COVID-19 and the unequal distribution of poverty risks: Evidence from Urban India

Archana Dang
Mausumi Das
Indrani Gupta

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COVID-19 and the unequal distribution of poverty risks: Evidence from Urban India

Archana Dang[1], Mausumi Das[2] and Indrani Gupta[3]

Abstract

This paper investigates poverty transitions and household predictors associated with different states of poverty transitions in India during the pandemic's first year (2020). Following the unexpected shock brought on by COVID, economic activity slowed down, presumably pushing many households into poverty. For poverty alleviation programmes, it is important to identify households that fell into poverty during COVID and remained in poverty subsequently. Our findings indicate that urban households were more severely affected, and about 19% individuals in urban areas who were not poor in the pre-COVID period (2019) qualified as poor in the COVID period. Estimating a multinomial logit model for urban households our analysis finds that vulnerable castes relative to upper castes had a higher probability of falling into poverty and remaining there. Moreover, households at the lower end of the expenditure distribution and those with household members with lower levels of education were more prone to falling back into poverty and more likely to remain in poverty. These findings suggest that those who were most vulnerable sustainably suffered the most; as a result, the pandemic worsened socio-economic gaps that already existed across households.

Keywords: COVID, poverty, India, caste, vulnerability, poverty transition

JEL: **I32, D63**

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[1] Junior Sir Ratan Tata Fellow, Institute of Economic Growth, University Enclave, New Delhi, North Delhi, -110007, Email: archana.dang@iegindia.org

[2] Professor, Department of Economics, Delhi School of Economics, University Enclave, New Delhi, North Delhi, -110007, Email: mausumi@econdse.org

[3] Professor and Head, Health Policy Research Unit, Institute of Economic Growth, University Enclave, University of Delhi (North Campus), Delhi -110007, India. Email: indrani@iegindia.org

1. Introduction

The impact of the COVID-19 pandemic on the global economy has been quite unparalleled in its magnitude as well as range. On the one hand, it led to a sharp contraction in output, creating supply chain disruptions and impacting the profitability of business enterprises. On the other hand, it caused huge job and income losses, pushing households into poverty. The economic impact has been particularly severe for emerging market economies like India. The Indian economy was already weak due to the slowdown since 2016, making it more vulnerable to the COVID-induced economic shock (Ramakumar and Kanitkar 2021; Subramanium and Felman 2019). Further, to stop the spread of COVID-19, the Indian government implemented one of the most stringent countrywide lockdowns beginning on March 24, 2020. While the lockdown was unavoidable given the nature of the disease, it halted all economic activities for a prolonged period of time, giving rise to widespread misery and hardship. Indeed, the COVID-19 pandemic and the associated lockdowns have caused the most significant economic crisis in recent times. In this paper we examine whether the ensuing economic hardship impacted different socioeconomic groups differentially, and identify the section of the population which ran the greatest risk of falling into poverty, and staying in poverty.

Using the PovcalNet dataset of the World Bank, Kochhar (2021) documented that about 75 million people are estimated to have become poor in India due to the COVID crisis, accounting for more than 50% of the global increase in poverty. Additionally, a few studies used the Consumer Pyramid Household Survey (CPHS) to show that poverty rates have risen in India. For instance, the State of Working India (2021) found that poverty rates rose by 15 percentage points in rural areas and by 20 percentage points in urban areas in 2020. The same dataset is also used by Dhingra and Ghatak (2021), who show an increase in poverty of 14 and 18 percentage points in rural and urban areas, respectively, from August 2019 to August 2020. According to Gupta et al. (2021 b) and Jha and Lahoti (2022), there was a significant increase in poverty during the initial lockdown, and recovery to pre-pandemic levels during the post-lockdown phase was only moderate. Moreover, poverty levels worsened during the second wave and although the scenario improved during the post-second wave period, overall poverty remained marginally higher than pre-covid levels (Jha and Lahoti, 2022).

These studies, however, present aggregate trends in poverty increases during COVID, which masks the movements in and out of poverty and the proportion of poor that continues to remain poor. To fill this gap, we trace the poverty dynamics of households over time. Our study has three objectives: a) to seek a better understanding of what proportion of individuals/households fell into poverty, escaped poverty, remained poor and remained non-poor during the first year of COVID compared to proportions with the pre-COVID years; b) examine the household characteristics of these poverty transition categories using a multivariate regression framework and c) compare estimates from the pre-COVID period to see the changes in probabilities.[4] The primary motivation of the study is to examine factors that determine the change in status of impoverished households. Analysis of poverty transitions requires observing the poverty status of units at different points in time, and this requires using panel data. Therefore, this study utilizes the Consumer Pyramid Household Survey (CPHS), a nationally representative panel dataset for the analysis.

Earlier studies on India have shown that urban regions were affected more by the economic slowdown prior to the epidemic and throughout the first year of the pandemic (see, for example,

[4] However, we must mention that the marginal effects for *escaping poverty* category have not been reported due to the small proportion of households in that group which may make the numbers unreliable.

Abraham et al., 2021 and Kesar et al., 2021). Jha and Lahoti (2020) also noted that incomes in urban areas were still 10% below February 2020 levels by the end of 2021, despite the fact that incomes in rural areas had returned to pre-pandemic levels. Thus, we focus on urban households/individuals in our study.

In order to get the right perspective, we examine the issue of poverty transitions not only during the COVID period, but also a year preceding the COVID crisis. There has been an ongoing debate about the impact of pre-COVID growth slowdown on households' economic well-being. A decade after the economic reforms of the 1990s, in the early 2000s, poverty reduction in India began to pick up speed. Between 2009–11 and 2011–12, poverty fell significantly (Dang and Lanjouw, 2018; Dang et al., 2021). However, household level survey data collected by the National Sample Survey Organization (NSSO) were unavailable after 2011–12, which made it difficult to estimate poverty for the period after 2011. This gap has been filled by some researchers using extrapolation methods or various other datasets. While these studies support a decrease in poverty in the years following 2011 (see, for example, Roy and Weide, 2022; Bhalla et al., 2022), their findings have been questioned on various methodological grounds. In this backdrop, we use CPHS panel dataset, the only dataset available during the pandemic, to analyse the poverty dynamics at the household level. This research question is important at the current juncture, especially because the outbreak has highlighted worries about a potential rise in poverty and possible reversal of the declining trend in poverty.

Close to our study, Dang et al., 2021 use pre-COVID data to construct synthetic panels - in the absence of panel data - from cross-sectional survey data in order to enquire into the characteristics of the chronically poor in India during the pre-COVID period (2004-05 and 2011-12), which was the period of rapid economic growth and poverty reduction. However, we use panel data and the COVID period to examine the dynamics of poverty during the COVID crisis.

