality, an economic asset, and a social indicator. By fostering the interdisciplinary convergence, we aim to elucidate complex policy connections and provide contributions that are not only academically sound but pragmatically transformative.

While the empirical evidence in this inaugural issue is primarily drawn from the Indian context, a nation navigating a profound epidemiological and demographic transition, the scope of Health Empirics extends well beyond these borders. We view India as a critical case study with significant extrapolative value for developing economies; however, our mandate is inclusive. We actively invite research contributions from the broader Global South and emerging markets to foster a comparative and comprehensive discourse on health and development.

In the current discourse on human well-being, health occupies the center stage, particularly as we strive to sustain the accomplishments of increased longevity and maximize the dividends of development. The opening analysis by Ahluwalia et al. offers a granular decomposition of India's multidimensional poverty. While the

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study confirms a commendable secular decline in headcount ratios, it concomitantly exposes deep-seated persistence in nutritional deprivation, identified here as the primary structural brake on further progress. However, the escape from poverty remains precarious. In a complementary analysis of household expenditure by Rajpal et al., this issue presents compelling evidence on the fragility of financial protection. With nearly half of inpatient cases necessitating 'distress financing', forced borrowing, or asset liquidation, the research highlights that without universal insurance coverage, the medical poverty trap remains a potent threat to economic stability.

Parallel to these economic challenges, the epidemiological landscape is undergoing a profound transition. We present two studies that map the contours of this shift. At the national level, Bhowmick et al. provide new estimates of the obesity epidemic, revealing a stark gendered vulnerability and a strong correlation with urbanization, signaling that 'diseases of affluence' are becoming entrenched. Simultaneously, a micro-level investigation by Das and Kar exposes the socioeconomic gradients of chronic disease among the elderly in Bankura district. Together, these contributions illuminate a complex reality where the vulnerabilities of aging are increasingly intersecting with the rising tide of non-communicable diseases. Finally, we turn to the industrial and labor dynamics examined by Rohilla and Nagarjuna that undergird the health sector. The efficiency of the pharmaceutical industry is examined through data envelopment analysis, where findings attribute superior technical progress in foreign firms to direct investment, linking macroeconomic policy directly to sectoral productivity. Yet, this industrial lens must not obscure the human cost of production. Another significant exploration of this issue is Nayak et al.'s assessment of the informal workforce in tobacco processing, revealing an abysmal landscape of occupational hazards. This serves as a stark reminder of the often-invisible health costs embedded within the supply chain.

This collection offers a nuanced, evidence-based outlook on the varying domains of health-related vulnerabilities. It stands as an exemplary assembly of works, indicating the potential for the scientific treatment of data to aid intervention. The evidence generated on this platform aims not merely to inform the discourse but to reform the course of action toward realizing our collective targets for a healthier society.

Finally, the realization of this inaugural issue would not have been possible without a collective effort. I extend my sincere gratitude to the Indian Health Economics and Policy Association, Editorial Board of Health Empirics, the Associate and Managing Editors, the reviewers and the journal support staff for their unwavering dedication to bringing this vision to fruition.

The Health Factor in Multidimensional Poverty: Trends and Inequalities in India, 2005-2021

Komal Ahluwalia[#*], Anirudhan P Edathil[*], Saroj Kumar[*], William Joe[*]

India's commitment to Sustainable Development Goal 1—to end poverty in all its forms—necessitates a multidimensional approach beyond conventional income measures. This study investigates the evolution and determinants of multidimensional poverty in India, analyzing its incidence, intensity, and structural drivers across demographic and social groups using the Alkire-Foster framework. Using data from three National Family Health Survey (NFHS) rounds (2005–06, 2015–16, and 2019–21), the study computes the Multidimensional Poverty Index (MPI) across health, education, and living standard dimensions. Advanced decomposition techniques such as Kitagawa and Blinder-Oaxaca were employed to quantify the relative contributions of headcount ratios, poverty intensity, and socioeconomic characteristics across caste, wealth quintiles, religion, and regions. India's MPI declined markedly from 0.282 in 2005–06 to 0.066 in 2019–21, driven by reductions in the headcount ratio (52.3% to 14.7%) and moderate improvement in intensity (53.9% to 44.5%). The Scheduled Tribes, children under 14 years, rural households, and females remained the most deprived groups. Decomposition analyses indicated that 85–89% of poverty reduction stemmed from falling headcount ratios, with improvements in endowments especially education, maternal health, and access to assets playing a key role. The nutrition indicator emerged as the single largest contributor to poverty, accounting for over one-third of total deprivations. Despite remarkable progress in reducing multidimensional poverty, substantial intergroup and regional disparities persist. Strengthening nutrition, education, and social inclusion policies is essential for accelerating equitable poverty reduction and achieving sustainable human development in India.

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

The United Nations' Sustainable Development Goal[1] established a mandate to end poverty in all its forms everywhere by 2030 (United Nations, 2024). Poverty is widely acknowledged as a multifaceted phenomenon that includes multiple deprivations, including but not limited to health, education, and other often overlooked dimensions. Consequently, an assessment of poverty necessitates a multidimensional approach. This multidimensional perspective on resource scarcity has gradually emerged as a critique of mainstream economic development paradigms, historically prioritizing growth in per capita Gross National Product (GNP) (Roy et al., 2019). Nevertheless, poverty analysis in many countries continues to be constrained by a unidimensional framework. These analyses rely solely on equivalent consumption as a proxy for poverty, thereby neglecting to capture the full extent of deprivations experienced by populations.

In response to these methodological limitations, scholars have proposed various refinements to poverty measurement frameworks. from the Human Poverty Index (HPI) and Human Development Index (HDI), which first introduced multidimensional perspectives in the late 1990s (Sen & Anand, 1997; UNDP, 1997) to the Multidimensional Poverty Index (MPI) developed by Alkire and Foster (Alkire & Foster, 2011; Alkire & Santos, 2011). The MPI represents a pivotal advancement, enabling direct measurement of cumulative deprivations at the household level through a dual-cutoff counting methodology for poverty classification. Unlike its predecessors, the MPI's theoretical architecture covers three dimensions operationalized through ten distinct indicators, facilitating granular analysis of both the nature and intensity of household-level deprivations. India has adopted a domestically adapted MPI developed by the NITI Aayog, adhering to the Alkire and Foster (AF) methodology employed in the global MPI. While incorporating all ten global MPI deprivation indicators, the national index expands its scope to include maternal health and bank accounts, aligning with India's development priorities (Alkire & Santos, 2011).

The Multidimensional Poverty Index offers valuable insights into the multifaceted nature of poverty beyond simple headcount measures. Existing research has explored multidimensional poverty patterns in India (Pradhan et al., 2022; Das et al., 2022), consistently demonstrating significant correlations between poverty indices and deprivation patterns among marginalized groups, particularly Scheduled Castes and Scheduled Tribes (Pradhan et al., 2022; Bagli & Tewari, 2019; Kaibarta et al., 2022), Muslim communities (Das et al., 2022) and rural inhabitants (Das et al., 2023). While existing literature has explored multidimensional poverty patterns in India, few studies have provided a long-term analysis spanning 15 years of demographic shifts. This study contributes to the literature by filling a critical methodological gap: the application of the Blinder-Oaxaca decomposition to the Multidimensional Poverty Index (MPI). Unlike previous studies that largely rely on descriptive trends or standard regression analyses, this paper systematically disentangles the ‘endowment effects’ (changes in population characteristics) from ‘coefficient effects’ (returns to those characteristics). This offers a perspective on whether the reduction in poverty among marginalized groups (SCs/STs) is due to improved attributes or structural reductions in the disadvantages they face.This comprehensive approach not only highlights intersectional disparities but also aims to identify targeted intervention opportunities, ultimately aiming to develop more precise and effective strategies for poverty alleviation.

Methodology

The global multidimensional poverty index has undergone important methodological evolutions since its inception in 2010. Currently, the dual-cutoff counting methodology developed by (Alkire and Foster., 2011) is being utilised in the calculation of global multidimensional poverty index. The Alkire-Foster framework for measuring multidimensional poverty is grounded in Amartya Sen’s concept of capability deprivation and Atkinson’s counting methods. This methodology employs a two-step approach: identification and aggregation. The dual cut-off method involves setting thresholds for both poverty and deprivation. An individual is considered poor if their deprivation score reaches or surpasses the poverty cutoff, ‘k’. A universal cutoff of one-third (k=0.333) has been established. The Alkire-Foster (AF) methodology is particularly advantageous for this analysis vis-à-vis other poverty measures because of its property of subgroup decomposability. Unlike standard headcount ratios or regression residuals, the AF method allows the Multidimensional Poverty Index (MPI) to be broken down by population subgroups (such as caste, religion, or region) and by dimensions (health, education, living standards). This feature is essential for identifying whether poverty reduction is driven by a decrease in the number of poor people (incidence) or a reduction in the intensity of their deprivation, a nuance often lost in unidimensional poverty measurements.

The global MPI structure constitutes of three dimensions including health, education and living standards and ten indicators with both dimensions and indicators equally weighted. A deprivation profile is established for each person pointing towards the deprived indicators. Along with it, a headcount ratio (H) indicating the proportion of multidimensionally poor people in the population and intensity of poverty (A) represented by the average percentage of weighted deprivations experienced by the poor is obtained. MPI is calculated as a multiplicative sum of H x A (NITI Aayog, 2023). The H and A are defined as :

$$H = \frac{1}{n}\sum_{i=1}^{n}\rho(g_i^0, w, k),\ A = \frac{1}{q}\sum_{i=1}^{n}(\rho(g_i^0, w, k) \times c_i),\ \text{where } q = \sum_{i=1}^{n}\rho(g_i^0, w, k)$$

Consequently, the adjusted poverty headcount ratio (MPI) is calculated as :

$$\text{MPI} = M_0 = H \times A = \frac{1}{n}\sum_{i=1}^{n}(\rho(g_i^0, w, k) \times c_i)$$

The NITI Aayog constructed a national MPI adhering to the Alkire and Foster (AF) methodology employed in the global MPI creating an indigenized measure of assessing multidimensional poverty. While incorporating all ten global MPI indicators, the national index expands its scope to include maternal health and bank accounts, aligning with India's development priorities (NITI Aayog, 2023). India's Multidimensional Poverty Index (MPI) approach defines individuals under five years of age and within the working-age range of 15 to 54 for men and 15 to 49 for women as relevant population segments. However, when assessing child-adolescent mortality, a narrower age group is employed, including children aged 0 to 59 months and adolescents aged 10 to 18 years. In contrast to traditional monetary poverty assessments based on consumption expenditure, the national MPI provides a granular analysis of deprivations at the district level.

The dual cut off methodology employs majorly two steps namely identification and aggregation. Identification involves building a deprivation profile by applying cutoffs within an indicator and identifying the incidence of multidimensional poverty by applying a cut-off across all indicators. The deprivation of each individual is marked as either 0 or 1 indicating not deprived (0) and deprived (1). If the achievement of an individual i in indicator j is denoted by x_{ij}, the first order cut off for indicator j is denoted by z_j, and the status of the individual is denoted by g_{ij° , then

$$g_{ij^\circ} = 1 \text{ if } x_{ij}, < z_j \text{ and } g_{ij^\circ} = 0 \text{ otherwise for all } i = 1,2,\ldots.n \text{ and } j = 1,2,\ldots.d$$

The counting vector or deprivation score is the sum of the weighted status of all the indicators for an individual.

The deprivation score of the individual i can be denoted as:

$$c_i = w_1 g_{i1}{}^0 + w_2 g_{i2}{}^0 + \ldots. + w_j g_{ij}{}^0, \text{ or } c_i = \textstyle\sum_{j=1}^{d} w_j g^0{}_{ij}$$

where c_i is the counting vector for individual i upto the j^{th} indicator, g_{ij° is the status of each indicator and w_j is the weight assigned to each indicator.

The poverty cut-off also mentioned as the second order cut-off is deployed to be 0.33 (33%) is the minimum deprivation score as individuals having a deprivation score greater than or equal to the second order cut off are considered to be multidimensionally poor. A score less than second order cut off is replaced with 0.

Headcount Ratio (H), where q is the total number of multidimensionally poor people in a population n is computed as,

$$H = \frac{q}{n}$$

Similarly, the average proportion of deprivations experienced by multidimensionally poor individuals denoted by Intensity of Poverty (A) is computed as,

$$A = \frac{1}{q}\sum_{i=1}^{q} c_i(k)$$

MPI is represented as $M_0 = H \times A$,

$$Or\ H \times A = \frac{q}{n} * \frac{1}{q}\sum_{i=1}^{q} c_i(k) = \frac{1}{n}\sum_{i=1}^{n} c_i(k) = \frac{1}{n}\sum_{i=1}^{n} \quad \sum_{j=1}^{d} w_j\, g_{ij}{}^{\circ}(k)$$

(where, c_i (k) is the censured deprivation score up to the i^{th} individual and q is the number of multidimensionally poor individuals. Further,g_{ij} is household member status and w_j is the weight of j^{th} indicator. Here, n is the total population and d is the number of dimensions)

Table 1: Dimension, Indicators, and Derivation conditions (NITI Aayog)

Dimension of Poverty	Indicator	Deprivation condition	Weight
Health (1/3)	Nutrition	Any person under 70 years of age for whom nutritional information is available is undernourished[1].	1/6
	Child -Adolescent Mortality	A child under 18 has died in the household in the five years preceding the survey	1/12
	Maternal Health	Any woman in the household who has given birth in the 5 years preceding the survey, has not received at least 4 antenatal care visits for the most recent birth or has not received assistance from trained skilled medical personnel during the most recent childbirth	1/12
Education (1/3)	Years of Schooling	No eligible household member has completed six years of schooling	1/6
	School Attendance	Any school-aged child3 is not attending school up to the age at which he/she would complete class 8	1/6
Standard of Living (1/3)	Cooking Fuel	A household cooks using solid fuel, such as dung, crops, shrubs, wood, charcoal, or coal	1/21
	Sanitation	The household has unimproved or no sanitation facility or it is improved but shared with other households	1/21
	Drinking Water	The household's source of drinking water is not safe or safe drinking water is a 30-minute walk or longer walk from home, roundtrip	1/21
	Electricity	The household has no electricity	1/21
	Housing	The household has inadequate housing materials in any of the three components: floor, roof, or wall	1/21
	Assets	The household does not own more than one of these assets: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car or truck	1/21
	Bank Account	No household member has a bank account or a post office account.	1/21

$$\text{Deprivation Score} = \frac{1}{3}\text{Health}_i + \frac{1}{3}\text{Education}_i + \frac{1}{3}\text{ Standard of Living}_i,$$

$$[\frac{1}{3}\text{Health}_i = \frac{1}{6}\text{Nutrition}_i + \frac{1}{12}\text{ Child – Adolescent Mortality}_i + \frac{1}{12}\text{ Maternal Health}_i$$

$$\frac{1}{3}\text{Education}_i = \frac{1}{6}\text{ Years of schooling}_i + \frac{1}{6}\text{ School Attendance}_i$$

$$\frac{1}{3}\text{ Standard of Living}_i = \frac{1}{21}\text{ Cooking Fuel}_i + \frac{1}{21}\text{Sanitation}_i + \frac{1}{21}\text{ Drinking Water}_i + \frac{1}{21}\text{Electricity}_i + \frac{1}{21}\text{Housing}_i + \frac{1}{21}\text{Assets}_i + \frac{1}{21}\text{ Bank Account}_i]$$

Data

The National Family Health Survey (NFHS), a representative of the Indian Demographic Health Survey (DHS), is executed by the International Institute for Population Sciences (IIPS), Mumbai under the mandate of India's Ministry of Health and Family Welfare. The primary objectives of the NFHS constitutes the provision of data and technical assistance to inform the formulation and implementation of health and family welfare policies and programs. Moreover, the NFHS offers valuable insights into contemporary health and family welfare challenges. This study employs micro survey data from three rounds of NFHS surveys, (NFHS-3, NFHS-4 and NFHS -5) analysing socio – economic characteristics such as age, caste, religion, place of residence, wealth status, household size etc of different social groups such as Scheduled Castes (SC), Scheduled Tribes (ST), Other Backward Classes (OBC) and Others (IIPS, n.d.).

Outcomes

Primarily, our research study presents a comprehensive analysis of multidimensional poverty across diverse socioeconomic and social groups in India, examining three critical time periods (2005-06, 2015-16, and 2019-21). Through the systematic computation of Multidimensional Poverty Index (MPI) values, we evaluated poverty dynamics across various socio-economic groups and geographical regions. Our investigation extended beyond conventional poverty metrics to capture the temporal evolution of multidimensional deprivation patterns across different social groups. The research systematically decomposed the contributing factors to MPI variations, with particular attention to the interplay between headcount ratios and intensity of poverty. Furthermore, we conducted an in-depth examination of specific deprivation indicators and their relative contributions to overall poverty measures. By implementing decomposition techniques to analyze mean differences in MPI across groups, we identified and quantified the fundamental drivers of poverty disparities, thereby providing insights into both observed characteristics and underlying structural factors that perpetuate poverty across different social segments.

Socioeconomic Status Characteristics

The analysis incorporated multiple socioeconomic status indicators through a comprehensive set of demographic and social parameters. Age stratification comprised four distinct categories: early childhood (0-5 years), school-age (6-14 years), working-age adults (15-59 years), and elderly (60+ years), enabling examination across the complete lifespan. Marital status was classified into three categories: married, unmarried, and widowed/separated/divorced. Household composition was categorized by size: small (≤4 members), medium (5-6 members), and large (>6 members). The analysis was deepened by examining the data through the lens of social groups, including caste (Scheduled Castes, Scheduled Tribes, Other Backward Classes, and Others) and religion (Hindu, Muslim, Christian, Sikh, and Others). Economic status was assessed through wealth quintiles (poorest, poorer, middle, richer, richest). Additional demographic variables comprising gender (male/female) and residential location (rural/urban) were also utilised in the analysis.

Statistical Analysis

Our analytical framework incorporates multiple methodological approaches to examine multidimensional poverty across social groups. Initially, we compute the Multidimensional Poverty Index (MPI) values across various socioeconomic status (SES) categories by calculating their respective headcount ratios and intensities spanning three National Family Health Survey (NFHS) periods (2005-06, 2015-16, and 2019-21). This analysis is extended to state-level disaggregation of MPI values across different social groups for the corresponding time periods.To assess the probability of experiencing multidimensional poverty by background characteristics, we employ pooled logistic regression analysis, generating odds ratios based on unadjusted headcount ratios while controlling for relevant covariates performed using STATA 17 and MLwiN 3.09. We further employ the Kitagawa Decomposition Method to analyze the relative contributions of headcount ratio and intensity to multidimensional poverty across social groups over consecutive NFHS periods (NFHS 3-4, NFHS 4-5, and NFHS 3-5), along with the net differences in MPI across these intervals. Finally, we implement the Blinder-Oaxaca Decomposition to analyse mean differences in multidimensional poverty across different groups over the appended time periods (NFHS 3-4, NFHS 4-5, and NFHS 3-5). To ensure the robustness of the trend analysis, the comparability of indicators across the three NFHS rounds was carefully maintained. While minor changes in survey questionnaires occurred over the 15-year period, the definitions of the core 12 indicators used for the MPI construction—specifically regarding nutrition, mortality, and standard of living assets—were harmonized to match the standardized definitions utilized by the Oxford Poverty and Human Development Initiative (OPHI) and NITI Aayog for longitudinal analysis. Finally, it is imperative to note that the factors identified through the logistic regression and decomposition analyses represent statistical associations. Given the cross-sectional nature of the NFHS data, these findings should be interpreted as correlational rather than establishing definitive causal relationships between socioeconomic characteristics and multidimensional poverty.

Decomposition

- **Kitagawa Decomposition**

Decomposition techniques serve as essential analytical tools for disaggregating demographic variables into their constituent components, thereby addressing the methodological challenges posed by confounding compositional effects (Canudas Romo, 2003). Building upon Kitagawa's (1955) seminal work on 'components of a difference between two rates,' which advanced beyond the limitations of traditional standardisation techniques, our analytical framework focuses on decomposing inequalities across distinct social groups (Scheduled Castes, Scheduled Tribes, Other Backward Classes, and Others). The temporal analysis spans three intervals of the National Family Health Survey (NFHS): between NFHS-3 and NFHS-4, NFHS-4 and NFHS-5, and the comprehensive period between NFHS-3 and NFHS-5. This approach enables the examination of variations in both the headcount ratio (H) and intensity (A) of multidimensional poverty across different socio-economic strata.

The overall rate of difference in headcount ratio across two groups can be decomposed as:

$$\Delta = MPI^A - MPI^B = \sum_i H_i^B . A_i^B - \sum_i H_i^A . A_i^A$$

where MPI denotes the value of Multidimensional Poverty Index, H denotes headcount ratio and A represents the intensity of poverty across two time periods A and B.

Each of these terms will be divided into two equal parts with certain additional terms added and subtracted, implying that the difference (Δ) will be constant:

$$\Delta = \frac{\Sigma_i H_i^B \cdot A_i^B}{2} + \frac{\Sigma_i H_i^B \cdot A_i^B}{2} - \frac{\Sigma_i H_i^A \cdot A_i^A}{2} - \frac{\Sigma_i H_i^A \cdot A_i^A}{2} + \frac{\Sigma_i H_i^B \cdot A_i^A}{2} - \frac{\Sigma_i H_i^B \cdot A_i^A}{2} + \frac{\Sigma_i H_i^A \cdot A_i^B}{2} - \frac{\Sigma_i H_i^A \cdot A_i^B}{2}$$

Therefore,

$$\Delta = \sum_i (H_i^B - H_i^A) . [\frac{A_i^B + A_i^A}{2}] + \sum_i (A_i^B - A_i^A) . [\frac{H_i^B + H_i^A}{2}] .$$

Here, the proposition attributable to each category is calculated over the specific decomposition time periods (Preston et al., 2001).

Oaxaca – Blinder Decomposition

The Oaxaca – Blinder decomposition facilitates an extension of the Kitagawa Decomposition method as a counterfactual decomposition technique applied in terms of linear regression models. Primarily, it sets forth the estimation of mean difference in the outcome variable between two different groups. This is further supplemented with the fact that the OB decomposition emphasizes on the interaction between the group parameter differences as well as the group characteristics (Oaxaca, 1973; Blinder, 1973).

Within this analytical framework, we designate two population groups, A and B, corresponding to the respective time periods in the National Family Health Survey (NFHS) rounds (3, 4, and 5). The outcome variable Y, designated for decomposition, represents the aggregate deprivations experienced by an individual, computed as the product of the unadjusted headcount ratio and the counting vector. The sample sizes for populations A and B are denoted by NA and NB respectively. The methodological approach incorporates a set of K mutually exclusive indicator variables, consolidated into a single categorical explanatory variable X, such that

$$\sum_{k=1}^{K} X_{ik} \; \forall \; i$$

i where i denotes the ith individual within a sample group. The outcome indicator variables for the respective population groups are represented by YiA and YiB (Oaxaco & Sierminska, 2025).

The group mean proportions are given by

$$\bar{Y}^{\mathrm{A}} = \frac{\sum_{i=1}^{N^A} Y_i^A}{N^A} = \frac{N_Y^A}{N^A}$$

$$\bar{Y}^{\mathrm{B}} = \frac{\sum_{i=1}^{N^B} Y_i^B}{N^B} = \frac{N_Y^B}{N^B}$$

Hence,

$$\bar{Y}^{\mathrm{A}} - \bar{Y}^{\mathrm{B}} = \frac{N_Y^A}{N^A} - \frac{N_Y^B}{N^B}$$

Let the outcome rates in the kth category of the predictor variable X for groups A and B be:

$$\bar{Y}_k^A = \frac{\sum_{i=1}^{N^A} Y_i^A X_{ik}}{N_k^A}, \text{ k = 1,....., K}$$

$$= \frac{N_{Yk}^A}{N_k^A}$$

$$\bar{Y}_k^B = \frac{\sum_{i=1}^{N^B} Y_i^B X_{ik}}{N_k^B}, \text{ k = 1,....., K}$$

$$= \frac{N_{Yk}^B}{N_k^B}$$

The linear probability regression model for the two population groups is presented as:

$$\mathrm{Y_i^A} = \sum_{k=1}^{K} X_{ik}\beta_k^A + \varepsilon_i, i = 1, \ldots, N^A$$

$$\mathrm{Y_i^B} = \sum_{k=1}^{K} X_{ik}\beta_k^B + \varepsilon_i, i = 1, \ldots, N^B$$

The OLS estimator corresponding to the separate linear regressions of Yi on each Xik indicator variable will be :

$$b_k^A = \frac{\sum_{i=1}^{N^A} X_{ik} Y_i^A}{\sum_{i=1}^{N^A} X_{ik}^2}, \text{ k = 1,....., K}$$

$$= \frac{N_{Yk}^A}{N_k^A} = \bar{Y}_k^A$$

$$b_k^B = \frac{\sum_{i=1}^{N^B} X_{ik} Y_i^B}{\sum_{i=1}^{N^B} X_{ik}^2}, \text{ k = 1,....., K}$$

$$= \frac{N_{Yk}^B}{N_k^B} = \bar{Y}_k^B$$

In Blinder Oaxaca Decomposition, one group is assigned as the reference group and we execute the simple averages of the two groups estimated coefficients such that,

$$b_k^* = \frac{(b_k^A + b_k^B)}{2}, \text{ k = 1,...., K } = \left(\frac{\bar{Y}_k^A + \bar{Y}_K^B}{2}\right)$$

Therefore, the OLS decomposition can be explained as the following :

$$\bar{Y}^{A} - \bar{Y}^{B} = \sum_{k=1}^{K} \bar{X}_k^A b_k^A - \sum_{k=1}^{K} \bar{X}_k^B b_k^B$$
$$= \sum_{k=1}^{K} \left(\bar{X}_k^A - \bar{X}_k^B\right) b_k^* + \sum_{k=1}^{K} \bar{X}_k^A \left(b_k^A - b_k^*\right) + \sum_{k=1}^{K} \bar{X}_k^B \left(b_k^* - b_k^B\right)$$

The initial component of the equation, represented by

$$\sum_{k=1}^{K} \left(\bar{X}_k^A - \bar{X}_k^B\right) b_k^*$$

quantifies the differential attributed to group variations in the explanatory variables, termed as the endowment effect . Along with it, the second component

$$\sum_{k=1}^{K} \bar{X}_k^A \left(b_k^A - b_k^*\right)$$

comprises the contribution arising from differences in coefficients, constituting the unexplained component, designated as the coefficients effect. Furthermore, interaction effect which is represented by the final part of the equation

$$\sum_{k=1}^{K} \bar{X}_k^B \left(b_k^* - b_k^B\right)$$

captures the simultaneous manifestation of differences in both endowments and coefficients between the two groups under consideration (Jann, 2008; Rahimi & Hashemi Nazari, 2021).

