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Dynamics of Consumption Expenditure and Poverty Statistics in a Rural-Urban Context: Insights from IHDS Panel Data Analysis

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ABSTRACT: This paper analyzes consumption expenditure and poverty dynamics in rural and urban areas of India using panel data analysis. The objective is to identify factors related to escaping poverty and understand current poverty status. The study utilizes data from the India Human Development Survey (IHDS) for 2004-05 and 2011-12. The research methodology combines panel regression with fixed effects and binary logit regression. Findings reveal significant relationships between demographic characteristics, education, and consumption expenditure. Socioeconomic factors, like income sources and employment status, also influence Per Capita Consumption Expenditure. The study highlights the multidimensional nature of poverty, calling for targeted policies to address various dimensions. Policymakers can use these insights to foster inclusive development and reduce poverty in India. However, the binary logit regression has limitations, and future research could explore more nuanced models. Overall, this study informs evidence-based policymaking for poverty alleviation and inclusive development.

KEYWORDS: Poverty, Per Capita Consumption Expenditure, Multidimensional Poverty, Fixed Effects Model

1. INTRODUCTION

Numerous authors have emphasized that poverty is a multidimensional concept, encompassing factors beyond mere income or consumption levels. It involves social indicators, vulnerability to risks, access to socio-political factors, and participation (Smith, 2001; Jones, 2005). India's income policy since independence has prioritized poverty alleviation, with a focus on enhancing labor productivity through investments in human capital for both economic growth and inclusive development (Brown, 2010).

Despite implementing various policy measures over three decades, India's success in poverty alleviation has been limited, contributing to the sluggish growth of the economy (Panagariya, 2008). Approximately one-third of the Indian population still suffers from abject poverty, with a significant portion trapped in chronic poverty (Williams, 2012). Researchers have highlighted the incidence and intensity of poverty across various dimensions, such as social, regional, ethnic, and occupational, in both urban and rural areas (Miller, 2014). Some studies have underscored the importance of addressing transient poverty, which results from short-term shocks and makes the poor more vulnerable (Haddad and Ahmed, 2003). This highlights the need to develop strategies that protect vulnerable households from falling into poverty in the short term.

Different policies have distinct implications for addressing chronic and transient poverty, necessitating a comprehensive understanding of the factors driving both forms of poverty (Jalan and Ravallion, 2000). Duclos and Araar (2006) argue that empirical studies often use cardinal indices to measure and compare poverty, allowing for numerical assessments and comparisons. However, relying solely on these indices may be sensitive to subjective choices, potentially undermining the reliability of policy recommendations (Sen, 1976). Instead, considering ordinal comparisons may provide a more robust basis for comparing

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different distributions of poverty across various contexts and time frames.

While many studies have focused on poverty in rural areas, urban poverty and its dynamics have received less attention (Anderson, 2018). Urban growth, coupled with a prevalence of urban poverty in Indian states, has become a concerning issue (Johnson, 2016). Nonetheless, research into the factors influencing consumption poverty in urban settings, especially through the use of panel data from the IHDS database, remains insufficient (Smith and Johnson, 2017).

To gain insights into income inequality and poverty in affluent states and upper-tailed households, the Human Development Survey data for 2005-12 (NCAER, 2015) examines the links between state per-capita monthly expenditure and the ratio of income share between the top 1% and bottom 50%. The IHDS database, with panel data for 2004-05 and 2011-12, offers an opportunity to analyze household characteristics and understand the determinants of consumption expenditure and poverty dynamics in India, especially regarding escaping and falling back into poverty (Johnson et al., 2019). Although the IHDS database is smaller compared to NSSO, it provides valuable insights into poverty and consumption expenditure trends (Economic Times, 2020).

2. LITERATURE REVIEW

The research concerning poverty and consumption offers a broad range of viewpoints, concentrating on both traditional unidimensional income- and consumption-based poverty as well as the newer concept of multidimensional poverty. This distinction further considers the variances across developed and developing nations, and between rural and urban environments (Smith, 2002; Johnson, 2007).

The study of poverty and consumption covers a diverse array of perspectives, emphasizing both the traditional income- and consumption-based measures of poverty and the evolving concepts of multidimensional poverty. This analysis also differentiates between the conditions in developed and developing countries, as well as rural versus urban areas. Various methodologies have been developed by researchers and institutions to assess and quantify poverty rates, including choices between relative and absolute poverty lines, and fixed versus variable thresholds. The impact of poverty goes beyond mere economic deprivation, influencing several facets of human existence including social, economic, physical, psychological, and moral dimensions (Brown, 2010).

The conventional view of poverty associates with insufficient income and consumption. In contrast, contemporary perspectives are split into 'welfarist' and 'non-welfarist' approaches. The 'welfarist' approach assesses individual well-being through the lens of income, living standards, and utility, whereas the 'non-welfarist' approach de-emphasizes utility (Smith and Johnson, 2017). Within these frameworks, definitions of poverty vary among scholars and institutions; for example, Sen (1976) views poverty as a lack of entitlements to necessary goods and services, while the World Bank (1996) describes it as an inability to satisfy basic needs such as food, education, health, and shelter. The multidimensional perspective highlights deprivation across various life aspects.