Our findings suggest that about 19% of urban individuals fell below the poverty line during the pandemic period (2020), given they were above the poverty line in the pre-COVID period (2019). A multinomial logit model for urban households that compared the pandemic year with the pre-pandemic year shows that SC/STs and OBCs relative to the upper castes have a higher likelihood of falling into and remaining in poverty. Moreover, the pandemic has amplified these caste-based gaps. Furthermore, households at the lower end of the expenditure distribution and those with household members with lower level of education are more prone to falling back into poverty, more likely to remain in poverty and less likely to remain non-poor. These results suggest that the most impoverished were hit the hardest during the pandemic.

The rest of the paper is organised as follows. The next section provides a brief review of the existing literature to contextualize our work. Section 3 describes the dataset used for the empirical analysis and sets out the outcome variable, while section 4 presents descriptive statistics. Sections 5 and 6 respectively describe the estimation strategy and report empirical findings. Finally, in section 6 we present our conclusions.

2. A Brief Review of the Literature

Our paper contributes to the emergent empirical literature that analyses the impact of COVID on different economic indicators for India. A large part of this literature focuses on the effect on employment. Kesar et al. (2021) and Abraham et al. (2021) were among the first few studies examining and documenting that urban workers were hit harder, at least during the first year of COVID. Moreover, in terms of gender, women relative to men were more likely to suffer job loss during the lockdown, and the recovery after the lockdown was faster among males (Abraham et al., 2021; Deshpande, 2022). Deshpande and Ramachandran (2020) and

Deshpande (2022) show that job loss was more among the disadvantaged group such as Scheduled caste (SC), Scheduled Tribe (ST), and Other Backward Classes (OBC). For example, SCs were 40% more likely than Upper Caste (UC) to suffer a job loss during lockdown (Deshpande and Ramachandran, 2020). However, after the lockdown, SC/STs were more likely to get a job (Abraham et al., 2021); Deshpande (2022) found the opposite result, i.e., only UC men could recover compared to men and women from other castes.

Daily wage, temporary salaried and self-employed workers (relative to permanent salaried), or workers in informal compared to formal jobs were more likely to lose a job during lockdown (Abraham et al. 2021). The recovery was faster among informal than formal workers, and the employment composition shifted towards self-employment and casual jobs in the post-lockdown period. (Abraham et al., 2021; Bussolo et al., 2021). Moreover, the decline in employment was the sharpest for less-educated workers (Abraham et al., 2021; Deshpande, 2022). The probability of finding a job conditional on being unemployed was higher for less-educated members (Abraham et al., 2021), while Deshpande (2022) found that recovery for illiterate men was slow.

Some studies have also examined how COVID affects other economic metrics including inequality and household spending/income. Gupta et al. (2021a) provide evidence of the fall in income and consumption among Indian households during lockdown. Additionally, they demonstrate that expenditure fell less than income did, demonstrating that households were able to smoothen their consumption slightly. Additionally, Gupta et al. (2020a) showed that households with higher incomes and higher expenditures saw a greater fall in income and expenditure. In contrast, according to Jha and Lahoti (2022) the bottom of the income distribution saw a more severe initial shock from the lockdown and a speedier recovery. The top end of the distribution, on the other hand, suffered from lesser reductions during the lockdown, but they took longer to recover. Bussolo et al. (2020) examined consumer expenditures and income for formal and informal workers and found that formal workers reported a bigger fall in consumption expenditure than informal workers, whereas informal relative to formal workers suffered a greater income loss. Finally, Gupta et al. (2021b) reported that the pandemic was linked to progressive social mobility, i.e., there was a decrease in both income and consumption inequality compared to the year prior to the COVID, as a result of households in the top (bottom) two quartiles moving down (up) more from 2019-2020 than from 2018-2019. In a similar vein, Jha and Lahoti (2022) study inequality (using metrics such as Gini, General Entropy Measures etc) and show a surge in inequality during lockdown followed by a decrease below pre-COVID levels. They argue that the decrease in inequality during the post-second wave period may have been due to the top end of the distribution's slow recovery.

Our study complements these analyses by providing a disaggregated household-level analysis of the impact of COVID on poverty transitions. The study makes several significant contributions to the body of literature. First, it seeks to investigate the extent of poverty transitions, which allows us to identify households that were at a higher risk of becoming impoverished during COVID crises, that is, households that entered poverty and stayed in poverty. Secondly, this paper examines the characteristics of households in different poverty transition status. Due to the unexpected shock brought on by COVID, economic activity slowed down, potentially pushing many vulnerable households into poverty. Determining which households remained poor and which households became poor is crucial. To make effective poverty alleviation policies and interventions, it is also critical to monitor how households transition into and out of poverty and why households remain impoverished. The former, however, would call for short-term assistance, such as safety-net-oriented policies (Garcés-Urzainqui et al., 2021), whereas the latter would necessitate longer-term policy measures.

3. Data

The study utilizes the Consumer Pyramid Survey (CPHS) conducted by the Centre for Monitoring Indian Economy (CMIE) for the analysis. CPHS is a representative longitudinal survey of over 1,50,000 households, covering almost all the states. It collects information on various indicators such as household demographics, income, expenses, employment status, ownership of assets, access to basic amenities, etc. Every year the data is collected in waves; January-April, May-August, and September-December. The first wave was administered during January-April 2014; more than 20 waves have been executed since then. Every household is interviewed once in four months, i.e., thrice a year. Within each wave, each household is slotted in a specific month, and every household is interviewed precisely four months after their last interview. So, for example, if a household is interviewed in February, that particular household will be re-interviewed in June and then in October in a calendar year.

We use data from waves beginning January-April 2017 (Wave 10) to September-December 2020 (Wave 21) for the analysis. Although households are visited once every four months, information on income and consumption expenditure (both in rupees) are obtained for the four months preceding the interview month, enabling a monthly time series of these variables for each household. The expenditure data includes information on food, education, health, clothing and footwear, cosmetics, recreation, power, and fuel. These categories are further subdivided into sub-categories.

3.1 Construction of Expenditure Variable

Wadhwa (2020) provides evidence that households seem to report the income/expenditure of the previous four months based on their current circumstances. Due to possible bias in the reporting for the previous months, they utilize the most recently available information. In our analysis, we also use *one-month* recall expenditure data. For example, we rely on their January expenditure data for a household interviewed in February. Thus, every household has three data points for each calendar year. We take an average of three months to determine every household's monthly per capita consumption expenditure (the sum total of food and non-food expenditures) for each calendar year. It is also used to categorize households into different quartiles. Finally, nominal expenditure data is converted into real terms using the Consumer Price Index (CPI), 2012 base to compare across years.[5]

3.2 Outcome Variable

The monthly per capita consumption expenditure (as described above) and the Rangarajan committee poverty line to determine the poverty status of households are used in the analysis.[6] We use panel data for two consecutive years from 2017 to 2020 (i.e., 2019-2020, 2018-2019, and 2018-2017) to categorize each household into different states of poverty transition. Based on the poverty status of two years, households are categorized into four mutually exclusive and exhaustive categories: i) fell into poverty (poor in year *t* and non-poor in year *t-1*), ii) remain poor (poor in both *t* and *t-1*), iii) escaped poverty (non-poor in *t* and poor in *t-1*) and lastly, iv) remain non-poor (non-poor in t and t-1).