Results

India's MPI exhibited significant reductions across three NFHS rounds (2005-06 to 2019-21), declining substantially from 0.282 to 0.066 (Table 2.1). This decline was driven by both a decrease in the headcount ratio (from 52.3% to 14.7%) and a moderate improvement in intensity (from 53.9% to 44.5%). The annual rate of reduction increased from 8.5% between NFHS 3 and 4 to 10.5% between NFHS 4 and 5. Among demographic groups, changes were observed in wealth quintiles, with the poorest wealth quintile experiencing a reduction in multidimensionally poor population, declining from 92.8% to 42.1% between NFHS 3 and 5. While children aged 0-14 years demonstrated improvements (from 63.0% to 23.4%), they consistently remained the most vulnerable age group across all rounds. The Scheduled Tribes consistently exhibited the highest poverty rates (26.8% in 2019-21), significantly exceeding other groups. The rural-urban divide persisted, with rural areas (18.9%) exhibiting higher multidimensionally poor populations compared to urban areas (5.3%) in 2019-21. Furthermore, despite similar household characteristics, females consistently displayed slightly higher MPI scores than males across all three rounds. (Table 2.2)

Table 2.1 : Multidimensional Poverty Headcount(H), Intensity(A), and Index values by background characteristics, India

Background Variables	NFHS-3 (2005-06)			NFHS-4 (2015-16)			NFHS-5 (2019-21)		
	H	A	MPI	H	A	MPI	H	A	MPI
Age									
0-14 yrs.	0.630	0.571	0.360	0.348	0.494	0.172	0.234	0.462	0.108
15-59 yrs.	0.466	0.522	0.243	0.200	0.461	0.092	0.116	0.436	0.051
60+ yrs.	0.500	0.490	0.245	0.217	0.436	0.094	0.115	0.413	0.048
Sex									
Male	0.512	0.537	0.275	0.232	0.470	0.109	0.139	0.444	0.062
Female	0.535	0.541	0.289	0.255	0.473	0.121	0.155	0.446	0.069
Household size									
<=4 members	0.437	0.502	0.22	0.173	0.453	0.078	0.097	0.432	0.042
5 to 6 members	0.515	0.547	0.281	0.234	0.481	0.113	0.148	0.455	0.067
6+ members	0.620	0.558	0.346	0.349	0.476	0.166	0.228	0.444	0.101
Marital Status									
Married	0.496	0.526	0.261	0.220	0.462	0.102	0.130	0.435	0.057
Unmarried	0.453	0.524	0.238	0.151	0.449	0.068	0.078	0.430	0.033
Widow/separated/ Divorced	0.535	0.506	0.271	0.237	0.446	0.106	0.129	0.423	0.055
Wealth Quintile									
Richest	0.055	0.404	0.022	0.012	0.376	0.004	0.010	0.380	0.004
Richer	0.259	0.440	0.114	0.051	0.398	0.020	0.033	0.390	0.013
Middle	0.596	0.477	0.284	0.148	0.413	0.061	0.077	0.403	0.031
Poorest	0.825	0.539	0.445	0.337	0.445	0.150	0.185	0.420	0.078
Poorer	0.928	0.619	0.575	0.654	0.506	0.331	0.421	0.469	0.198
Caste									
SC	0.632	0.545	0.345	0.286	0.474	0.136	0.182	0.450	0.082
ST	0.778	0.587	0.457	0.436	0.490	0.214	0.268	0.458	0.123
OBC	0.552	0.532	0.294	0.240	0.468	0.112	0.138	0.439	0.061
Others	0.341	0.514	0.176	0.137	0.457	0.063	0.074	0.433	0.032
Religion									
Hindu	0.524	0.532	0.279	0.242	0.467	0.113	0.144	0.441	0.063
Muslim	0.590	0.583	0.344	0.297	0.498	0.148	0.189	0.46	0.087
Christian	0.367	0.513	0.188	0.140	0.463	0.065	0.101	0.453	0.046
Sikh	0.218	0.473	0.103	0.058	0.433	0.025	0.048	0.419	0.020
Others	0.477	0.529	0.252	0.211	0.472	0.099	0.140	0.446	0.062
Place of Residence									
Rural	0.651	0.547	0.356	0.319	0.474	0.151	0.189	0.446	0.085
Urban	0.243	0.492	0.120	0.084	0.454	0.038	0.053	0.432	0.023
All India	0.523	0.539	0.282	0.243	0.472	0.115	0.147	0.445	0.066

Table 2.2: Multidimensional Poverty Index for Social Groups, Indian States (NFHS-5)

State /UT	SC			ST			OBC			Others			All India
	H	A	MPI	H	A	MPI	H	A	MPI	H	A	MPI	MPI
A & N Island	0.078	0.345	0.027	0.036	0.403	0.014	0.003	0.413	0.001	0.032	0.41	0.013	0.01
Andhra Pradesh	0.076	0.411	0.031	0.256	0.433	0.111	0.062	0.404	0.025	0.018	0.371	0.007	0.026
Arunachal Pradesh	0.127	0.427	0.054	0.129	0.419	0.054	0.219	0.475	0.104	0.168	0.456	0.076	0.06
Assam	0.164	0.431	0.071	0.126	0.432	0.054	0.159	0.451	0.072	0.173	0.439	0.076	0.086
Bihar	0.458	0.492	0.225	0.466	0.502	0.234	0.308	0.462	0.142	0.197	0.463	0.091	0.158
Chandigarh	0.03	0.381	0.011	-	-	-	0.06	0.433	0.026	0.025	0.586	0.015	0.017
Chhattisgarh	0.143	0.416	0.059	0.268	0.444	0.119	0.109	0.41	0.045	0.041	0.391	0.016	0.067
D & NH	0.023	0.436	0.01	0.169	0.414	0.07	0.048	0.421	0.02	0.041	0.463	0.019	0.042
Goa	0	.	0	0.016	0.346	0.006	0.001	0.357	0	0.004	0.341	0.001	0.003
Gujarat	0.109	0.418	0.045	0.256	0.451	0.116	0.111	0.425	0.047	0.031	0.403	0.013	0.051
Haryana	0.101	0.419	0.042	0.094	0.428	0.04	0.102	0.449	0.046	0.027	0.426	0.012	0.032
Himachal Pradesh	0.089	0.393	0.035	0.077	0.392	0.03	0.022	0.4	0.009	0.037	0.408	0.015	0.02
Jammu & Kashmir	0.061	0.417	0.026	0.145	0.439	0.064	0.091	0.422	0.038	0.03	0.413	0.012	0.021
Jharkhand	0.35	0.46	0.161	0.384	0.479	0.184	0.216	0.434	0.094	0.13	0.436	0.057	0.128
Karnataka	0.098	0.412	0.04	0.133	0.436	0.058	0.062	0.405	0.025	0.049	0.395	0.02	0.032
Kerala	0.012	0.374	0.005	0.066	0.405	0.027	0.006	0.356	0.002	0.001	0.352	0	0.002
Ladakh	0	.	0	0.046	0.408	0.019	-	-	-	0.008	0.405	0.003	0.017
Lakshadweep	0	.	0	0.009	0.376	0.003	0	.	0	0	.	0	0.003
Madhya Pradesh	0.225	0.434	0.098	0.357	0.457	0.163	0.157	0.423	0.066	0.076	0.409	0.031	0.087
Maharashtra	0.067	0.405	0.027	0.243	0.445	0.108	0.047	0.393	0.019	0.047	0.405	0.019	0.032
Manipur	0.116	0.429	0.05	0.155	0.424	0.066	0.062	0.399	0.025	0.047	0.404	0.019	0.036
Meghalaya	0.033	0.425	0.014	0.302	0.479	0.145	0.171	0.589	0.101	0.199	0.468	0.093	0.136
Mizoram	0.189	0.469	0.089	0.051	0.451	0.023	0.333	0.478	0.159	-	-	-	0.026
Nagaland	0.133	0.429	0.057	0.157	0.424	0.066	0.041	0.421	0.017	0.223	0.423	0.095	0.066

Table 2.2: Multidimensional Poverty Index for Social Groups, Indian States (NFHS-5)

State /UT	SC			ST			OBC			Others			All India
	H	A	MPI	H	A	MPI	H	A	MPI	H	A	MPI	MPI
NCT of Delhi	0.047	0.423	0.02	0.039	0.51	0.02	0.03	0.425	0.013	0.026	0.415	0.011	0.015
Odisha	0.15	0.429	0.064	0.328	0.468	0.154	0.078	0.419	0.033	0.038	0.4	0.015	0.067
Puducherry	0.01	0.393	0.004	0	.	0	0.009	0.376	0.003	0	.	0	0.003
Punjab	0.077	0.414	0.032	0.064	0.399	0.025	0.03	0.412	0.013	0.016	0.39	0.006	0.02
Rajasthan	0.19	0.432	0.082	0.262	0.446	0.117	0.13	0.419	0.054	0.074	0.411	0.03	0.065
Sikkim	0.057	0.43	0.025	0.035	0.39	0.014	0.021	0.431	0.009	0	.	0	0.012
Tamil Nadu	0.036	0.384	0.014	0.065	0.425	0.028	0.018	0.383	0.007	0.007	0.419	0.003	0.009
Telangana	0.065	0.408	0.027	0.124	0.425	0.053	0.05	0.402	0.02	0.022	0.393	0.009	0.024
Tripura	0.121	0.41	0.05	0.205	0.443	0.091	0.066	0.411	0.027	0.076	0.42	0.032	0.056
Uttar Pradesh	0.287	0.451	0.13	0.353	0.484	0.171	0.227	0.446	0.101	0.129	0.445	0.058	0.101
Uttarakhand	0.119	0.426	0.051	0.083	0.407	0.034	0.149	0.423	0.063	0.052	0.401	0.021	0.039
West Bengal	0.123	0.421	0.052	0.235	0.447	0.105	0.075	0.417	0.031	0.094	0.43	0.041	0.05
All India	0.182	0.449	0.082	0.269	0.458	0.123	0.138	0.439	0.061	0.075	0.433	0.032	0.066

H: Headcount Ratio, A: Intensity, MPI: Multidimensional Poverty Index Scores

The MPI for Indian states reveals significant disparities in poverty levels across different social groups in India (Table 3). Examining the NFHS-5 (2019-21) data, the Scheduled Tribe population emerges as the most disadvantaged population group with several states showing high headcount ratios and MPI scores. Jharkhand (H: 54.6%, MPI: 0.271), Chhattisgarh (H: 42.1%, MPI: 0.185), and Madhya Pradesh (H: 57.1%, MPI: 0.280) have the highest poverty levels among the ST population. The Scheduled Caste and Other Backward Classes also exhibit elevated poverty, though generally lower than the STs. Comparing the NFHS-4 (2015-16) and NFHS-3 (2005-06) data, some states have shown progress in reducing multidimensional poverty, particularly among the ST population. For instance, Andhra Pradesh witnessed a significant decrease in ST headcount ratio (from 73% to 40.2%) and MPI (from 0.420 to 0.181) over this period. Rajasthan also saw a decline in ST headcount ratio (from 89.1% to 58.8%) and MPI (from 0.532 to 0.304). However, other states like Uttar Pradesh and Jharkhand continue to struggle with high poverty levels, especially among the ST and SC communities, with limited improvement over the years. Notably, the intensity values, remain relatively similar across social groups and states.

A pooled regression analysis examining the multidimensional poverty headcount ratio revealed that Scheduled Castes (NFHS-5: OR 1.62, 95%, CI: 1.59-1.65), Scheduled Tribes (NFHS-5: OR 1.75, CI: 1.71-1.78), and Other Backward Classes (NFHS-5: OR 1.42, CI: 1.4-1.44) consistently demonstrated significantly higher likelihood of being multidimensionally poor across all three rounds (2005-06 to 2019-21) (Table 4). The poorest quantile showed a substantial reduction in the percentage of population experiencing multidimensional poverty, decreasing from 203.17 in NFHS-3 to 76.82 in NFHS-5. Similarly, the middle and poorer wealth quintiles showed significant decrease in odds of being multidimensional poor over the three rounds while being relatively higher in the same round than the richest and richer wealth quintiles. Households with more than six members exhibited increased likelihood of being multidimensionally poor (NFHS-5: OR 3.8, 95% CI: 3.75-3.84), while the 15-59 years' age cohort demonstrated a lower probability of multidimensional poverty (NFHS-5: OR 0.79, CI: 0.77-0.81) than under 14 age group. Rural populations, and certain religious groups, like Hindus and Muslims, also faced significantly higher risks of being multidimensionally poor. Despite similar household characteristics, females showed slightly more odds of being multidimensionally poor than males across all three rounds (NFHS-5: OR 1,07, CI:1.06-1.08).

The Kitagawa Decomposition analysis of multidimensional poverty headcount ratio and intensity across three NFHS survey periods was conducted (Table 5). The maximum net reduction in the MPI was observed between the NFHS 3 and NFHS 5 (0.216). The net MPI reductions observed between the consecutive survey rounds of NFHS 3-4 and NFHS 4-5 were 0.167 and 0.049, respectively. The headcount ratio

Table 3: Pooled logistic Regression based odds ratio (OR) for unadjusted headcount (H) by background characteristics

Background Characteristics	NFHS-3	NFHS-4	NFHS-5
	OR [95% CI]	OR [95% CI]	OR [95% CI]
Age			
0-14 yrs. (ref)	1	1	1
15-59 yrs.	0.69*** (0.66, 0.71)	0.84*** (0.83, 0.86)	0.79*** (0.77, 0.81)
60+ yrs.	0.59*** (0.56, 0.62)	0.77*** (0.75, 0.78)	0.68*** (0.66, 0.70)
Sex			
Male (ref)	1	1	1
Female	1.06*** (1.04, 1.08)	1.08*** (1.07, 1.09)	1.07*** (1.06, 1.08)
Household Size			
Household size <= 4 (ref)	1	1	1
Household size 5-6	1.39*** (1.36, 1.42)	1.33* (1.31, 1.34)	1.55*** (1.53, 1.56)
Household size >6	3.28*** (3.21, 3.36)	3.27*** (3.24, 3.31)	3.80*** (3.75, 3.84)
Marital Status			
Married	1.75*** (1.70, 1.79)	2.16*** (2.13, 2.18)	2.33*** (2.30, 2.36)
Unmarried (ref)	1	1	1
Widow/Seperated/Divorced	1.81*** (1.73, 1.89)	2.29*** (2.25, 2.34)	
Wealth Quintile			
Richest (ref)	1	1	1
Richer	5.50*** (5.29, 5.73)	4.09*** (3.95, 4.24)	3.17*** (3.05, 3.30)
Middle	25.12*** (24.13, 26.15)	12.75*** (12.33, 13.19)	7.89*** (7.60, 8.21)
Poorer	78.01*** (74.70, 81.46)	38.64*** (37.36, 39.95)	21.21*** (20.43, 22.03)
Poorest	203.17*** (193.44, 213.40)	153.29*** (148.19, 158.56)	76.82*** (73.97, 79.79)
Caste			
SC	1.57*** (1.52, 1.61)	1.37*** (1.35, 1.39)	1.62*** (1.59, 1.65)
ST	1.83*** (1.76, 1.91)	1.71*** (1.69, 1.74)	1.75*** (1.71, 1.78)
OBC	1.38*** (1.35, 1.41)	1.36*** (1.34, 1.38)	1.42*** (1.40, 1.44)
Others (ref)	1	1	1
Religion			
Hindu	1.15*** (1.09, 1.22)	1.12*** (1.08, 1.15)	0.98* (0.94, 1.01)
Muslim	2.21*** (2.07, 2.35)	2.16*** (2.10, 2.24)	1.84*** (1.77, 1.92)
Christian	0.97* (0.89, 1.05)	0.81*** (0.77, 0.85)	0.75*** (0.71, 0.79)
Others (ref)	1	1	1
Area			
Rural	1.26*** (1.23, 1.28)	1.14*** (1.13, 1.16)	1.02*** (1.01, 1.04)
Urban (ref)	1	1	1

demonstrated a substantial contribution to the observed MPI reduction throughout all survey rounds, increasing from 85% to 89% across consecutive periods (NFHS 3-4 and NFHS 4-5). The most significant MPI reduction was reported among the ST population, which experienced a 0.334 reduction between NFHS 3 and NFHS 5. This substantial improvement can be attributed to both a decrease in the proportion of the ST population living in multidimensional poverty and a decrease in the intensity of their poverty. In contrast, the proportion attributable to intensity marginally decreased across other social groups.

The analysis of the contribution of various indicators across the NFHS periods reveals that the Standard of Living dimension had the most significant contribution to the overall MPI in NFHS 3 (Table 5). However, this trend shifted over time, with the Health dimension emerging as the largest contributor, accounting for 42.8% of the MPI in NFHS 5. The Nutrition indicator was consistently the most significant contributor across all three NFHS rounds, demonstrating almost 6% increase in its contribution, from NFHS 3 to NFHS 5. This was followed by the education dimension, with the Years of Schooling indicator showing an increase from 13% in NFHS 3 to 17% in NFHS 5 accompanied by a decreasing headcount ratio. Within the Standard of Living dimension, the Bank Account indicator saw a significant decline, decreasing from a 7% contribution in NFHS 3 to just 1% in NFHS 5. While, certain other indicators, such as Assets, and Electricity, demonstrated substantial reductions in their contributions, indicators such as Housing and Cooking Fuel, maintained relatively consistent contributions.

The Blinder-Oaxaca decomposition analysis of the changes in the MPI across the NFHS periods was conducted (Table 6). Examining the household size, the endowment effect shows a positive contribution of 1.32% between NFHS 3-4 and 3.04% between NFHS 4-5, indicating that that population shift towards smaller household sizes has been potentially favourable in reducing multidimensional poverty. The positive coefficient effect for larger household sizes is 6.93% and 9.04%, respectively, suggesting that the adverse impact of larger household sizes on multidimensional poverty has decreased over time. The endowment effects for the Poorest and Poorer wealth groups are substantial and negative, at -3.11% and -1.48% respectively, implying that the population movements towards these economically disadvantaged groups have hindered progress in alleviating multidimensional poverty. However, the coefficient effects for the Poorest (87.25%), Poorer (94.52%), and Middle (38.54%) wealth quintiles are positive and significant, indicating that the relationship between poverty and these wealth groups has become less severe. The analysis of social groups shows that the endowment effects for Scheduled Castes (-0.54%), Scheduled Tribes (-0.42%), and Other Backward Classes (-0.18%) are negative, suggesting that the demographic shifts towards these socially marginalized communities have contributed to the persistence of multidimensional deprivation. The coefficient effects for these social

Table 4: Kitagawa Decomposition for Contribution of Headcount(H) & Intensity(A) to Multidimensional Poverty Index

	MPI Difference			MPI Difference			MPI Difference		
	NFHS 3- NFHS 4			NFHS 4- NFHS 5			NFHS 3- NFHS 5		
Caste Groups	**Prop. Att. To H**	**Prop. Att. To A**	**Net Difference**	**Prop. Att. To H**	**Prop. Att. To A**	**Net Difference**	**Prop. Att. To H**	**Prop. Att. To A**	**Net Difference**
SC	84%	16%	0.209	89%	11%	0.054	85%	15%	0.263
ST	76%	24%	0.243	88%	12%	0.091	80%	20%	0.334
OBC	86%	14%	0.182	90%	10%	0.052	86%	14%	0.233
Others	88%	12%	0.113	92%	8%	0.03	88%	12%	0.143
All India	85%	15%	0.167	89%	11%	0.049	85%	15%	0.216

Table 5: Contribution of deprivations to Multidimensional Poverty Index Headcount Values

Dimensions	Indicators	Adjusted HCR			Indicator Contribution			Dimension Contribution		
		NFHS-3	NFHS-4	NFHS-5	NFHS-3	NFHS-4	NFHS-5	NFHS-3	NFHS-4	NFHS-5
Education	Years of schooling	0.04	0.02	0.01	13.30%	15.50%	16.80%	24.30%	23.00%	26.00%
	School Attendance	0.03	0.01	0.01	11.10%	7.60%	9.20%			
Health	Nutrition	0.07	0.03	0.02	24.40%	28.00%	29.80%	32.30%	39.20%	42.80%
	Child-Adolescent Mortality	0	0	0	1.00%	1.30%	1.50%			
	Maternal Health	0.02	0.01	0.01	6.90%	9.90%	11.50%			
Standard of Living	Electricity	0.01	0	0	4.60%	3.40%	1.30%	43.40%	37.70%	31.20%
	Sanitation	0.02	0.01	0	8.00%	8.60%	6.60%			
	Drinking Water	0.01	0	0	2.60%	2.10%	1.60%			
	Housing	0.02	0.01	0.01	7.10%	8.40%	8.60%			
	Cooking Fuel	0.02	0.01	0.01	8.40%	9.40%	8.80%			
	Bank Account	0.02	0	0	6.60%	2.20%	0.80%			
	Assets	0.02	0	0	6.00%	3.70%	3.40%			
Total		0.282	0.115	0.066	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table 6: Blinder-Oaxaca Decomposition of the Multidimensional Poverty Index by Background Characteristics: Contribution to Total Effects

	NFHS 3-4	NFHS 3-5	NFHS 4-5
Endowment Effect			
Age	1.26%	1.25%	1.62%
Sex	0.06%	0.00%	0.00%
Household Size	1.32%	1.52%	3.04%
Marital Status	0.06%	0.14%	0.00%
WQ	-3.11%	-1.48%	-0.20%
Caste	-0.54%	-0.42%	-0.41%
Religion	-0.18%	0.00%	0.41%
Area	0.00%	0.00%	0.20%
States/UTs	-1.50%	-5.08%	-27.59%
Coefficient effect			
Age	-5.03%	-5.54%	-6.49%
Sex	4.91%	-0.79%	-2.23%
Household Size	9.04%	6.93%	2.03%
Marital Status	-1.38%	-1.06%	0.00%
WQ	84.91%	87.25%	94.52%
Caste	8.14%	6.93%	2.43%
Religion	2.40%	2.91%	5.07%
Area	4.73%	4.20%	2.03%
States/UTs	17.07%	16.95%	38.54%
Cons.	-22.04%	-28.45%	-67.95%
Interaction effect			
Age	0.42%	0.60%	0.20%
Sex	-0.12%	0.00%	0.00%
Household Size	0.72%	1.34%	0.41%
Marital Status	-0.30%	-0.28%	0.00%
WQ	-2.28%	-2.91%	0.00%
Caste	-0.66%	-0.74%	0.00%
Religion	-0.12%	0.00%	0.20%
Area	0.06%	-0.05%	0.00%
States/UTs	1.92%	16.49%	54.36%
Total Effect	0.167	0.217	0.049

groups are also positive, implying that the inherent disadvantages associated with these communities have diminished.

Examining regional disparities, the endowment effect for states such as Bihar (-1.50%), Odisha (-1.50%), and Jharkhand (-5.08%) is negative, reflecting that the concentration of vulnerable populations within these regions continues to pose a challenge to overall poverty reduction. Conversely, the coefficient effects for Uttar

Pradesh (38.54%), Bihar (38.54%), West Bengal (38.54%), and Andhra Pradesh (4.73%) are positive and significant. This suggests that state-specific structural factors and regional characteristics, such as governance, infrastructure, and state-level policy implementation, have become less associated with multidimensional poverty over time, indicating a relative improvement in the environment for poverty reduction in these states.

Discussion

The analysis of multidimensional poverty across three NFHS rounds revealed several key insights. Firstly, the Multidimensional Poverty Index demonstrated a significant decline across the three NFHS rounds, with the most substantial reductions observed among the poorest wealth quintiles, rural populations, and children aged 0-14 years. Notably, children, Scheduled Tribes, rural populations, and females consistently exhibited the highest poverty rates, with states like Uttar Pradesh and Jharkhand continuing to manifest multidimensional poverty. Additionally, despite overall national-level improvements, the Scheduled Tribe population's multidimensional poverty remained relatively high. Furthermore, the health dimension, particularly the nutrition indicator, emerged as the most significant contributor to MPI, accounting for the largest share of multidimensional poverty in 2019-21. The reductions in MPI were primarily attributable to improvements in weighted headcount ratios, with notable advancements in publicly provided variables such as health, education (years of schooling), bank accounts, assets, and electricity access. Lastly, the Blinder-Oaxaca decomposition revealed that, while population movements towards economically disadvantaged groups appeared to hinder poverty reduction, the analysis showed some improvements. The coefficient effects were positive and significant for the Poorest, Poorer, and Middle wealth quintiles, indicating a diminishing severity of poverty. Conversely, for Scheduled Castes, Scheduled Tribes, and Other Backward Classes, negative endowment effects suggested persistent demographic challenges, even as the coefficient effects implied reducing inherent disadvantages across different social groups and states.

The analysis reveals a significant reduction in multidimensional poverty in India, declining to 0.066 by 2019-21, aligning with NITI Aayog's findings (NITI Aayog, 2023). The national headcount ratio demonstrated a substantial 38% reduction between 2005-06 and 2019-21, effectively challenging South Asia's historical narrative of widespread poverty (OPHI, 2018). This reduction was most pronounced among the poorest wealth quintiles, with vulnerable populations experiencing more substantial improvements in absolute terms (Alkire & Seth, 2015; Alkire et al., 2021). Geographically, the poverty landscape revealed significant disparities, with states like Bihar, Meghalaya, Jharkhand, and Uttar Pradesh consistently demonstrating the highest Multidimensional Poverty Index (MPI) levels (Tripathi &

Yenneti, 2020). Furthermore, the poverty indicators remained significantly higher in rural areas compared to urban regions (Das et al., 2021). Additionally, women consistently experienced a higher likelihood of being multidimensionally poor. This trend extends beyond India, as evidenced by research on African nations, where women face similar challenges due to factors such as limited access to education, healthcare, and economic opportunities, as well as social norms and cultural practices that perpetuate gender inequality (Rogan, 2016).

The percentage of children living in severe child food poverty accounts for 40% in India (UNICEF, 2024). Furthermore, health emerged as the most critical dimension, contributing over 40% to the MPI, with nutrition alone accounting for nearly 30% of multidimensional poverty. The Global Hunger Index's ranking of India at 105th further highlights the persistent challenges of the 'Triple Burden of Malnutrition' (Undernutrition, Overnutrition, and Micronutrient Deficiency) (UNICEF, 2024; WHH et al., 2024). Approximately 40% of children experience severe food poverty, with alarming rates of stunting (35.5%), wasting (19.3%), and underweight (32.1%) conditions (NFHS, 2021). Low-quality infant and young child feeding (IYCF) practices significantly contribute to poor nutritional outcomes (Menon et al., 2015; Ramachandran, 2010), while the burden of nutritional deprivation disproportionately affects vulnerable groups, including poor households, scheduled castes, children of underweight mothers, and illiterate women compared to affluent groups (Prasad et al., 2021). Raghunathan et al. (2021) estimated that 63-76% of rural poor cannot afford recommended diets, highlighting the critical need for targeted nutrition interventions and safety net programs. Studies have consistently emphasized that affordable prices coupled with safety net programs covering nutritional norms, dietary allowance, and adjusted calorie intake are vital in mitigating the multidimensional aspects of nutrition deprivation (Raghunathan et al., 2021; Ryckman et al., 2021; Bhuyan et al., 2020).

Consistent with the existing literature, our analysis revealed that the Scheduled Tribe population demonstrated the highest Multidimensional poverty index values (Alkire et al., 2021; Pradhan et al., 2022). The rate of multidimensional poverty among Scheduled Tribes and Scheduled Castes significantly exceeds other socioeconomic groups in India, stemming from complex historical and contemporary social dynamics characterized by systemic discrimination and social injustice (Sahoo et al., 2023; Rupavath, 2023). Scheduled Tribes face a compounded disadvantage of socio-economic and spatial marginalization, with job insecurity in the unorganized sector being a substantial contributor to their economic vulnerability (Singh, 2019). The limited participation in economic growth among STs substantially widens the inequality scale, with chronic poverty largely attributable to social exclusion that systematically denies equitable resource access (Dubey, 2009; Mehta & Shah, 2003). Empirical studies, including our findings and research by Kaibarta et al. (2022) and Pradhan et al. (2022), consistently demonstrate that the standard of living dimension contributes most significantly to the ST population's multidimensional poverty. While the Government of India has established the Ministry of Social Justice and Empowerment to address these issues, further efforts are needed to improve the coverage and quality of existing public welfare programs, ensuring they effectively target these vulnerable sections of society. These bottlenecks could be largely addressed by improving the coverageand provisions of existing public welfare programs such as Pradhan Mantri Awas Yojana (PMAY), Jal Jeevan Mission (JJM), Swachh Bharat Mission (SBM), Pradhan Mantri Sahaj Bijli Har Ghar Yojana (Saubhagya) and Pradhan Mantri Ujjwala Yojana (PMUY) or setting up of more targeted programs designed to address vulnerabilities of the population.

The Multidimensional Poverty approach, as envisaged by the UNDP, enables significant flexibility in incorporating country-specific indicators and weights. India's NITI Aayog, utilizing the Alkire-Foster methodology, innovatively added bank account (weight = 1/21) and maternal health (weight = 1/12) as additional indicators, reflecting the nation's unique developmental context (NITI Aayog, 2023). This methodological adaptation, driven by the success of large-scale policy programs such as Janani Suraksha Yojana(JSY), Pradhan Mantri Surakshit Matritva Abhiyan(PMSMA), and Pradhan Mantri Jan-Dhan Yojana(PMJDY), resulted in marginal variations in MPI calculations. While UNDP reported India's MPI for 2019-21 to be 0.069, the NITI Aayog report estimated it to be 0.066 (UNDP, 2023). Similarly, UNDP reported a poverty intensity of 42% for 2019-21, while NITI Aayog estimated it to be 44.39%. These findings indicate substantial progress in reducing multidimensional poverty in India, highlighting the effectiveness of equitable pro-poor programs and policy initiatives. The inclusion of additional indicators relevant to India's specific context provides a more comprehensive picture of poverty reduction efforts.

Targeted government interventions have been pivotal in addressing multidimensional poverty. Government interventions have been pivotal in addressing the specific deprivations tracked by the 12 MPI indicators. For Health (Nutrition, Child Mortality, Maternal Health), schemes such as Poshan Abhiyaan (Poshan 2.0), Janani Suraksha Yojana (JSY), and the Pradhan Mantri Matru Vandana Yojana (PMMVY) have directly targeted nutritional intake and maternal care coverage. In Education (Schooling and Attendance), the Samagra Shiksha Abhiyan and the Right to Education Act have been instrumental in improving enrollment and retention. The Standard of Living indicators have been addressed through targeted infrastructure missions: Pradhan Mantri Ujjwala Yojana (Cooking Fuel), Swachh Bharat Mission (Sanitation), Jal Jeevan Mission (Drinking Water), Saubhagya (Electricity), and Pradhan Mantri Awas Yojana (Housing). The Pradhan Mantri Jan Dhan Yojana (PMJDY) has specifically addressed the Bank Account indicator.Furthermore, specific interventions have been crucial for vulnerable groups. Income-enhancing schemes such as the Mahatma Gandhi National Rural

Employment Guarantee Act (MGNREGA) and the Deendayal Antyodaya Yojana-National Rural Livelihoods Mission (DAY-NRLM) have empowered rural households, particularly SCs and STs, by providing wage employment and strengthening self-help groups. For women, schemes like Stand Up India and Mahila Samman Savings Certificate promote financial independence, while the Beta Bachao Beti Padhao scheme addresses gender disparities in education, indirectly influencing future household income potential.

The Ministry of Social Justice and Empowerment has played a crucial role in improving public provisioning for marginalized communities. However, persistent multidimensional poverty remains evident among vulnerable populations. Flow characteristics suggest that continued focus on health, nutrition, and education dimensions could further reduce MPI, particularly among dependent populations and marginalized communities. For instance, the Integrated Child Development Programme played a major role in uplifting nutritional standards (Das et al., 2022). Nevertheless, continued refinement of intervention strategies remains crucial for sustained poverty reduction (Roy, 2025). Regular follow-up and evaluation of these programs are pivotal to ensure they achieve their objectives in the targeted groups. Furthermore, analysis at the administrative level is required to rigorously understand the causes of implementation gaps.

This study was subject to several methodological limitations that warrant careful consideration. The cross-sectional nature of the data inherently restricted our ability to establish any causal relationships. Methodological constraints require the omission of variables with missing values, and the reliance on self-reported data from the National Family Health Survey (NFHS) introduces potential reporting inaccuracies and bias. While our findings demonstrated broad consistency with the NITI Aayog report, slight variations arose from the nuanced methodology of indicator specification and weighting. The study was constrained to utilizing NITI Aayog's predefined indicators, predominantly focused on publicly provisioned metrics, which may not comprehensively capture the full complexity of individual poverty experiences. While this study analyzes social groups across states, it does not explicitly weight for the varying population shares of these groups within specific regions. For instance, while the share of the SC population may be proportionally higher in Punjab compared to Kerala, the economic and human development outcomes for SC households in Kerala may differ significantly due to state-specific socio-political histories. Such nuances regarding the interplay between population share and development outcomes require further granular research and were beyond the scope of this decomposition analysis.While we incorporated the two country-specific indicators (maternal health and bank accounts) to align with the NITI Aayog's national MPI, minor discrepancies in our estimates compared to the official report may persist due to slight variations in indicator operationalization within the Alkire-Foster framework.These methodological limitations highlight the need for further research to develop more refined approaches that can comprehensively capture the multidimensional nature of poverty. Future research could benefit from incorporating more granular data collection and analysis techniques to provide a nuanced understanding of socioeconomic deprivation.

The analysis reveals a significant decline in multidimensional poverty in India, primarily driven by targeted government interventions. However, disparities persist across regions and socioeconomic groups. While the headcount ratio has shown substantial improvement, the intensity of poverty remains a concern. Several Government initiatives have made strides in addressing these issues; however, the health dimension, particularly nutrition, continues to be a significant contributor to the MPI. To further accelerate poverty reduction, a sustained focus on vulnerable groups, especially Scheduled Tribes, females, children under 14 years of age, and rural populations, is essential. Additionally, enhancing the quality and coverage of public services, promoting inclusive growth, and addressing the root causes of poverty, such as inequality and social exclusion, will be crucial for achieving equitable growth.

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• **Author Contributions:** WJ conceived and designed the study and provided supervision and project administration. Data acquisition was carried out by KA, APE, and SK , while KA and APE performed the data analysis and interpretation. The manuscript was drafted by KA, APE, and SK. All authors (KA, APE, SK, and WJ) critically revised the manuscript, approved the final version to be published, and agreed to be accountable for all aspects of the work.