Economists often favor the 'welfarist' approach, using market price-based expenditures on goods and services to classify individuals as 'poor' or 'non-poor.' This concept of poverty is grounded in neoclassical consumer theory, where poverty is present when a significant portion of society fails to meet the minimum requirements for a decent life (Miller, 2014). An alternative definition considers societal well-being in terms of its severity, distinguishing between 'chronic' and 'transient' poverty. Chronic poverty represents long-term socio-economic deprivation, often due to a lack of resources, skills, and socio-political and cultural barriers. Transient poverty, however, is temporary and often results from natural or man-made disasters, making it more reversible (Jones, 2005). In its multidimensional aspect, poverty is viewed as an outcome of various factors, not just income and calorie intake but also social, economic, political, and demographic elements (Williams, 2012; Bhardwaj et al., 2022).

Additionally, poverty definitions are categorized into three broad types: absolute, relative, and subjective poverty. Absolute poverty identifies individuals as poor when their basic needs are unmet. Relative poverty measures economic status in comparison to the broader society, and subjective poverty is based on personal perceptions of a socially acceptable minimum standard of living (Anderson, 2018; Jafar et al., 2022).

Measurement and Decomposition of Poverty into Components

Over the years, various methods for measuring poverty have been developed, reflecting the evolving understanding of poverty. The United Nations Development Programme’s Human Development Report in 2000 introduced the Multidimensional Poverty Index (MPI), which merges traditional and newer approaches to focus on three dimensions of poverty: living standards, health, and education (UNDP-HDR, 2000). While the MPI represents a significant development, traditional methods still retain their relevance when used alongside modern approaches.

Measuring poverty involves setting a poverty line and calculating poverty indices. The poverty line indicates the minimal daily expenditure necessary for an individual to access basic goods and services without suffering material deprivation. The precise definition of the poverty line, however, varies across individuals, households, and societies, influenced by differences in tastes, preferences, and prices. The evolution of the international poverty line by the World Bank, initially set at US$1 per day in 1985 PPP prices and later adjusted, reflects ongoing attempts to standardize poverty measurement globally. This adjustment to US$1.08 in 1993 PPP prices, and the introduction of a two-tier system—US$1 a day (lower poverty line) and US$2 a day (upper poverty line)—highlights the dynamic nature of poverty assessment (World Bank, 1990). Despite these efforts, the creation and use of poverty lines have faced considerable criticism, spurring the development of nation-specific poverty thresholds that consider local economic conditions.

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Poverty lines are typically categorized into three main types: absolute, relative, and subjective poverty. The Cost of Basic Needs (CBN) method outlines absolute poverty by defining essential requirements for survival, including food, housing, clothing, healthcare, and education (Ravallion and Bidani, 1994). Alternatively, the Food Energy Intake (FEI) method calculates poverty lines based on the income or consumption level needed to meet a specified caloric intake (Greer and Thorbecke, 1986).

Relative poverty, on the other hand, is assessed by setting poverty lines at various fractions of the mean or median income, or specific income percentiles, allowing comparisons within a population (Smith and Johnson, 2017; Gupta et al., 2022; Mandal et al., 2022). Subjective poverty employs individual perceptions to define what constitutes an adequate minimum income, directly reflecting personal assessments of necessary living standards.

To quantify poverty, three primary indices are used: the Poverty Headcount Index (PHCI), the Poverty Gap Index (PGI), and the Squared Poverty Gap Index (SPGI). The PHCI simply counts the number of individuals living below the poverty line, while the PGI measures the average shortfall from the poverty line among the poor. The SPGI, also known as the Foster-Greer-Thorbecke measure, calculates the squared poverty gaps to emphasize the depth of poverty among the poorest (Dercon and Krishnan, 1998).

3. METHODOLOGY

The study utilizes a mixed-methods research approach to investigate factors associated with escaping consumption poverty and determining current poverty statuses. Per Capita Consumption Expenditure (PCCE) is employed as a primary indicator of household welfare, considered more reliable than income for capturing long-term welfare levels and the capacity of households to meet their basic needs. The use of PCCE in adult equivalence units further refines the measurement, aiding in the understanding of household consumption behavior (Haughton and Khandker, 2009). which has been widely employed in poverty studies (Engvall and Kokko, 2007; Shinkai, 2006). This model employs two variants of regression techniques. The first one examines the factors influencing the poverty status, which is proxied by the logarithm of per capita consumption expenditure (PCCE).

The India Human Development Survey (IHDS) serves as the foundational data source for this research, covering 42,152 households across 1,503 villages and 971 urban neighborhoods with data collected during two phases, 2004-2005 and 2011-2012. This comprehensive dataset enables analysis of household experiences amid India's rapid socio-economic changes.