4. Descriptive Statistics

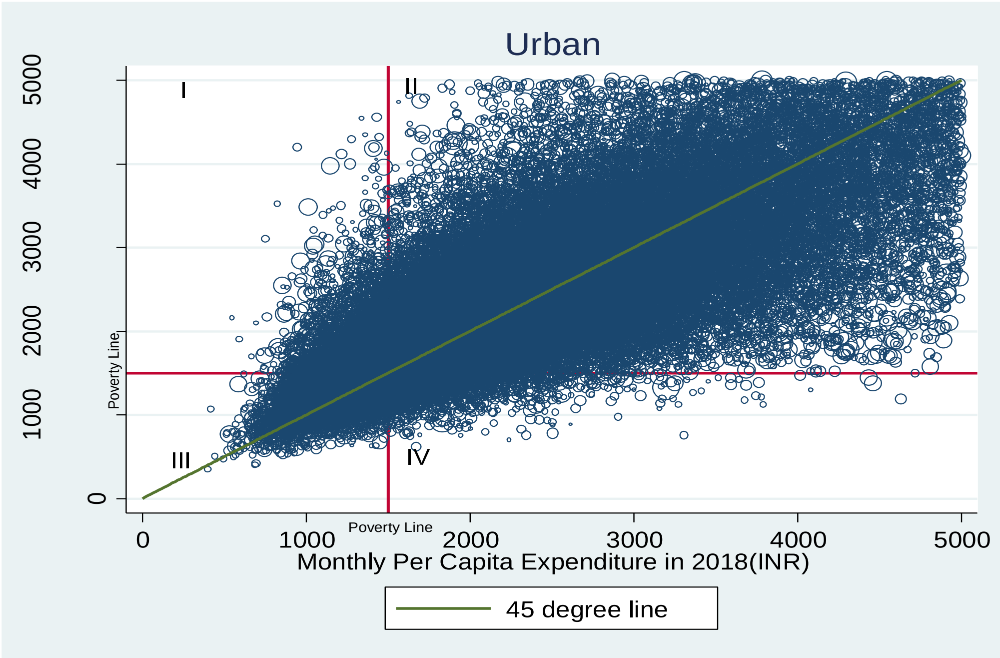
Figure 1, Panel A below displays the monthly per capita expenditure of households (in Rs) for 2018 and 2019 on the x- and y-axis, respectively, while Panel B of Figure 1 displays scatter plots of the same for 2019 and 2020 on the x- and y-axis, respectively. Red lines indicate the poverty line, whereas the green line is the 45-degree line (equity line). These figures show

[5] Data for CPI is obtained from RBI's (https://dbie.rbi.org.in/DBIE/dbie.rbi?site=home) website.
[6] The Rangarajan committee poverty line for rural is Rs 972 and urban is Rs 1410 in 2011-12 prices but we use CPI 2012 to convert these poverty lines in 2012 terms.

transition of households from one status to another between 2018 and 2019 (pre-COVID years), and 2019 and 2020 (COVID year).

Two observations are immediately apparent from Figure 1. First, most households saw a decrease in spending during the first year of COVID compared to the years prior (see Panel B of Figure 1). This is seen by a greater number of households in Panel B of Figure 1 than in Panel A of Figure 1, that are below the 45-degree line. Second, many households that were not poor in 2019 moved into a quadrant IV i.e., they slid below poverty line, and the magnitude compared to pre-COVID years is significantly higher (compare quadrant IV in Panel A with quadrant IV in Panel B of Figure 1).

Panel A



Panel B

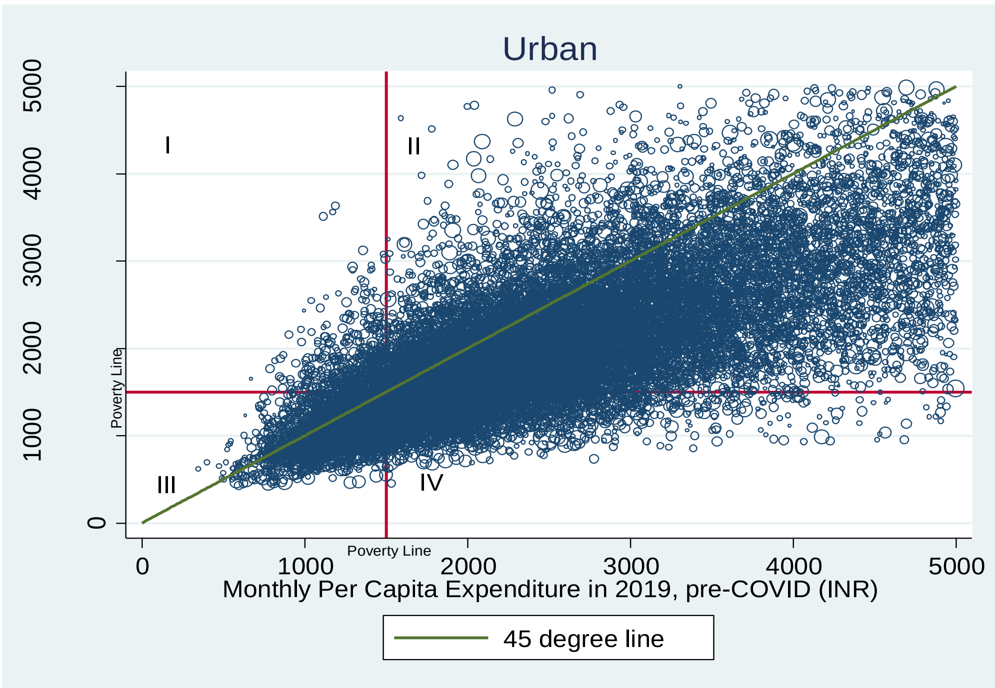


Figure 1: Scatter plot of monthly per capita expenditure (in Rs) in 2018 and 2019 (pre-covid years) and 2019 and 2020(covid year) for urban households.

Source: Estimates computed using unit record data from the Consumer Pyramid Household Survey (CPHS).
Notes: Monthly per capita expenditure is in 2012 terms.