• **Supplementary Material:** Visit https://healthempirics.org/ for more information

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Prevalence and Correlates of Overweight and Obesity in Adults and Older Adults in India; Population-Level Estimates Based on Nationally Representative Surveys (2015-21)

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In the current epidemiological transition, a rapid increase in the prevalence of overweight is observed in low-middle-income countries. There is a prominent shift towards a sedentary lifestyle and unhealthy food consumption which has triggered the risk of NCDs. The situation is similar in India. A holistic understanding of obesity epidemiology is the need of the hour with a target-oriented intervention approach. Though multiple studies have been a part of the research pool, insights are limited in the case of the whole prevalence as per the National estimate. This study attempts to understand the epidemiology of overweight/obesity in India concerning the entire population. The study is unique in the sense that it utilizes National-level estimates to understand the epidemiology of obesity concerning the entire population. It aims to explore the state-level prevalence of overweight/obesity and understand the implications as per socio-economic indicators and age-sex groups. The study takes up cross-sectional analysis, using two National Representative data sets. It identifies key anthropometric parameters and socio-economic correlates to run descriptive analysis and logistic regression. The descriptive analysis provided us with the age-sex prevalence of obesity, while logistic regression was used to establish the SES gradient by age. Lastly, to measure the inequality of obesity among males and females by different age groups, concentration indices is used. The findings reveal a higher prevalence of overweight/obesity among females than males. The prevalence among females is 19.2 percent, whereas it is 16.8 percent in the case of males. The highest prevalence is observed in NCT Delhi (33.9%) and the lowest in Meghalaya (10%). With respect to socio-economic determinants, the prevalence is noticeably higher among those residing in urban areas, belonging to the richest wealth index, identifying in the 'others' social groups and who have 10 or more years of education across the age groups. The paper presents all-inclusive results of obesity/overweight epidemiology in India, giving a holistic understanding of obesity implications with regard to age and SES-wise determinants. Thus, providing probable pathways for intervention.

Keywords: Obesity, Overweight, India, Nutrition, Body Mass Index

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The rapid increase in the prevalence of overweight/obesity in low- and middle-income countries (LMICs) is a more relatively recent trend globally (McLachlan & NCD-RisC, 2016). An increase has been noted in both rural and urban areas, with the rural areas displaying a recent pattern of intensified escalation (NCD- RisC, 2019). The rise in overweight and obesity rates across age groups has been relatively higher in LMICs and plateauing in high-income countries (HICs). As of 2016, over two billion (70%) globally overweight or obese individuals, reside in LMICs (Abay et al., 2022). While the major direct cause is the rapid increase in consumption of ultra-processed food along with other junk foods high in added saturated fats, sodium and sugar, underlying factors include rapid social and economic changes such as urbanisation, globalization, and economic growth accompanied by increased income per capita (Wen et al., 2009). Increased sedentary living occurred earlier and now it is the diet that directly impacts these changes (Popkin & Ng, 2022). Certain subpopulations also experience the dual challenge of malnutrition, resulting in both hunger-induced undernutrition and stunting. The rising consumption of ultra-processed food and beverages, and increased prevalence of overweight and obesity have triggered the risks of multiple Non-Communicable Diseases (NCDs) such as cardiovascular diseases (CVDs), diabetes, hypertension and 13 of the 16 major cancers (WCRF & AICR, 2018). The increased mortality from CVD and cancer is also very concerning (Popkin, 2003). Over the last few decades, the prevalence of NCDs has sharply increased in many LMICs, while it is somewhat declining in the HICs (Abdelaal et al., 2017).

India is going through a similar nutrition transition (Popkin & Ng, 2022). Amidst rapid economic growth and income development, the prevalence of overweight/obesity and associated NCDs has been consistently increasing across all age groups and regions in India (Miranda et al., 2019). Moreover, the figures are expected to triple among Indian adults (20-69 years) between 2010 and 2040 with higher risk among the rural residents and older Indians, if not intervened timely (Ranjani et al., 2016). This is mainly linked with the rapid increase in consumption of ultra-processed food by the Indian population, particularly those under 40 years of age.

The cross-sectional analysis presented in this study has a two-fold advantage. Firstly, it provides evidence on the age group where the rise of obesity prevalence is triggered. Secondly, when compared with lagged estimates across the age-sex group, it can provide an understanding of metabolic problems accumulating over time. More importantly, the paper is an insight into the reliability of the outcomes as obtained from using 2 different data sets positioned in different time frames. Though the issue being addressed here is very pertinent to public health, the current data repository on obesity may not potentially produce a reliable glimpse of the actual epidemiological status. It is established that the pattern of BMI changes in accordance with age (Luhar et al., 2020). Thus, for ideal quantification, taking up a life course pattern is critical to understanding the magnitude of the burden.

Currently, the literature on prevalence and correlates has mostly focused on socioeconomic status (SES) and its association with overweight and obesity. Studies have reported a positive association between SES indicators and obesity across age groups (Neuman et al., 2013). However, evidence suggests that the association vary by economic development, region, and gender within countries (Monteiro et al., 2004). There is a complex linkage between SES levels and obesity. While decades ago, SES in LMICs was linked positively with obesity, more recently the shifts have been complex and many countries such as China, Indonesia, and others have higher levels of obesity among the poor than the higher SES groups (Popkin et al., 2020).

In LMICs, a positive association is likely across age groups and sex (adult men and women and children), while in developed countries, a negative association is more common among women (inconsistent in men and children) (Pavela et al., 2016). A recent review by Templin et al., (2019), reveals that as national economies increase to higher levels, the burden of overweight/obesity shifts over time to poorer sections of the population within these countries. The impact factor shows a considerable increase in prevalence amongst the poorer sections of the population whilst, for the wealthiest sub-populations, the prevalence rate remains more or less unchanged (Cohen et al., 2013).

The present paper answers the following research questions specifically for adults and older adults using India's two nationally representative surveys: (a) What is the prevalence of overweight/obesity in India? (b) Are wealthy/educated more likely to be overweight/obese in India? (c) Whether thinning set in earlier for men than women? (d) Whether the current data set is reliable for quantifying the magnitude of obesity in India?

The question aims to understand the epidemiology of overweight/obesity in India concerning the entire population. It takes into consideration the respective age-sex groups, their experiences and socio-economic status. To round up the analysis and its implications we also explore the state-level associations of overweight/obesity prevalence.

Methodology

- **Study Design**

The study is a cross-sectional analytical study using two National Representative data sets. It identifies anthropometric parameters and socio-economic correlates to run descriptive analysis and logistic regression. Additionally, an "Obesity Tree/ Pyramid" depicting age-sex-wise prevalence was also plotted.

- **Variables**

The main variables used are the anthropometric parameters to estimate the prevalence of overweight and obesity. WHO adult BMI cut-offs, BMI for age Z score (BAZ), and weight-for-height Z-score (WHZ) as per WHO standard are used for adults respectively. Body mass index (BMI) is defined as a person's weight in kilograms divided by the square of the height in meters (kg/m2) that is commonly used to classify overweight and obesity in adults (Pavela et al., 2016)..

For adults (all ages), WHO defines overweight as BMI >= 25 and obesity as BMI >= 30 (Templin et al., 2019).

Alternate measures to identify abdominal obesity in adults i.e., waist-to-hip ratio were also used. In accordance with the WHO, a waist-to-hip ratio above 90 cm in men and >85 cm in women is classified as abdominal obesity.

Other background variables used in the analysis consisted of a few correlates including socioeconomic factors including i) place of residence (urban/rural); ii) wealth quintiles as poorest, poor, middle, rich and richest; iii) social groups as SC, ST, OBC and 'Others' and iv) education in years as <5 years, 5-9 years and 10 years and more.

- **Data Sources**

The study is based on nationally representative surveys namely National Family Health Survey (NFHS), 2019-21, and Longitudinal Ageing Study in India (LASI) Wave 1, 2020. A brief overview of the surveys is given below.

- **National Family Health Survey, 2019-21**

The National Family Health Survey, 2019-21 survey was conducted by International Institute for Population Sciences (IIPS), Mumbai across all India's States and UTs using a two-stage, stratified cluster sample, wherein 724,115 women (15-49 years) and 101,839 men (15-54 years) were selected from a random sample of 636,699 households. The survey yielded an analytical sample of 423843 adult women (20–49 years) and 65196 men (20–49 years) after adjusting missing data which were used in the present analysis. For more information on the sampling procedure of the NFHS-2019-2021 survey, visit the link http://rchiips.org/nfhs/NFHS-5Reports/NFHS-5_INDIA_REPORT.pdf

- **Longitudinal Ageing Study in India (LASI) Wave 1, 2017-19**

Longitudinal Ageing Study in India (LASI) 2020 (Wave-I) is a nationally demonstrative survey of the health, economic, and social determinants and consequences of older adults (45 and above years) and population ageing in India. The LASI Wave 1 was conducted across India's States and UTs (excluding Sikkim) by International Institute for Population Sciences (IIPS), Mumbai using a stratified, multistage stratified area probability cluster sampling design wherein 72,250 older adults and elderly men and women aged 45 and above were selected.

The present study used 45105 observations after adjusting missing data of the older population who were 50 and above years. For more information on the sampling design and method of the LASI-2020 (Wave-I) survey, visit the link https://www.iipsindia.ac.in/content/lasi-publications, https://www.iipsindia.ac.in/content/lasi-publications.

- **Statistical methods**

Descriptive statistics were conducted to estimate prevalence by correlates. To estimate the state-level prevalence of obesity, NFHS-4 data were used for 15-49 years, and LASI datasets for 50-59 years, 60-69 years and 70 years and above. The weighted prevalence population data for 2021 was obtained from the Population Projection Report 2011-2036. The share for each age group was calculated in the total population which served as weights to calculate the weighted prevalence. This was done at both the national and the State levels.

Logistic regression analyses were carried out; the odds ratio for correlates to establish the SES gradient by age. Interactions of wealth quintile/education to examine the SES gradient by age have also been made. To measure the inequality of obesity among males and females by different age groups we have used the concentration indices.

Results

Among the male population, the prevalence of obesity increases with age up to 40-49 years and starts to decline thereafter. Whereas, among females, the percentage of obesity increases up to the age of 50-54 years and declines after that. The overall prevalence of overweight and obesity is 17 percent among 20-29 years, 31.7 percent among 30-39 years, 36.4 percent among 40-49 years, 32 percent among 50-59 years, 25.3 percent among 60-69 years and 16.9 percent among >=70 years (Table 1). As per the SES determinants, the prevalence is comparatively higher among those belonging to urban areas, the richest community, 'others' social groups and higher education experience. (Table 1). Hereafter we use the term obesity but it combines both overweight and obesity. We combined the figures as in India the risk of diabetes and many other NCDs rises at a BMI of 22 (Wen et al., 2009).

The prevalence of obesity is highest in Delhi (33.9 %) with females accounting for 37.3 percent and males accounting for 30.9 percent. The prevalence is lowest in Meghalaya (10 %) with females having a 9.9 percent prevalence rate and males recording 10.5 percent (Table 2).

Table 1: Age-group-wise prevalence of overweight and obesity by SES for total population

Background Variables	20-29 Years	30-39 Years	40-49 Years	50-59 Years	60-69 Years	>=70+ Years
Place of residence	%	%	%	%	%	%
Urban	22.8	41.9	48.3	52.4	43.3	32.6
Rural	14.3	26.6	30.3	22.8	18.2	11.1
Wealth Index						
Poorest	7.3	13.7	16.0	23.1	16.3	10.6
Poor	12.1	22.8	24.8	27.2	21	13.1
Middle	17.0	31.7	35.1	29.4	25	17
Rich	21.2	40.4	44.4	35.3	31.9	19.4
Richest	26.0	47.7	55.9	47.4	35.4	27.6
Social Groups						
SC	15.7	29.4	32.6	22.8	19.2	9.1
ST	9.1	17.5	20.1	15.4	8.8	5.5
OBC	17.4	32.8	37.7	36	26.2	19
Others	20.4	37.1	42.3	38.7	34.2	22
Education in years						
No schooling	10.3	20.6	26.9	23.4	17.9	11.3
<5 years	12.3	24.9	33.3	24.2	24.1	19
5-9 years	16.0	32.6	41.1	37.6	32.8	20.2
10+ years	19.1	40.9	49.0	51.3	42.2	39.5
Total	17.0	31.7	36.4	32	25.3	16.9

Note- N is the weighted total sample.

The values of concentration indices are positive across all age groups indicating that overweight/obesity is concentrated among the wealthy population as compared to the poor (Table 3).

It is observed that the odds of obesity were greater for urban dwellers as compared to their rural counterparts. For urban adults aged 20-29 and 30-39 years, odds are 1.18 (95% CI: 1.15-1.21) and 1.14 (95% CI: 1.11,1.16) times the odds of obesity. The figure is similar for adults aged 40-49 years i.e., 1.20 times. The odds go comparatively higher for older adults and the elderly. Within the age group 50-59, 60-69 and 70+, there are 2.61 (95%, CI: 2.43, 2.80), 2.64 (95% CI: 2.45, 2.86) and 2.86 (95% CI: 2.56, 3.19) times the odds of obesity, respectively (Table 4). At the same time, it is important to note the rapid increases in rural obesity over the past decade (NCD- RisC, 2019).

As per the wealth index, the odds of obesity are higher for the wealthier population. This section states the odds as compared between the poorest and the richest. The richest adults belonging to age groups 20-29, 30-39 and 40-49 years had 3.93

Table 2: State standard estimates of obesity and overweight

State/UT	Male %	Female %	Total %
Andhra Pradesh	25.7	31.9	28.8
Assam	13.9	13.4	13.7
Bihar	11.5	11.8	11.6
Chhattisgarh	12.7	11.4	12.1
Gujarat	16.8	21.9	19.2
Haryana	21.5	25.7	23.5
Himachal Pradesh	23.9	29.1	26.5
Jammu & Kashmir	24.8	27.9	26.2
Jharkhand	11.1	9.6	10.4
Karnataka	26.1	30.1	28.1
Kerala	28.0	34.7	31.4
Madhya Pradesh	12.4	13.4	12.8
Maharashtra	20.5	22.7	21.5
NCT Of Delhi	30.9	37.3	33.9
Odisha	18.0	17.7	17.2
Punjab	27.9	37.0	32.2
Rajasthan	12.2	12.5	12.4
Tamil Nadu	27.6	33.9	30.7
Telangana	23.4	24.9	24.1
Uttar Pradesh	13.8	16.3	15.0
Uttarakhand	21.9	24.3	23.1
West Bengal	15.6	18.8	17.1
Arunachal Pradesh	20.9	19.4	20
Goa	26.8	32.9	30
Manipur	23.3	26.7	25
Meghalaya	10.5	9.9	10
Mizoram	22.6	17.9	20
Nagaland	18.9	14.5	17
Sikkim	NA	NA	NA
Tripura	18.5	17.1	18

(95% CI: 3.70, 4.07), 4.41 (95% CI: 4.23, 4.58) and 4.95 (95% CI: 4.84, 5.25) times the odds of obesity, respectively. In the same wealth index, older adults and the elderly aged 50-59, 60-69 and 70+ years accounted for comparatively lesser odds of obesity i.e., 2.38 (95% CI: 2.14, 2.66), 2.36 (95% CI: 2.09, 2.66) and 2.44 (95% CI: 2.04, 2.91), respectively.

Concerning social identity, it is observed that the likelihood of obesity in the category of 'others' is higher than those belonging to the Scheduled Caste category.

Table 3: Concentration index values for the total population

Age group	Index value	Std. error	p-value	No. of obs.
20 to 29 years	0.23	0.00	0.00	232154
30 to 39 years	0.23	0.00	0.00	212355
40 to 49 years	0.23	0.00	0.00	180963
50 to 59 years	0.14	0.01	0.00	18225
60 to 69 years	0.15	0.01	0.00	16529
70+ years	0.18	0.01	0.00	10351

Table 4: Logistic regression on overweight and obesity by SES for total population

Background Variables	20-29 Years	30-39 Years	40-49 Years	50-59 Years	60-69 Years	>=70+ Years
Place of residence						
OR [95%, C.I.]						
Rural	1	1	1	1	1	1
Urban	1.18***	26.6	30.3	22.8	18.2	11.1
Wealth Index						
Poorest	1	1	1	1	1	1
Poor	"1.69*** [1.62, 1.77]"	"1.77*** [1.71, 1.84]"	"1.66*** [1.60, 1.72]"	1.19** [1.07, 1.33]	1.26*** [1.11, 1.42]	"1.29** [1.08, 1.54]"
Middle	"2.42*** [2.31, 2.53]"	"2.59*** [2.50, 2.68]"	"2.50*** [2.41, 2.59]"	1.33*** [1.19, 1.49]	1.51*** [1.34, 1.71]	1.52*** [1.27, 1.81]
Rich	"3.10*** [2.95, 3.25]"	"3.43*** [3.30, 3.56]"	"3.43*** [3.29, 3.56]"	1.72*** [1.55, 1.92]	1.96*** [1.74, 2.21]	2.08*** [1.75, 2.48]
Richest	3.93***[3.74, 4.14]	4.41***[4.23, 4.60]	4.95***[4.74, 5.17]	2.38*** [2.14, 2.66]	2.36*** [2.09, 2.66]	2.44*** [2.04, 2.91]
Social Groups						
SC	1	1	1	1	1	1
ST	"0.82*** [0.79, 0.85]"	"0.75*** [0.73, 0.78]"	"0.82*** [0.79, 0.85]"	0.72*** [0.64, 0.81]	0.77*** [0.67, 0.88]	0.81 [0.66, 1.00]
OBC	"1.01 [0.98, 1.04]"	"0.95*** [0.93, 0.98]"	"0.99 [0.96, 1.02]"	1.18*** [1.07, 1.30]	1.25*** [1.12, 1.39]	"1.21* [1.02, 1.43]"
Others	"1.17*** [1.13, 1.21]"	"1.09*** [1.06, 1.12]"	"1.11*** [1.08, 1.15]"	1.49*** [1.34, 1.65]	1.47*** [1.30, 1.65]	1.49*** [1.25, 1.78]
Education						
No schooling	1	1	1	1	1	1
<5 years	"1.08 [1.00, 1.17]"	"1.12*** [1.07, 1.18]"	"1.17*** [1.13, 1.22]"	"1.00 [0.90, 1.13]"	1.20** [1.07, 1.36]	"1.20* [1.03, 1.41]"
5-9 years	"1.18*** [1.13, 1.24]"	"1.30*** [1.26, 1.33]"	"1.28*** [1.25, 1.32]"	1.43*** [1.32, 1.56]	1.45*** [1.32, 1.59]	"1.22** [1.05, 1.40]"
10 years & more	"1.10*** [1.05, 1.15]"	"1.33*** [1.29, 1.37]"	"1.34*** [1.30, 1.38]"	1.59*** [1.44, 1.74]	1.69*** [1.53, 1.88]	1.53*** [1.31, 1.78]

Note- P <0.01***, P <0.05** and *<0.10

Table 5: Logistic regression of Interactions between years of schooling and wealth index for total population on obesity

Schooling years and wealth	**20-29 years**	**30-39 years**	**40-49 years**	**50-59 years**	**60-69 years**	**70+ years**
	OR [95%, C.I.]	**OR [95%, C.I.]**	**OR [95%, C.I.]**	**OR [95%, C.I.]**	**OR [95%, C.I.]**	**OR [95%, C.I.]**
No school & poorest	1	1	1	1	1	1
No school & poorer	1.77***[1.59, 1.96]	1.96***[1.86, 2.08]	1.71***[1.63, 1.80]	1.15 [0.98, 1.35]	1.32** [1.11, 1.56]	1.39** [1.10, 1.76]
No school & middle	2.64***[2.35, 2.96]	2.92***[2.75, 3.10]	2.68***[2.56, 2.82]	1.41*** [1.21, 1.66]	1.74*** [1.47, 2.06]	1.73*** [1.37, 2.17]
No school & richer	3.96***[3.47, 4.53]	4.45***[4.15, 4.77]	3.88***[3.68, 4.09]	1.81*** [1.55, 2.12]	2.15*** [1.81, 2.54]	2.12*** [1.69, 2.66]
No school & richest	4.87***[4.02, 5.90]	5.98***[5.41, 6.61]	6.08***[5.69, 6.51]	2.38*** [2.02, 2.80]	2.62*** [2.20, 3.12]	2.74*** [2.16, 3.47]
<5 years & poorest	1.06[0.91, 1.23]	1.20***[1.09, 1.32]	1.07[0.97, 1.19]	1.17 [0.90, 1.51]	1.61*** [1.22, 2.11]	1.71** [1.18, 2.46]
<5 years & poorer	1.95***[1.69, 2.25]	2.05***[1.88, 2.24]	2.07***[1.91, 2.24]	1.28* [1.01, 1.64]	1.95*** [1.52, 2.50]	1.76** [1.23, 2.52]
<5 years & middle	2.86***[2.43, 3.37]	3.42***[3.13, 3.74]	3.16***[2.93, 3.42]	1.56*** [1.23, 1.98]	2.25*** [1.76, 2.89]	1.96*** [1.37, 2.80]
<5 years & richer	4.03***[3.31, 4.90]	4.68***[4.20, 5.23]	4.68***[4.29, 5.10]	1.82*** [1.44, 2.29]	3.00*** [2.33, 3.87]	3.13*** [2.27, 4.31]
<5 years & richest	6.56***[4.86, 8.86]	6.39***[5.32, 7.68]	6.99***[6.12, 7.98]	3.02*** [2.38, 3.83]	3.15*** [2.43, 4.09]	4.48*** [3.26, 6.14]
5 9years & poorest	1.16**[1.06, 1.28]	1.41***[1.32, 1.50]	1.34***[1.24, 1.45]	2.02*** [1.68, 2.44]	2.42*** [1.95, 3.01]	2.29*** [1.61, 3.26]
5 9years & poorer	2.08***[1.91, 2.26]	2.45***[2.32, 2.58]	2.16***[2.05, 2.29]	2.41*** [2.03, 2.86]	2.87*** [2.35, 3.50]	2.56*** [1.88, 3.48]
5 9years & middle	3.27***[3.00, 3.55]	3.84***[3.65, 4.04]	3.42***[3.25, 3.60]	2.66*** [2.24, 3.16]	2.88*** [2.37, 3.50]	2.35*** [1.73, 3.20]
5 9years & richer	4.29***[3.93, 4.67]	5.31***[5.04, 5.60]	4.97***[4.73, 5.23]	3.36*** [2.85, 3.96]	3.70*** [3.05, 4.48]	3.62*** [2.73, 4.82]
5 9years & richest	5.57***[5.05, 6.15]	7.33***[6.91, 7.79]	7.91***[7.48, 8.35]	3.92*** [3.32, 4.62]	4.32*** [3.57, 5.24]	3.60*** [2.67, 4.85]
10+more & poorest	1.21***[1.09, 1.35]	1.73***[1.56, 1.93]	1.49***[1.28, 1.73]	3.39*** [2.66, 4.33]	3.72*** [2.81, 4.91]	2.97*** [1.87, 4.73]
10+more & poorer	2.02***[1.85, 2.19]	2.80***[2.62, 2.99]	2.53***[2.33, 2.75]	3.42*** [2.78, 4.21]	4.27*** [3.37, 5.42]	3.75*** [2.58, 5.44]
10+more # middle	2.86***[2.64, 3.10]	3.87***[3.67, 4.09]	3.79***[3.56, 4.04]	3.23*** [2.67, 3.92]	4.49*** [3.64, 5.54]	4.56*** [3.30, 6.31]
10+more& richer	3.89***[3.60, 4.20]	5.25***[5.00, 5.52]	5.24***[4.97, 5.52]	4.34*** [3.66, 5.15]	5.35*** [4.40, 6.52]	6.17*** [4.64, 8.22]
10+more & richest	5.36***[4.97, 5.79]	7.32***[6.98, 7.67]	8.01***[7.65, 8.39]	5.79*** [4.96, 6.76]	6.71*** [5.63, 8.01]	6.24*** [4.85, 8.01]

Note- P <0.01***, P <0.05** and *<0.10

Adults in the 'others' category, aged 20-29, 30-39 and 40-49 years have 1.17 (95% CI: 1.12, 1.20), 1.09 (95% CI: 1.06, 1.12) and 1.11(95% CI: 1.08, 1.15) times higher odds of obesity, respectively. Lastly, older adults and elderly aged 50-59 (95% CI: 1.34,1.65) and 70+ years (95% CI: 1.25,1.78) have 1.47 times and 1.49 times the odds of obesity, respectively.

Education being the final determinant, the propensity of obesity is higher among the population having ten or more years of education. Obesity holds 1.10 times higher odds among adults aged 20-29 years (95% CI: 1.08,1.18), having ten years and more education. The odds are 1.33 and 1.34 for age groups 30-39 and 40-49 years, respectively, within the same education parameter. Among the older adults and the elderly, the population aged 50-59, 60-69 and 70+ years have 1.59 (95% CI: 1.44, 1.74), 1.69 (95% CI: 1.53, 1.88) and 1.53 (95% CI: 1.31, 1.78) times the odds of obesity.

Table 5 shows the logistic regression between the level of education (in years) and the wealth index on obesity for the total population. Interaction analysis reports that those with an education of ten or more years and belonging to the richest section were significantly more likely to be obese as compared to those who had no education and belonged to the poorest wealth index.

Discussion

According to the available data, this study is a one-of-a-kind insight into the epidemiology of obesity/overweight in India. It uses two nationally representative surveys. This paper also provides India-based evidence on the association of overweight/obesity with SES indicators (income and education) by sex.

- **Key Findings**

The analysis reveals that the national prevalence of obesity across age groups is 19.2 percent in females which is sufficiently higher than in males who record a figure of 16.8 percent. The highest prevalence is observed in NCT Delhi and the lowest in Meghalaya. The prevalence is noticeably higher among those residing in urban areas, belonging to the richest wealth index, identifying in the 'others' social groups and who have 10 or more years of education across the age groups.

Thus, it is evident from the findings that the prevalence of overweight/obesity among females is higher than in males. In adults and adolescents in developing countries, a higher prevalence of obesity was seen among females, while in developed countries, the case was essentially the opposite (Mistry & Puthussery, 2015; Garrido-Miguel et al., 2019). This study estimates national overweight/obesity prevalence across all age groups. There are twofold advantages to estimating the national level prevalence i.e.; (a) It reveals a particular age group which requires priority focus by the national programs and policies and (b) It provides an understanding of the metabolic factors accumulating over time when compared with lagged estimates across the age-sex groups.

A consistent gender disadvantage in obesity in adulthood was observed in our study. This is in line with the findings from the studies from other LMICs, where they found a much higher prevalence of obesity in women aged 20 years and above than in men (Skinner et al., 2018). The most common explanations regarding gender disparities in overweight and obesity were physical activity, cultural values, biological factors (e.g., menopause), and urbanization (Mistry & Puthussery, 2015). In contrast, Ameye & Swinnen (2019) suggests an absence of a significant gender difference in average obesity prevalence in high-income level countries. Additionally, there's a reversal of the obesity gap in high-income level countries, with males becoming the more obese gender in Japan, Scandinavian countries, and in Northern European countries like Belgium, France, Switzerland and Germany (Kanter & Caballero, 2012).

A positive SES gradient was observed for females where the prevalence of obesity increased with increasing education level and wealth quintile, which is also in line with earlier evidence from India (Bhurtyal & Adhikari, 2022). Indian studies have linked this to cultural norms that may favour fat body shapes, higher consumption of energy-dense diets, and traditional narratives which bars high-SES women in India to engage in physical activities and healthy dietary practices, despite more knowledge, awareness and resources (Kanter & Caballero, 2012). Our finding slightly deviates from the findings in developing countries. It has been observed that the women with higher SES throughout their life, have lower BMI, and the findings among men were less consistent (Ameye & Swinnen, 2019). These could be attributed to having weight-related standards among wealthy females resulting in regular exercise and healthy diets, which are of course easier to maintain with higher income.

A meta-analysis of prospective cohort studies found that individuals with obesity were associated with a 7- and 3-times higher risk of diabetes and being overweight respectively, as compared to normal-weight individuals (Abdullah et al., 2010). Our analysis found positive associations among overweight/obesity, NCD burden and out-of-pocket health expenditure. Therefore, addressing the growing overweight and obesity prevalence is of great urgency. Preventive measures such as screening for NCDs like diabetes and hypertension among overweight/obese individuals especially. among high-risk individuals should be integrated into the health system. The existing government initiatives such as the National Multisectoral Action Plan for Prevention and Control of NCDs (2017-22), which partly aims to reduce out-of-pocket expenditure on NCD healthcare should be implemented across India (Luhar et al., 2020)..

This section not only elaborates on the limits but also puts forth essential suggestions significant for obesity-related research. There are multiple issues which need to be kept in mind while considering the findings of this study. Firstly, the survey took into consideration a basic method of measurement i.e., BMI (derived from weight and height) to measure the prevalence of overweight and obesity. BMI is a measurement of only relative body weight, so it does not distinguish between body fat and lean mass. There are many other better alternate anthropometric measurements such as waist circumference and waist-to-hip ratio that are strongly associated with CVD risk factors (Goh et al., 2014) along with skinfold thickness which predicts body fat.

Secondly, we have used WHO's standard global adult cut-offs i.e., >=25 kg/m2 for overweight and BMI >= 30 for obesity. However, some studies have suggested that the proposed BMI standards aren't appropriate and the recommendation is to use lower BMI cut-offs for overweight/obese (≥23) and obese (≥25) for South Asians (Misra et al., 2009). This is because South Asians are at risk of developing obesity-related co-morbidities at lower levels of body mass index (BMI) and waist circumference (WC). Yet, we have chosen to use global cut-offs in order to ease the direct comparison with other studies.

Thirdly, the rising threat of obesity is alarming and a comprehensive understanding of it is thus important and relevant. The situation is equally precarious in India, and research minds have expressed the need for integrated data repositories for fruitful outcomes and forecastable status quo (world obesity report- India). The paucity of data at the population level makes estimation even more challenging. In spite of the impacts being significant population-wise, survey methods and data repositories have confined themselves to targeted age groups be it the children, elderly or reproductive women. Like poverty, obesity is associated with multiple causalities and consequences including social and economic points of view (Egger et al., 2012). However, though the former approaches the issue through National-level holistic estimates, the latter is mainly assessed along certain target groups. The similarity of the context of both issues suggests the adoption of alike approaches- in this case, using population-level estimates. This study intends to do the same by using the available datasets across each age group. However, the datasets being disintegrated are difficult to standardise. The standard deviation calculated for each State (Table S7) shows a wide range of dispersion ranging between 0.39 (Jharkhand) to 10.78 (Nagaland) among males and 0.19 (Madhya Pradesh) to 6.87 (Nagaland) among females. The high variability of the values questions the consistency of the outcomes, especially in order to generate meaningful population-level insights. The pooled data also had minor year variations.

The appropriateness of BMI as the standard measure for obesity across age groups has been a persistent topic of deliberation. Multiple studies note how physiological status among humans may vary with ageing, making obesity measurement challenging (Goran, 1998). It is observed that ageing is associated with decreasing body weight and height. There is also the redistribution of adipose tissues along with a decrease in muscle mass (Batsis et al., 2016). These added complexities make it difficult to accurately diagnose obesity among the elderly, especially through the BMI index. In the study done by Batsis et al. (2016), the authors strategically emphasised the diagnostic inaccuracy of BMI application on elderly populations. Their findings show that BMI may fail to interpret adiposity, which is an important determinant among elderly populations. In a systematic and meta-analytical study carried out by Correa et al. (2016), the findings reveal that out of the 13 chosen articles, 5 manuscripts present evidence of the waist-to-height ratio (WHtR) being the “best anthropometric index” when applied alone.

The study also drew an association between obesity assessed via WHtR and the capacity to predict NCD risk factors, proving its efficiency greater than BMI. Similar criticism was obtained in the study conducted by Perissinotto et al. (2002). The cross-sectional analysis revealed the drawbacks associated with the standardization of homogenous anthropometric measurements to represent every age group. The paper investigates the cross-sectional sample of an elderly population and results show marked redistribution of body fat among the elderly. Since BMI does not quite reflect this redistribution, the homogenous BMI standards misinterpret obesity among elderly subjects. Ageing is usually coupled with an increase in fat mass and a decrease in fat-free mass. Thus, the threshold values in the case of the elderly population need careful re-considerations.