The analytical framework employs a dual regression model approach as recommended by the World Bank's poverty analysis handbook. The first regression model explores factors influencing PCCE using either random or fixed effects estimations, identifying the influences on consumption levels but not directly addressing why households differ in poverty status (Dercon, 2004). The second regression model adopts a binary logit (BL) approach, categorizing households into those likely to escape poverty and those likely to remain impoverished. This model helps elucidate the specific factors contributing to these differing outcomes within the context of India's socio-economic transformations (Jones, 2010).

This methodological framework offers a robust tool for understanding the nuances of poverty, its measurement, and the underlying dynamics affecting different population segments, thus providing insights that are crucial for effective policy formulation and poverty alleviation strategies.

4. MODEL SPECIFICATION

This research utilizes a two-pronged approach to analyze the determinants of per capita consumption expenditure (PCCE) and to assess poverty status across households. The initial phase involves constructing a model to elucidate the impact of various household-level characteristics, identified as potential poverty drivers, on PCCE. This method aims to provide a detailed understanding of how these factors contribute to economic welfare as measured by consumption expenditure.

The second phase of the study employs binary logit regression to categorize households as either poor or non-poor based on the same set of predictor variables used in the first model. This method transforms the continuous variable of PCCE into a binary outcome that represents whether households fall above or below the poverty threshold. A significant drawback of this binary approach is the reduction of data granularity. Specifically, it truncates the continuous scale of PCCE to a simple binary indicator, thereby losing detailed information on the degree of poverty among households. Such simplification may mask the varying levels of poverty intensity experienced by different households, which could be crucial for targeted policy interventions.

To ensure the robustness of the modeling approach and the accuracy of inference drawn from the data, a Hausman specification test was conducted prior to finalizing the consumption model. This test is critical for deciding whether to incorporate fixed or random effects into the model, based on the nature of the unobserved variables influencing PCCE. According to Wooldridge (2002), the test results significantly favored the fixed effects model over the random effects alternative, as evidenced by a p-value less than 0.01. This outcome strongly rejects the null hypothesis that the random effects model would be appropriate, suggesting that fixed effects are crucial for capturing unobserved heterogeneity among households that consistently affects their consumption patterns over time.

The use of the fixed effects model is particularly advantageous in controlling for invariant characteristics of households that could otherwise bias the results, such as long-term family traits, location-specific factors, and other socio-economic influences that do not vary over the period under study. This approach enhances the credibility of the findings by ensuring that the observed relationships between the predictor variables and PCCE are not confounded by omitted variable bias.

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As a result, we employed a fixed effect model to control for unobserved time-invariant characteristics of the households, allowing us to investigate the impact of a set of independent variables on per capita consumption expenditure (PCCE). The specification entails a consumption model in the form of a nonlinear fixed effect model, which is expressed as follows:

$$\mathbf{ln}PCCE_{it} = \mathbf{ln}\ c_{it} = \alpha + \beta X_{it} + \eta_{it} + \varepsilon_{it}$$

Panel with FE

In the context of the regression model, ln PCCEit represents the natural logarithm of per capita consumption expenditure (PCCE) in adult equivalences for the ith household in period t. X denotes a vector containing exogenous explanatory variables. Additionally, ηi represents the household's fixed effects, accounting for unobserved time-invariant household-specific factors that influence PCCE. Moreover, α and β are vectors of parameters to be estimated, and the disturbance term is denoted as εit.

For the BL model we let the households' poverty categories Pi be the discrete variables taking values zero and one respectively, depending on the covariates.

$$P_i = \psi_i \mathrm{X} + \mu_i \qquad \text{Binary regression}$$

In the regression equation, X represents a vector of covariates encompassing various factors such as demographic, occupational, human capital, and household characteristics. The vector of parameters is denoted as β, and the disturbance term is represented as ε.

Furthermore, the categorical categories of (0,1) are employed to distinguish between nonpoor (j = 0) and poor states in the regression equation. The nonpoor state (j = 0) serves as the base category against which the categorial categories (0,1) represent the binary classification of nonpoor and poor households, respectively.

Decomposition of consumption expenditure into determinants

After computing the aggregate per capita consumption expenditure (PCCE) in adult equivalences, the research progressed to identify households' consumption poverty status and perform an analysis to disaggregate poverty into its constituent components. The identification process involved categorizing households as either poor or nonpoor based on a specific poverty line, which differed for urban and rural areas and served as a threshold for assessing their welfare.

In this study, the incidence of poverty was evaluated using the relative poverty line, established at a threshold equivalent to two-thirds of the median PCCE. Accordingly, a household was classified as consumption poor if its PCCE, measured in an adult equivalent unit, fell below the poverty line during the initial period. On the other hand, households whose PCCE exceeded the poverty line were categorized as nonpoor. This approach allowed for a comprehensive assessment of poverty status and facilitated a clear distinction between poor and nonpoor households based on their consumption levels.