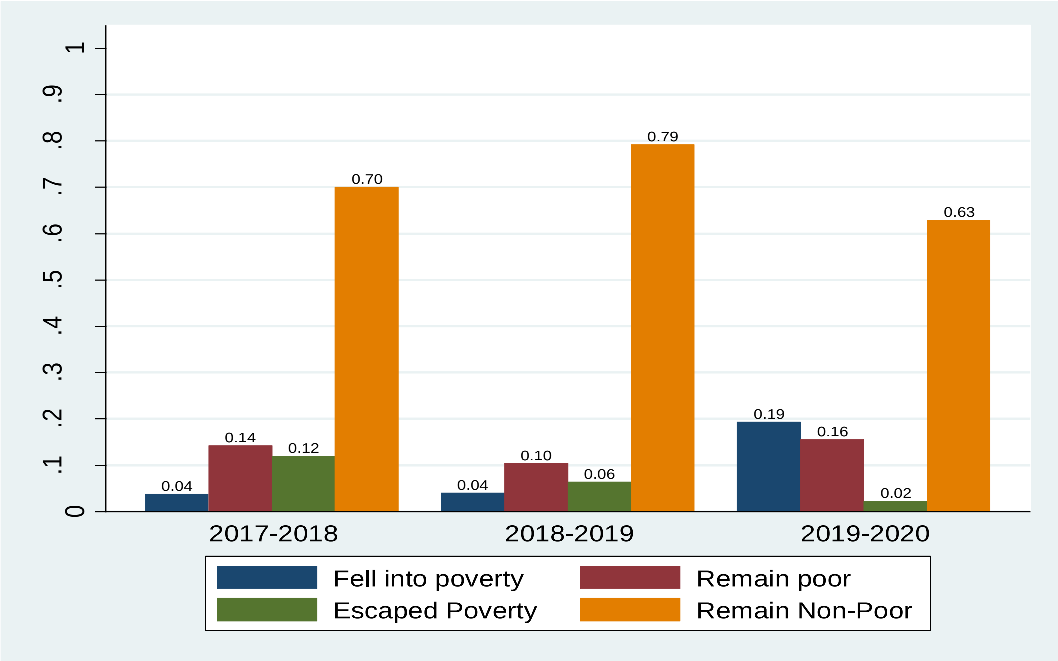


Figure 3: Poverty Transition Categories as a Percentage of Individuals by Year (urban).

Source: Estimates computed using unit record data of the Consumer Pyramid Household Survey (CPHS).
Notes: Monthly per capita expenditure is in 2012 prices.

Figure 2 displays the extent of poverty transition. Only 4% of urban individuals who were non-poor in the previous year fell into poverty in the pre-COVID years (i.e., between 2017-2018 and 2018-2019), while in 2019-2020 - which takes into account the first year of pandemic - this proportion increased to 19%.

Poverty persistence, i.e., the proportion of individuals that remain poor, increased in 2019-2020 (16%) compared to pre-COVID years because fewer individuals could escape poverty due to the COVID crisis. Twelve percent of individuals escaped poverty between 2017-2018, but this percentage dropped to 6% in 2018-2019; in the pandemic period, it decreased further to 2%.

5. Empirical Methodology

The outcome variable is a discrete variable with four mutually exclusive and exhaustive categories. Therefore, among discrete-choice models, we use the multinomial (MNL) regression model to examine factors associated with different states of poverty transition. Households are categorized as a) fell into poverty, b) remain poor, c) escaped poverty, and d) remain non-poor.

$$P_{hj} = \Pr(y_h = j) = \frac{\exp(X_h\beta_j)}{\sum_{l=1}^{4}\exp(X_h\beta_l)} \quad (1)$$

where P_{hj} is the probability of household h, in state *j*. In our model, *j* = fell into poverty, remain poor, escaped poverty, and remain non-poor. X_h is a vector of independent household variables and $\beta_j s$ are the set of the coefficients to be estimated, with one of the categories set as the base category. The coefficients of MNL models are not generally directly interpretable, therefore, we report and interpret marginal effects ($\frac{\partial p}{\partial x}$) in the paper.

For estimating determinants of the different states of poverty transition for 2019-2020, we use 2019 household characteristics as explanatory variables to see how their initial endowments of human and physical capital, occupational choices, and socio-religious profile predisposed them to descend, escape or remain in poverty.

X_h include following household characteristics that are guided by prior literature and are briefly discussed below.

Social group characteristics: caste is divided into four categories: Scheduled Caste (SC)/Scheduled Tribes (ST), Other Backward Classes (OBC), intermediate caste, and UCs (reference category).[7] The earlier analyses find lower escape rates, higher poverty persistence and higher descent rates for disadvantaged groups (such as SC/STs, OBC) compared to forward castes (or UCs) (see, for example, Dhamija and Bhide, 2013; Krishna and Shariff, 2011; Mehta and Bhide, 2003).

Mehta and Bhide (2003) and Krishna and Shariff (2011) have found differences across religions, i.e., Hindus have higher escape and lower descent rates than Muslims. We utilize religion as one of the household characteristics: Muslims, Hindus (reference category), and others (such as Sikhs, Christian, Buddhists, etc.)

Household demographics: Edig & Schwarze (2011), Quisumbing (2007), and Ahmed and Tauseef (2021) find that the likelihood of a household being chronically poor and to be in transient poverty increases with household size and higher dependency ratio.[8] Household demographics include variables such as household size and proportion of dependent members (number of non-working members/total household members).

Highest education – Evidence indicates that education provides protecting role, i.e., higher education prevents households from falling into poverty (see, for instance, Ahmed and Tauseef, 2022; Thorat et al., 2017). This variable captures the *highest education level of any adult aged 21 or above in the household*. We categorize the years of schooling into three categories – 0-5 years of education, 6-12 years of education, and graduation and above (reference category).

Occupation type: A very small proportion of the Indian workforce comprises workers in formal sectors. Lockdown resulted in the forced stoppage of economic activities, resulting in

[7] The CPHS data on caste variable divides non-SC-ST-OBC castes into two broad groups: Upper Castes (UCs) and Intermediate Castes.
[8] Transient poor housheholds' consumption expenditure is sometimes above and sometimes below the poverty line i.e., they move in and out of poverty over time. They constitute household that escaped poverty and households that fell into poverty.

the loss of work. Kesar et al. (2020) and Abraham et al. (2020) suggest that casual and self-employed workers were more likely to suffer job loss and more significant decline in income than those in regular jobs. Therefore, we take the *occupation of the major income-earning member* of the household and categorize it into four categories: casual, self-employed (reference category), salaried workers employed in private firms/companies, and salaried workers employed in government jobs, and others (such as retired, etc.).

Expenditure quintile: Household's economic status is captured by including household expenditure quartiles as covariates, where the first quintile is the reference category.

The analysis pertains to urban households, and all standard errors are clustered at the district level.

6. Regression Results

6.1 Results for the Pandemic year, 2019-2020

Table 1 shows the average marginal effects of the MNL model predictors on households that *fell into poverty, remained poor, and remained non-poor*. Although coefficients were derived for all four groups, the marginal effects for *escaping poverty* category are not reported due to the small proportion of households in that group. In any case, the focus of the study is to determine factors associated with impoverished households.

The objective is to address the following question: how does the probability of being in a particular state of poverty change for a household when only demographics and social group variables are taken into account, and how does this change when employment arrangement, education, and expenditure quintile are controlled for. Therefore, in Table 1, we report two specifications: correlates in the first specification include social and demographic household characteristics (see columns 1, 3 and 5 of Table 1), and in the second specification, we also include economic factors, such as highest education, type of employment arrangement and household's expenditure quartile (see columns 2, 4 and 6 of Table 1). In addition, in both models, state-fixed effects are included. Recall that we use initial or prior household characteristics, and thus present results for 2019-2020 (i.e., COVID period) by utilizing 2019 household characteristics.