Despite the ongoing criticism, BMI continues to be the most frequently used index. It is not only an easy tool but has also predicted adverse outcomes in global scenarios. Though multiple studies have recommended alternate measurement indices, BMI along with waist circumference (WC) continue to receive special attention for analytical purposes. In fact, the systematic review by Correa et al (2016) also included two such studies which recognized WHtR, WC and BMI as having the same performance level.

Fourth is a limitation associated with interpreting cross-sectional association as one cannot draw any conclusions regarding causality out of the cross-sectional association.

Conclusion

In conclusion, the findings from our analysis show a higher prevalence of obesity in women compared to men, especially among those with higher socioeconomic status. The prevalence is also more pronounced among women and adults. This indicates that India is experiencing a rapid increase in overweight/obesity prevalence.

In addition, the presence of gender disadvantage (high prevalence in adult women) and positive SES gradient for females indicate where interventions should be targeted. Rapid urbanisation and economic growth, leading to shifting towards unhealthy food consumption, fatty diets, free sugars and/or salt and a sedentary lifestyle are the major causes of overweight and obesity globally. Therefore, implementing comprehensive food policies as recommended by the World Health Organization such as food and beverage taxes, marketing restrictions on unhealthy foods and beverages, and mandatory Front-of-Pack Labelling (FOPL) system with warning labels (which has worked wonders in Chile and Mexico, and among many other countries), should be implemented in India to control the obesogenic environment and promotion of healthy dietary habits.

All age groups in India are increasingly consuming excessive ultra-processed food which foretells a future increase in overweight/obesity and all nutrition-related NCDs. The strengthening, scaling up and redesigning of existing undernutrition-related interventions, programmes and policies can be done to tackle the growing burden of overweight and obesity. It is important to realize the increasing intake of ultra-processed food among infants and toddlers. A cost-effective approach known as double duty actions may be applied. Most importantly, we must find a way to reduce intake of ultra-processed food consumed by preschoolers (Pries et al., 2019). Thus, policies and programs in low and middle-income countries must prioritize safeguarding child nutrition through increased micronutrient intake and capping the heightened distribution of ultra-processed food and beverages.

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- **Conflict of Interest:** None

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- **Supplementary Material:** Visit https://healthempirics.org/ for more information

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Economic Inequality of Health Outcomes Among the Elderly in Bankura District: A Decomposition Analysis

Ujjwal Das[#*] and Nishamani Kar[^]

Economic inequality plays a critical role in shaping population health. This study examines the extent of socio-economic inequality in health outcomes among the elderly population in the Bankura district of West Bengal. A cross-sectional survey was conducted using a multi-stage random sampling design among 480 older residents. Socio-economic inequality in health outcomes was assessed using the Concentration Index, concentration curves, and a regression-based decomposition approach to identify the major contributors to observed inequalities. Overall, 92% of the elderly reported at least one chronic disease. The Concentration Index indicated that cholesterol (0.40), diabetes (0.29), and hypertension (0.04) were more concentrated among the richer population, whereas bone diseases (-0.11), lung diseases (-0.24), and heart diseases (-0.04) were more prevalent among the poorer groups. Decomposition analysis showed that non-vegetarian food preference (64.5%), poverty status (15.4%), smoking (13.2%), alcohol consumption (26.2%), and being aged 60 years or above (3.8%) were key contributors to pro-rich inequality. The probit model further revealed higher odds of chronic morbidity with increasing age, living alone, alcohol intake, and smoking. The findings highlight the need for strengthened health infrastructure and targeted interventions in rural areas, especially for the oldest old.

Keywords: socio-economic inequalities, multi-stage random sampling, concentration index, decomposition, smoking

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Health inequality has become a major public health issue and challenge globally. Reducing health inequalities and developing effective public health policies for individuals is one of the important targets of the Sustainable Development Goals (SDG-10) (Bradby, 2008). Generally, health is defined as physical, mental, and social well-being, not merely the absence of disease. It is a necessary basis for people to realize their capabilities (Sen et al., 2004). However, when inequality exists, society falls short of moderating socio-economically disadvantaged individuals through social and economic policies (Fonta et al., 2020). A growing number of studies have revealed that economic inequality can negatively affect health outcomes (Neufcourt et al., 2021). Economic inequalities affect population health both directly and indirectly (Truesdale, 2016). Social theory suggests that socioeconomic inequality widens the gap in health outcomes through income inequality and exacerbates social instability. Furthermore, it increases unemployment and poverty, which are crucial challenges for social stability (Xie, 2009). Evidence from high-income countries suggests that higher levels of income inequality increase the burden of non-communicable diseases, particularly among poorer populations (Melaku et al., 2019). A study conducted by Xie found a significant pro-rich inequality in health outcomes, where richer people tend to have better health outcomes than poorer individuals (Xie, 2011). By contrast, in low- and middle-income countries, this relationship can be reversed, as rapid economic growth often results in health service utilization being more concentrated among poorer people than among the wealthier (Gu, 2019).

India is one of the middle-income countries, with an unprecedented population growth rate and currently the second most populous nation in the world. India is also experiencing rapid growth in its aging population due to an increase in life expectancy at birth (Smith, 2012). According to the 2011 Census, the 60+ population in the country accounted for 8.6%, which has increased from 5% in 1951 (Census of India, 2011). It is estimated that this share will reach 20% of the total population (323 million) by 2050 (Agarwal et al., 2020). The increasing aging population, along with rising life expectancy, raises critical concerns about whether longer lives are accompanied by healthy years. Older people are generally more vulnerable, as they are more likely to suffer from non-communicable diseases and disability (Jiao, 2019). According to the Global Burden of Disease (GBD) study, cardiovascular disease and diabetes accounted for 34.3% and 2.5% of the mortality burden in India, respectively (Tandon et al., 2018). Older people often suffer from multiple chronic diseases, such as hypertension, diabetes, stroke, heart disease, bone disease, hearing loss, and visual impairment. Furthermore, many older adults are lonely and sometimes suffer from depression when their children leave home for education or work, do not provide financial support, or fail to provide care when needed (Zeng et al., 2018). Not all older adults face these issues equally; some fare better than others depending on socio-economic factors (Marmot et al., 2008). Established literature suggests that socioeconomic status is a key determinant contributing to the unequal distribution of chronic diseases both across and within communities (Ataguba et al., 2011). The relationship between non-communicable diseases and economic status varies depending on the distribution of resources in society (Corsi & Subramanian, 2019). Studies show that non-communicable diseases manifest differently between the wealthy and the deprived, and these differences are major predictors of premature mortality and life expectancy disparities among older people (Di Cesare et al., 2013)

In the context of the Bankura district, older people residents have little or no education, and only a small proportion are economically active in the formal sector (Manna & Mistri, 2018). Regarding health disparities, older adults in this district are more prone to various diseases at higher ages, and they tend to report more illnesses due to limited access to medical facilities (Kumar et al., 2013). Older people residents in rural areas are more likely to report poor health compared to their urban counterparts. Additionally, a substantial proportion of the population belongs to the poorest economic groups. These individuals often do not utilize preventive care services and are more likely to experience premature mortality from chronic diseases than wealthier groups (Singh et al., 2019).

Despite the growing literature, little is known about district-level health disparities among older adults in Bankura, creating a critical research gap that this study seeks to address. While previous studies have highlighted the burden of non-communicable diseases and the role of socioeconomic inequality in shaping health outcomes, limited research has focused specifically on rural districts such as Bankura, where structural disadvantages in education, healthcare access, and economic resources amplify these disparities. The findings of this study will provide valuable insights for policymakers to strengthen healthcare facilities for older people residents in vulnerable rural areas such as Bankura. By focusing on older people residents, this study addresses a key research gap and generates district-level evidence to inform policies aligned with the National Programme for Health Care of the Elderly and the Sustainable Development Goals, particularly reducing health inequalities and ensuring healthy aging. Therefore, the aim of the study is to measure socio-economic health disparities among the older people in the Bankura district

- **Study Area**

The study was conducted in Bankura district, located in the western part of West Bengal, India. The district is predominantly rural with significant socio-economic and health disparities. For the present study, five blocks—Khatra, Taldangra, Simlapal, Sarenga, and Raipur—were purposively selected. Supplementary Figure S1 illustrates the geographical location of the study area.

Data and Methods

Data for the present study were drawn from a primary survey conducted using a multi-stage random sampling procedure among older adults (aged 45 and above) in the Bankura district of West Bengal, from May 2023 to September 2023. Data were collected through face-to-face interviews using a pre-tested structured questionnaire. The sample size was estimated based on a chronic morbidity prevalence of 50%, as reported in an earlier study conducted in West Bengal (Kumar et al., 2013). The calculated total sample size was 480, with a 95% confidence interval and a 5% margin of error. The sampling formula is placed in the supplementary material.

- **Study Design**

A three-stage sampling procedure was employed for the selection of the study sample. In the first stage, blocks were selected; in the second stage, villages were chosen; and in the third stage, the target population was identified. The study adopted a stratified systematic random sampling design. Initially, all 22 blocks of the district were arranged in ascending order according to the percentage of the elderly population. The blocks were stratified into three categories: low, middle, and high percentages of older people residents. From these, five blocks in the southern part of the district were purposively selected, and within each block, three villages were chosen, resulting in a total of 15 villages.

In each village, 32 respondents (16 male and 16 female) were surveyed to achieve the required sample size (Supplementary Figure S2). This strategy was employed to ensure balanced gender representation in the sample, thereby allowing meaningful comparisons between elderly men and women with respect to chronic morbidity and economic inequality. The household survey began from roadside houses, targeting individuals aged 45 years and above, and continued until the required number of respondents was reached in each village. Ethical approval for the study was obtained from the Institutional Ethics Committee of Rajiv Gandhi University prior to data collection (Approval ID: RGU/IEC/2023/017). Data were collected using pre-tested, pre-designed, semi-structured questionnaires. Information on morbidity was based on self-reporting by participants, except for hypertension, which was measured directly. The validity of the questionnaire was ensured through pilot testing before the main survey. Face validity was assessed through a pilot survey among 30 elderly respondents in a non-sampled village of Bankura district. Feedback from the pilot was used to refine question wording, sequencing, and response options to improve clarity and cultural appropriateness.

Variable Description

- **Dependent Variable**

The present study used eight Non-Communicable Diseases to measure economic inequality in health outcomes among older adults aged 45 years and above. These include Hypertension, Diabetes, Heart disease, Depression, Cholesterol, Stroke, Lung disease, and Bone disease. If a respondent reported suffering from at least one of these diseases, it was considered as the presence of chronic morbidity. The presence of any of the eight chronic conditions was coded as 1 (yes) and 0 (no).

- **Independent Variable**

As established reviewed literature suggested that several socio-demographic and behavioral factors have a significant effect on chronic diseases among the elderly aged people (Mini, 2017; Muksor, 2018). The age of the elderly is categorized into two groups: older adults (45-49 years) and Older old (60 years and above). For marital status, respondents were categorized into married and single (never married, separated, divorced, or widowed). The socio-economic factors, education categorized into three groups (no education, primary and secondary), working status two categorized formed (currently working as yes and never worked), income ranked into five quintiles (poorest, poorer, middle, richer and richest). We regrouped the quintiles into two groups. The first group is defined as non-poor if respondents belong to the last two income quintiles (richer and richest) and the poorest, poorer, and middle quintiles are defined as poor. The lifestyle behavior factors, such as food preference categorized into two choices (vegetarian and non-vegetarian), and intake of smoking, alcohol, and tobacco are formed into two groups either yes or no.

- **Statistical Methods**

For the measurements of inequality, concentration curve and concentration index were applied in the study population. "The concentration curve provides a visual impression of socioeconomic inequality in the distribution of health outcomes and depicts how shares of the health outcome variable (y-axis) are accounted for by the cumulative percentage of adults ranked by household income from the poorest to the richest (x-axis)" (Xu, 2016).

Furthermore, the value of the concentration index ranges between -1 to +1. When the concentration curve lies above the line of equality, it indicates that this outcome variable is more concentrated among the poor disadvantage groups and vice versa. The mathematical notion of concentration index is as shown below,

$$C = \frac{2}{\mu} cov(h, r)$$

Where C represents the overall index, h is the health outcome variable μ is its mean, and r is the factional rank of household income.

Furthermore, Wagstaff decomposition methods of concentration index was established to quantify each determinant's contribution to health outcomes (Wagstaff et al. 2007). The health outcome variables such as the presence of chronic diseases is a binary variable. It has codded 0 and 1. The study employed the decomposition method based on the probit regression model to conduct the decomposition Concentration Index.

In Probit regression, the cumulative standard normal distribution function Φ (·) is used to model the regression function when the dependent variable is binary, which could be specified as

$$E(Y|X) = P(Y = 1|X) = \Phi(\beta_0 + \beta_1 X)$$

The presence of chronic disease Y is a binary variable. The Model is

$$Y = \beta_0 + \beta_1 + X_1 + \beta_2 X_2 + \cdots + \beta_K X_K + \mu$$

X is the vector of regressors or socio-economic factors, x1, x2, ...xn . **β** is a vector of parameters β1,β2,…….βn

The decomposition of the concentration index could be explained as

$$C = \sum k \quad (\frac{\beta_{k\bar{x}_k}}{\mu}) C_k + GC_\varepsilon \;/\mu$$

Where C is the concentration index of health outcome, βk are the coefficients, and (x)¯_k represents the mean ofC=2/μ cov(h,r), μ stands for the mean health outcome, C_k is the concentration index for xk and GC_ε denotes the generalized concentration index for ε.

Results

Table 1 summarizes the socio-demographic characteristics of the study population and the prevalence of any morbidity. The study population consisted of 480 elderly respondents, with a nearly equal distribution of men (49.4%) and women (50.6%). More than half of the respondents were in the older old age group (60 years and above, 56.9%), while 43.1% belonged to the younger elderly (45–59 years). In terms of education, more than half (55%) had attained secondary education, whereas 22.9% had no formal education.

Table 1: Descriptive summary of the study population and prevalence of any morbidity among the Older people in Bankura district (N = 480)

Background Characteristics	Total	Percentage	% of Any morbidity (N)
Sex			
Male	237	49.38	93.25 (221)
Female	243	50.63	92.59 (92.59)
Chronic Diseases			
Absent	34	7.08	-
Present	446	92.92	-
Age			
Older Adult (45-59 Years)	207	43.13	86.96 (180)
Older Old (60Year and above)	273	56.88	97.44 (266)
Marital status			
Married	354	73.75	90.66 (332)
Single	126	26.25	98.41 (124)
Education			
No Education	110	22.92	92.73 (102)
Primary	106	22.08	94.34 (100)
Secondary	264	55.00	92.42 (244)
Currently Working			
Yes	187	38.96	87.70 (164)
Never worked	292	61.04	96.25 (282)
Economic Status			
Poor	138	28.75	92.03 (127)
Non-Poor	342	71.25	93.27 (319)
Food Preference			
Vegetarian	91	19.83	84.62 (77)
Non-Vegetarian	368	80.17	94.57 (348)
Health Insurance			
No	292	60.83	88.70 (259)
Yes	188	39.17	99.47 (187)
Smoking Status			
Yes	159	33.13	97.48 (155)
No	321	66.88	90.65 (291)
Tobacco Consumption			
Yes	259	53.96	93.44 (242)
No	221	46.04	92.31 (204)
Alcohol Consumption			
Yes	206	42.92	97.57 (201)
No	274	57.08	89.42 (245)

Table 2: Prevalence of chronic diseases among the elderly by their wealth status

Background Characteristics	Wealth Status				
	Q1	Q2	Q3	Q4	Q5
Sex					
Male	22 (9.95)	31 (14.03)	43 (19.46)	33 (14.93)	92 (41.63)
Female	25 (11.11)	49 (21.78)	42 (18.67)	33 (14.67)	76 (33.78)
Age					
Older Adult (45-59 Years)	19 (10.56)	36 (20.0)	35 (19.44)	23 (12.78)	67 (37.22)
Older Old (60Year and above)	28 (10.53)	44 (16.54)	50 (18.80)	43 (16.17)	101 (37.97)
Marital status					
Married	34 (10.56)	55 (17.08)	60 (18.63)	42 (13.04)	131 (40.68)
Single	13 (10.48)	25 (20.16)	25 (20.16)	24 (19.35)	37 (29.84)
Education					
No Education	25 (24.51)	30 (29.41)	27 (26.47)	11 (10.78)	9 (8.82)
Primary	13 (13.00)	32 (32.0)	23 (23.00)	21 (21.00)	11 (11.00)
Secondary	9 (3.69)	18 (7.38)	35 (14.34)	34 (13.93)	148 (60.66)
Currently Working					
Yes	16 (9.76)	29 (17.68)	38 (23.17)	16 (9.76)	65 (39.63)
Never worked	31 (11.03)	50 (17.79)	47 (16.73)	50 (17.79)	103 (36.65)
Food Preference					
Vegetarian	8 (10.39)	13 (16.88)	16 (20.78)	13 (16.88)	27 (35.06)
Non-Vegetarian	39 (11.21)	60 (17.24)	65 (18.68)	53 (15.23)	131 (37.64)
Health Insurance					
No	46 (17.76)	63 (24.32)	59 (22.78)	47 (18.15)	44 (16.99)
Yes	1 (0.53)	17 (9.09)	26 (13.90)	19 (10.16)	124 (66.31)
Smoking Status					
Yes	14 (9.03)	24 (15.48)	22 (14.19)	30 (19.35)	65 (41.94)
No	33 (11.34)	56 (19.24)	63 (21.65)	36 (12.37)	103 (35.40)
Tobacco Consumption					
Yes	38 (15.70)	42 (17.36)	54 (22.31)	48 (19.83)	60 (24.79)
No	9 (4.41)	38 (18.63)	31 (15.20)	18 (8.82)	108 (52.94)
Alcohol Consumption					
Yes	14 (6.97)	29 (14.43)	24 (11.94)	25 (12.44)	109 (54.23)
No	33 (13.47)	51 (20.82)	61 (24.90)	41 (16.73)	59 (24.08)

Table 3: Concentration Index in wealth quintile by different chronic diseases

Wealth Quintile						
Variables	**Poorest**	**Poorer**	**Middle**	**Richer**	**Richest**	**Total**
Hypertension	0.06	-0.11	0.03	0.01	0.15	0.04
Diabetes	0.29	-0.04	0.24	0.07	0.14	0.29
Heart Diseases	0.14	0.23	-0.09	0.24	0.09	-0.01
Lung Diseases	-0.05	0.26	0.37	-0.77	-0.56	-0.24
Depression	-0.13	-0.15	0.37	-0.28	-0.18	0.06
Bone diseases	0.08	-0.2	-0.06	-0.04	-0.22	-0.11
Cholesterol	-0.02	0.13	-0.1	0.13	-0.03	0.4
Stroke	-0.14	-0.3	-0.25	0.14	-0.11	-0.01
All	0.00039	0.0233	0.0271	-0.0252	0.0319	0.013

Overall, 92.9% of the respondents reported at least one morbidity. The prevalence of morbidity was slightly higher among men (93.3%) than women (92.6%). Older adults aged 60 years and above had a markedly higher prevalence (97.4%) compared to those aged 45–59 years (87.0%). Similarly, widowed/single respondents reported a higher burden of morbidity (98.4%) than married respondents (90.7%).Those who had never worked (96.3%) reported more morbidity than those currently working (87.7%). By economic status, prevalence was comparable—92.0% among the poor and 93.3% among the non-poor. Notably, non-vegetarians (94.6%) had a higher morbidity prevalence than vegetarians (84.6%). Behavioral risk factors also showed strong associations: smokers (97.5%), alcohol users (97.6%), and tobacco users (93.4%) had higher prevalence of morbidity compared to their counterparts.

Table 2 presents the prevalence of chronic diseases among the study population by household wealth status. The results show that both males and females from the richest households (Q5) had a higher prevalence of chronic diseases (41.6% and 33.8%, respectively) compared to those from the poorest households (Q1). Older adults in the richest households also reported a higher prevalence (37.9%). Interestingly, non-educated individuals from the poorest households had a greater burden of chronic diseases than their counterparts in the richest households (24.5% vs. 8.8%). In addition, the richest households had the highest proportion of health insurance coverage and reported more chronic diseases (66.3%). Overall, wealth and lifestyle behaviors were positively associated with a higher prevalence of chronic diseases in the study population.

Table 3 shows the estimated concentration index of different chronic diseases across wealth quintiles. A negative value implies pro-poor inequality, meaning that poorer older people have suffered more from these diseases. For example, the concentration indices of heart disease (-0.01), lung diseases (-0.24), bone disease (-0.11), and stroke (-0.01) indicate that these conditions were more prevalent among individuals with lower wealth status. In contrast, hypertension (0.04), diabetes (0.29), depression (0.06), and cholesterol (0.40) were more concentrated among individuals with higher wealth status (Fig. 3).

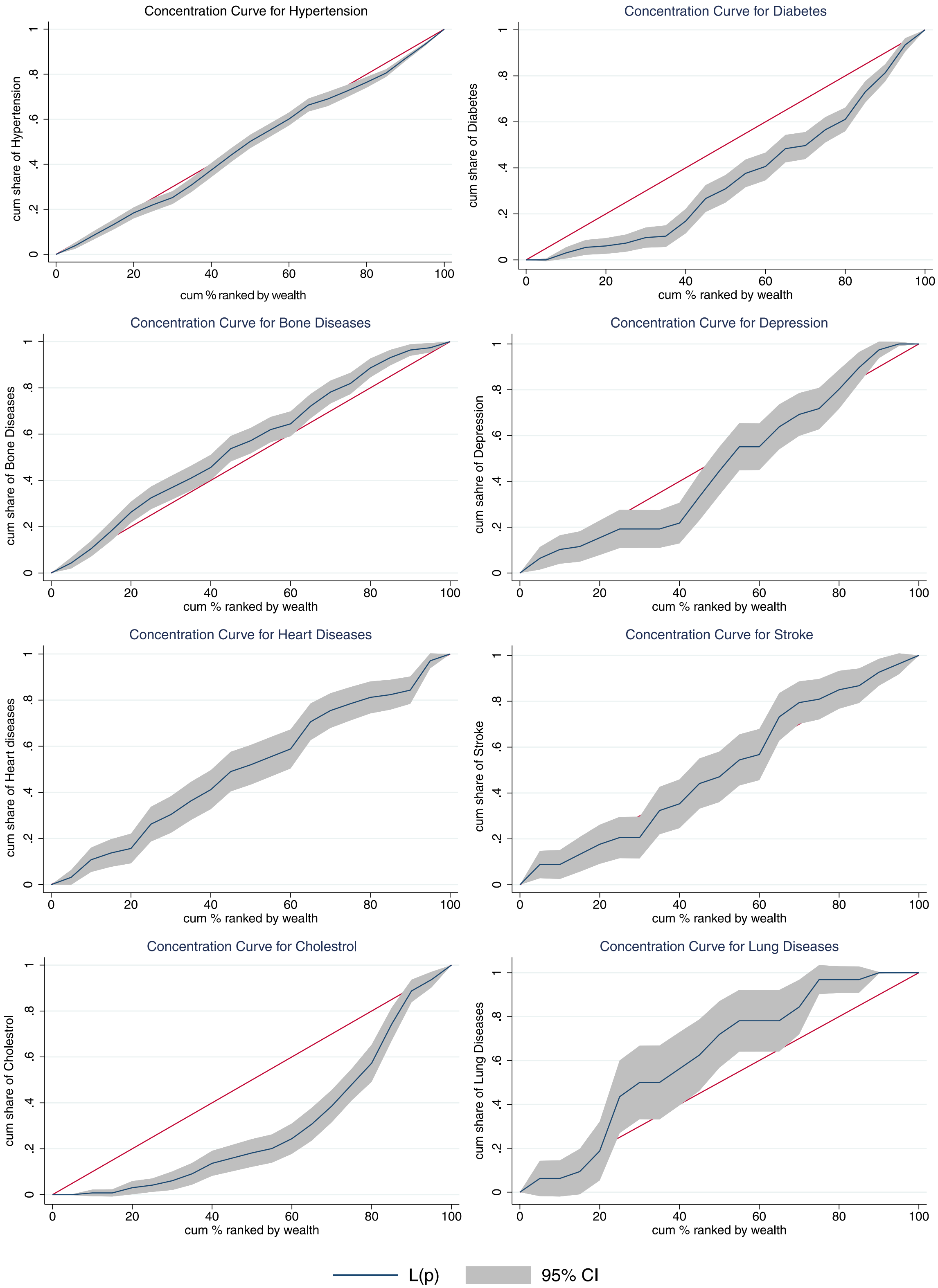
Table 4 depicts the results of the decomposition analysis of the concentration index for the presence of chronic diseases. The prevalence of chronic diseases was higher among those aged 60 years and above (CI = 0.001), individuals with secondary education, those living alone (CI = -0.0017), the economically poor (CI = 0.0302), and those who consumed tobacco or alcohol. Further decomposition of the CI contribution factors revealed that non-vegetarian food preference (64.5%), poverty (15.4%), smoking (13.2%), alcohol consumption (26.2%), and age 60 years and above (3.8%) were the major contributors explaining the pro-rich inequality in the presence of chronic diseases. By contrast, the contribution of health insurance to the concentration index was only 0.08%, indicating that coverage by health insurance made a relatively smaller contribution to pro-rich inequality in disease prevalence.

Table 4: Decomposition analysis of probit regression and contributions to inequality in the presence of chronic diseases among the elderly

Background Characteristics	Coeff.	95% CI	Elasticity	CIs	Absolute contribution	Percentage contribution
Age						
Older Adult (45-59 Years)	Ref.					
Older Old (60 and above)	0.82	(0.31 – 0.93)	0.502	0.001	0.0003	0.038
Marital status						
Married	Ref.					
Single	0.32	(0.11– 0.69)	0.089	-0.0017	-0.0002	-0.0182
Education						
No Education	Ref.					
Primary	-0.03	(-0.69 – 0.62)	-0.008	-0.0393	0.0003	0.0372
Secondary	0.01	(-0.54 – 0.57)	0.008	0.0368	0.0003	0.0369
Currently Working						
Never worked	Ref.					
Yes	-0.50	(-0.97 – -0.04)	-0.211	0.0098	-0.0021	-0.2446
Economic Status						
Non-Poor	Ref.					
Poor	0.14	(-0.31 – 0.59)	0.043	0.0302	0.0013	0.1546
Health Insurance						
No	Ref.					
Yes	1.31	(0.49 – 2.14)	0.553	0.0001	0.0001	0.0080
Food Preference						
Vegetarian	Ref.					
Non-Vegetarian	0.43	(-0.03 – 0.89)	0.371	0.0146	0.0054	0.6459
Smoking Status						
No	Ref.					
Yes	0.21	(-0.51 – 0.93)	0.076	0.0146	0.0011	0.1327
Tobacco Consumption						
No	Ref.					
Yes	0.13	(-0.31 – 0.56)	0.075	-0.0060	-0.0004	-0.0531
Alcohol Consumption						
No	Ref.					
Yes	0.37	(-0.32 – 1.05)	0.170	0.0130	0.0022	0.2625
Total					0.008	1.000

Moreover, the probability of chronic diseases increased with age—older adults aged 60 years and above (coeff = 0.82, $p < 0.001$), those living alone (coeff = 0.32, $p < 0.05$), the elderly with health insurance (coeff = 1.31, $p < 0.001$), and those with a non-vegetarian food preference (coeff = 0.43, $p = 0.07$) had higher risks. In contrast, older people who were currently working had a reduced risk of chronic diseases (coeff = -0.50, $p < 0.05$) compared to those who were not working.

Figure 3: Concentration curve of chronic diseases



Discussion

The present study investigated the economic inequality of health outcomes among older adult people in the Bankura district. About 92% of individual were suffer from at least one chronic diseases. The prevalence of these diseases was higher among the oldest old (60 years and above) compared to older adults (45 years and above). These results are consistent with previous findings that elderly individuals aged 60 years and above had higher odds of suffering from chronic diseases (Bardage et al., 2005). Literate older people had a higher likelihood of reporting chronic diseases than non-literate older people. Other studies have mentioned that individuals with different education levels may evaluate their health differently; for example, lower health ratings are more strongly associated with mortality among adults with higher education (Srivastava et al., 2021). Older people from poor households had a higher likelihood of chronic diseases than those from non-poor households. A study by Beckfield et al. (2013) also noted that poor health is significantly associated with individuals from lower socio-economic backgrounds and low-income families. Poverty plays an influential role in the presence of chronic diseases. An earlier study conducted in China found that the prevalence of chronic diseases was three times higher among low-income earners compared to high-income earners (Feng et al., 2012).

Our findings further suggested that older people living alone were more likely to report chronic diseases compared to those not living alone. This aligns with previous research, which found that elderly men without spousal support are often exposed to poor diets, undisciplined lifestyles, difficulties in carrying out household chores, and lack of personal care, making them more vulnerable to poor psychological well-being compared to those in relationships (Khura et al., 2022). In addition, older people living in rural areas are structurally disadvantaged due to limited healthcare resources, poor socio-economic status, unhealthy lifestyles, risky behaviors such as smoking, alcohol, and tobacco consumption, and lower levels of educational attainment. As a result, they are more vulnerable to chronic diseases. Furthermore, the suffering from multiple chronic conditions among poor elderly individuals is exacerbated by lack of access to quality healthcare services, advanced medical technology, and the burden of out-of-pocket expenditures—another significant finding of this study (Jiao, 2016).

The key findings of the study indicate that economic inequality in chronic diseases among the elderly varied widely across different socio-economic statuses in the district. Chronic morbidity emerged as a significant predictor of poor health among older adults. The observed inequalities suggest that elderly individuals from lower socio-economic backgrounds may face barriers in accessing timely therapy for conditions such as hypertension and diabetes, potentially due to the burden of out-of-pocket expenditure. This interpretation is consistent with a large number of studies conducted in low- and middle-income nations, which have documented a significant association between economic gradients and health outcomes (Vellakkal et al., 2015). Therefore, differences in social, cultural, economic, and health care systems contribute to the unequal distribution of non-communicable disease prevalence in households.

Results from the decomposition analysis suggested that food preference, specifically being non-vegetarian, was identified as the biggest contributor to pro-rich inequality in the presence of chronic diseases. The study also revealed that economic status was the second most important contributor to pro-rich inequality in elderly health, which is consistent with the earlier findings of Xu et al. (2016). In middle-income countries, evidence shows that NCDs are more prevalent among low socio-economic households due to poor access to healthcare, psychosocial stress, and lack of awareness and control of NCDs. Risky lifestyle behaviors, such as alcohol intake and smoking, further widened economic inequality in elderly health outcomes. A prior study mentioned that the "DALY rate of alcohol abuse in men is 16 times more affected by economic inequality than the DALY rate of alcohol abuse in women" (Pinkhasov et al., 2010).