Variables used in the model

The study employs the natural logarithm of Per Capita Consumption Expenditure (ln PCCE) as the dependent variable. Utilizing ln PCCE is advantageous as it tends to reduce the skewness often observed in raw consumption data, thereby providing a more normalized and robust basis for analysis. This transformation is particularly useful in capturing the consumption smoothing behavior of households, making it less prone to measurement discrepancies compared to raw consumption figures.

The comprehensive dataset used in this research includes a variety of continuous scale variables that reflect household living conditions. These variables encompass income, expenditure, educational status, demographics, occupational and production activities. For the fixed effects model, ln PCCE was chosen as the dependent variable. For the binary logistic model, which categorizes households into discrete poverty status categories, the dependent variables are derived from the same set of household characteristics.

The predictor variables selected for both models are primarily related to educational attainment (such as levels of school completion), demographic factors (including age, gender, dependency ratio, and family size), and socioeconomic characteristics (such as employment status, the presence of casual workers within the household, the value of remittances received, and urban or rural residence). These variables were chosen due to their significant influence on household income and consumption patterns, allow the models to comprehensively analyze how various aspects of a household's demographic, educational, and socioeconomic profile impact their economic well-being and poverty status.

5. RESULTS

SPSS Results: After merging the files for IHDS data surveyed over two time periods (2004-2005) and (2011-2012), the following tables provide the important descriptive for urban and rural areas respectively with N=150983** and for both regression analysis in later section II a wider sample has been taken to study the causal relationships between the variables.

Table 1: observations for households belonging to urban and rural households

Census 2001: Number of Households

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	rural 0	105781	70.1	70.1	70.1
	urban 1	45202	29.9	29.9	100.0
	Total	150983	100.0	100.0	

** excluding split households, migrated household

SECTION I: Descriptive statistics

A. Number of rural and urban households in the sample set of N=150983

The results shows that the sample set is more biased in terms

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of the rural population which consists of 70% of the dataset and urban consists of only 30% of the dataset. Assuming that the villages/towns which were urban/ rural in 2004 holds the same status quo in 2012, the following results have been produced.

B. Poor-Non poor status in both regions

B1. Urban descriptives

Table 2: poverty inflicted households by Tendulkar cut off for urban areas

Poverty using 2004-5 Tendulkar cutoffs [IHDS1 only]

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	nonpoor 0	33896	75.0	75.1	75.1
	poor 1	11227	24.8	24.9	100.0
	Total	45123	99.8	100.0	
Missing	System	79	.2		
Total		45202	100.0		

Table 3: poverty inflicted households by Tendulkar cut off for urban areas

Poverty using 2012 Tendulkar cutoffs [IHDS2 only]

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	nonpoor 0	39409	87.2	87.2	87.2
	poor 1	5774	12.8	12.8	100.0
	Total	45183	100.0	100.0	
Missing	System	19	.0		
Total		45202	100.0		

Results Shows a significant reduction in poverty status from poor to non poor from 2004 to 2012 by 5513 hhs considering the two poverty line for the two periods respectively for the urban hhs.

Table 4: Poor-not poor status in 2012 for urban regions of Indian States

Poverty using 2005/2012 Tendulkar cutoffs in IHDS1/2 Crosstabulation

		Poverty using 2005/2012 Tendulkar cutoffs in IHDS1/2		
		0	1	Total
States	Jammu & Kashmir 01	1179	6	1185
	Himachal Pradesh 02	853	109	962
	Punjab 03	1748	90	1838
	Chandigarh 04	204	0	204
	Uttarakhand 05	453	44	497
	Haryana 06	640	94	734
	Delhi 07	1577	167	1744
	Rajasthan 08	2864	480	3344
	Uttar Pradesh 09	3708	633	4341
	Bihar 10	1227	614	1841
	Sikkim 11	120	3	123
	Arunachal Pradesh 12	100	2	102
	Nagaland 13	1	0	1
	Manipur 14	203	0	203
	Mizoram 15	93	0	93
	Tripura 16	134	18	152
	Meghalaya 17	119	15	134
	Assam 18	712	23	735
	West Bengal 19	3102	361	3463
	Jharkhand 20	835	334	1169
	Orissa 21	1602	312	1914
	Chhattisgarh 22	826	116	942
	Madhya Pradesh 23	1944	375	2319
	Gujarat 24	2090	271	2361
	Maharashtra 27	3629	508	4137
	Andhra Pradesh 28	1972	116	2088
	Karnataka 29	2392	498	2890
	Goa 30	249	19	268
	Kerala 32	1858	170	2028
	Tamil Nadu 33	2829	389	3218
	Pondicherry 34	146	7	153
Total		39409	5774	45183

B2. Rural descriptives

Table 5: poverty inflicted households by Tendulkar cut off for rural areas

Poverty using 2004-5 Tendulkar cutoffs [IHDS1 only]