Parsimonious specification, i.e., column 1 of Table 1, shows that SC/STs and OBC (relative to UC) have a higher probability of falling into poverty, at 6% and 4%, respectively. Similarly, if household size increases by one member, the likelihood of descending into poverty increases by 4%. However, these effects diminish, but they remain significant when we control for economic characteristics, such as education, employment, and expenditure quartile (column 2 of Table 1). For example, SC/STs and OBC (compared to UC) are 3% more likely to fall into poverty in 2020, if they were non-poor in 2019, while the marginal effect of household size reduces to 1%. This suggests that the greater likelihood of households of disadvantaged caste groups falling into poverty in 2020 is somewhat explained by differences between these groups in terms of education, occupation, and prior expenditure levels.

Table 1: Average Marginal effects of 2019 household characteristics on poverty states in 2019 and 2020: MNL estimates for Urban households.

	Fell into poverty		**Remain poor**		**Remain Non-poor**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
SC/ST (Upper caste)	0.056*** (0.009)	0.028*** (0.009)	0.097*** (0.009)	0.031*** (0.006)	-0.154*** (0.012)	-0.050*** (0.010)
OBC (Upper caste)	0.043*** (0.008)	0.024*** (0.007)	0.045*** (0.007)	0.016*** (0.005)	0.002 (0.003)	-0.036*** (0.008)
Intermediate Caste (Upper caste)	0.023 (0.014)	0.001 (0.013)	-0.011 (0.014)	-0.001 (0.011)	-0.091*** (0.010)	-0.000 (0.015)
Muslim (Hindus)	0.019 (0.014)	-0.005 (0.012)	0.050*** (0.013)	0.007 (0.007)	0.012* (0.007)	-0.006 (0.012)
Others (Hindus)	-0.022 (0.020)	-0.016 (0.019)	-0.025 (0.018)	-0.016 (0.012)	-0.012 (0.021)	0.048*** (0.017)
Dependent ratio	0.000 (0.000)	0.000 (0.000)	0.001*** (0.000)	0.001*** (0.000)	-0.000 (0.000)	-0.001*** (0.000)
Household size	0.038*** (0.003)	0.011*** (0.004)	0.060*** (0.004)	0.041*** (0.003)	-0.081*** (0.015)	-0.057*** (0.004)
Highest education - 6-12 standard (graduates & above)	-	0.017*** (0.006)	-	0.034*** (0.004)	-	-0.054*** (0.006)
Highest education ≤ 5th standard (graduates & above)	-	0.024** (0.010)	-	0.067*** (0.006)	-	-0.086*** (0.010)
Casual Lab (self-employed)	-	-0.010 (0.007)	-	0.036*** (0.004)	-	-0.026*** (0.007)
Salaried-government (self-employed)	-	0.012 (0.013)	-	-0.033*** (0.008)	-	0.025** (0.012)
Salaried-private (self-employed)	-	0.003 (0.008)	-	0.001 (0.005)	-	-0.000 (0.007)
others-retired (self-employed)	-	-0.001 (0.013)	-	-0.029*** (0.007)	-	0.023* (0.012)
2nd quartile (1st quartile)	-	-0.036** (0.016)	-	-0.163*** (0.006)	-	0.243*** (0.016)
3rd quartile (1st quartile)	-	-0.129*** (0.019)	-	-0.163*** (0.006)	-	0.337*** (0.020)
4th quartile (1st quartile)	-	-0.190*** (0.023)	-	-0.163*** (0.006)	-	0.398*** (0.024)
State Fixed effects	✓	✓	✓	✓	✓	✓
Observations	25,125	25,096	25,125	25,096	25,125	25,096

Source: Estimates from Consumer Household Pyramid Survey.

Notes: Data in columns 1 and 2 refers to households interviewed in 2019 and 2020. Standard errors reported in parentheses are clustered at the district level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In addition, socio-economic factors such as education are significant: households with members with less than five years of schooling compared to those with members who are at least graduate and above are 2% more likely to descend into poverty. The probability is slightly lower for households with six-twelve years of schooling.

The results indicate that employment/occupation did not seem to matter, but households in the upper expenditure quartiles in 2019 were less likely to descend into poverty than those in the lowest quartile. Moreover, these probabilities are higher in magnitude for higher quartiles. For example, households in the second quartile are 4% less likely, while those in the fourth quartile are 20% less likely compared to those in the first quartile to fall into poverty.

Turning to the predictors of households that remained poor, results (see column 3 of Table 1) show that SC/STs and OBC relative to UCs, and Muslims relative to Hindus are more likely to remain poor, and these probabilities decrease but remain significant while the religion variable becomes insignificant once we control for human capital and other economic factors (column 4 of Table 1). The full specification suggests that disadvantaged groups are more likely to remain poor compared to UCs, and household size does matter. Also, much of the difference across caste and religion is explained by the economic factors. Similarly, households with a member with at least a graduate degree are less likely to remain in poverty than those who have only completed schooling (or a few years of schooling) or are illiterate (see column 4 of Table 1).

As for occupation, casual labour relative to self-employed workers are more likely to remain poor and workers employed in government salaries jobs are less likely to stay poor compared to self-employed workers. As expected, households in higher quartiles are less likely to remain poor than those in the lowest quartile.

As for household characteristics that are associated with household being able to resist poverty or remain non-poor, we find similar results: once we control for education, occupation and level of economic status, a large proportion of the difference across SC/ST and UC, and OBC and UC diminishes. In the parsimonious specification, SC/STs relative to UCs were 15% less likely to remain non-poor but in the full specification, this difference reduces to 5%. Similarly, all of the difference between Muslims and Hindu households is explained by these human and physical capital factors (see column 5 and 6 of Table 1). Households belonging to the other minority groups such as Sikhs, Christians etc relative to Hindus are 4.8% more likely to remain non-poor.

Further, households with higher household size are less likely to remain non-poor. Education has enduring property, household with less educated members are less likely to remain non-poor. In terms of magnitude, the absolute marginal effect of education is larger for resisting poverty or remaining non-poor compared to education's marginal effect on descending and remaining into poverty.

If the main income earning member of the household is casual labour relative to being self-employed, that household is less likely to remain non-poor. Similarly, those employed in salaried government jobs compared to self-employed jobs are more likely to remain non-poor. Lastly, households belonging to higher economic status category relative to lowest are more likely to remain non-poor with increasing magnitude across quartile.

6.2 Regression Results of Pandemic with Pre-Pandemic year – A comparison

We also estimate these regressions for households in the pre-pandemic period, i.e., 2018-2019 and compare them with the pandemic period, i.e., 2019-2020. Regression results are presented in Table 2 below.