Another important finding of the study is that older people who were currently working contributed to reduced inequality in health outcomes. From these findings, it is well documented that the burden of non-communicable diseases intensifies economic inequality at the household level, with the effect being higher in households that include the oldest old population (65 years and above) (Liu et al., 2016). A higher level of income inequality has been shown to increase the risk of depression, though not anxiety, as demonstrated in an earlier cross-sectional study (Chiavegatto et al., 2013). Non-communicable diseases often stem from lifelong exposure to detrimental health and socio-economic conditions within households.

The economic inequality in the distribution of these diseases indicates that individuals with higher socio-economic status generally experience higher levels of NCDs on average. Simultaneously, economic inequality may influence population health through multiple pathways—for example, the impact of social factors that increase the risk of cardiovascular disease prevalence (Karriker-Jaffe et al., 2013), and reduced healthcare utilization caused by high out-of-pocket expenditures (Pinkhasov et al., 2010). The reduction of economic inequality alongside addressing the burden of non-communicable diseases are critical strategies embedded within the Sustainable Development Goals, namely SDG 10 and SDG 3 (Gaspar et al., 2021). Therefore, comprehensive healthcare services are urgently required for the rural elderly population in the Bankura district to reduce the high burden of NCDs while simultaneously addressing socio-economic inequality.

Limitations of the study

This study has certain limitations that should be acknowledged. First, the data on morbidity were self-reported, which may be subject to recall bias and could affect the accuracy of the estimates. Second, the study did not include information on communicable diseases, limiting the scope of health outcomes assessed. Third, the cross-sectional design restricts the ability to establish causal relationships between socioeconomic status and health outcomes. Fourth, while the sample size was adequate for the objectives, the findings are drawn from a single district and may not be fully generalizable to other regions of India. Finally, as with any survey-based study, issues related to reporting errors and data quality cannot be entirely ruled out.

Conclusion

This study highlights substantial economic inequalities in health outcomes among the elderly in Bankura, with chronic diseases being highly prevalent. The burden was particularly pronounced among the oldest old (60 years and above), elderly without spousal support, those with secondary education, and individuals from economically poor households. These findings underscore the need for targeted interventions addressing vulnerable subgroups rather than adopting a one-size-fits-all approach.

From a policy perspective, strengthening geriatric healthcare services in rural areas is essential. Government agencies should prioritize expanding the National Programme for Health Care of the Elderly (NPHCE) at the district level, with a focus on screening and early detection of chronic diseases. NGOs and community-based organizations can play a vital role in promoting health awareness, reducing risky behaviors such as smoking and alcohol use, and offering psychosocial support for elderly living alone. Strengthening primary healthcare infrastructure, ensuring affordable access to medicines, and integrating health insurance coverage for chronic disease management are also critical steps. By addressing both medical and socio-economic determinants, these measures can reduce inequalities and promote healthy aging in vulnerable rural populations.

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- **Conflict of Interest:** None

- **Author Contributions:** UD and NK contributed to the conception and design of the study. UD was responsible for the acquisition, analysis, and interpretation of data, as well as drafting and writing the manuscript. NK provided supervision and project administration. Both authors critically revised the manuscript, approved the final version to be published, and agreed to be accountable for all aspects of the work.

- **Supplementary Material:** Visit https://healthempirics.org/ for more information

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Livelihood and Status of Tobacco Processing Workers: Insights from Selected States in India

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Processing is one of the prime activities in tobacco production and is a labour-intensive activity in India. It involves processes starting from cleaning raw tobacco leaves to crushing them into different sizes/particles or making fine dust in accordance with the requirements of the industries producing bidi, cigarette, zarda, mouth freshener, pan masala, khaini, snuff, and chewing tobacco. There is also a lack of information on the number of processing workers, their livelihood, and, the health hazards of working in tobacco processing units in India. This paper discusses the working conditions and livelihoods of tobacco processing workers and their health status. The study followed snowball sampling to identify a sample of 500 processing workers spread out in the states of Andhra Pradesh, Gujarat, Karnataka, Maharashtra, and West Bengal. The poor working conditions, lack of social security benefits, low standard of living among a majority of workers, reporting of chronic illness among processing workers, absence of scientific studies on the health conditions of workers, and a majority of processing workers not being happy with their employment are the reasons enough for policy intervention to look into their working conditions and find out ways and means to rehabilitate them in other occupations and wean away the new entrants into tobacco processing job market. There is a need for scientific studies based on a large sample of processing workers capturing both clinically diagnosed and self-reported health symptoms for validating the linkage between exposure to tobacco dust and health problems among workers.

Keywords: Tobacco, Processing, Livelihood, Workers

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The final product of tobacco before reaching the consumer involves activities ranging from farming, harvesting, curing, processing, grading, packaging, marketing, manufacturing, distribution, and retailing. Processing is one of the prime activities in tobacco production and is a labour-intensive activity in India. It involves processes starting from cleaning raw tobacco leaves to crushing them into different sizes or fine dust. The crushed leaves differ in size and substance in accordance with the requirements of the industries producing bidi, cigarette, zarda, mouth freshener, pan masala, khaini, snuff, and chewing tobacco. In total it involves processes transforming leaves in to powder.

Women are largely involved in processing activities. Tobacco processing is carried out mainly in Karnataka, Gujarat, Andhra Pradesh, West Bengal, and Maharashtra. These are the states, which cultivate different varieties of tobacco.

There is a dearth of information on tobacco processing in India as it is largely in the unorganized sector. Taking into account the production estimates for the entire bidi and chewing tobacco in the country (around 60% of 750 million kg of raw tobacco produced annually in the country), the number of workers involved in the tobacco processing industry in India can be roughly estimated to be less than one lakh workers (Nayak, 2018). There is also a lack of information on the livelihood and health hazards of the workers in tobacco processing in India. While the hazards of habitual tobacco usage are well established, very little information is available about the effects of occupational tobacco exposure, particularly the processing of raw tobacco. The research on tobacco processing workers is a grey area. Although many attempts have been made to look into the life and working conditions of bidi rollers who are engaged in making a final tobacco product, very little information is available on processing workers who deal mainly with raw tobacco used for making tobacco products.

Studies indicate that the workers in tobacco processing industries are exposed to dust and work under unhygienic conditions without using masks and gloves and, many of them being unregistered workers without identity cards (IDs) (Mahurkar, 1990; Rudrama & Naik, 2012; Sabale et al., 2012; Khanna et al., 2013; Kaup et al., 2017; Bhalshankar & Ugle, 2020). Mahurkar (1990) reported that in many cases filed against the owners of ‘Kharis’ (in Gujarat processing units are known as ‘Kharis’), the workers could not win as their names were not entered in the register of the unit either because they were minor or were taken on a temporary basis. It was also noted that there was no proper ventilation in the processing units. Although most of the units are registered, there was neither inspection of the working conditions nor scrutiny of the application of the labour laws in these workplaces. Bagwe & Bhisey (1993) report that although the prosperity brought by cultivation and processing of tobacco was visible by the material assets owned by the processors in the Kheda district of central Gujarat, it did not trickle down to poor workers who toiled for hours to shower prosperity to their owners. And there are no scientific reports found off late on their improved conditions in the 'Kharis'.

A pioneering study on occupational health problems of tobacco processing workers in India carried out by Ghosh et al. (1985) revealed self-reported symptoms of vomiting, giddiness, and headache during and after processing work among 69% of workers. These workers had higher rates of nicotine and cotinine in urine excretion. Similarly, a study by Bagwe & Bhisey (1993) revealed cotinine levels in the saliva of 19% bidi workers and 100% of tobacco processing plant workers not in the habit of tobacco consumption. Mahimkar & Bhisey (1995) monitored workers engaged in the processing of bidi tobacco in India using peripheral blood lymphocytes as the test system and found increased chromosomal aberrations in tobacco processing workers compared to those in the control group, which indicates genotoxicity among tobacco processors. Bhalshankar & Ugle (2020) study found a relationship between tobacco dust exposure and changes in total thiol status. A significant decrease in levels of total thiol was found in all groups of bidi workers as compared to those in the control group. Singi & Hallikeri (2023) studied 825 tobacco processing workers in tobacco factories of Nippani city in Belagavi district of Karnataka to examine the health status of the workers. The results reveal that around 40% reported back pain caused due to being in uncomfortable posture for a prolonged time, 37% reported hand/arm fatigue 19% reported headaches, 17% reported breathing problems, 14% had vision problems and 12% reported issues with dental care. Nausea, skin diseases and palpitation were other problems reported by the workers. Despite these problems, 56% of the workers did not use protective measures like masks and gloves. In a limited study carried out by Patel et al. (2022) with fifty tobacco workers in factories of Kheda found that cough (84%), wheezing (48%), Rhinitis, back problems (40%), redness of eyes (64%), skin rashes (44%) and fever (62%) were the major health problems reported by workers.

Similar findings have emerged from studies conducted in the other countries too. The effects of occupational exposure to tobacco dust on the respiratory system of 1020 tobacco workers was attempted in Greece by Chloros et al. (2004). No significant association was found in chronic diseases in the lower respiratory systems and pollutants as against, a slightly higher reporting of disorders of upper respiratory systems in work sites compared to the participants in the control group. A study carried out by Rawan and Suzan (2023) in the city of Lattakia in Syria in a cigarette manufacturing factory revealed that more than 50% of the factory workers had respiratory problems, musculoskeletal and varicose veins problems in addition to physical and psychological fatigue and stress. However, the authors revealed that due to lack of use information on occupational hazards, there was a low reporting of occupational hazards due to environmental factors. However, it throws light on the health problems of the workers in selected factories of the district.

These studies provide useful information on the health status of tobacco workers. However, they do not explore how the conditions at the workplaces exacerbate the health hazards of the poor and unprotected workers. As we mentioned earlier, tobacco processing is largely an unorganised activity in India. It is carried out in isolated locations in closely supervised units that often accommodate the workers and their families within the premises. The current study attempts to understand the association between health problems experienced by processing workers and their conditions of living and working including access to social security benefits. It also investigates the skills these workers possess, their perceptions about the prospects of their children taking up such a hazardous activity, and the possibility of moving to other sources of livelihoods The study aims to help policy in understanding the likelihood of future generation taking up this work, the skills required for entering alternative occupations, and the opportunities that exist for such alternatives. For the existing workers, the study identifies the gaps in availing social security benefits.

Research methodology

The study covers tobacco processing workers in Karnataka, Gujarat, Maharashtra, Andhra Pradesh (AP) and West Bengal (WB). Tobacco processing is found mainly in these five states in India.

- **Sampling**

The study adopted purposive sampling or snowball sampling methods chosen according to convenience in each of the selected states. Since the spread of the units and employment therein is not readily available, we choose to keep the sample to 100 tobacco processing workers in each state with a total sample of 500 tobacco processing workers. Since the number of processing workers in India is not recorded and their details are not known, we limited the sample to 100 per state. This is one of the limitations of the study. In all states actual sampling finally done was 512; 103 each in states of Andhra Pradesh, West Bengal, Gujarat, 102 in Maharashtra and 101 in Karnataka. This is because in all states 1-3 more samples have been collected by the respective teams.

It was initially decided to sample five processing units and 20 processing workers per unit selected randomly in each of the selected state for detailed interviews. However, in most of the states, we could not get entry into processing companies and the employers did not allow talking to workers. Therefore, we met workers in colonies and neighbourhoods where most of the them resided. The interviews were done at workers' homes in the morning (before going to work) and at night (after returning from work). The selected tobacco processing workers were interviewed in

Prakasam and Guntur districts of AP, Charotar region (Anand and Kheda districts) of Gujarat, Nippani tract of Belgaum district in Karnataka, Cooch Behar district in West Bengal and Sangli and Kolhapur districts in Maharashtra. These are the main centres of tobacco processing in the selected states. Given that given the sample is collected through snowball method, for analysis we have used basic statistical tools and non-parametric tests for comparing groups.

The tobacco processing workers have been defined as those who are engaged in processing work for at least six months in a year and it's the major source of livelihood for the household. The tobacco processing units we visited are basically those units which process dry tobacco leaves from the farm into different grades of tobacco dust to be used in various chewing and smoking tobacco products.

Tobacco processing: Empirical findings

The tobacco processing worker was the respondent in the survey and answered most of the questions related to processing. The study covered workers of about 110 units across the five selected states - 10 in AP, 40 in Gujarat, 20 in Karnataka, 20 in Maharashtra and 20 in West Bengal. In Gujarat, tobacco processing units or kharis did not have names as the processing was done mainly in backyards of residences of owners of these tobacco processing units. Most of these houses and processing units are built in their farm lands which makes them ideal with required space for drying, processing and packaging the dried tobacco leaves.

- **Socio-economic background and living/working conditions of the processing workers**

A majority (53%) of the respondents available for discussion during the survey were female processing workers. In Gujarat, however, as high as 92% of the workers available for discussion were men. It may be noted that male migrant workers from AP constituted the largest chunk of processing workforce in Gujarat. Men formed more than half of the workers interviewed in AP and WB. In AP most of the workers were found to be intra-state migrants from the neighbouring districts. In WB, while the women mainly rolled the bidis, men do processing work.

And, 66% of the respondents in the sample were in the age group of 30 to 60 years. Around 9% of the sample processing workers were working even after the age of 60, most of them being in Karnataka and Maharashtra. In Gujarat, none of the workers were above the age of 60 possibly indicating that only able-bodied migrant workers are offered employment in the industry. Overall, 20% of the workers from the survey were widows or widowers. Nearly 81% of the sample workers were Hindus, 15% Muslims, and 4% Christians. More than half (56%) of them were illiterates with only 1% being graduates. A majority (60%) of the workers lived in slums ranging from 17% in AP to 96% in Maharashtra. Most (73%) of the dwellings were owned by the workers, while 11% of the workers reported living in rented houses. The rest were staying in parental houses.

Liquefied Petroleum Gas (LPG) is available to 63% of households while 36% still use fuelwood as the main source and the remaining 1% use kerosene and cow dung for cooking purposes. The toilet facility is available to only 67% of the households. Others used community toilets or openly defecated.

Most of the workers belonged to weaker sections with 41% being SCs and STs. Around 37% belonged to OBCs and the remaining 28% were from the general category of the population. Around 27% were working as labour in the tobacco processing units for 10-25 years, while 17% were working for more than 25 years. While a majority started working in processing activity during the age of 25 to 50 years, around 3% had started working even after the age of 50. But it was deeply troubling to note that a few processing workers whom we interviewed, had started working as young children - even before attaining eight years of age (3%). Another 11% said that they had entered the workforce before they attained 16 years of age.

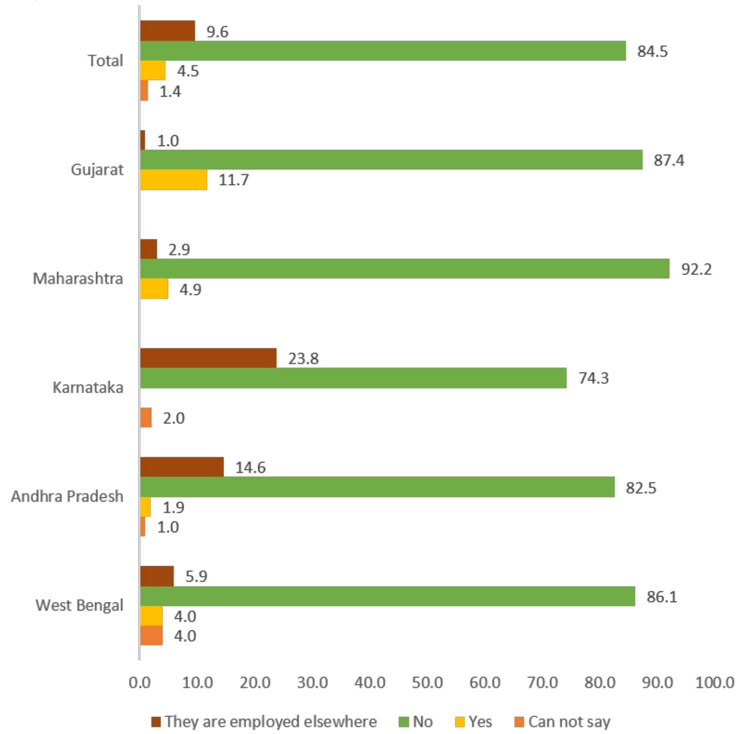
The responses of the sample processing workers on the choice of occupation reveal that processing is not a family occupation like bidi rolling, which is generally passed on inter-generationally, say, from the mother to her children, particularly, girls. Only 25% of the total sample of 512 processing workers' parents were involved in tobacco processing. Further, only in 23% of the sample households, we find other members were engaged in tobacco processing during the survey. Around 85% of the processing workers did not want their children to take up processing as their occupation (see Figure 1). And 10% of the sample processing workers reported that their children were already employed in other activities.

Only half of the processing workers are lucky to get the work throughout the year. Around 11% received work for less than three months. Around one-third of the workers in AP, WB and Maharashtra received work for more than nine months. On average around 60% of the workers work mostly 5-8 hours per day. In AP, 42% of the processing workers reported working for more than 8 hours per day.

Workers generally tie scarves or cloth on their faces to avoid dust, while a few work without it. The work is carried out from mid-October to January and from April to June. Tobacco processing is halted during monsoons to avoid dampness. As reported by the workers and the employer, the workers get a daily wage of Rs. 200 and benefits such as provident fund, pension and bonus. But these are available only to registered workers.

Most of the processing workers, except in WB, reported that their workplace had proper ventilation. Safety measures taken by processing units seem to be higher in AP as nearly half of the workers used gloves and 70% of the workers reported using

Figure 1: Distribution of Respondents by their Opinion on Children Taking Up Processing Work (%), N = 512



Source: Field Survey

masks. Usage of masks and gloves was observed to be the lowest in Gujarat. Only 18% and 31% of the workers used gloves and masks respectively while working. In 'Kharis' in Gujarat, none of the workers used gloves or masks. Most of the tasks like winnowing, grading, and packaging are carried out with bare hands in small premises surrounded by tobacco dust and residues. Nicotine observation through bare palms in the absence of gloves and exposure to dust without mask is likely to cause health problems to processing workers. It should be noted that the percentage of workers having IDs (28%), using masks (70%) and gloves (54%) is higher in AP. The working conditions seem to be better in AP as these men are involved in the processing of cigarette tobacco also. Mahurkar (1990) and Bagwe and Bhisey (1993) also indicate the harsh realities of the processing work wherein workers are denied of basic benefits and institutional recognition. Beyond these, it appears that there is no updated information regarding tobacco processing workers in the country.

Overall, only 10% of the workers possessed IDs. None of the workers in Gujarat and WB and, barely 8% of the processing workers in Maharashtra had IDs issued by the companies. This indicates the informal nature of tobacco processing wherein workers must work at the mercy of the employer without demanding any social and economic benefits. One-fifth of the processing workers seem to be migrants. The share of migrants appears to be higher (48%) in Gujarat where it was reported that workers from Rajasthan are brought by companies specifically for processing work. A separate living arrangement is made for these workers who toil day and night within the premises of the units.

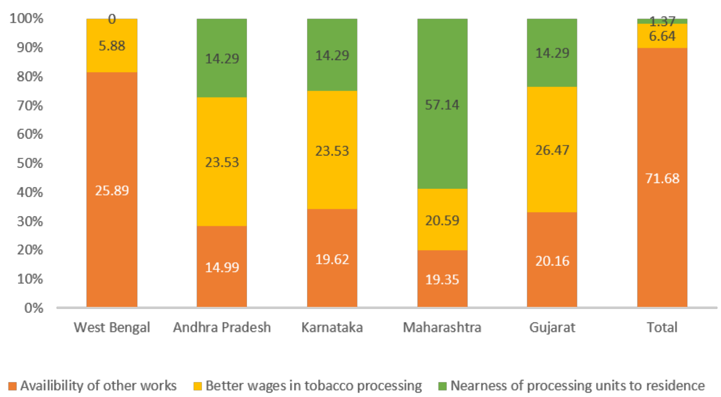
- **Sub occupations of the processing workers and Alternate employment opportunities**

Apart from processing work, workers are engaged in some other activities which are additional sources of earnings for them. The other sources of employment available to processing workers include Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGA), reported by 3% households, agriculture labour reported by 11% households, non-agriculture labour reported by 8% households and self-employment reported by 2% households. Tobacco processing on an average gave 291 days of labour to the workers with lowest man-days of 206 in Karnataka and highest man-days of 351 days in Gujarat. This indicates that there is very little scope for processing workers to take up alternative jobs in Gujarat.

Although only 12% of the workers reported the availability of alternative employment opportunities in WB, 81% expressed their desire to shift from processing work if opportunities exist. More than half of the workers said that they were interested in shifting to alternate work in all the selected states except Karnataka (42%). In total, 56% of the workers wish to take up other works if such opportunities were available. Availability of alternate employment opportunities was reported by a higher percentage (38%) of workers in Karnataka. Overall, 30% of the workers think that alternate employment opportunities exist near their place of stay.

We tried to find the capabilities and skills of processing workers as it could help in understanding the scope for finding alternative employment opportunities available to workers in the region. Around 42% responded to the question on what employable skills they possess in addition to processing work. Of this, 56% revealed a single skill while the remaining reported possession of more than one skill. And the number of reported skills to the number of workers is in the ratio of 1:1.5 indicating that many possess additional skills. About a fourth of the workers reported being familiar with agricultural operations. This percentage corresponds with the proportion of workers who possess agricultural land (21%). Expertise in cooking was reported by 19% presumably due to the larger representation of women in the sample (53%). The other major skill reported by workers was livestock rearing (13%). As the processing workers are from rural background and agricultural families, they are aware of livestock rearing. Around 7% possess the skill of tailoring and embroidery,

Figure 2: Distribution of Workers According to the Reasons for Continuing Work in Tobacco Processing Despite Knowing that it is Harmful (%), N= 512



Source: Field Survey

2% knew bidi rolling and, less than 1% reported possessing knowledge of account keeping and computer operations, which are essential for getting employment in the current digitalized economy. Most of the business activities require the latter two skills. And, fetching sustained alternate jobs based on the skills of cooking, agriculture and livestock rearing is very difficult in rural and non-commercial areas as these are basics to many households and most of them carry out these activities for their households. They are less employable skills

- **Health awareness**

In response to the question how do they rate their health, only 41% of the processing workers said that they perceive their health to be good, while 45% said not so good and 14% rated their health as poor.

As reported from the field, while a majority (78%) of the processing workers knows that tobacco dust is harmful, 15% did not agree with it and 7% did not know whether it is harmful or not. But, 89.95% of the workers who felt tobacco dust was harmful across the selected five states have continued to work in the processing sector because no other work was available to them (see Fig 2). The availability of better wages is another major reason cited by 8.33% of the workers for continuing the processing work despite knowing about its adverse effects on the health of the workers.

The extant studies support the observation of high incidence of chronic illness among tobacco workers. Respiratory issues from continued inhaling of tobacco dust and other particles, musculoskeletal disorders from prolonged awkward postures, eye/ skin irritation, headaches, and dizziness were reported in many studies. Table 1 presents the distribution of workers in the sample according to self-reported chronic illnesses. The presence of long-term illness (such as asthma, body pain, chest pain and cough, headache, acidity and gastric problems) is reported by 42% of the workers in the sample (Table 1). Self-reported illness during the reference

Table 1: Distribution of Workers According to Self-Reporting of Chronic Illness (%), N=512

States	Yes	No
West Bengal	68.93	31.07
Andhra Pradesh	80.58	19.42
Karnataka	33.63	66.37
Maharashtra	26.47	73.53
Gujarat	0.97	99.03
Total	216 (42.19	296 (57.81)

Source: Field Survey

period of past 30 days was noted among 44% of the workers. Recent studies by Singi and Hallikeri (2023) and Patel et al. (2022) respectively in Karnataka and Gujarat also have found widespread reporting of illnesses among the processing workers.

We recognise that self-reported health status needs to be validated with bio-markers/clinical test in a larger sample for generalisation. How, it is a good indicator about feeling good physically and mentally.

We recognise that self-reported health status needs to be validated with bio-markers/clinical test in a larger sample for generalisation. How, it is a good indicator about feeling good physically and mentally.

- **Wages and Social Security Benefits**

Processing workers are paid in different modes - piece rates, daily wages, and monthly salaries. The wage rate for tobacco processing was found to be very low being Rs 6-7 per kg. The daily earnings varied between Rs. 150 in WB to Rs.227.49 in Karnataka (including employer's contribution towards EPF).

The owners of the processing units were worried by the labour regulations that require registered units to provide social security benefits like 10% Employee Provident Fund (EPF), 20% bonus, holidays on national festivals, gratuity, leave with wage, and minimum wages. Hence, they do not register all the employees.

They feel that it is better to close the units if all these norms are to be followed by them.

It was found that except for bonus payment, processing workers are mostly deprived of other benefits like EPF, Employee State Insurance (ESI) coverage, maternity benefits, payment of gratuity, workmen compensation in the case of death, housing facility, educational aid and group insurance. This is more so in WB where workers have not been allotted IDs. The workers in all the selected states reported receipt of bonuses though the percentage of workers receiving these benefits varies from 16% in WB to 97% in Maharashtra. Payment of bonus, however, depended on attendance. Some workers reported that their owners took them out for picnics every year at company expenses.

A few workers in AP reported the availability of many of these benefits. The payment of DA and housing facilities was reported only in Gujarat. EPF, a major social security benefit is available to only 48% of the workers in AP and 16% in Karnataka. Maternity benefit was reported by only one or two workers in AP and Gujarat. And ESI facility is reported only by 17% of the workers in AP. Around 2.5% of the workers had some kind of group insurance coverage (reported by 11% of the workers in AP and one worker in Gujarat). The payment of gratuity was reported by around 10% of the workers only in AP and Karnataka. Overall, the information available from five selected states reveals that workers in AP have most of the benefits although it is not uniform and not available to all. It could be mainly because at least 28% of the workers in AP have IDs, which means they are legally recognized.

- **Annual Earnings of Tobacco Processing Workers**

Tobacco processing is the main earning activity for the workers as shown in figure -3. The average annual income from tobacco processing per worker varied from a meagre amount of Rs.28,000 in Gujarat to Rs. 84,000 in AP. The earnings are higher in AP because 100% of the workers reported processing work to be available for the entire year and more than 40% reported working for more than 8 hours a day. In addition, the total sample workers in five selected states earned an average income of Rs. 15,000 annually from other activities the minimum being Rs. 7,000 in WB to a maximum of Rs. 31,000 in AP. Most (57%) of the workers take the payment weekly from their employers. Daily wagers include around 20% of the workers. Despite low wages, 27% of the workers reported some savings from their earnings.

The average income as well as median income from tobacco processing is found to be the highest in the state of Andhra Pradesh followed by West Bengal, Maharashtra, Karnataka and Gujarat in that order (Table 2). What is to be noted is the higher share of migrant workers in Gujarat. Wages in processing are the same to both male and female in respective states and there is a great demand for processing workers as the younger generation is not inclined to processing work.

We attempted to compare the mean income of tobacco processing workers across the states if these are statistically significant or not. Kolmogorov-Smirnov (K-S) test was done to find out if the income from tobacco is normally distributed across the states and results show the statistical significance (P values) for respective K-S statistics are > 0.05 for West Bengal, Andhra Pradesh and Karnataka, indicating normal distribution but not for Maharashtra and Gujarat (<0.05). The corresponding histograms also confirmed the same. Since we want to compare the income from tobacco processing for workers across the five states, we applied independent sample Kruskal-Wallis non-parametric test (K-W) to compare the median income for these states. It was found that the reported income from tobacco processing is statistically different across the states (N =512, K-S statistic = 194.428, degree of freedom (df) = 4 and p-value < 0.05.

Out of 512 sample tobacco processing workers whom we interviewed, in total, 218 were males (42.6%) and rest 294 were female (57.4%). Despite women workers in our sample are largely involved in processing work and also work for longer duration in a given year than their male counterparts, we found on an average our sample male workers earn higher than female workers, Rs. 56743.6 (± Rs. 34045.7) and Rs. 44202.9 (± Rs. 25695.5), respectively. We applied statistical tests to determine if this difference in income from tobacco processing between male and female workers is statistically significant or not. Applying the Kolmogorov-Smirnov (K-S) test, we found the wage income from tobacco processing for our sample workers by gender was not normal.

Therefore, we have used Mann Whitney-U (MW-U) non-parametric test to compare the difference in income. It was found, the income from wage towards tobacco processing between male and female workers were different and this difference was statistically significant (N =512, MW-U statistic = -3.310 and p-value < 0.05. All these tests were run using SPSS 16.0 and non-parametric tests were run applying auto-run option which employs appropriate model given the data. Further the data on bidi worker was collected through snowball sampling from willing processing workers in absence of a consolidated data base from which sample could have been drawn, so above non-parametric tests are apt tools to compare the group averages here.

Tobacco processing workers in addition to processing earn from their/family members' engagement as labour in MGNREGA, agriculture, bidi rolling, livestock rearing, rentals from buildings, casual labour, salaried employment and self-employment (Figure 3). The total household income of workers from several of the reported occupations including tobacco processing was reported to be on an average

Table 2: Average Annual Earnings from Tobacco Processing for Sample Workers (Rs.)

States	Mean Income (± S.D.)	Median Income	Number of Sample Farmers
West Bengal	54894.56 ± 23324.41	54000.0	103
Andhra Pradesh	84320.39 ± 37573.30	80000.0	103
Karnataka	40769.75 ± 15423.94	40500.0	101
Maharashtra	47745.10 ± 13519.26	49400.0	102
Gujarat	28213.59 ± 18187.28	25000.0	103
Total	51236.10 ± 29888.85	48000.0	512

Source: Field Survey

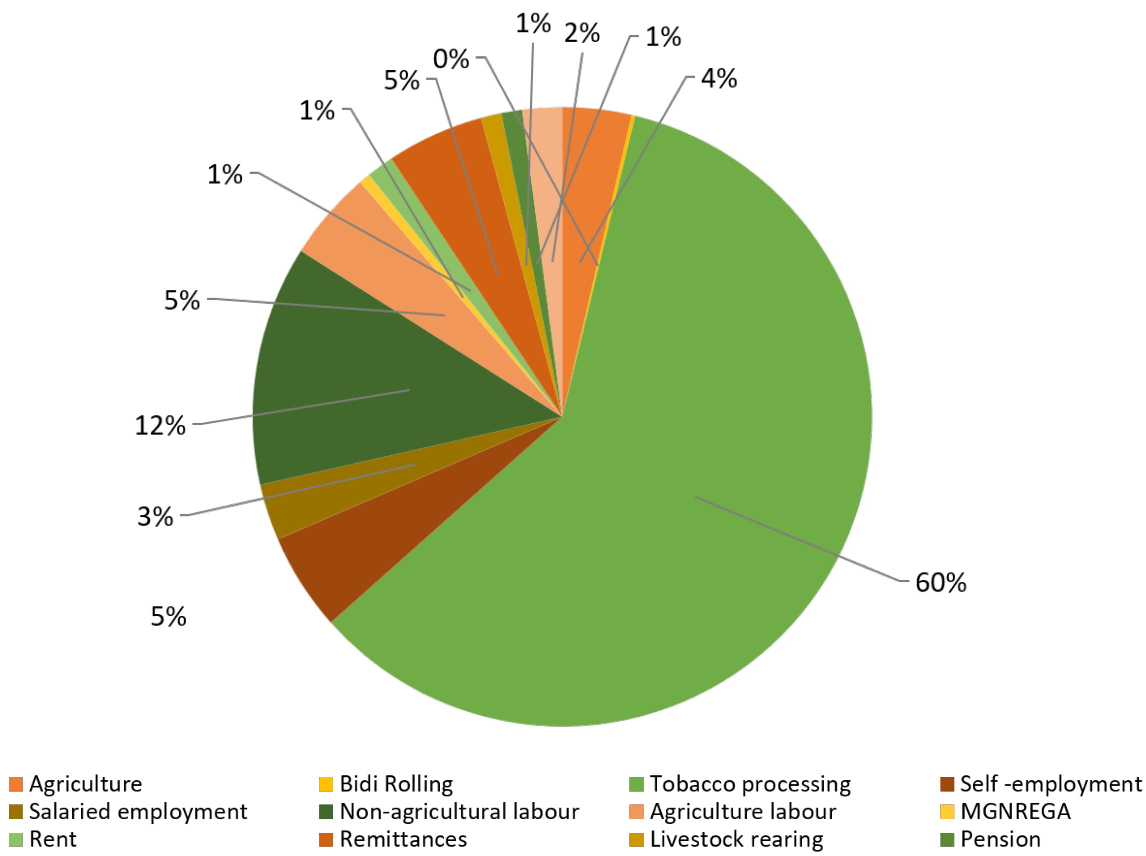
Rs. 44,482 per annum and was found to be the highest in AP (Rs. 53,938) and the lowest in Gujarat (Rs. 25,254).