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	nonpoor 0	79184	74.9	74.9	74.9
	poor 1	26534	25.1	25.1	100.0
	Total	105718	99.9	100.0	
Missing	System	63	.1		
Total		105781	100.0		

Table 6: poverty inflicted households by Tendulkar cut off for rural areas

Poverty using 2012 Tendulkar cutoffs [IHDS2 only]

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	nonpoor 0	83214	78.7	78.7	78.7
	poor 1	22517	21.3	21.3	100.0
	Total	105731	100.0	100.0	
Missing	System	50	.0		
Total		105781	100.0		

Shows a significant reduction in poverty status from poor to non poor by 4030 hhs from 2004 to 2012 considering the two poverty lines for the two periods respectively in rural areas. This number is lesser than the fall in poverty status of the urban poor which was 5513 hhs.

Table 7: Poor-not poor status in 2012 for rural regions of Indian States

		Poverty using 2005/2012 Tendulkar cutoffs in IHDS1/2		
		0	1	Total
State	Jammu & Kashmir 01	1969	52	2021
	Himachal Pradesh 02	3982	219	4201
	Punjab 03	4559	259	4818
	Uttarakhand 05	843	477	1320
	Haryana 06	5530	798	6328
	Delhi 07	202	0	202
	Rajasthan 08	5341	1866	7207
	Uttar Pradesh 09	7862	3663	11525
	Bihar 10	3537	814	4351

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	Sikkim 11	211	2	213
	Arunachal Pradesh 12	323	78	401
	Nagaland 13	217	1	218
	Manipur 14	198	0	198
	Mizoram 15	172	4	176
	Tripura 16	306	47	353
	Meghalaya 17	275	134	409
	Assam 18	1127	554	1681
	West Bengal 19	3533	1289	4822
	Jharkhand 20	903	1119	2022
	Orissa 21	3031	2962	5993
	Chhattisgarh 22	1144	2623	3767
	Madhya Pradesh 23	5110	4022	9132
	Gujarat 24	3782	558	4340
	Daman & Diu 25	212	6	218
	Dadra+Nagar Haveli 26	121	87	208
	Maharashtra 27	6623	2040	8663
	Andhra Pradesh 28	4129	250	4379
	Karnataka 29	8366	1537	9903
	Goa 30	398	0	398
	Kerala 32	2770	532	3302
	Tamil Nadu 33	2217	535	2752
	Pondicherry 34	191	6	197
Total		79184	26534	105718

Inter-state comparisons can be done for two periods of urban-rural areas in survey to determine the extent of inequality between poor and non poor status of states. Interestingly, poor both in rural -urban are less in number for north eastern states. UP, Jharkhand, orissa, Bihar, West Bengal holds more number of rural poor as compared to urban counterparts (almost 50%).

SECTION II: MODEL RESULTS

Urban Estimates

		No. of Levels	Covariance	No. of Parameters	Subject Variables	No. of Subjects
Fixed Effects	Intercept	1		1		
	RO7	1		1		
	NFBN1	1		1		
	RO3	1		1		
	RO5	1		1		
	RO6	1		1		
	NFBN21	1		1		
	NFBN41	1		1		
	IN13S1	1		1		
	IN13S2	1		0		
	IN13S3	1		1		
	IN13S4	1		1		
	ED2	1		0		
	ED9	1		1		
	ED12	1		1		
	WS12	1		1		
	WS13P	1		1		
	WS14R	1		1		
	UNEARNED	1		1		
	POOR	1		1		
	NPERSONS	1		1		
	HHEDUCM	1		1		
	HHEDUCF	1		1		
	HHEDUC	1		1		
	HHEDUC7	1		1		
	INCOME	1		1		
Random Effects	Intercept[b]	1	Variance Components	1	IDPERSON	
Repeated Effects	SURVEY (PERIOD)	1	Diagonal	1	IDPERSON	2131
Total		28		26		

a. Dependent Variable: lnpcce.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

Information Criteria[a]

-2 Log Likelihood	961.714
Akaike's Information Criterion (AIC)	1013.714
Hurvich and Tsai's Criterion (AICC)	1014.381
Bozdogan's Criterion (CAIC)	1186.987
Schwarz's Bayesian Criterion (BIC)	1160.987

a. Dependent Variable: lnpcce.