Comparing predictors of households that fell into poverty before and after COVID, we do not find any significant association between SC/STs and OBCs (relative to UC) and the probability of falling into poverty, except that the intermediate caste was less likely in the pre-pandemic period (see column 2 of Table 2) to fall into poverty. However, in the pandemic period (i.e., 2019-2020), SC/STs and OBCs, compared to UCs, are more likely to descend into poverty (see column 1 of Table 2). Moreover, household size is a significant predictor in both periods.

While households with educated members are less likely to become poor in both the periods, the probability has slightly increased in the pandemic, reflecting the possible protection offered by human capital. In the pre and pandemic period, those in the upper quartiles are less likely to fall into poverty than those in the lowest quartile. But it is important to note that the magnitude of these probabilities has increased during the pandemic period, suggesting that the most economically vulnerable were relatively more affected by the pandemic (columns 1 and 2 of Table 2).

Table 2: Average Marginal effects of household characteristics on poverty states by year: MNL estimates for Urban households

	Fell into poverty		**Remain poor**		**Remain Non-Poor**	
	2019-2020	2018-2019	2019-2020	2018-2019	2019-2020	2018-2019
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
SC/ST (Upper caste)	0.028***	0.001	0.031***	0.029***	-0.050***	-0.029***
	(0.009)	(0.003)	(0.006)	(0.005)	(0.010)	(0.005)
OBC (Upper caste)	0.024***	0.003	0.016***	0.015***	-0.036***	-0.021***
	(0.007)	(0.003)	(0.005)	(0.004)	(0.008)	(0.005)
Intermediate Caste (Upper caste)	0.001	-0.012**	-0.001	0.006	-0.000	0.011
	(0.013)	(0.005)	(0.011)	(0.008)	(0.015)	(0.009)
Muslim (Hindus)	-0.005	-0.001	0.007	0.009*	-0.006	-0.015**
	(0.012)	(0.004)	(0.007)	(0.005)	(0.012)	(0.006)
Others (Hindus)	-0.016	-0.004	-0.016	-0.026**	0.048***	0.027**
	(0.019)	(0.007)	(0.012)	(0.013)	(0.017)	(0.011)
Dependent ratio	0.000	-0.000	0.001***	0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household size	0.011***	0.007***	0.041***	0.027***	-0.057***	-0.040***
	(0.004)	(0.001)	(0.003)	(0.001)	(0.004)	(0.002)
Highest education - 6-12 standard (graduates & above)	0.017***	0.006**	0.034***	0.024***	-0.054***	-0.030***
	(0.006)	(0.003)	(0.004)	(0.003)	(0.006)	(0.004)
Highest education ≤ 5^{th} standard (graduates & above)	0.024**	0.014***	0.067***	0.047***	-0.086***	-0.058***
	(0.010)	(0.002)	(0.006)	(0.003)	(0.010)	(0.004)
Casual Lab (self-employed)	-0.010	0.001	0.036***	0.024***	-0.026***	-0.030***
	(0.007)	(0.002)	(0.004)	(0.003)	(0.007)	(0.004)
Salaried-government (self-employed)	0.012	-0.006	-0.033***	-0.027***	0.025**	0.034***
	(0.013)	(0.004)	(0.008)	(0.005)	(0.012)	(0.006)
Salaried-private (self-employed)	0.003	-0.008***	0.001	-0.000	-0.000	0.005
	(0.008)	(0.002)	(0.005)	(0.004)	(0.007)	(0.004)
others-retired (self-employed)	-0.001	0.002	-0.029***	-0.017***	0.023*	0.014*
	(0.013)	(0.005)	(0.007)	(0.005)	(0.012)	(0.008)
2^{nd} quartile (1^{st} quartile)	-0.036**	0.008	-0.163***	-0.112***	0.243***	0.243***
	(0.016)	(0.006)	(0.006)	(0.004)	(0.016)	(0.011)
3^{rd} quartile (1^{st} quartile)	-0.129***	-0.031***	-0.163***	-0.112***	0.337***	0.282***
	(0.019)	(0.006)	(0.006)	(0.004)	(0.020)	(0.011)
4^{th} quartile (1^{st} quartile)	-0.190***	-0.039***	-0.163***	-0.112***	0.398***	0.290***
	(0.023)	(0.006)	(0.006)	(0.004)	(0.024)	(0.011)
State Fixed effects	✓	✓	✓	✓	✓	✓
Observations	25,096	57,261	25,096	57,261	25,096	57,261

Source: Estimates from Consumer Household Pyramid Survey.

Notes: Data in columns 1, 3, and 4 refers to households interviewed in both 2019 and 2020, while data in columns 2, 4, and 6 refers to households interviewed in both 2018 and 2019. Standard errors reported in parentheses are clustered at the district level. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

Almost the same predictors (such as caste, household size, education, occupation, and economic status) predict the probability of households remaining poor in the pre and pandemic periods. Except for religion, that is, Muslims (relative to Hindus) were more likely in 2018-19, while households belonging to other religious groups (compared to Hindus) in the pre-pandemic period were less likely to remain poor, but this difference has become insignificant in the COVID year (see column 3 and 4 of Table 2).

The coefficient for predictors such as highest education and expenditure quintiles have increased in the COVID year, showing that the relationship has become more strong in the time of crisis and, therefore, highlighting the vulnerability-reducing nature of education.

Comparing factors correlated with households remaining non-poor, we find that probability of SC/STs relative to UC, and OBC relative to UC of resisting poverty has gone down i.e., in the pandemic period they are less likely to remain non-poor compared to pre-pandemic period. The difference between Muslims and Hindus have disappeared while the difference between other minority group and Hindus have gone up in the COVID period.

The marginal effect of education on remaining non-poor has gone up i.e., households with members with less than 5 years of education compared to those with members who are graduate and above were 7% less likely to remain non-poor and this probability has increased to 9% in the pandemic period. Similarly, already richer households are more likely to remain non-poor compared to the poorest and the magnitude of this likelihood has increased in the pandemic period.

6.3 Robustness checks

To test the robustness of our results, we use an alternative poverty line since poverty analyses/estimates are often sensitive to changes in the poverty line. According to the World

Bank ranking, India transitioned from a low-income to a lower-middle-income country in 2009. To examine if our main findings are robust to a change in the poverty line, we utilize the $3.20/day poverty line, which is the World Bank's poverty line for lower-middle-income countries. Similarly, we check the sensitivity of our results using the household head's education and occupation.

Results using the $3.20/day poverty line and the household head's education and occupation type are presented in Table A2 and Table A3, respectively, in the Appendix. The main conclusions described above are not affected by the choice of poverty measure or household head characteristics as predictors.

We did more checks regarding attrition in the year 2020, which happened due to the lockdowns imposed by the government leading to a drastic fall in response rates, introducing the possibility of selection bias. To address this issue, we re-run the regressions on same households between 2018-2019 and 2019-2020 i.e., we follow same cohort of households and find that results are qualitatively similar to results presented in section 6.1 and 6.2 (see Table A4 in the appendix).