Since the workers are engaged in tobacco processing on an average for 291 days, there is very little scope for processing workers to take up alternative jobs. As said earlier, only those who own agricultural land (around one-fourth) have an opportunity to work in their agriculture land and rear livestock, which is complimentary to agriculture. Although women tobacco processing workers we had interviewed in these five states reported having skills of tailoring, embroidery, cooking and computer, these are not reflected in to earnings as workers are engaged in processing and household chores.

- **Are processing workers happy with their work?**

Fifty-nine percent of the processing workers reported not being happy. Of those who were not happy, a third (31%) said that they were not happy because of the sole reason that tobacco dust was harmful and they had no option to stop this activity due to absence of alternate sources of employment. Around 16% said that the wages were meagre while 11% reported health problems as the reasons for their unhappiness. Apart from these reasons, 11% reported meagre wages as well as exposure to tobacco dust as reasons for unhappiness, while 17% reported tobacco dust and health problems, 2% reported meagre wages and health problems and 12% reported all three problems as reasons for unhappiness. It should be noted that as the study reveals, around 56% of the workers (Table 3) desired to shift from tobacco processing if there exists an opportunity. Despite the non-availability of alternative employment opportunities near their residence, around 79% of the workers are willing to shift from processing in WB. As against this, although more than half of the processing workers are not happy with their current work, a significant 44% are not interested in shifting. A majority being in the middle age and the non-availability of other opportunities to work near their location (the reporting of employment opportunities is lesser in states other than WB) are the reasons for their responses in this regard. Although only 30% of the workers reported availability

Figure 3: Different Sources of Income for Sample Tobacco Processing Workers Interviewed Across Five States (% share), N = 512



Source: Field Survey

Table 3: Tobacco Processing Workers According to their Interest to Shift to Alternative Employment (in %), N=512

States	Yes	No
West Bengal	78.64	21.36
Andhra Pradesh	55.88	44.12
Karnataka	42.00	58.00
Maharashtra	53.92	46.08
Gujarat	50.49	49.51
Total	56.19	43.81

Source: Field Survey

of alternate employment opportunities near their location, 56% are willing to shift to other works if support is available. So, in the absence of alternate employment opportunities, workers may not properly answer this questions.

It should be noted that the skilling programmes of the government with respect to the provision of alternate employment to tobacco workers is negligible considering the quantum of employment in the sector, and is currently limited to bidi rollers. Both the Labour Ministry and the NGOs have targeted their skilling programmes to bidi rollers. A majority of the tobacco processing workers in our sample, do not receive social security benefits like assistance for housing, minimum wages, EPF etc., as the study found that only 10% of the workers possessed ID cards.

Summary and Policy Recommendation

There is a dearth of information on tobacco processing in India as it is largely in the unorganized sector. There is no concrete information on the location of tobacco processing units, number of units, number of workers, type of tobacco processed, internal or domestic sale, exports, etc. Processing appears to be an activity restricted to locations near the tobacco cultivation area.

The review of the available literature indicates that exposure to tobacco dust causes some adverse health effects especially respiratory outcomes such as asthma, chronic obstructive bronchitis, and allergic respiratory or nasal diseases in workers. Tobacco processing workers had self-reported symptoms of vomiting, giddiness, and headache during and after processing work and, higher rate of nicotine and cotinine in urine excretion identified in clinical studies. Many of the workers, despite being involved in hazardous work, do not receive minimum worker benefits like EPF, gratuity, bonuses, medical allowances, and minimum wages.

There appears to be a reduction in the quantum of tobacco being processed in the last 10 years. It was reported that some units have been closed, while others have shifted from three shifts to one shift and some others have become seasonal. Availability of raw materials was a major concern to tobacco processors and they assume that could be due to a reduction in tobacco production area. Electricity supply was another major issue hitting tobacco processing. More than half (58%) of the workers in the sample felt that there was a reduction in tobacco processing activity over the years. Once booming with activities, some of the processing units now look like abandoned old castles in some of these locations visited by the survey team across five states. Workers say that anti-tobacco movement, prohibition on public smoking, restrictions on the sale and, introduction of Goods and Services Tax (GST) have cast a spell of doom on tobacco processing work. The fact that the production of tobacco remaining the same, the reported reduction in processing activity needs to be researched further for examining the real causes.

Processing is not a family occupation like bidi rolling, which is generally passed on by the mother to her children particularly the girl child. Most of the processing workers (86%) do not want their children to take up processing as their occupation. The wages for tobacco processing were found to be very low being Rs 6-7 per kg and varied between Rs. 150 in WB to Rs.227.49 per day in Karnataka. The poor working conditions, lack of social security benefits, low standard of living among a majority of workers, reporting of chronic illness among processing workers, absence of scientific studies on the health conditions of workers, and a majority of processing workers not being happy with their employment are the reasons enough for policy intervention to look into their working conditions and find out ways and means to rehabilitate them in other occupations and wean away the new entrants into tobacco processing job market.

A majority of the workers in the sample were poor slum dwellers holding BPL cards, and 20% of were widows or widowers. This highlights the vulnerable position of processing workers doomed to survive amidst the hazards of toxic dust inhalation and back-breaking hard work. Further, the fact that overall, only 10% of the workers possessed IDs indicates the informal nature of tobacco processing wherein workers must work at the mercy of the employer without demanding any social and economic benefits. Although it is a major livelihood option for processing workers who do not have access to any other alternative employment opportunity, it appears to be an exploitative work. The absence of social security benefits like housing and maternity benefits, and disparities in the availability of EPF, bonus, gratuity, etc. across the five selected states calls for bringing in uniformity in the provision of these basic social security measures to tobacco processing workers or skilling at least the younger generation who constitute around one-fourth of the processors' work force. This can enable shifting gradually from the hazardous tobacco processing.

This study should be viewed as a small step made to throw light on the living conditions and work environment of the tobacco processing in states employing a higher number of tobacco processing workers. Additional studies may be required to understand their health status in comparison to the general population using clinically diagnosed reporting and biomarkers to validate the linkage between exposure to tobacco dust and health problems among workers.

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- **Conflict of Interest:** None

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• **Author Contributions:** NSN contributed to the conception or design of the study. NSN, RN, KM, TN, and NLN were responsible for the acquisition of data as well as supervision and project administration. NSN and RN handled the analysis and interpretation of data , and the drafting and writing of the manuscript. The critical revision of the manuscript was carried out by NSN, RN, and TN. All authors approved the final version to be published , while NSN and RN agreed to be accountable for all aspects of the work

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Productivity and Technical Change in the Indian Pharmaceutical Sector: A Comparison of Foreign and Domestic Firms

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The effect of foreign investment on the productivity of a knowledge-intensive industry such as pharmaceuticals holds much importance. The present firm-level study uses a non-parametric mathematical linear programming model, Data Envelopment Analysis based on Malmquist Productivity Index to calculate and compare productivity, efficiency change and technical change of foreign and domestic firms of Indian pharmaceutical sector for the period 2001-2020. The findings include that foreign investment has a positive impact on the productivity of the firms. Foreign firms adapted better to the technological progress as compared to the domestic firms. The sector also experienced a regression in efficiency, especially in the years registering technological progress suggesting that a majority of firms are not able to enjoy the benefits but certain firms have progressed due to foreign investment and shifted the production frontier outwards. Domestic firms' productivity would improve through mergers and acquisitions, government support for public–private technical collaborations, expansion of research and development capabilities, and assistance in importing raw materials.

Keywords: Data Envelopment Analysis, Malmquist Productivity Index, Productivity, Technical Change, Foreign Direct Investment

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The Indian pharmaceutical industry has been one of the fastest growing industries in the country since independence. According to the annual report of the Department of Pharmaceuticals (2019), it ranks tenth largest in the world in terms of value and third in volume. It accounts for 1.72 percent of the country's GDP and is projected to grow to USD 80-90 billion by 2030 (Indian Pharmaceuticals Alliance, 2019). It is one of the top FDI attracting sectors with 100 percent FDI permissible throughout automatic route in greenfield investment and 74 percent in brownfield investment.

The process of globalisation started in the 19th century and slowly engulfed the whole world. World integration is the by-product of the process. With the globalisation movement in such stride, there has been an ease in the movement of trade, flow of personnel and capital across cross-national borders. Foreign Direct Investment (FDI) has played a key role in facilitating such movements. With the remarkable development of technology, every kind of exchange, may it be business skills, production techniques or market know-how began to happen swiftly and with much ease.

The Indian pharmaceutical sector, being a high-skill, research-intensive industry has been at the centre of this transformation. At the time of independence, the Indian pharmaceutical industry did not have a prominent position. Over a period of time, it grew to be one of the most important sectors on account of a series of favourable steps taken up by the government and the initiatives of the entrepreneurs. The Patents Act, 1970 came into effect in 1972. This act provided special provisions for food, chemicals and pharmaceutical sectors which led to the abolition of product patents with the retention of process patents (Nair, 2003; Nair, 2008). It provided restrictive industrial policies which act as a stimulus in the speedy growth of the pharmaceutical sector. It also provided a base for the manufacturing of the bulk drugs as well as for the formulations (Ganguli, 2003; Nair, 2003).

The process patent regime lasted a while but since 1990s, the world has been going through a transformation regarding intellectual property protection rights in the form of Trade- Related Aspects of Intellectual Property Rights (TRIPS) Agreement. The implementation of the agreement for developing countries was done phase-wise and got completed on January 1, 2005. The objective of the transformation was to revolutionize the areas associated with intellectual property such as patents, copyrights, trademarks etc. by setting a minimum impartial level of protection for the same across the countries. TRIPS Agreement was widely accepted by the developed nations as it was seen as a tool to promote innovation and R&D in developing nations and lead to overall growth. Shapiro et al. (2014) found that stronger Intellectual Property Rights (IPRs) are associated with the transfer of the technological and innovative capabilities from developed to developing countries. This transfer generally takes place via FDI. MNCs that have patented drugs in the developed markets are more comfortable with transferring their technology, business models and management to the countries that have stronger IPRs.

It is also a common belief that the influx of foreign investment leads to a change in firm or industry technology (Driffield & Love, 2007). The change in technical knowledge, modernization of production processes, world market integration with domestic markets and strengthening of forward and backward linkages have a positive impact on the efficiency and productivity of the firms in the sector (De Mello, 1997; Ernst, 2005). The global shift in the paradigm lead to a need for domestic firms to increase their productivity and efficiency. They took the steps of acquiring firms, new products, stepping into newer therapeutic segments, taking up better management practices and finding access to new markets (Mahajan, 2020).

Given this background, the rest of the paper has been divided as follows. Section 2 gives a brief review of earlier literature on productivity. Section 3 explains the methodology adopted in the analysis and section 4 gives the details of the data collection. Results are explained in section 5 and section 6 concludes the paper.

Literature Review

There is ample literature regarding productivity analysis which covers vast portions of theoretical as well as empirical analysis. To narrow down the literature as per the requirement of the present research, the papers highlighting the effect of foreign investment on productivity in Indian markets have been considered.

One of the most prominent researched areas while considering productivity is the productivity of the Indian manufacturing industry but the studies provide ambiguous results. Krishna & Mitra (1998) using firm-level data from different Indian manufacturing industries studied the impact of liberalization reforms on productivity and reported an increase in productivity in the time followed by the reforms. Another study by Manjappa & Mahesha (2008) examined the productivity growth and its components for manufacturing industries and found that the capital-intensive industries reported a positive productivity growth owing to positive technological change but the labour-intensive industries showed a decline in technological progress and thus a regress in productivity. Certain studies have also indicated a decline in productivity. Goldar (1986) used a multiple regression framework to understand the total factor productivity (TFP) pattern of Indian manufacturing industries in 1960-70 and recorded it be negative for majority of the firms. Another study by Balakrishnan & Pushpangadan (1994) found the productivity of Indian manufacturing firms in 1980s to be lesser than the previous decades. Jena & Chattopadhyay (2016) demonstrated positive effects of FDI on manufacturing sector provided the economy has absorptive capacity else it leads to crowding out of domestic firms.

As the Indian pharmaceutical sector is a technologically advanced sector with skilled labour and firms investing in R&D, many studies have analysed the growth, reasons and pattern of productivity of the sector. Certain studies found that the Indian pharmaceutical sector experienced technological advancements owing to technological change, investment and R&D but the benefits were not enjoyed by all firms (Mazumdar & Rajeev, 2009; Saranga & Banker, 2010; Mahajan, 2020). The implementation of TRIPS also contributed to a rise in productivity as well as profitability of Indian pharmaceutical firms (Bajaj & Nigam, 2007). Technical Efficiency Change (TEC) has been majorly found responsible for the increase in Total Factor Productivity Growth (TFPG) (Chakraborty & Pal, 2020). Firms with larger size exhibited higher productivity compared to medium and smaller enterprises (Mahajan, 2020; Das & Hoque, 2024). The level of productivity also has a direct effect on the absorption of R&D benefits of the firms (Goldar, 2013).

A certain number of studies have also highlighted the role of foreign investment on the level of productivity. As foreign firms are expected to bring better opportunities, managerial staff and technical know-how, the productivity of the firms is expected to increase. Sharma (2011) used firm level data of Indian pharmaceutical firms and stated that firms receiving FDI have better sensitivity to R&D which leads to an increase in productivity of the firms. Similar results were traced by Sharma (2015) and found out that the foreign investment received by the Indian pharmaceutical firms in the post-reform period led to a sizeable impact on the productivity of the firms. Foreign investment has also shown a positive effect on productivity growth via ownership (Thangavelu & Pattnayak, 2006), technological advancements and research efforts (Pattnayak & Thangavelu, 2011) as well as due to presence of foreign equity (Arora & Lohani, 2017). It also has a positive effect on exports which in turn leads to a rise in productivity (Mathiyazhagan & Sahoo, 2008). Foreign investment has aided the rise in productivity of the Indian pharmaceutical firms in the post-patent regime with innovation and R&D playing a decisive role (Pannu et al., 2011; Tripathy et al., 2013). Another study by Dhanora et al. (2020) examined the effect of technological innovations and foreign investment on 168 Indian pharmaceutical firms for the period 2000-2013 and found that both R&D and FDI have a positive effect on the productivity of the firms. On the other hand, an absence of horizontal spillovers from foreign firms to domestic ones has also been noted due to their ability to prevent technological outflow within the same industry (Desai et al., 2022).

As there are certain number of studies that have tried to examine the effect of foreign investment on the productivity of Indian pharmaceutical firms but most of those studies show an effect of the foreign investment on the technological innovations of the firm which in turn has an effect on the productivity of the firm. As the literature is scarce to examine the effect of foreign investment and draw a comparison with the domestic firms over a significant period of time on the productivity of Indian pharmaceutical firms, this paper attempts to make a comparison between foreign and domestic firms of the Indian pharmaceutical sector for the period 2001-2020.

Methodology

While considering the productivity analysis, the calculation can be done either by Single Factor Productivity (SFP) or Total Factor Productivity (TFP) technique. SFP is the method of calculation by dividing the total output by only one input (Manjappa & Mahesha, 2008). It fails to provide a complete picture as it disregards the effect of other inputs in productivity of the units. It only provides partial information. TFP solves this problem as it is defined as the ratio of weighted sum of outputs to the weighted sum of inputs. It includes the effect of all the inputs on the productivity and provides comprehensive results. Total factor productivity takes into account both the changes in technical progress as well as technical efficiency.

Over a course of time, the parametric Stochastic Frontier Analysis (SFA) and the non-parametric DEA-based Malmquist Productivity Index (MPI) have become the favoured approaches for productivity analysis as they presume that the decision-making units (DMUs) are not operating at their maximum efficiency (Singh & Agarwal, 2006).

In our study, MPI has been used as it takes the efficiency of the firms into account while calculating productivity. It was first introduced by Caves et al. (1982). He used distance functions or technical efficiency functions to estimate the productivity of the firms. The technical progress and efficiency were included in the model by Fare et al. (1994). The firms in the pharmaceutical industry are expected to go through continuous technological progress which makes the adjacent period version of Fare et al. (1989) of MPI, which is defined in terms of distance functions for period t and t+1, the correct approach for the analysis.

The distance function measures, keeping inputs constant for period t, the maximum proportion by which outputs can be expanded for the firm in period t. Similarly, the expansion of the same output bundle relative to the frontier in the period t+1 is also measured. These two frontiers, for the initial as well the target period, are used to calculate the productivity changes of a firm for adjacent periods. To minimise the effect of randomly chosen technology set, the MPI production indices are calculated as the geometric mean of period t and t+1 ratios (Manjappa & Mahesha, 2008).

Grifell-Tatje & Lovell (1996) states certain reasons which makes MPI a popular approach in productivity analysis. The approach only uses quantity data and thus the information on input or output prices is not required. This provides a clear picture even if the information on prices is unavailable or distorted. MPI also does not follow any particular assumption of profit maximization or cost minimization. Lastly, it decomposes the productivity indices into technical progress (outward shifting of the frontier) and the change in technical efficiency (movement along the frontier). This segregation of the indices into its two components helps in acquiring an in-depth knowledge of the whole procedure (Ma et al., 2002).

The adjacent period version of Malmquist productivity index can be expressed as

$$\mathrm{MI} = \left[\frac{D^t(X^{t+1},Y^{t+1})}{D^t(X^t,Y^t)} * \frac{D^{t+1}(X^{t+1},Y^{t+1})}{D^{t+1}\,(X^t,Y^t)}\right]^{\frac{1}{2}}$$

Where Dt(xt+yt) represents the distance function which gives the maximum proportion expansion of the output bundle in period t relative to the frontier in period t. Similarly, Dt+1(xt+yt) is the distance function that gives the maximum proportion expansion of the output bundle in period t relative to the frontier in period t+1.

While measuring the productivity using adjacent periods, two sperate frontiers, namely, base and final period frontiers are created. The two portions of the equation 1 represents the changes in productivity taking different periods as benchmark.

$$\frac{D^t(X^{t+1},Y^{t+1})}{D^t(X^t,Y^t)}$$

considers the frontier for base period as the benchmark while

$$\frac{D^{t+1}(X^{t+1},Y^{t+1})}{D^{t+1}(X^t,Y^t)}$$

captures the productivity changes keeping the frontier of the final period as the benchmark for comparison.

As there is no preference between the base and the final period frontiers as benchmarks, a geometric mean of both is taken to calculate the Malmquist Productivity Index.

Malmquist Index can be decomposed into its two components i.e. Technical Change (TC) and Efficiency Change (EC).

According to the definition of Malmquist Index:

$$\mathrm{MI} = \mathrm{TC} * \mathrm{EC}$$

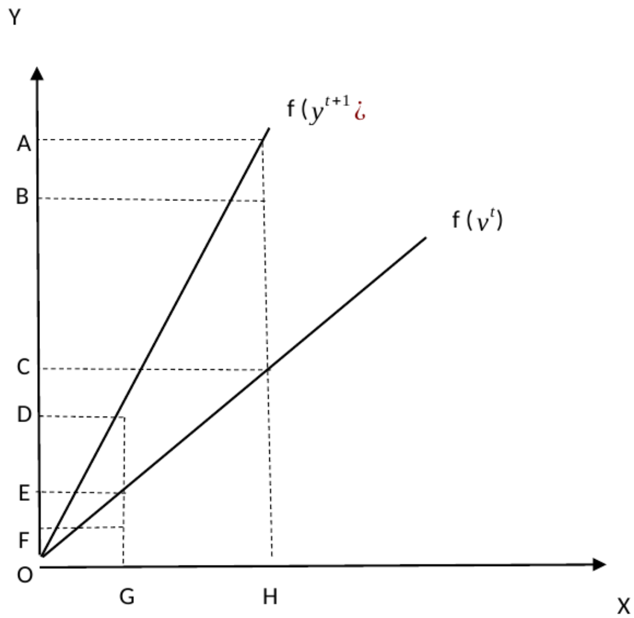
$$\text{Where EC} = \left[\frac{D^{t+1}\,(X^{t+1},Y^{t+1})}{D^t(X^t,Y^t)}\right]$$

and,

$$\mathrm{TC} = \left[\frac{D^t(X^{t+1},Y^{t+1})}{D^{t+1}(X^{t+1},Y^{t+1})} * \frac{D^t(X^t,Y^t)}{D^{t+1}(X^t,Y^t)}\right]$$

Technological progress is indicated by a value greater than one of TC and technological regress is indicated by a less than one value of TC. Similarly, EC indicates a relative shift of an inefficient firms towards or away from the frontier.

Figure 1: Decomposition of Productivity into Efficiency Change and Technical Chang



Source: Mazumdar (2013)

Mazumdar (2013) also explains the decomposition of Malmquist Index into its two components using a graph as depicted below:

Let f (yt) and f (yt+1) be the two frontiers representing base period and final period. The position of the firm relative to base period is F and relative to final period is B.

The efficiency change of the firm is given as:

$$EC = \frac{OB}{OA} \Big/ \frac{OF}{OE}$$

As, while calculating technical change, MPI allows the frontier to shift in non-uniform manner, TC can be different at different inputs levels. As stated earlier, the technical change component is expressed in two portions. The first part is the TC measured relative to base period and can be expressed as

$$\frac{OB}{OC} \Big/ \frac{OB}{OA}$$

The TC component measured relative to the final period can be expressed as

$$\frac{OF}{OE} \Big/ \frac{OF}{OD}$$

Therefore, the technical change component of a firm relative to MPI can be expressed as:

$$TC = \left[\frac{OF}{OE} \Big/ \frac{OF}{OD} * \frac{OB}{OC} \Big/ \frac{OB}{OA} \right]^{\frac{1}{2}}$$

Data

The data for the study has been collected from the Prowess package of Centre for Monitoring Indian Economy (CMIE). It is the firm- level data of Indian pharmaceutical industry for the period 2001-2020. Following Ghali & Rezgui (2001), any firm with more than 10 percent foreign equity participation is classified as a foreign firm. The study includes 38 such foreign firms. To select a comparable group of domestic firms, the asset sizes of the foreign firms were divided into ten percentile ranges. From each percentile range, domestic firms with similar asset sizes were randomly selected to ensure comparability. In total, 38 domestic firms were included in the study.

- **MPI**

The model used for calculating the productivity of the firms has one output and four inputs. The inputs included are labour, capital, material input and energy input. Total output is defined as the value of total sales plus change in stock which in turn is measured as opening stock minus the closing stock in output. The inputs of the model are defined as follows: (1) labour is measured in terms of wages and salaries of the workers; (2) capital is the book value of plant and machinery; (3) material input is the firm's expenditure on raw materials; and (4) energy input is the value of the firm's expenditure on power, fuel and water.

Table 1 presents the different variables and their definitions used in the model. As all the variables are expressed in monetary terms, they are appropriately deflated using price indices collected from the monthly bulletins of Reserve Bank of India (RBI). They are presented in table 2. Perpetual Inventory Method (PIM) (Balakrishnan et al., 2000) has been used to deflate capital taking 2011 as the benchmark year (Mazumdar, 2013).

Results

In the analysis of productivity, it is important to measure the extent of variation in efficiency due to technological changes. Productivity, in general terms, is defined as the ratio of outputs and inputs. It is a very similar concept to efficiency. The

Table 1: Variables and definitions used in the MPI model

Variable	Definition
Total Output	Total sales combined with change in stock (opening stock minus closing stock)
Labour	Salaries given to workers
Capital	Book value of plant and machinery
Material Input	Expenditure on raw materials
Energy Input	Expenditure in power, fuel and water

Table 2: Deflators

Variable	Deflator
Output	Wholesale Price Index for drugs and pharmaceuticals
Labour	Consumer Price Index for industrial workers
Capital	Perpetual Inventory Method
Material Input	Wholesale Price Index for chemical and chemical products
Energy Input	Wholesale Price Index for machinery and equipment

two concepts go hand -in -hand. A firm performing at a high level of efficiency would yield higher productivity. Such a firm, eventually, would cover the distance to the frontier and become one of the best performing firms in the sample under consideration. To further increase its efficiency, keeping the production frontier constant, the firm could employ more inputs to produce more outputs. This way the firm moves along the frontier. As the variable returns to scale are under consideration, the diminishing marginal returns would set in and employing more inputs no longer remains a choice. Thus, the only way to increase productivity is to experience a positive technical change and an outwards shift of the production frontier. Innovation is the prime source of such positive technical change. In conclusion, it is evident that there are two ways for a firm to experience productivity gains, one is with an increase in efficiency and the other is via positive technical change. While the first mentioned is calculated by the distance from the frontier, the latter is calculated by the shift in the production frontier.

MPI is a frontier approach that takes efficiency into consideration. It has been applied to calculate efficiency and technical change for a panel of 38 foreign and 38 domestic firms to see the effect of foreign investment on the productivity of the firms of Indian pharmaceutical sector for a period of 20 years (2001-2020).

Table 3 gives the values of the MPI and its components. A value of more than 1 for MPI suggest a percentage increment for the total factor productivity. Similarly, a value less than 1 for MPI suggest a percentage decrease in total factor productivity for an average firm. A value of 1.101 in 2004 implies that, in comparison to 2003,

Table 3: Technical Change and Efficiency Change of foreign firms of Indian pharmaceutical sector, 2001-2020

Year	Total Factor Productivity	Technical Change	Efficiency Change
2001	-	-	-
2002	0.942	0.720	1.038
2003	1.024	1.085	0.944
2004	1.101	1.072	1.027
2005	1.033	1.142	0.904
2006	1.023	1.068	0.958
2007	0.857	1.014	0.845
2008	0.972	1.049	0.926
2009	1.007	0.939	1.072
2010	1.032	0.952	1.084
2011	1.137	1.056	1.077
2012	0.963	1.024	0.941
2013	1.028	1.058	0.972
2014	1.089	0.975	1.117
2015	1.010	1.079	0.936
2016	1.099	1.089	1.010
2017	1.042	1.113	0.936
2018	1.124	1.106	1.016
2019	1.040	1.083	0.961
2020	0.925	1.084	0.853

there was an increment of 10 percent in total productivity of foreign firms, whereas, a value of 0.942 in 2002 implies that total productivity regressed by 6 percent compared to 2001. Similarly, table 4 represents the same calculations for domestic firms. The value of 1.036 for 2003 represents that total productivity increased by 3 percent in 2003 compared to 2002. A value of 0.997 in 2006 means that total productivity decreased by almost 1 percent as compared to 2005. For foreign firms, out of 19 years, total productivity shows increment for 14 years whereas for domestic firms, total productivity shows increment for 11 years. This is an initial indication that foreign investment has a positive impact on the productivity of firms. A further analysis into its components will provide a clearer picture.

Colum 3 of table 3 represents technical change for the foreign firms. A value of greater than unity represents technological progress while a value less than unity represents technological regress. A value of 0.72 for technical change in 2002 implies that technology regressed by 28 percent for foreign firms as compared to 2001. A value of 1.142 for 2005 implies that relative to 2004, technology progressed or the production frontier shifted out by 14 percent. While interpreting the technical change values for domestic firms using table 4, we see a value of 0.982 in 2002 means an average firm faced a technological regression by 2 percent as

Table 4: Technical Change and Efficiency Change of domestic firms of Indian pharmaceutical sector, 2001-2020

Year	Total Factor Productivity	Technical Change	Efficiency Change
2001	-	-	-
2002	0.998	0.982	1.016
2003	1.036	1.016	1.020
2004	1.032	0.958	1.078
2005	1.145	1.106	1.035
2006	0.997	0.937	1.065
2007	0.836	1.008	0.830
2008	1.226	0.985	1.244
2009	1.033	1.015	1.018
2010	1.033	1.031	1.002
2011	0.937	0.946	0.991
2012	1.040	1.059	0.982
2013	1.071	1.077	0.995
2014	1.166	0.835	1.396
2015	0.950	0.900	1.055
2016	1.005	1.046	0.961
2017	0.886	0.914	0.969
2018	1.033	1.059	0.976
2019	0.981	0.973	1.009
2020	0.905	0.939	0.964

compared to 2001. A value of 1.016 for 2003 suggests the production frontier shifted out by 1 percent for domestic firms as compared to 2002. Foreign firms register technological progress for 15 years and technological regress for only 4 years while domestic firms register a positive technical change for just 9 years and a regress for 10 years out of a total of 19 years.

This suggests that due to foreign investment, firms are experiencing technological progress with an outward shift in the production frontier for the majority of the years while the domestic firms are unable to adapt with technical progress and are seen facing technological regress for most of the period. Such technical progress suggests that due to investment, the sector is facing new production possibilities or new efficient firms have entered the market with superior technology.

A shift in the production frontier also increases the distance of output of firms from the frontier. This increase in distance increases average inefficiency. For foreign firms, the column 4 of table 3 represents the efficiency change component. A value of 0.944 for the efficiency change in 2003 implies that compared to 2002, the average efficiency of firms regressed by 6 percent, whereas, a value of 1.027 in 2004, implies that, on an average, the efficiency of firms has improved by 2 percent in 2004 as compared to their efficiency in 2003. The efficiency component can be interpreted in the same manner for domestic firms using table 4.

Indian pharmaceutical sector as a whole project that during the years that the industry experienced technological progress, it also witnessed a regression in its efficiency. This signifies that most of the firms are not able to enjoy the benefits that the technological progress brings along with it to the sector. As the production frontier shifts outwards, simultaneously, the fall in the level of average efficiency is also registered (Mazumdar, 2013). This implies that the technical and efficiency components in the sector have a strong negative correlation. This correlation is seen to be higher for foreign firms (79 percent) than in domestic firms (50 percent). It also suggests that a large number of firms entered the market due to lack of strong patent protection (Mazumdar, 2013). Such firms lack R&D activities and their original products. As foreign investment brings better opportunities along with it, the shift of the production frontier and also increase in inefficiency is noted more in foreign firms as compared to domestic firms.