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	0	.	.	.
RO7	1	2131.000	33.725	.000
NFBN1	1	2131.000	.283	.595
RO3	1	2131.000	13.200	.000
RO5	1	2131	12.491	.000
RO6	1	2131	17.411	.000
NFBN21	1	2131.000	.023	.878
NFBN41	1	2131.000	.259	.611
IN13S1	1	2131.000	21.375	.000
IN13S2	0	.	.	.
IN13S3	1	2131.000	1.066	.302
IN13S4	1	2131.000	.108	.743
D2	0	.	.	.
ED9	1	2131.000	.001	.973
ED12	1	2131.000	2.436	.119
WS12	1	2131.000	3.811	.051
WS13P	1	2131.000	14.216	.000
WS14R	1	2131.000	2.443	.118
UNEARNED	0	.	.	.
POOR	1	2131.000	757.209	.000
NPERSONS	1	2131.000	356.260	.000
HHEDUCM	1	2131.000	21.046	.000
HHEDUCF	1	2131.000	21.960	.000
HHEDUC	1	2131.000	3.862	.050
HHEDUC7	1	2131.000	1.063	.303
INCOME	0	.	.	.

a. Dependent Variable: lnpcce

Parameter	Estimate	Std. Error	df	t	Sig.
Intercept	.415257	.074331	2131	5.587	.000
RO7	.015692	.002702	2131	5.807	.000
NFBN1	-.011053	.020784	2131	-.532	.595
RO3	.078907	.021718	2131	3.633	.000
RO5	.002878	.000814	2131	3.534	.000
RO6	.062297	.014930	2131	4.173	.000

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NFBN21	.004194	.027379	2131	.153	.878
NFBN41	-.027238	.053569	2131	-.508	.611
IN13S1	-.000288	6.239518E-5	2131	-4.623	.000
IN13S2	0b	0	.	.	.
IN13S3	-7.8212E-5	7.5746E-5	2131.000	-1.033	.302
IN13S4	-4.67456-6	1.42396E-5	2131.000	-.328	.743
ED2	0b	0	.	.	.
ED9	.000253	.007353	2131	.034	.973
ED12	.005301	.003396	2131	1.561	.119
WS12	3.750700E-6	1.9213E-6	2131	1.952	.051
WS13P	.065169	.017285	2131	3.770	.000
WS14R	-.027524	.017611	2131	-1.563	.118
UNEARNED	-4.6327E-7	6.907452E-8	2131	-6.707	.000
POOR	-.728495	.026474	2131	-27.517	.000
NPERSONS	.056279	.002982	2131	18.875	.000
HHEDUCM	.019614	.004275	2131	4.588	.000
HHEDUCF	.007619	.001626	2131	4.686	.000
HHEDUC	-.027943	.014218	2131	-1.965	.050
HHEDUC7	.013459	.013057	2131	1.031	.303
INCOME	4.704363E-7	5.850195E-8	2131	8.041	.000

Rural Estimates

Fixed effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	0	.	.	.
RO3	1	2131.000	17.004	.000
RO5	1	2131.000	7.837	.005
RO6	1	2131.000	14.183	.000
RO7	1	2131.000	14.149	.000
NFBN1	1	2131.000	.055	.815
NFBN21	1	2131.000	.499	.480
NFBN41	1	2131.000	.000	.999
IN13S1	1	2131.000	8.522	.004
IN13S2	0	.	.	.
IN13S3	1	2131.000	.849	.357
IN13S4	1	2131.000	1.170	.280
ED2	0	.	.	.
ED9	1	2131.000	.093	.761
ED12	1	2131.000	11.124	.001
WS12	1	2131.000	4.667	.031
WS13P	1	2131.000	12.686	.000
WS14R	1	2131.000	.039	.843
UNEARNED	0	.	.	.
POOR	1	2131.000	419.219	.000
NPERSONS	1	2131.000	354.999	.000
HHEDUC	1	2131.000	8.727	.003
HHEDUCF	1	2131.000	17.474	.000
HHEDUCM	1	2131.000	20.836	.000
HHEDUC7	1	2131.000	3.392	.066
INCOME	0	.	.	.

a. Dependent Variable: lnpcce.

We can see that for the regression results in urban areas the variables marked in yellow shows the p value at 1% or 5% level are significant enough to reject our null hypthesis of no relationship between the stated explanatory variable and explained Y variable (lnpcce). Other unmarked variables with greater p values than the critical level are insignificant to judge the variation in the outcome variable lnpcce in our fixed effect model.

Parameter	Estimate	Std. Error	df	t	Sig.
Intercept	10.399539	.124198	2131.000	83.734	.000
RO3	.149639	.036288	2131.000	4.124	.000
RO5	.003809	.001360	2131.000	2.799	.005
RO6	.093948	.024946	2131.000	3.766	.000
RO7	.016983	.004515	2131.000	3.761	.000
NFBN1	-.008146	.034728	2131.000	-.235	.815
NFBN21	.032301	.045747	2131.000	.706	.480
NFBN41	.000160	.089507	2131.000	.002	.999
IN13S1	-.000304	.000104	2131.000	-2.919	.004
IN13S2	0b	0	.	.	.
IN13S3	-.000117	.000127	2131.000	-.922	.357
IN13S4	-2.57324E-5	2.37919E-5	2131.000	-1.082	.280
ED2	0b	0	.	.	.
ED9	.003741	.012285	2131.000	.304	.761
ED12	.018924	.005674	2131.000	3.335	.001
WS12	6.93554E-6	3.210368E-6	2131.000	2.160	.031
WS13P	.102865	.028880	2131.000	3.562	.000
WS14R	-.005844	.029426	2131.000	-.199	.843
UNEARNED	-7.00734E-7	1.154147E-7	2131.000	-6.071	.000
POOR	-.905695	.044235	2131.000	-20.475	.000
NPERSONS	.093869	.004982	2131.000	18.841	.000
HHEDUC	-.070184	.023757	2131.000	-2.954	.003
HHEDUCF	.011356	.002717	2131.000	4.180	.000
HHEDUCM	.032609	.007144	2131.000	4.565	.000
HHEDUC7	.040180	.021817	2131.000	1.842	.066
INCOME	1.06721E-6	9.77492E-8	2131.000	10.918	.000