7. Summary and Conclusions

This paper analysed poverty transitions during the COVID crises and explored factors associated with different states of poverty in pre-COVID and COVID years (between 2017-2020) using panel data from the Consumer Pyramid Household Survey.

Since earlier analyses suggested that urban areas were worse impacted, we did the analysis for urban households to investigate the household variables that predict whether households fell into poverty, remained in poverty, and remained non-poor. The results indicate an increase in poverty by about 19% in urban areas in 2020, while the corresponding figures was 4% for the pre-pandemic years.

Using multinomial regression, we find that disadvantaged households (such as SC/STs and OBCs), members with low levels of education, larger household size, and those at the lower end of the expenditure distribution were more likely to sink below the poverty line during the pandemic period. Comparing these factors and the estimates with the pre-pandemic period, we find the probability of SC/STs and OBCs relative to UCs of falling below poverty line was not significant in the pre-pandemic year. Moreover, the original economic status matters i.e., those households that were better placed in the expenditure ladder were more protected and the marginal effects become higher in magnitude for the pandemic year than in the pre-pandemic period.

On the other hand, apart from caste, a larger household size, lower expenditure levels, type of occupation are significant predictor of households that remain in poverty. For example, casual laborers relative to the self-employed are more likely, while those employed as salaried government workers relative to self-employed workers are less likely to stay in poverty. Lastly, education reduces the chances of staying in poverty, helps avoid falling into poverty and enables resistance to poverty. These results are consistent across several robustness checks. The study results align with other studies studying poverty dynamics (for example, Ahmed and Tauseef, 2022; Thorat et al., 2017).

We conclude that the pandemic has exacerbated the pre-existing caste-based inequalities as they are more likely to remain in poverty, and now because of economic crises due to COVID, they are also more likely to slide below the poverty line. SC/STs and OBCs suffer the double impact of falling into poverty and remaining there. Moreover, those who were economically better placed before the pandemic period were protected than those who were more vulnerable.

The results indicate that the risk of disadvantaged castes falling into poverty can be lowered with better education and occupation, indicating the need for continuous human capital strengthening at all times, but also specific areas of policy intervention that might be required to lift people out of poverty after an economic shock.

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Appendix Tables

Table A1: Average Marginal effects of household characteristics on households that escaped poverty by year: MNL estimates for Urban households

	Escaped Poverty	
	2019-2020	**2018-2019**
SC/ST (Upper caste)	-0.008**	-0.000
	(0.004)	(0.003)
OBC (Upper caste)	-0.004	0.002
	(0.004)	(0.003)
Intermediate Caste (Upper caste)	0.000	-0.005
	(0.009)	(0.006)
Muslim (Hindus)	0.005	0.006*
	(0.005)	(0.004)
Others (Hindus)	-0.016***	0.004
	(0.005)	(0.008)
Dependent ratio	-0.000**	-0.000**
	(0.000)	(0.000)
Household size	0.004***	0.006***
	(0.001)	(0.001)
Highest education - 6-12 standard (graduates & above)	0.003	0.000
	(0.003)	(0.003)
Highest education ≤ 5th standard (graduates & above)	-0.005*	-0.003
	(0.003)	(0.003)
Casual Lab (self-employed)	0.000	0.005**
	(0.002)	(0.003)
Salaried-government (self-employed)	-0.004	-0.000
	(0.006)	(0.004)
Salaried-private (self-employed)	-0.004	0.003
	(0.003)	(0.003)
others-retired (self-employed)	0.008	0.001
	(0.006)	(0.007)
2nd quartile (1st quartile)	-0.044***	-0.139***
	(0.005)	(0.008)
3rd quartile (1st quartile)	-0.044***	-0.139***
	(0.005)	(0.008)
4th quartile (1st quartile)	-0.044***	-0.139***
	(0.005)	(0.008)
State Fixed effects	✓	✓
Observations	25,096	57,261

Source: Estimates from Consumer Household Pyramid Survey.

Notes: Data in columns 1, 3, and 4 refers to households interviewed in both 2019 and 2020, while data in columns 2, 4, and 6 refers to households interviewed in both 2018 and 2019. Standard errors reported in parentheses are clustered at the district level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Average Marginal effects of household characteristics on poverty states by year: MNL estimates for Urban households, using World Bank low-middle income poverty line.

	Non-poor to poor		**Remain poor**		**Remain non-poor**	
	2019-2020	**2018-2019**	**2019-2020**	**2018-2019**	**2019-2020**	**2018-2019**
SC/ST (Upper caste)	0.024**	0.005	0.033***	0.030***	-0.047***	-0.031***
	(0.010)	(0.004)	(0.007)	(0.005)	(0.010)	(0.005)
OBC (Upper caste)	0.020***	0.007**	0.019***	0.016***	-0.031***	-0.022***
	(0.007)	(0.003)	(0.006)	(0.004)	(0.008)	(0.005)
Intermediate Caste (Upper caste)	-0.007	-0.010*	0.001	0.002	0.012	0.009
	(0.014)	(0.006)	(0.012)	(0.008)	(0.015)	(0.008)
Muslim (Hindus)	-0.006	-0.002	0.009	0.012**	0.001	-0.014**
	(0.012)	(0.005)	(0.008)	(0.005)	(0.005)	(0.006)
Others (Hindus)	-0.009	-0.009	-0.021*	-0.021*	0.038**	0.016*
	(0.018)	(0.006)	(0.012)	(0.013)	(0.018)	(0.009)
Dependent ratio	0.000	0.000	0.001***	0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household size	0.012***	0.008***	0.042***	0.030***	-0.058***	-0.039***
	(0.004)	(0.001)	(0.003)	(0.001)	(0.005)	(0.002)
Highest education - 6-12 standard (graduates & above)	0.018***	0.014***	0.039***	0.040***	-0.058***	-0.043***
	(0.007)	(0.002)	(0.004)	(0.003)	(0.007)	(0.004)
Highest education ≤ 5th standard (graduates & above)	0.020*	0.015***	0.068***	0.066***	-0.079***	-0.067***
	(0.011)	(0.004)	(0.006)	(0.004)	(0.011)	(0.006)
Casual Lab (self-employed)	-0.010	0.006**	0.036***	0.026***	-0.025***	-0.029***
	(0.007)	(0.003)	(0.005)	(0.003)	(0.007)	(0.003)
Salaried-government (self-employed)	0.004	-0.004	-0.041***	-0.032***	0.036***	0.027***
	(0.013)	(0.004)	(0.008)	(0.005)	(0.013)	(0.006)
Salaried-private (self-employed)	0.005	-0.004	-0.000	-0.004	0.000	0.006
	(0.008)	(0.003)	(0.005)	(0.004)	(0.008)	(0.004)
others-retired (self-employed)	-0.001	0.001	-0.031***	-0.027***	0.020*	0.013*
	(0.012)	(0.005)	(0.008)	(0.005)	(0.012)	(0.008)
2nd quartile (1st quartile)	0.017	0.027***	-0.219***	-0.154***	0.256***	0.321***
	(0.015)	(0.007)	(0.008)	(0.005)	(0.017)	(0.013)
3rd quartile (1st quartile)	-0.112***	-0.022***	-0.219***	-0.154***	0.385***	0.371***
	(0.020)	(0.007)	(0.008)	(0.005)	(0.022)	(0.013)
4th quartile (1st quartile)	-0.188***	-0.039***	-0.219***	-0.154***	0.461***	0.388***
	(0.025)	(0.007)	(0.008)	(0.005)	(0.027)	(0.013)
State Fixed effects	✓	✓	✓	✓		✓
Observations	25,096	57,261	25,096	57,261	25,096	57,261