Conclusion and Policy Recommendations

The present research extends the literature of the effect of foreign investment on the productivity and its components on the firms of the Indian pharmaceutical sector for the period 2001-2020. There are two ways for a firm to experience productivity gains, either by efficiency change (movement along the frontier) or a gain in technical change (outwards shift of the frontier). The study draws a comparison between the foreign and the domestic firms of the sector and list out the reasons for the differences in their productivities. The non-parametric MPI approach is used to decompose the productivity in efficiency change and technical change. The data comprises of 38 foreign firms and 38 domestic firms which is collected from CMIE.

The study concluded that foreign investment has a positive impact on the productivity of the firms. Foreign firms also adapted better to the technological progress as compared to the domestic firms. The sector also experienced a regression in efficiency, especially in the years registering technological progress suggesting that a majority of firms are not able to enjoy the benefits but certain firms have progressed due to foreign investment and shifted the production frontier outwards. Thus, we conclude that foreign investment is paramount for firms to perform better and improve their productivity but certain policy changes are required for the whole sector to enjoy the benefits brought along with it. The firms would benefit from mergers and acquisitions as it would overall increase their size which in turn would increase their absorptive capacity and lead to reap better benefits from investments. With an increase in size, the firms might also be able to use the unutilised plant and machinery and this might lead to capital efficiency as well.

Smaller firms do not possess the resources necessary to engage in importing which would also lead to increase in productivity. These firms might receive assistance from the government in one of two ways: either by providing financial assistance or by establishing markets. These markets would facilitate firms to do business by purchasing medicines at a lower price which would help the firms in recouping the money that they invested.

Research and development is also known to be an important determinant in productivity enhancement. Hence, it is recommended that all businesses invest in R&D. This investment should be done in order to develop new goods as well as processes. Scale economies are also present for firms that invest in R&D. However, not all firms are able to absorb foreign investment by assuming the risk of investing in R&D-related activities. In order to facilitate these processes, the government might engage in public-private technical collaborations and contribute to the expansion of research and development endowment, which in turn would assist in more effective utilisation of the received foreign investment.

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• **Author Contributions:** TR and BN contributed to the conception and design of the study. TR was responsible for the acquisition, analysis, and interpretation of data, as well as drafting and writing the manuscript. BN provided supervision and project administration. Both authors critically revised the manuscript, approved the final version to be published, and agreed to be accountable for all aspects of the work.

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Burden of Distress Financing for Hospitalization in India: Prevalence and Patterns from Household Health Care Consumption Survey, 2017-18

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The Indian health system is predominantly characterized by out-of-pocket healthcare expenditure and limited insurance coverage. While affluent households typically finance treatment through income and savings, economically disadvantaged households to rely on distressed sources like selling assets and borrowing to meet the healthcare needs. This study examines the levels and patterns of distress financing for hospitalization care in India across various demographic and socioeconomic groups. Furthermore, it compares the prevalence of distress financing across major ailment categories. The analysis utilizes data from the 75th round of the National Sample Survey 2017-18 to examine the overall prevalence of distress financing and the final analytic sample consists of 66237 participants. The key respondents include individuals who were hospitalized within the last 365 days. The binary outcome variable indicates whether patients funded their inpatient care through household income/savings (0), or distress means borrowings, sale of physical assets, contributions from friends and relatives, and other sources. The explanatory variables include MPCE quintiles, education, and place of residence. Four ailment categories were cancer, cardiovascular diseases, diabetes, and accidents. The analysis indicates that overall, 43.9% of inpatient cases relied on distress means of financing as either primary or secondary source. Across private and public facilities, the prevalence of distress financing was 35.9% and 49.4% respectively. Within private hospitalization facilities, a sharp gradient was observed across MPCE quintiles with a prevalence of 58.5% amongst the poorest as compared to 35.0% amongst the richest households. These findings highlight the need for strengthened social protection policies and expanded healthcare coverage to alleviate the reliance on distressed healthcare financing. Furthermore, prioritizing insurance-based healthcare systems is critical to achieving equitable and sustainable reductions in the financial burden of healthcare.

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Rising healthcare costs impose a significant financial burden, particularly on low-income households, who are disproportionately vulnerable. In developing countries, over one-third of healthcare expenditure is financed through out-of-pocket (OOP) expenditure by households. The rising burden of out-of-pocket health expenditure is one of the prominent health policy concerns, particularly in low-income and densely populated countries like India. Universal Health Coverage is, therefore, is one of the primary health agendas to achieve two fundamental objectives: (a) equity in healthcare access, and (b) financial protection from the high treatment cost of non-communicable diseases (NCDs). Additionally, studies before the implementation of the National Health Mission (NHM) have shown a distinct pro-rich bias towards access and utilization of healthcare facilities in India. Moreover, the OOP healthcare expenditure for those seeking care in private facilities has increased exponentially in India, thereby worsening the economic challenges faced by financially disadvantaged households. It is important to highlight that the treatment cost of chronic diseases like cancer and cardiovascular diseases (CVDs) is substantially higher, often driving households into economic hardship and compelling them to distress modes of financing. Distressed financing encompasses borrowings, contributions (with or without repayment obligations), and the sale of assets by households to address healthcare expenses. Previous studies indicate that approximately 60% and 32% households in India rely on borrowings and contributions from friends and relatives, respectively, for financing cancer hospitalization in India (Joe, 2015). The widespread reliance on distress modes of financing reflects the regressive nature of the healthcare system and calls for urgent policy intervention. Similar findings from other low-income countries corroborate that unpredictable and high OOP payments on healthcare lead to severe financial distress among households (Bonu et al., 2005; Bonu et al., 2009; Narayan et al., 2000a; Narayan et al., 2000b; Sauerborn et al., 1996; Damme et al., 2004).

In response to the critical need to address these challenges, the Government of India has formulated policies emphasising financial protection and equitable access to healthcare services. The National Health Policy (NHP), 2017, accorded 'affordability' as a key principle. For instance, the NHP states that "[a]s costs of care increase, affordability, as distinct from equity, requires emphasis. Catastrophic household health care expenditures, defined as health expenditure exceeding 10% of its total monthly consumption expenditure or 40% of its monthly non-food consumption expenditure, are unacceptable" (MoHFW, 2017). One crucial issue requiring immediate policy attention is the financing of healthcare, particularly for the elderly population, who are disproportionately exposed to chronic non-communicable diseases (NCDs). The rise in healthcare expenditures is primarily driven by the combined effects of an increasing aging population and the growing prevalence of NCDs. The age factor in the increasing prevalence of NCDs is inevitable, as adults and the elderly are more susceptible to chronic diseases. Moreover, the treatment of NCDs, particularly cardiovascular diseases (CVDs), is not only prolonged in duration, but also incurs high costs, with comparatively lower survival rates. In addition to the fact that India, like many other developing countries, lacks infrastructure to accommodate the increasing burden, policymakers must prioritize addressing the issue of skyrocketing health spending by households, financed through distress modes of financing at the household level.

There is a dearth of studies examining the incidence of distress financing for healthcare for both public and private health facilities. Although previous studies have underscored the significant burden of OOP expenditure, there is a notable lack of evidence investigating distress financing patterns independently for public and private health care facilities in India, particularly on a nationwide basis. In addition to this, given the wide array of improvements in health system financing and infrastructure, it is critical to examine the patterns in distress modes of financing healthcare separately for public and private hospitals. Although the NHP 2017 explicitly prioritizes healthcare affordability, it is essential to assess the role of both public and private health facilities in the overall burden of healthcare-related borrowings in India. Furthermore, it will also help determine whether investments in public health care have significant protective effects on household health financing and whether these interventions need to be further strengthened.

Drawing on the data from the health round of the National Sample Survey (2017-18), this paper aims to examine the incidence and modes of hospitalization financing at the household level. Beyond examining prevalence, the study explores how key socioeconomic correlates are associated with distressed healthcare financing (borrowings, sale of assets, and contributions from friends or relatives). The analysis uncovers the complex dynamics of distress modes of financing across the intersections of multiple factors, including gender, social categories, and economic status, that can have a significant impact while deciding upon the use of various sources of healthcare financing (Van Doorslaer et al., 2007). In this regard, a small area study on Koppal district in Karnataka in India provides compelling evidence that economically challenged men had better access to credit markets and were more likely to take loans or sell assets to finance healthcare expenses (Sen & Iyer, 2012). Even though the prevailing evidence comes from small-area studies, from a policy perspective, it is essential to analyse the broader scope, proportionate impact, and correlates of distressed healthcare financing.

Data and Methods

- **Data**

This study draws upon nationally representative data from Social Consumption: Health survey (75th round) of India (NSSO, 2018). The survey was conducted in 2017-18 by the National Sample Survey Organization (NSSO), Ministry of Statistics and Program Implementation, Government of India. The Social Consumption: Health survey collects information on morbidity, treatment-seeking, and financing of hospitalization (inpatient) and ambulatory (outpatient) care services for reference periods of 365 days and 15 days, respectively. The survey also details ailments treated through medical care, the extent of utilization of Government hospitals, and treatment-related expenditures in public and private sectors. Additionally, the survey provides household-level characteristics on demographics and access to services and utilities as well as individual-level data on age, sex, education, monthly per capita expenditure, and primary occupation.

- **Survey Design**

The Social Consumption: Health Survey covers a representative sample of households adopting a stratified multi-stage survey design covering India. A rural/urban stratification is created within clusters called state regions, which constitute a contiguous group of districts within a State or union territory with similar features. Within each district of a State/Union Territory, rural and urban strata are formed. The first-stage units are selected using the circular systematic sampling system of census-identified villages (rural sector) and urban frame survey blocks (urban sector) of each district. Villages and blocks with larger sample sizes are divided into multiple “hamlet groups” or “sub-blocks” and households belonging to only two “hamlet groups” and one randomly selected “sub- blocks” are selected as part of the second stage sampling process. The households within each village are further categorized into two strata based on their level of affluence and are then circular systematically selected to form the final sample. The 75th round of the Morbidity and Healthcare Survey covers a sample of 113822 households and 555351 individuals.

- **Outcomes**

We investigated the percentage of individuals largely relying on distress financing mechanisms to receive inpatient treatment. The survey collects information on the major source of financing to capture whether the majority of out-of-pocket expenditure was incurred through distressed means or not. Components such as borrowings (with or without interest), contribution from friends and relatives (with or without repaying option), and sale of assets are together defined as distressed financing. We further categorize it into “First source” and “Second source” to highlight the differences in cases that rely on distress mechanisms as the primary mode of financing and those that do so as a supplementary source. “Either source” reflects the total burden of distress financing.

- **Socioeconomic Indicators**

The study focuses on indicators of socioeconomic status including household monthly per capita expenditure (MPCE) quintile, education, and social group of the patient. Years of education was used to categorize the patients as illiterate (no formal schooling), upto primary education (1-5 years), upto middle school education (6-10 years), secondary education (11-12 years) and higher education (graduate school and above). Social group was categorized into the three historically marginalized groups of scheduled tribes (ST), scheduled castes (SC), other backward classes (OBC), alongside other castes. In addition, we also include information on place of residence (urban vs. rural), sex of the patient, religion (Hinduism, Muslim, Christianity, others), and region.

Statistical Analyses

The study reports the of prevalence of distress financing for inpatient care across socioeconomic categories. The concentration index (CI) is used to discern the socioeconomic gradient in inpatient care (Wagstaff et al., 1991; Erreygers, 2009) with a focus on public and private hospitals separately. The value of CI ranges between +1 and -1 with zero depicting no inequality and large positive values indicating greater concentration of distress financing cases among the richer households. Further, we employ logistic regression (adjusting for state and community-level fixed effects) to understand the mutually adjusted associations of distress financing prevalence with various socioeconomic indicators in a multivariate framework. The logistic regression estimates are reported in the form of Odds Ratio (OR) with 95 percent confidence intervals. These OR are the relative measure of effect which allows comparisons of groups relative to the reference group. The analysis was carried out in Stata 15 (StataCorp, 2013; Leckie & Charlton, 2013). All the analyses use multipliers as prescribed by the NSSO (NSSO, 2018).

Results

About 45.7% of inpatient cases were reported to resort to distress modes of financing with 18.9% and 29.2% as a primary and secondary source respectively (Table 1). Compared to the highest MPCE quintile, resorting to distress financing was more common among poorer sections. For instance, 37% of inpatient cases in the fifth quintile against 49.5% in the first quintile went for distress financing sources.

Across public and private facilities, 37.8% and 51.2% of hospitalization cases were financed through distress sources respectively (Table 2). For private hospitals, a clear gradient was observed across MPCE quintiles with 60.6% prevalence among the poorest households and 37.6% among the richest households. However, such a gradient was not observed in the case of public hospitals. We could not find notable differences in the prevalence across genders in both public and private facilities. For private hospitalization cases, socially affluent sections are less prone to finance through distress modes compared to categories with social reservations. For example, the prevalence among cases from ST households and unreserved households was 56.9% and 43.2% respectively. Such a pattern was missing in the case of inpatient cases in public hospitals. Interestingly, private inpatient cases also depict a stark difference across rural (57.2%) and urban (42.0%) areas in the prevalence of distress financing.

Across states, Andhra Pradesh reported to have the highest percentage (64.2%) of inpatient cases resorting to distress sources of financing followed by Manipur (62.3%), Goa (59.5%), Arunachal Pradesh (59.4%), and Karnataka (59.3%) (Fig1 - All). On the other hand, states like Himachal Pradesh (23.5%), Gujarat (30.3%) and Madhya Pradesh (31.1%) had relatively much lower burden. These findings were consistent across public and private facilities with higher magnitude in private hospitalization cases. For instance, the north-eastern states of Nagaland (Public: 63.9%; Private: 82.6%), and Manipur (Public: 59.8%; Private: 72.2%) had a much higher burden of distress financing.

We also quantified the magnitude of distress financing burden across major ailment groups for inpatient treatment, i.e., CVDs, Diabetes, Cancer, and Accidents. The prevalence of distress financing was highest for Cancer (67.8%), followed by accidents (52.6%), diabetes (47.4%), and CVDs (47.4%) (Fig 2). This pattern was consistent for both the first source and the second source. For private hospitals, the magnitude of burden was relatively higher for all groups with 72.9% of cases with distress financing for cancer, 61.2% for accidents, 53.4% for CVDs, and 50.7% for diabetes. In the case of public hospitals as well, distress financing was highest for cancer inpatient cases, followed by accidents and CVDs.

Estimates from the concentration index depict a pro-rich bias with a higher burden of distress financing for inpatient cases among poor households (Fig3). Econometric estimates from logistic regression reflect higher odds of distress financing for the treatment of adults (OR: 1.30; 95% CI: 1.24; 1.36) and the elderly population (OR: 1.24; 95% CI: 1.15; 1.31) compared to the younger cohort (Table 3). Across the MPCE quintiles, the likelihood of relying on borrowings and other distress means for adult hospitalization was significantly higher among households in the poorest (OR: 1.53; 95% CI: 1.44; 1.63) and poorer households (OR: 1.48; 95% CI: 1.39; 1.57) compared to those in the richest quintile.

These observations were consistent for both public and private facilities. For inpatient treatment of cancer, distress financing was reported as two times more likely than those with any other ailments (OR: 2.71; 95% CI: 2.36; 3.12). The probability of distress financing for inpatient treatment was reported significantly higher for rural areas (OR: 1.24; 95% CI: 1.19; 1.29) compared to urban areas. We also assessed the econometric association of distressed financing cases with the

Table 1. Prevalence (%) of Distress Modes of Financing Hospitalization Care by Socioeconomic Background, India, NSS 2017–18

	First Source			Second Source			Either Source		
Characteristics	**Proportion (%)**	**Standard Error**	**Sample (N)**	**Proportion (%)**	**Standard Error**	**Sample (N)**	**Proportion (%)**	**Standard Error**	**Sample (N)**
Age group (years)									
0–15	16.75	1.01	11207	25.96	0.50	11207	41.22	0.65	11207
15–60	19.24	0.43	41170	29.75	0.28	41170	46.60	0.33	41170
60+	19.93	0.97	13860	29.82	0.58	13860	46.74	0.68	13860
MPCE Quintiles									
Poorest	18.59	0.80	9030	33.54	0.59	9030	49.46	0.66	9030
Poorer	19.59	0.76	11139	31.94	0.54	11139	49.04	0.63	11139
Middle	21.58	0.79	13070	31.06	0.50	13070	49.46	0.60	13070
Richer	19.68	0.82	16415	28.09	0.48	16415	45.61	0.58	16415
Richest	15.48	1.07	16583	23.08	0.47	16583	37.04	0.55	16583
Education									
Illiterate	21.56	0.61	18864	29.38	0.41	18864	48.14	0.49	18864
Primary	14.35	3.36	463	33.44	2.73	463	45.68	3.01	463
Secondary	17.82	3.81	351	25.75	3.29	351	42.27	3.61	351
Higher	17.86	0.48	46559	29.03	0.28	46559	44.69	0.33	46559
Gender									
Male	20.25	0.57	34589	29.57	0.33	34589	46.95	0.39	34589
Female	17.64	0.48	31642	28.70	0.32	31642	44.49	0.37	31642
Social Group									
Scheduled Tribes	16.74	0.71	7425	30.73	0.62	7425	44.34	0.69	7425
Scheduled Castes	20.77	0.89	11090	31.35	0.60	11090	49.15	0.68	11090
Other Backward Classes	20.30	0.64	26641	30.52	0.37	26641	48.38	0.43	26641
Others	16.51	0.70	21081	25.63	0.38	21081	40.35	0.47	21081
Religion									
Hinduism	18.85	0.43	50204	29.24	0.26	50204	45.81	0.31	50204
Islam	19.92	1.09	8997	28.89	0.62	8997	46.17	0.78	8997
Others	18.58	1.08	7036	28.55	0.74	7036	44.17	0.86	7036
Sector									
Rural	20.54	0.48	36862	31.27	0.32	36862	49.00	0.37	36862
Urban	16.12	0.57	29375	25.25	0.32	29375	39.81	0.38	29375
All	18.98	0.37	66237	29.15	0.23	66237	45.76	0.27	66237

Table 2. Prevalence (%) of Distress Modes of Financing (First or Second) by Public and Private Hospital Facilities across Socioeconomic Background, India, NSS 2017-18

	Public			Private		
Characteristics	**Proportion (%)**	**Standard Error**	**Sample (N)**	**Proportion (%)**	**Standard Error**	**Sample (N)**
Age group (years)						
0-16	33.14	1.02	5432	46.81	0.80	5775
15-60	38.25	0.43	19222	52.52	0.43	21948
60+	40.44	0.98	5935	50.91	0.85	7925
MPCE Quintiles						
Poorest	38.98	0.80	5221	60.64	0.95	3809
Poorer	38.63	0.76	6115	59.26	0.92	5024
Middle	38.87	0.80	6586	57.67	0.79	6484
Richer	36.56	0.83	7569	51.83	0.75	8846
Richest	35.75	1.07	5098	37.36	0.61	11485
Education						
Illiterate	38.59	0.61	9399	55.87	0.67	9465
Primary	35.11	3.52	280	57.95	4.81	183
Secondary	35.59	3.81	194	48.79	6.01	157
Higher	37.57	0.48	20716	49.24	0.41	25843
Gender						
Male	39.30	0.58	15608	52.27	0.48	18981
Female	36.44	0.48	14977	50.06	0.51	16665
Social Group						
Scheduled Tribes	37.51	0.72	5369	56.86	1.43	2056
Scheduled Castes	40.21	0.90	5951	58.06	0.89	5139
Other Backward Classes	38.57	0.65	10855	54.45	0.53	15786
Others	35.01	0.71	8414	43.16	0.58	12667
Religion						
Hinduism	37.41	0.43	21938	51.61	0.39	28266
Islam	38.57	1.10	4743	52.63	1.01	4254
Others	43.21	1.09	3908	44.57	1.29	3128
Sector						
Rural	38.83	0.48	19225	57.20	0.51	17637
Urban	35.63	0.58	11364	42.01	0.47	18011
All	37.88	0.38	30589	51.22	0.35	35648

intersection of social category and MPCE quintiles (Fig 4). A clear gradient was observed with a significantly higher likelihood of resorting to distress means among the socially deprived and poorest MPCE quintile households in both public and private hospitals (Fig 4). Further, compared to the patients with the highest education from the richest households, the odds for patients from less educated backgrounds from poorer households have a significantly higher probability of resorting to borrowings and other (Fig 5).

Figure 1: Prevalence of Distress Modes of Financing for Hospitalization Care by Type of Facilities and States, India, NSS, 2017–18

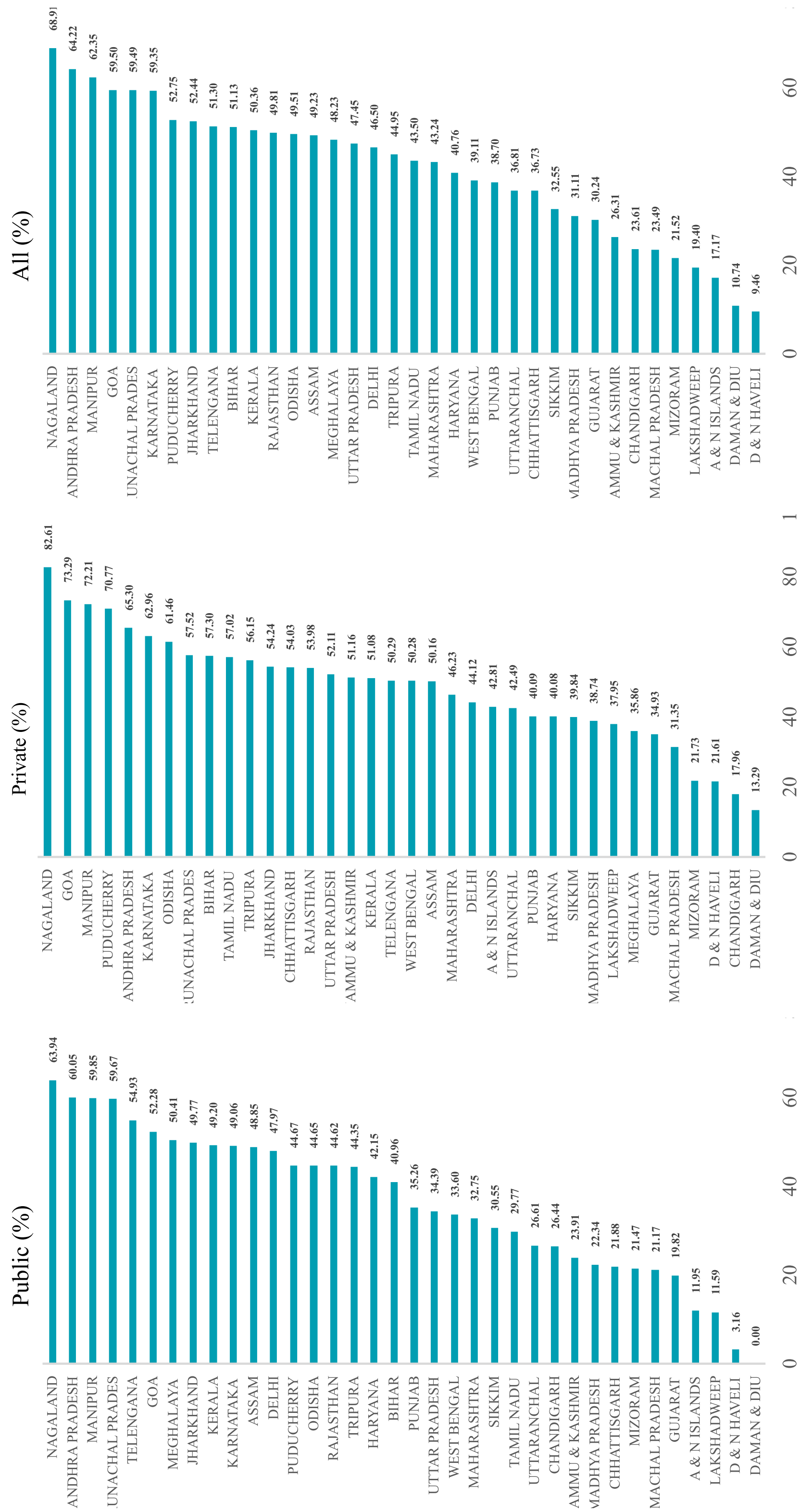


Figure 2: Prevalence (%) of Distress Modes of Financing Hospitalization Care by Broad Ailment Categories, India, NSS 2017-18

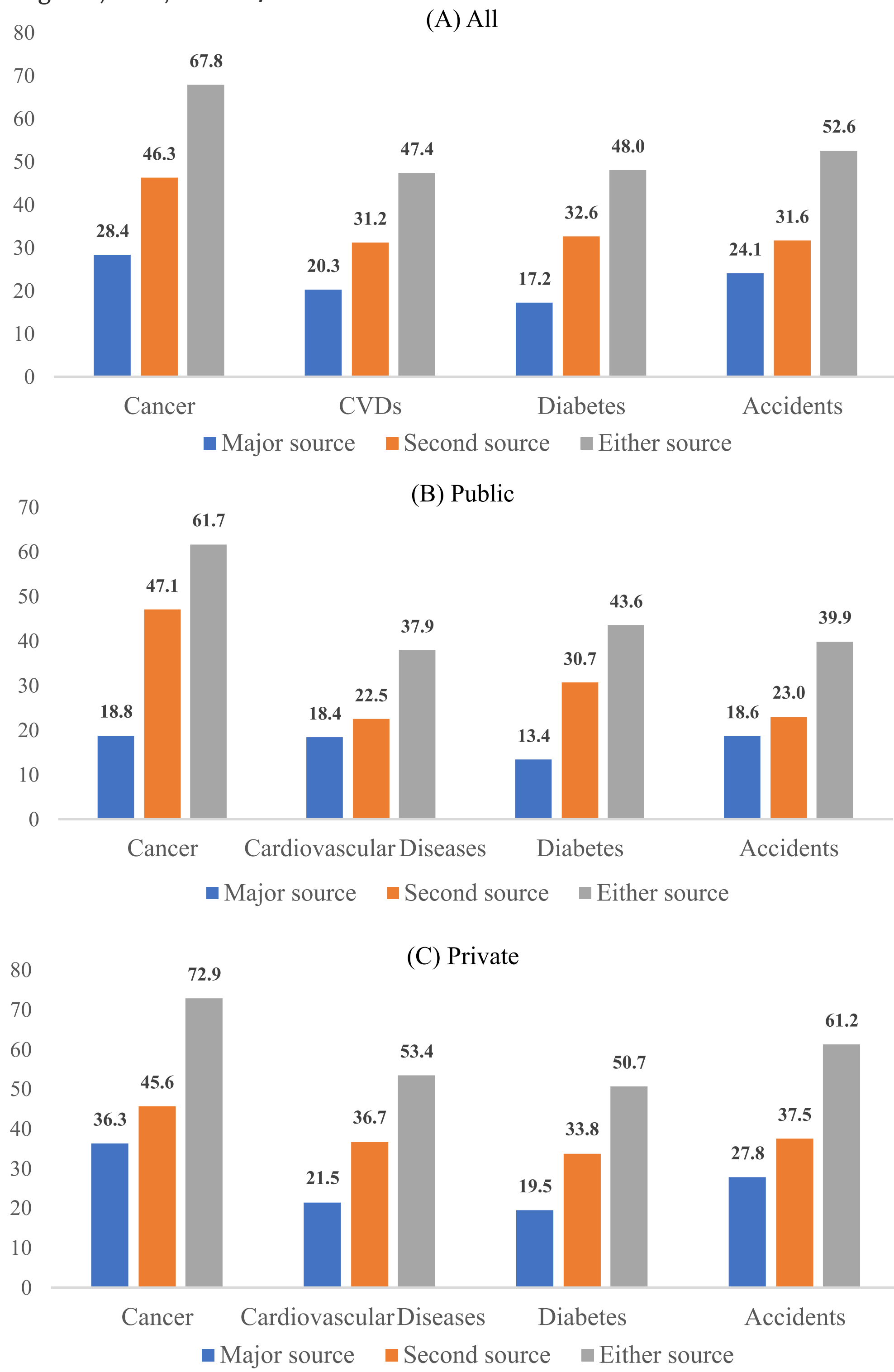


Figure 3: Prevalence (%) of Distress Modes of Financing by Public and Private Hospital Facilities across Rural and Urban sectors, India, NSS 2017–18

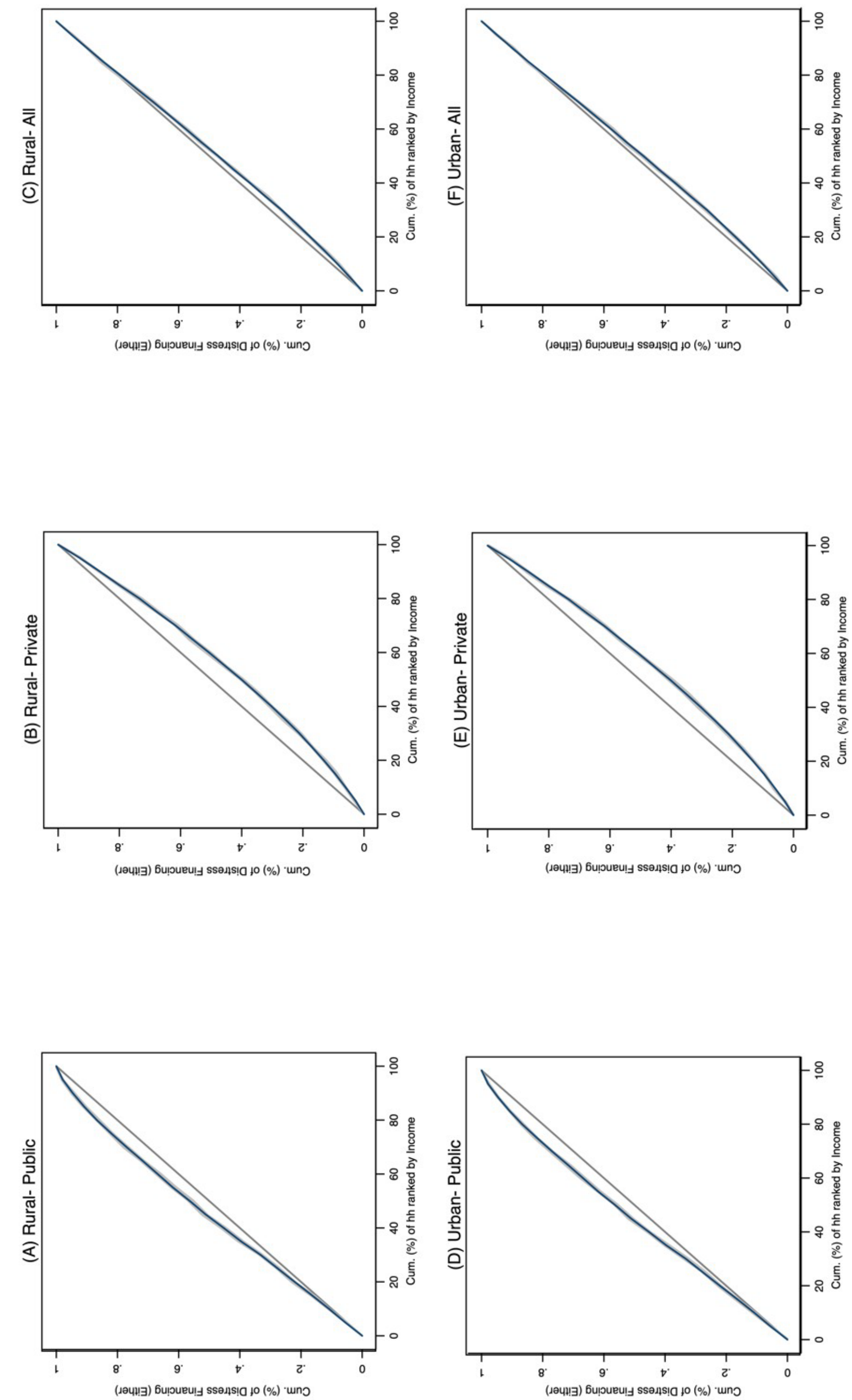


Table 3. Econometric association between distress financing for hospitalization and socio-economic correlates, by public and private hospitals, India, NSS 2017-18