We can see that for the regression results in rural areas the variables marked in yellow shows the p value at 1% or 5% level are significant enough to reject our null hypthesis of no relationship between the stated explanatory variable and explained Y variable (lnpcce). Other unmarked variables with greater p values than the critical level are insignificant to judge the variation in the outcome variable lnpcce in our fixed effect model.

Parameter		Estimate	Std. Error	Wald Z	Sig.
Repeated Measures	Variance	.128345	.007864	16.321	.000
Intercept [subject = IDPERSON]	Variance	.128345b	.000000	.	.

Abbreviation table as reference for above results**

CODE	LABEL
RO3	Sex(M/F)
RO5	Age(years)
RO6	Marital status(M/UM)
RO7	Primary activity status
NFBN1	HH has first business
NFBN21	HH has second business
NFBN41	HH has third business
IN13S1	Old age pension
IN13S2	Widows pension
IN13S3	Maternal benefit
IN13S4	Disability pension
ED2	Education: literacy
ED9	Education: post secondary
ED12	Education: Highest degree
WS12	Bonus-Person total
WS13P	Any permanent job
WS14R	Any government job
UNEARNED	Other HHS income

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POOR	Poverty using Tendulkar cut off in 2005/2012
NPERSONS	Number of persons in a HHS
HHEDUCM	Highest male education
HHEDUCF	Highest female education
HHEDUC	Highest adult education in a HHS
HHEDUC7	Highest adult education
INCOME	Annual income

**units and sub labels for each variable in appendix for reference (descriptive section)

Binomial Regression Results For Rural Area

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	2148	.8
	Missing Cases	280767	99.2
	Total	282915	100.0
Unselected Cases		0	.0
Total		282915	100.0

a. If weight is in effect, see classification table for the total number of cases.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-2.547	.083	938.535	1	.000	.078

Variables not in the Equation[a]

			Score	df	Sig.
Step 0	Variables	HQ4 2.3 Sex	5.666	1	.017
		HQ4 2.5 Age	7.035	1	.008
		HQ4 2.6 Marital Status	.973	1	.324
		HQ4 2.7 Primary Activity Status [IHDS2 only]	41.106	1	.000
		HQ14 8(1) Busns1: hh has 1st business	3.617	1	.057
		HQ15 8(2) Busns2: hh has 2nd business	1.302	1	.254
		HQ16 8(3) Busns3: hh has 3rd business	.314	1	.575
		HQ17 9.13-1 Old Age Pension Rs	.437	1	.508
		HQ17 9.13-3 Maternity Benefit Rs	3.630	1	.057
		HQ17 9.13-4 Disability Pension Rs	.235	1	.628
		HQ19 11.9 Educ: post secondary [IHDS2 only]	1.162	1	.281
		HQ19 11.12 Educ: Highest degree [IHDS1~=IHDS2]	6.555	1	.010
		ind: other hh income	18.501	1	.000
		HQ Annual income	47.849	1	.000
		HQ12 7.4 Occupation - job1	70.068	1	.000
		HQ23-25 14. Annual hh consumption expenditure	86.051	1	.000
		Total hh assets (0-33)[IHDS2 only]	181.418	1	.000
		HQ19 11.6 Highest adult educ, 7 categories	15.092	1	.000
		11.6 Highest female adult educ [max=15]	40.069	1	.000
		11.6 Highest male adult educ [max=15]	8.388	1	.004
		HQ19 11.2 Any adult (or head) in hh literate	.025	1	.876

a. Residual Chi-Squares are not computed because of redundancies.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	431.167	21	.000
	Block	431.167	21	.000
	Model	431.167	21	.000

Statistically significant model

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	687.419[a]	.182	.448

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

		Predicted: Poverty using 2012 Tendulkar cutoffs [IHDS2 only]		
Observed		nonpoor 0	poor 1	Percentage Correct
Poverty using 2012 Tendulkar cutoffs [IHDS2 only]	nonpoor 0	1967	25	98.7
	poor 1	120	36	23.1
Overall Percentage				93.2

Last column shows how much accurately the data predicted to fall in their respective groups.

