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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). However, there is a lack of research on the determinants of consumption poverty in urban areas, particularly using panel data from IHDS database (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 literature on poverty and consumption presents a wide array of perspectives, with a focus on both unidimensional income- and consumption-based poverty and the more recent emergence of multidimensional poverty concepts. This distinction also takes into account differences between developed and developing countries as well as rural and urban areas (Smith, 2002; Johnson, 2007).

Researchers and institutions have explored various approaches to measure and evaluate poverty rates, including the choice between relative and absolute poverty lines, and variable versus fixed poverty lines. The consequences of poverty extend beyond material deprivation and income scarcity, affecting multiple dimensions of human life, such as social, economic, physical, psychological, and moral aspects (Brown, 2010). Consequently, diverse approaches are followed to define and understand the nature of poverty.

The traditional approach links poverty to the lack of consumption and income. On the other hand, the modern approach can be divided into two dimensions - the 'welfarist' and 'non-welfarist' approaches. The former focuses on an individual's well-being based on the connection between income, standard of living, and utility, while the latter places little emphasis on utility (Smith and Johnson, 2017). Scholars and institutions have varied interpretations of poverty within these frameworks. For instance, Sen (1976) sees poverty as the failure to have entitlements to various goods and services, while the World Bank (1996) defines it as the inability to meet basic needs like food, education, health, and shelter. The multidimensional perspective of poverty emphasizes deprivation across various aspects of life.

Economists, however, often prefer the 'welfarist' approach, using expenditures on goods and services at market prices to categorize individuals as 'poor' or 'non-poor.' The concept of poverty within this approach is based on the neoclassical consumer theory, wherein poverty exists when a significant portion of society cannot meet the minimum basic requirements for a decent life (Miller, 2014).

Another approach to defining poverty considers societal well-being in terms of severity, distinguishing between 'chronic' and 'transient' poverty. Chronic poverty refers to persistent socio-economic deprivations, often resulting from a lack of productive resources, skills, and socio-political and cultural factors. In contrast, transient poverty is temporary and can be linked to natural or man-made disasters, and it is more easily reversible (Jones, 2005). In its multidimensional aspect, poverty is seen as an outcome of various factors, encompassing not only income and calorie intake but also social, economic, political, and demographic elements (Williams, 2012; Bhardwaj et. al., 2022).

Furthermore, there are three broad categories of poverty definitions: absolute poverty, relative poverty, and subjective poverty. Absolute poverty identifies individuals as poor when their essential needs are not adequately met. Relative poverty, on the other hand, defines poverty based on a person's lower economic status in comparison to others. Subjective poverty relies on individual perceptions of what constitutes a socially acceptable minimum standard of living within their society (Anderson, 2018; Jafar et al., 2022).

Measurement and Decomposition of Poverty into Components

Over time, various methods to measure poverty have been developed alongside the evolving concept of poverty. Notably, the United Nations Development Programme's Human Development Report in 2000 introduced the Multidimensional Poverty Index (MPI). This index combines conventional and new approaches, focusing on three dimensions of poverty: living standards, health, and education (UNDP-HDR, 2000). While the MPI is a significant advancement, conventional methods still hold value when used in conjunction with more contemporary approaches.

Measuring poverty involves establishing a poverty line and computing poverty indices. The poverty line represents the minimum amount of money an individual should spend daily to afford basic goods and services without facing material deprivation. However, the true definition of the poverty line varies across individuals, households, and societies due to factors like differences in tastes, preferences, and prices.

Initially, the international poverty line was set by the World Bank at US$1 per day per person in 1985 PPP prices, which was later updated to US$1.08 in 1993 PPP prices. The World Bank then introduced two international poverty lines: US$1 a day (lower poverty line) and US$2 a day (upper poverty line) (World Bank, 1990). However, poverty lines face criticism and limitations, leading to the development of country-specific poverty lines for different nations.

Defining poverty lines can be classified into three main categories: absolute poverty, relative poverty, and subjective poverty. For absolute poverty, various methods

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exist, including the CBN approach, which defines the minimum requirements for basic needs like food, housing, clothing, healthcare, and education (Ravallion and Bidani, 1994). Another method is the FEI approach, which sets poverty lines based on the consumption/income level needed to meet the normative nutritional requirement of 2,200 kcal per adult per month (Greer and Thorbecke, 1986).

In relative poverty, poverty lines are based on fractions of mean or median income or percentiles of income distribution (Gupta et al., 2022; Mandal et al.,2022). The poverty line can be set at one-half, one-third, or two-thirds of the mean/median income or specific percentiles of the income distribution, with the researcher deciding which population falls below the line and is considered poor (Smith and Johnson, 2017).

Subjective poverty takes a different approach, relying directly on the opinions and feelings of individuals to determine the minimum income level they consider necessary for themselves. After establishing the poverty line using one of these approaches, poverty indices are calculated. There are three main classes of poverty indices: the poverty headcount index (PHCI), the poverty gap index (PGI), and the squared poverty gap index (SPGI) (Sen, 1976). The PHCI simply measures the ratio of the number of poor individuals to the total population. The PGI evaluates the average gap between the income of the poor and the poverty line, while the SPGI, also known as the Foster-Greer-Thorbecke measure, assesses the intensity of poverty by squaring the transfers needed to provide substantial weight to the very poor households (Dercon and Krishnan, 1998).