Correlates	Public		Private		All	
	Odds Ratio	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Age group (years)						
0-15 ®	-	-	-	-	-	-
15-60	1.24***	[1.16 ; 1.33]	1.39***	[1.30 ; 1.48]	1.30***	[1.24 ; 1.36]
60+	1.28***	[1.07 ; 1.40]	1.26***	[1.16 ; 1.36]	1.24***	[1.16 ; 1.31]
Gender						
Female ®	-	-	-	-	-	-
Male	1.13***	[1.07 ; 1.87]	1.15***	[1.10 ; 1.21]	1.15***	[1.11 ; 1.19]
Sector						
Urban ®	-	-	-	-	-	-
Rural	1.17***	[1.10 ; 1.24]	1.36***	[1.29 ; 1.43]	1.24***	[1.19 ; 1.29]
MPCE Quintiles						
Richest ®	-	-	-	-	-	-
Poorest	1.63***	[1.48 ; 1.80]	1.78***	[1.62 ; 1.95]	1.53***	[1.44 ; 1.63]
Poorer	1.53***	[1.39 ; 1.68]	1.69***	[1.56 ; 1.83]	1.48***	[1.39 ; 1.57]
Middle	1.41***	[1.29 ; 1.54]	1.61***	[1.50 ; 1.74]	1.43***	[1.35 ; 1.51]
Richer	1.20***	[1.10 ; 1.30]	1.38***	[1.29 ; 1.47]	1.25***	[1.19 ; 1.31]
Education						
Higher ®	-	-	-	-	-	-
Illiterate	1.03	[0.97 ; 1.09]	1.23***	[1.16 ; 1.30]	1.12***	[1.07 ; 1.16]
Primary	1.25	[0.97 ; 1.61]	1.29	[0.95 ; 1.76]	1.18	[0.97 ; 1.43]
Secondary	1.29	[0.95 ; 1.74]	1.14	[0.80 ; 1.61]	1.13	[0.90 ; 1.42]
Social Group						
Others ®	-	-	-	-	-	-
Scheduled Tribes	1.12	[1.02 ; 1.22]	1.51***	[1.36 ; 1.68]	1.14***	[1.07 ; 1.22]
Scheduled Castes	1.17***	[1.08 ; 1.27]	1.12	[0.99 ; 1.25]	1.36***	[1.29 ; 1.43]
Other Backward Classes	1.19***	[1.12 ; 1.28]	0.96	[0.87 ; 1.07]	1.40***	[1.34 ; 1.46]
Diseases						
Cancer- No ®	-	-	-	-	-	-
Cancer- Yes	3.03***	[2.45 ; 3.75]	2.45***	[2.04 ; 2.95]	2.71***	[2.36 ; 3.12]
Cardiovascular Diseases- No ®	-	-	-	-	-	-
Cardiovascular Diseases- Yes	1.16***	[1.05 ; 1.27]	1.22***	[1.13 ; 1.32]	1.20***	[1.12 ; 1.27]
Diabetes- No ®	-	-	-	-	-	-
Diabetes- Yes	1.17	[0.89 ; 1.29]	0.93	[0.80 ; 1.09]	1.00	[0.89 ; 1.13]
Accidents- No ®	-	-	-	-	-	-
Accidents- Yes	1.07***	[1.08 ; 1.26]	1.47***	[1.37 ; 1.58]	1.34***	[1.28 ; 1.41]
N	27,526		31,732		58,209	

Note: Odds ratios are estimated employing logistic regression, adjusting for insurance status, chronic ailment (any), religion, and state-fixed effects. Estimations are *significant at 0.10, ** at 0.05, *** at 0.01 level. ® refers to the reference category for the correlates.

Figure 4: Econometric association between distress financing for hospitalization and Social category*MPCE Quintiles, by public and private hospitals, India, NSS 2017-18

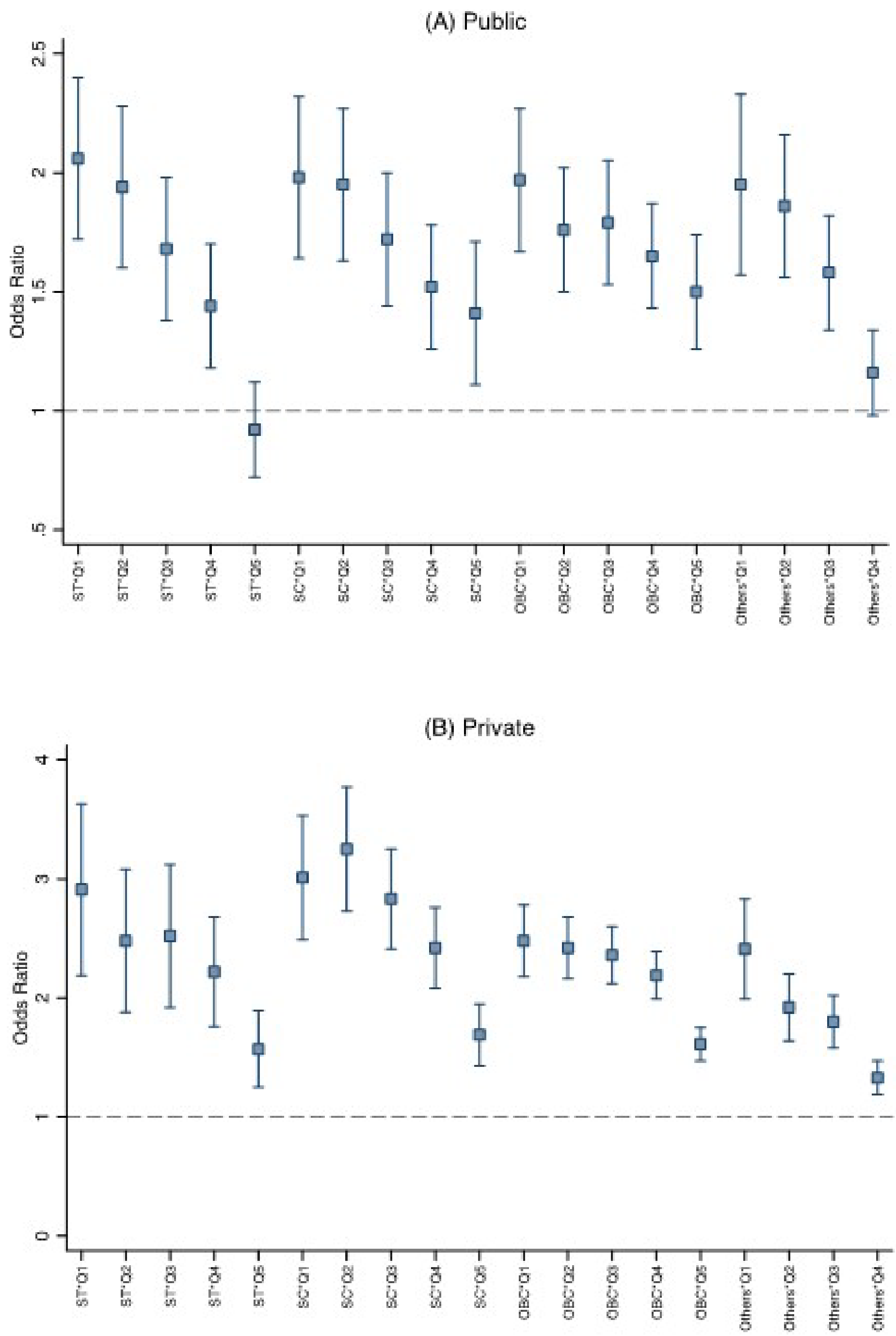
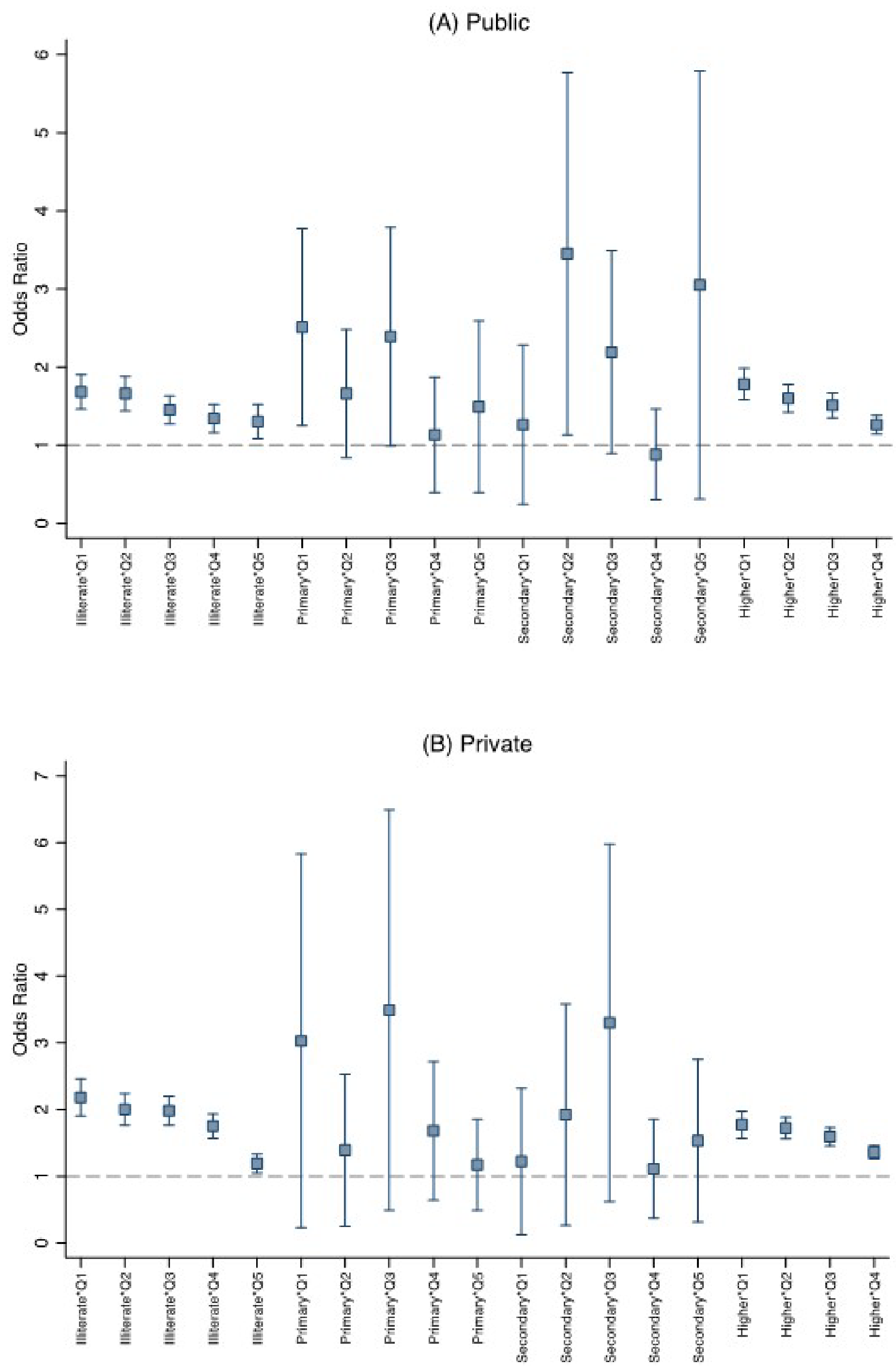


Figure 5: Econometric association between distress financing for hospitalization and Education Groups*MPCE Quintiles, by public and private hospitals, India, NSS 2017-18



Discussion

The study identifies four key findings. First, nearly half of the inpatient cases in India rely on distress financing mechanisms to meet healthcare expenses, with a disproportionately higher burden in rural areas. Second, the reliance on distress financing is substantially more pronounced for treatments sought in private hospitals compared to public ones, a trend that remains consistent across various demographic and socioeconomic strata. Third, the econometric analysis reveal a significantly higher probability of resorting to distress financing for inpatient treatment among socioeconomically vulnerable households, indicating borrowing as a potential marker of economic vulnerability. Fourth, the burden for distress financing was particularly higher for hospitalization related to cancer treatments across the broad ailment categories. Notably, inpatient treatment for accident cases also exhibited a substantial reliance on distress financing. This could be attributed to the fact that cancer treatment often entails prolonged and expensive medical care, which burdens households with limited financial resources, thereby rising their dependence on distress financing. Whereas, accident injuries necessitate immediate and unplanned medical interventions, leading to sudden financial pressures that force households to resort to distress financing mechanisms.

Our findings are consistent with previous studies on the subject matter. Existing literature from low-income countries highlights that a notable proportion of households incur financial debt or sell household assets to manage healthcare expenses (Sauerborn et al., 1996; Wagstaff et al., 1991; Leive & Xu, 2008; Kruk et al., 2009). For instance, the World Health Survey (2002-04) conducted across several low- and middle-income countries, reported a mean prevalence of borrowing and asset sales at 22% and 10%, respectively (Kruk et al., 2009). In light of these figures, it is expected that households in a low-income and densely populated country like India would rely heavily on distress financing mechanisms to access health care, particularly inpatient care.

From a policy perspective, it is crucial to note that a substantial proportion of household indebtedness in India can be attributed to a general preference for private-sector hospitals (Dilip & Duggal, 2002). Our findings further indicate that indebtedness associated with financing hospitalization care was significantly higher for private healthcare facilities. The data also reveal that the average OOP expenditure in private hospitals is considerably higher than that is incurred at public hospitals. These findings are in line with existing literature on in-patient care in India showing that public facilities and publicly funded insurance programmes such as the Rashtriya Swasthya Bima Yojana (RSBY) and PMJAY have demonstrated protective effects against distress modes of financing (Thomas et al., 2024). In light of these observations, it is apparent that the situation of healthcare financing could worsen if the public health system is unable to address the increasing burden of

NCDs in India (Reddy et al., 2005). Such cautionary evidence has emerged from our results, as households seeking care for cancer or CVD are much more likely to incur substantial medical debt (Mahal et al., 2013; Rahman et al., 2013). In this context, although a few social insurance policies (such as Ayushman Bharat, RSBY, and Rajiv Arogyasri Community Insurance Scheme) focus on providing financial protection in India, there remains a lack of comprehensive data on their effectiveness in reducing distressed financing. Nevertheless, given such initiatives, there is a pressing need for investments to expand the public provision of tertiary healthcare, with an exclusive focus on essential diagnostics, drugs and non-medical costs.

The present study, however, is not without limitations, which warrant acknowledgement. First, the non-medical costs associated with treatment-seeking, which can be substantially high, where not captured in the analysis. Additionally, the analysis presented here does not include OOP expenditures related to institutional deliveries. Moreover, several critical but unresolved policy questions remain unaddressed. For instance, there is a lack of information regarding the interest rates and costs associated with borrowing for healthcare expenses. Similarly, the implications of borrowings on basic investments in food and education, as well as the various trade-offs between investing in other competing alternatives, are not well understood. Consequently, deeper insights into coping mechanisms and determinants of successful coping are essential for designing social protection policies, to improve fairness in health care financing.

In conclusion, the heavy reliance on distressed modes of financing, such as borrowings, contributions, and sale of assets, indirectly implies that patients from only affluent sections are reported to afford to access tertiary care, whereas economically vulnerable households might have to compromise with both quantity and quality of care. Furthermore, the findings from this study raise concerns that the situation may worsen with the rising burden of NCDs and the increasing share of aging population.

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• **Conflict of Interest:** None

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• **Author Contributions:** SR contributed to the conception and design of the study, acquisition of data, and provided supervision and project administration. SR and SG were responsible for the analysis of data. SR, SG, and SRon handled the interpretation of data and the drafting and writing of the manuscript. The critical revision of the manuscript was carried out by SR and SRon. All authors (SR, SG, and SRon) approved the final version to be published and agreed to be accountable for all aspects of the work.

• **Supplementary Material:** Visit https://healthempirics.org/ for more information

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Dr. Mayanka Ambade (1991–2025)

In Memory

Sunil Rajpal[#]

Dr. Mayanka Ambade, a rising figure in the fields of health policy, population sciences, and social epidemiology, sadly passed away on 26 January 2025. As an Assistant Professor at the Indian Institute of Technology (IIT) Mandi and an esteemed member of the IHEPA General Council, Dr. Ambade was deeply committed to improving the lives of India's most vulnerable populations through rigorous research. Her academic journey, spanning from the International Institute for Population Sciences to a fellowship at Harvard University, was defined by her insightful analysis of aging, healthcare access, and gender inequality. She leaves behind a legacy of scholarly excellence and is remembered by the academic community as an inspiring researcher, a dedicated mentor, and a remarkably kind human being.

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Email: sunil.rajpal@flame.edu.in

The IHEPA community is deeply saddened by the untimely loss of Dr. Mayanka Ambade, Assistant Professor in the Department of Humanities and Social Sciences at the Indian Institute of Technology (IIT) Mandi, who passed away on 26 January 2025. Her sudden departure has left a profound void in the fields of health policy, population sciences, and social epidemiology. Dr. Ambade was an esteemed member of the General Council of the IHEPA and contributed actively to the initiatives with utmost enthusiasm. Despite her young age, Dr. Ambade built a distinguished and impactful body of work, marked by relevant questions, intellectual rigor, remarkable clarity of purpose, and a deep commitment to improving the lives of India's most vulnerable populations.

Born on 9th May 1991, Dr. Ambade graduated in Economics from the University of Mumbai, after which she pursued her Master's and subsequently her PhD in Population Studies at the International Institute for Population Sciences (IIPS), Mumbai. Her doctoral research demonstrated a strong grasp of interdisciplinary methods, blending economics, demography, and public health to produce insights that would characterize much of her later work. Following her PhD, she contributed to several of India's important national health initiatives, working with key datasets such as the National Family Health Survey (NFHS) and the Global Adult Tobacco Survey (GATS).

Dr. Ambade realized the deep significance of socioeconomic gradients in health outcomes early in her career. Her scholarly curiosity took her beyond India, leading to international collaborations across Europe, including work with the University of Lausanne and the Erasmus Mundus Programme. Her postdoctoral journey eventually brought her to the Lakshmi Mittal and Family South Asia Institute at Harvard University, where she served as the inaugural Mittal Institute India Fellow. During this period, she deepened her research on aging and healthcare utilization, examining how socioeconomic disparities shape patterns of morbidity among older adults.

In May 2023, Dr. Ambade joined IIT Mandi as a faculty member, where she quickly established herself as a valued colleague. Her courses on public health and research methodology were appreciated for their clarity and ability to inspire critical thinking. Dr. Ambade particularly enjoyed interacting with students; she was an inspiring teacher and mentor who guided young researchers with patience and enthusiasm. Many students fondly remember her as approachable and deeply invested in their academic growth.

Dr. Ambade's scholarly output reflected commendable depth. Among her notable works was her article in Economic and Political Weekly, titled "Economic Growth and Women's Empowerment: A Repeated Cross-sectional Study from India,"1 which exemplified her ability to tackle complex demographic questions with methodological robustness. Alongside her research, she contributed actively to the broader professional community, serving as a member of the Early Career Perspectives Panel of the IUSSP and organizing workshops to support early-career scholars.

Beyond academia, Dr. Ambade was passionate about reading, traveling, and experimenting with global cuisines, personal interests that enriched her life and gave her a groundedness that many fondly remember. She possessed an ability to connect with people through genuine empathy and intellectual generosity. Dr. Ambade leaves behind a legacy defined not only by scholarly excellence but also by kindness and integrity. She will be remembered as an inspiring researcher and a remarkable human being whose work and spirit touched many.

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Health, Nutrition, and Wellbeing: Evidence, Evaluation, and Way Forward

13th Annual Conference, 12-13 December 2025

Indian Health Economics and Policy Association

Organized by

School of Humanities and Social Sciences, Indian Institute of Technology, Mandi

List of papers selected for Oral Presentation

Technical Session 1A

Md Mohsin, Aligarh Muslim University

Health and Hunger: The Role of Physical, Mental, and Functional Health in Shaping Severe Food Insecurity Among Older Adults in India—Evidence from LASI Wave 1

Kshirabdhi Tanaya Patra, National Institute of Technology Rourkela

Does Social Capital Matter? Insights into Healthy Ageing in India

Aditi, Population Council Consulting P Ltd

Frailty among Older Adults in India: Economic Burden and Insights from LASI

Kripa Nandan, Indian Institute of Technology Roorkee

A Cross-Sectional Study of Healthcare Responsiveness for Migrant and Non-Migrant Middle-Aged and Older Adults in India: Analysis using Longitudinal Ageing Study

Amrendra Kumar Kushwaha, Indian Institute of Technology Mandi

Cooking Fuel, Gendered Exposure, and Lung Function Among Older Adults in India

Technical Session 1B

Raza Mohammad, International Institute for Population Sciences, Mumbai

Age at Childbearing Initiation: A Double-Edged Sword for Child Anthropometric Deficits in South and Southeast Asia

Arpita Shah, Mumbai School of Economics and Public Policy

A multi-scalar spatial analysis of child undernutrition in Gujarat: Districts, Parliamentary Constituencies (PCs) and Villages

Dr Ramesh Athe, Indian Institute of Information Technology Dharwad

Food Fortification to Combat Hidden Hunger in Children: A Systematic Review and Meta-Analysis of Randomized Controlled Trials

Ritika Kapoor, Foundation of Healthcare Technologies Society

Enhancing Nutritional Knowledge and Dietary Practices among Middle School Children: Evidence from Educational Interventions in Delhi and Chandigarh, India

Dr Anjali Dash, Panchayat College, Bargarh

Nutritional variation among children in India: Special reference to Gujarat and Odisha

Technical Session 1C

Abhishek Anand, International Institute for Population Sciences, Mumbai Financial Toxicity Among Gastric and Pancreatic Cancer Survivors in India and Its Impact on Quality of Life

Pubali Das, Department of Economics, Tripura University

In-State vs. Out of State Hospitalization and Catastrophic Health Expenditure Burden for the Patients of Tripura: Evidences from NSS 75th Round Health Data

Dibyendu Biswas, Jindal School of Government and Public Policy, O.P. Jindal Global University, India

Provider Choices and Out-of-Pocket Health Expenditure (OOPE) for Outpatient Care: Evidence From a Multistage Sample Survey in West Bengal, 2024

Ashkar K, Gulati Institute of Finance and Taxation

Does Population Ageing Drive Public Health Expenditure in Indian States? A Dynamic Panel Analysis

Dr Prerana Patil, Indian Council of Medical Research-NIRRCH

Out-of-Pocket Expenditure Experienced by Couples Seeking In Vitro Fertilization (IVF) Services at Tertiary Care Facilities in India

Technical Session 2A

Gayathri B, Indian Institute of Technology Mandi

Assessing Cardiovascular Disease Vulnerability in India: A District-Level Index-Based Analysis

Shubham Ranjan, JK Lakshmipat University

Beyond Female Breast Cancer: Gender-Specific Profiles and Outcomes in India

Shruti Hiremath, KLE Academy of Higher Education & Research

Assessing the Temporal Burden of Diabetes Mellitus Attributable to Dietary Risk Factors in India: Insights from Global Burden of Diseases Study: 1990-2021

Priyadarshini Rathore, Manipal University Jaipur

Epidemiology of Cardiovascular Diseases in India: Determinants and Developmental Implications

Shreya Thakur, Quality Council India

Intergenerational Persistence of Smoking Behavior: Evidence From NFHS- 5, 2019-21

Technical Session 2B

Diksha Rani, Indian Institute of Population Sciences, Mumbai

An Analysis of the Age Distribution of Stunting in Countries with Accelerated Reduction Rates, Using Demographic and Health Survey Data

Pramit Chhetri, Sri Sathya Sai Institute of Higher Learning

Water, Sanitation, and Hygiene (WASH) and Malnutrition Among Under-Five Children in India

Dr Archana Singh, RML Awadh University, Ayodhya, Uttar Pradesh

Child Stunting, Caste Discrimination, and Program Effectiveness: Evaluating Heterogeneous Treatment Effects of Integrated Child Development Services in India.

Dr Rudra Narayan Mishra, Gujarat Institute of Development Research, Ahmedabad

Integrated Community-Facility and Policy Frameworks to Combat Malnutrition and Accelerate Development in Aspirational Districts of India

Meenu Bhaskar, Indian Institute of Technology Bombay

The Impact of PMUY on Household Nutrition: Evidence from India

Technical Session 2C

Vishnu Priya V V, Department of Humanities and Social Sciences, Indian Institute of Space Science and Technology

Gendered Access to Information and Public Health Insurance Enrollment Among Poor Households in India

Dr Godwin S K, Government College for Women, Thiruvananthapuram

Moving from Health Insurance to Health Assurance: Kerala's Experience of Contingent Health Security

Prateek Khanna, Amity University

The Road to Universal Health Coverage in India

Sayantani Manna, O P Jindal Global University

Awareness and Utilisation of Health Financing Models: A Study of Insurance Schemes in West Bengal

Shambhavi Mani, Vivekananda College, University of Delhi

Beyond the Frontlines: ASHA workers, Maternal Health and the Social Determinants of Reproductive Wellbeing in Madhya Pradesh.

Technical Session 3A

Ambarish Majumder, ICFAI University, Tripura

Voice-Based Health Technologies for Low-Literacy Populations: A Systematic Review of Accessibility and Effectiveness

Mandeep Bhardwaj, Lovely Professional University

Climate Change, Agricultural Vulnerability, and Public Health Risks in Indian Agricultural Districts: A Spatial Analysis

Pinaki Das, Vidyasagar University

Impact of the ICDS on the Health Status of Pregnant and Lactating Mothers in India: Evidence from NFHS-5

Basant Kumar Panda, Population Council Consulting Pvt. Ltd.

Unlocking the Potential of young women through skilling: Evidence from an evaluation Study in Rajasthan, India

Veeresh Tadahal, Indian Institute of Information Technology, Trichy

Solarization of Primary Health Centers and Health Outcomes: Community Perspectives Using Three Delay Model in Yadgir Aspirational District, Karnataka, India

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Shalem Balla, Indian Institute of Technology Mandi

Voltage drops (transitions) in economic empowerment to intrinsic empowerment of women in India

Prateek Singh, Indian Institute of Technology Mandi

Family Transition in Three Decades and Its Effect on Young Married Women's Health in India

Kareena Kaushik, Banasthali Vidyapith

Women's experiences with infertility and the role of assisted reproductive technologies: A qualitative study from Haryana

Juliet F Lalzarzoliani, The ICFAI University, Mizoram

Work-life balance, mental well-being, and family support among working mothers in Aizawl city: A cross-sectional study

Dr Paramasivam P., Takshashila University

Determinants of mental health and wellbeing: evidence from women IT employees in Chennai, Tamil Nadu

Technical Session 3C

Abishek Paul, Institute of Development Studies Kolkata

Does 'Where They Live' Matter? Exploring the Link Between Living Arrangements and Quality of Life Among the Elderly in India

Sasmita Behera, MIT World Peace University, Pune

Does Energy Poverty Influence Healthcare Expenditure? Evidence from Longitudinal Ageing Study in India

Isha Tanwar, Manipal University Jaipur

Impact of Multimorbidity on Labor Force Participation in India: Evidence from LASI

Ali Abbas Rizvi, International Institute for Population Sciences, Mumbai

Family and Elderly Care: Addressing Unmet Needs in Activities of Daily Living Among Older Populations in India

Sabhya Yadav, Birla Institute of Technology and Sciences, Pilani, K K Birla Goa Campus

Cyclicality of Public Health Expenditure Among Indian States: Fiscal and Political Determinants

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Tejal Rajaram Varekar, ICMR-National Institute for Research in Reproductive and Child Health

A Systematic Review and Meta-Analysis of Preconception Care Interventions and their Effects on Maternal and Child Health in South-East Asia: Economic and Feasibility Implications for India

Illias K Sheikh, Development Management Institute

Spousal Violence and Risky Birth Spacing Among Indian Women: Insights from NFHS-5

Sachin Saini, Indian Institute of Technology Mandi

Autonomy Under Scrutiny: Women, Abortion Laws and Reproductive Decision Making

Anisha Ojha, IISER, Pune

Pre-Marital Sexual Behaviour Among Women in India: Evidence from NFHS Series

Siddika Banu, Duliajan College

Status of Maternal Health Across the States of India: A Multidimensional Approach

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Amal Tomy, Sikkim Manipal Institute of Technology

Digital and Gamified Assessments as Innovations in Adolescent Health and Wellbeing: A Meta-Analytical Review

Debashree Paul, Indian Institute of Technology Kharagpur

Demystifying Adolescent Malnutrition in West Bengal with Ground Realities: Issues and Implications for Policies and Institutions

Kajal Kumari, Central University of Gujarat, Vadodara, Gujarat, India

Navigating Menstrual Equity: A Critical Enquiry into Social Innovation Practices in Kerala, India

Vysagh R K, University of Calicut

Descriptive Profile of eHealth Initiatives in Kerala: Objectives, Implementation and Challenges

Jatinder Singh, Indian Institute of Technology Roorkee

Does Internet Use Shape Lifestyle: Benefits for Healthy Vs Unhealthy Consumption

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Dr Sunil Khosla, VIT-AP University

Impact of Financial Inclusion on Multidimensional Health Poverty Among Rural Households in Eastern India

Welisou Mero, Nagaland University

Assessing Public Healthcare Service Quality in Nagaland: Insights from a Case Study in Phek District

Aakriti Aggarwal, Indian Institute of Technology Kanpur

Can Neighbourhood Clinics Deliver? Causal Evidence from Delhi's Mohalla Clinics

Dr Shailendra Kumar, Department of Community Medicine & School of Public Health, PGIMER, Chandigarh

Assessing State-Level Efficiency Using District Hospital Performance Indicators: A Data Envelopment Analysis Approach

Blessy Sarah Mathew, Lovely Professional University, Punjab

Beyond Coverage: Why Ayushman Bharat–Pradhan Mantri Jan Arogya Yojana Struggles to Deliver Healthcare in Jammu and Kashmir

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