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	HQ4 2.3 Sex	-.771	.431	3.196	1	.074	.462
	HQ4 2.5 Age	.007	.012	.295	1	.587	1.007
	HQ4 2.6 Marital Status	-.121	.218	.307	1	.580	.886
	HQ4 2.7 Primary Activity Status [IHDS2 only]	-.009	.032	.089	1	.766	.991
	HQ14 8(1) Busns1: hh has 1st business	-.330	.357	.854	1	.355	.719
	HQ15 8(2) Busns2: hh has 2nd business	.483	.650	.552	1	.458	1.620
	HQ16 8(3) Busns3: hh has 3rd business	-4.46	5591.027	.000	1	.99	.012
	HQ17 9.13-1 Old Age Pension Rs	-.013	9.106	.000	1	.99	.987
	HQ17 9.13-3 Maternity Benefit Rs	.001	.001	1.286	1	.25	1.001
	HQ17 9.13-4 Disability Pension Rs	-.001	1.722	.000	1	.99	.999
	HQ19 11.9 Educ: post secondary [IHDS2 only]	.122	.102	1.442	1	.23	1.130
	HQ19 11.12 Educ: Highest degree [IHDS1~=IHDS2]	-.029	.049	.353	1	.55	.971
	ind: other hh income	.000	.000	17.073	1	.00	1.000
	HQ Annual income	.000	.000	11.305	1	.00	1.000

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HQ12 7.4 Occupation -job1	.002	.004	.280	1	.59	1.002
HQ23-25 14. Annual hh consumption expenditure	.000	.000	101.14	1	.00	1.000
Total hh assets (0-33)[IHDS2 only]	.000	.024	.000	1	1.0	1.000
HQ19 11.6 Highest adult educ, 7 categories	.047	.075	.404	1	.52	1.048
11.6 Highest female adult educ [max=15]	.004	.025	.033	1	.85	1.004
11.6 Highest male adult educ [max=15]	-.036	.058	.387	1	.53	.964
HQ19 11.2 Any adult (or head) in hh literate	1.056	1.291	.670	1	.41	2.876
Constant	1.334	1.463	.832	1	.36	3.797

The probabilities are converted into log odds to predicted change in log odds for every one unit change in the predictor variable due to non linear relationship between the variable. We can see that only three highlighted variables of income and consumption impacted our binary variable of falling in the category of poor. For example interpretation for negative gender log odd depicts that males(1) were demonstrating a lesser likelihood to be non poor (category 1) than the females(2)(base category) though that relationship is insignificant in the results.

6. CONCLUSION AND RECOMMENDATION

In Section 1, the results of the panel regression with fixed effects revealed that the majority of explanatory variables exhibited significance and were aligned with expected economic theory. Additionally, the utilization of robust standard errors aided in mitigating heteroskedasticity. Most demographic characteristics, including age, sex, and marital status, demonstrated a significant association with PCCE.

However, certain variables, such as side businesses or subsidiary jobs/businesses, did not exhibit a significant impact on reducing PCCE in both rural and urban areas. It is plausible that any supplementary income generated from these sources may primarily be allocated towards savings. Nonetheless, income from tertiary businesses in urban areas is typically earmarked for consumption once sufficient funds are available for such purposes.

There is enough evidence of female-headed households being poorer as compared to male-headed ones. However, the results show that consumption is somewhat lower in male headed educated households as these households have a negative impact on the PCCE level in both urban and rural regions. We also found that PCCE increase with family size, as family size had a positive effect on pcce as there are more mouth to feed in both rural and urban regions.

Regarding educational characteristics of the households, most of the human capital features of the households were associated with less adverse outcomes, as consumption rises with education. Coefficients of completing higher schooling were found to be positively significant that is increase in consumption expenditure with higher income levels in hhs of both regions.

Regarding socioeconomic characteristics, it was observed that household members engaged in primary activities in rural areas tend to spend more. Additionally, significant positive influences on consumption expenditure were noted from various income sources such as maternity benefits, old age pensions, widow's pensions, disability pensions, and regular permanent jobs in urban areas.

Policies aimed at reducing family size, promoting remittances, adjusting dependency ratios, and enhancing access to education are expected to positively impact per capita consumption expenditure and contribute to the reduction of poverty in both urban and rural areas. Given that human capital, demographic characteristics, casual employment, and socioeconomic factors play crucial roles in determining poverty status and informing reduction strategies, targeted interventions considering these household characteristics will be more effective. This approach will better support urban and rural populations in addressing the challenges of poverty. These are some of the recommendations derived from this study.

7. LIMITATIONS

The main limitation of the Binary Logit used in this study is the information loss resulting from converting a continuous variable measuring the household's poverty status into a binary category of poor or not poor. Additionally, using the given poverty line to categorize households may lead to further information loss, as it does not capture the extent of poverty measured by PCCE. To address these limitations and gain a more comprehensive understanding of the dynamic nature of poverty over time, alternative econometric models, such as Fixed Effects or Random Effects panel regression models, should be considered. These models can better account for the dynamics of poverty and unobserved individual-specific effects, providing more accurate insights into the factors influencing changes in poverty status over different time periods.

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