Approach to measure the household welfare

This research employed a mixed research methods approach to enhance the findings aimed at identifying the underlying factors related to escaping consumption poverty and determining the current poverty status. The study utilized per capita consumption expenditure (PCCE) as a measure of households' welfare levels, recognizing that households' per capita incomes could also serve this purpose. However, the consumption measure was deemed more suitable as it provides a better representation of the long-term welfare level and the households' ability to meet their basic needs. Additionally, using PCCE in an adult equivalence unit allows for a more accurate reflection of households' consumption smoothing behavior and is therefore preferred as a more robust indicator of welfare. Moreover, this approach is less susceptible to measurement errors, enhancing the reliability of the study's findings (Haughton and Khandker, 2009).

3. METHODOLOGY

The India Human Development Survey (IHDS)** is a comprehensive, nationally representative survey conducted across 42,152 households in 1,503 villages and 971 urban neighborhoods in India. The original data collection took place during 2004-2005, with follow-up interviews conducted in 2011-2012 with the same households. The primary objective of the IHDS program is to analyze how Indian households are experiencing changes in their daily lives during a period of rapid societal transition.

This particular data collection combines the two segments of IHDS, IHDS-I, and IHDS-II, into a harmonized dataset, considering the perspectives of households, individuals, and eligible women aged 15 years and above. The data are available in three formats: wide, cross-sectional, and long, providing various options for conducting comprehensive analyses.

The study utilizes a model recommended in the World Bank's handbook of poverty analysis (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). This can be estimated using either a random or fixed effects estimation technique (Dercon, 2004). However, it is important to note that the panel regression in the first variant only identifies the factors that affect PCCE but does not explain why some households are poor while others are not.

To gain insights into why certain households experience poverty while others do not, the study treats poverty categories as a nominal variable and employs the second type of regression model. This model utilizes the BL (binary logit) model to examine the factors affecting either of the two poverty categories, distinguishing between households likely to escape poverty and those persistently trapped in poverty (Jones, 2010). This approach allows for a more comprehensive understanding of the dynamics of poverty and its determinants in the context of India's socio-economic changes.

4. MODEL SPECIFICATION

The first section of this study involves modeling welfare indicators and their changes to explain the level of per capita consumption expenditure (PCCE) as a function of predictor variables representing household-level characteristics considered as causes of poverty.

In the second method, binary logit regression is utilized to determine whether a household is poor or not, using the same predictor variables as in the first method. However, the dependent variable in this case is binary, representing the poverty status of the household. One limitation of this approach is the loss of information during the conversion of a continuous variable (PCCE) into a binary representation of poverty. Additionally, valuable information about the extent of poverty, as indicated by PCCE, is lost when relying on a poverty line scale.

Before specifying the consumption model, a Hausman-specification test (Wooldridge, 2002) was conducted to determine whether the unobserved fixed effect should be treated as a random or fixed effect. This test aimed to select the most appropriate method. The results indicated that the fixed effects model is more efficient than the random effects model, as its p-value was less than the 1% critical level, strongly rejecting the null hypothesis of the random effect model.

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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

In order to mitigate measurement error and endogeneity concerns, the natural logarithm of Per Capita Consumption Expenditure (PCCE) has been employed as a preferred welfare status indicator. This choice is based on the rationale that ln PCCE better captures households' consumption smoothing behavior and is considered to be less susceptible to measurement errors.

The dataset was comprehensive and addressed household living conditions, including income, expenditure, educational status, demographics, occupation and production activities, are there on a continuous scale. PCCE in logarithm term was selected as the dependent variable for the fixed effect model and discrete variable poverty categories as dependent variables for the Binary Logistic model using the households' characteristics that are mostly related to the educational, demographic, and socioeconomic characteristics as predictor variables for both models.

Demographic characteristics such as age, gender, dependency ratio, family size, and other characteristics of households have direct as well as indirect impacts on household income and consumption. Educational characteristics include primary, secondary, and tertiary school completion, and other socioeconomic characteristics including employment status, that is being a casual worker and number of casual-worker-members, value of remittances received and residence.

Family size, female headed households, dependency status on head and other socio- economic factors have been taken to evaluate the appropriate determinants on consumption expenditure.

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	0^{b}	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	0^{b}	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	0^{b}	0	.	.	.
IN13S3	-.000117	.000127	2131.000	-.922	.357
IN13S4	-2.57324E-5	2.37919E-5	2131.000	-1.082	.280
ED2	0^{b}	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	.128345[b]	.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.

Observed		Predicted Poverty using 2012 Tendulkar cutoffs [IHDS2 only] 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

The results in section 1 for panel regression with fixed effects showed most of the explanatory variables in the regression result were significant and of the appropriate sign in conformity with the economic theory. Moreover, the use of robust standard errors helped to reduce heteroskedasticity. Most of the demographic characteristics that is age, sex and marital status were significantly related to PCCE. Then there were a few variables which did not show their influence in reducing PCCE significantly in both rural and urban areas like the side businesses or subsidiary jobs/business. It could be possible that that part of extra income generated by other sources of income is used for savings only. However, income from 3rd business in urban areas is used for consumption when there is enough money to use for consumption.

There is enough evidence of female-headed households being more poor 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, coefficients on household members engaged in primary activities repeated more consumption expenditure in rural areas. Other important variable that affected consumption expenditure positively and strongly were various forms of income sources like the maternity benefits, old age pensions, widows pension, disability pension and regular permanent jobs in urban regions.

Policies that aim at reducing family size, encouraging remittances, dependency ratio, and improving access to education, will exert a positive effect on PCCE and help in reducing urban and rural poverty. Because human capital, demographic characteristics and casual employment and socioeconomic characteristics are important determinants of either of the poverty categories and reduction strategies, and targeting will be more effective if they take the enumerated households' characteristics into consideration to support the urban and rural poor to tackle poverty incidences. These are the some of the recommendations indicated from this study.

7. LIMITATIONS

The main limitation of the second method (Binary Logit - BL) 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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