Source: Estimates from Consumer Household Pyramid Survey.
Notes: Data in columns 1, 3, and 4 refers to households interviewed in both 2019 and 2020, while data in columns 2, 4, and 6 refers to households interviewed in both 2018 and 2019. Standard errors reported in parentheses are clustered at the district level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Average Marginal effects of household characteristics on poverty states by year: MNL estimates for Urban households, using household head's characteristics.

	Non-poor to poor		Remain poor		Remain Non -poor	
	2019-2020	**2018-2019**	**2019-2020**	**2018-2019**	**2019-2020**	**2018-2019**
SC/ST (Upper caste)	0.025***	0.002	0.037***	0.034***	-0.055***	-0.034***
	(0.009)	(0.004)	(0.006)	(0.005)	(0.010)	(0.005)
OBC (Upper caste)	0.023***	0.004	0.019***	0.018***	-0.038***	-0.023***
	(0.008)	(0.003)	(0.005)	(0.004)	(0.008)	(0.005)
Intermediate Caste (Upper caste)	0.001	-0.013**	-0.000	0.007	-0.001	0.012
	(0.014)	(0.005)	(0.012)	(0.008)	(0.015)	(0.009)
Muslim (Hindus)	-0.007	0.001	0.011	0.014***	-0.010	-0.020***
	(0.012)	(0.004)	(0.008)	(0.005)	(0.012)	(0.006)
Others (Hindus)	-0.016	-0.005	-0.015	-0.027**	0.048***	0.028**
	(0.019)	(0.007)	(0.013)	(0.013)	(0.017)	(0.011)
Dependent ratio	0.000*	0.000	0.001***	0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household size	0.011***	0.006***	0.039***	0.026***	-0.054***	-0.037***
	(0.004)	(0.001)	(0.003)	(0.001)	(0.004)	(0.002)
Highest education - 6-12 standard (graduates & above)	0.025***	0.013***	0.027***	0.029***	-0.051***	-0.047***
	(0.008)	(0.002)	(0.005)	(0.003)	(0.008)	(0.004)
Highest education ≤ 5^{th} standard (graduates & above)	0.031***	0.015***	0.051***	0.048***	-0.078***	-0.068***
	(0.010)	(0.003)	(0.006)	(0.004)	(0.010)	(0.005)
Casual Lab (self-employed)	-0.007	0.004	0.035***	0.026***	-0.028***	-0.034***
	(0.007)	(0.003)	(0.005)	(0.003)	(0.007)	(0.004)
Salaried-government (self-employed)	0.008	-0.009**	-0.035***	-0.026***	0.035**	0.033***
	(0.015)	(0.004)	(0.010)	(0.005)	(0.014)	(0.007)
Salaried-private (self-employed)	0.005	-0.007**	0.003	0.001	-0.002	0.002
	(0.009)	(0.003)	(0.007)	(0.004)	(0.008)	(0.004)
others-retired (self-employed)	-0.015**	-0.004*	-0.008*	-0.010***	0.016**	0.006*
	(0.007)	(0.002)	(0.004)	(0.003)	(0.007)	(0.003)
2^{nd} quartile (1^{st} quartile)	-0.036**	0.005	-0.167***	-0.116***	0.249***	0.251***
	(0.015)	(0.006)	(0.007)	(0.005)	(0.016)	(0.011)
3^{rd} quartile (1^{st} quartile)	-0.130***	-0.033***	-0.167***	-0.116***	0.344***	0.289***
	(0.019)	(0.005)	(0.007)	(0.005)	(0.020)	(0.011)
4^{th} quartile (1^{st} quartile)	-0.190***	-0.041***	-0.167***	-0.116***	0.404***	0.296***
	(0.023)	(0.005)	(0.007)	(0.005)	(0.024)	(0.011)
State Fixed effects	✓	✓	✓	✓	✓	✓
Observations	25,125	57,320	25,125	57,320	25,125	57,320

Source: Estimates from Consumer Household Pyramid Survey.
Notes: Data in columns 1, 3, and 4 refers to households interviewed in both 2019 and 2020, while data in columns 2, 4, and 6 refers to households interviewed in both 2018 and 2019. Standard errors reported in parentheses are clustered at the district level.
Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

Table A4: Average Marginal effects of household characteristics on poverty states by year: MNL estimates for Urban households, using 2018-19 cohort of households.

	Non-poor to poor		Remain poor		Remain Non -poor	
	2019-2020	2018-2019	2019-2020	2018-2019	2019-2020	2018-2019
SC/ST (Upper caste)	0.033***	-0.001	0.029***	0.032***	-0.052***	-0.024***
	(0.010)	(0.004)	(0.006)	(0.008)	(0.011)	(0.006)
OBC (Upper caste)	0.028***	0.003	0.017***	0.017***	-0.040***	-0.017***
	(0.008)	(0.003)	(0.006)	(0.006)	(0.008)	(0.004)
Intermediate Caste (Upper caste)	0.016	-0.005	-0.015	-0.011	0.002	0.028***
	(0.017)	(0.014)	(0.015)	(0.017)	(0.016)	(0.010)
Muslim (Hindus)	0.003	0.004	0.009	0.006**	-0.014	-0.015
	(0.014)	(0.006)	(0.007)	(0.003)	(0.013)	(0.010)
Others (Hindus)	-0.014	-0.017*	-0.013	-0.038***	0.042**	0.054***
	(0.023)	(0.009)	(0.017)	(0.012)	(0.018)	(0.009)
Dependent ratio	0.000	-0.000	0.001***	0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household size	0.009**	0.010***	0.042***	0.035***	-0.056***	-0.049***
	(0.005)	(0.002)	(0.003)	(0.004)	(0.005)	(0.004)
Highest education - 6-12 standard (graduates & above)	0.016**	0.012***	0.034***	0.040***	-0.052***	-0.050***
	(0.007)	(0.003)	(0.004)	(0.001)	(0.007)	(0.004)
Highest education ≤ 5th standard (graduates & above)	0.018*	0.013**	0.066***	0.072***	-0.079***	-0.077***
	(0.011)	(0.006)	(0.007)	(0.005)	(0.011)	(0.009)
Casual Lab (self-employed)	-0.015*	0.003	0.038***	0.031***	-0.025***	-0.038***
	(0.008)	(0.006)	(0.005)	(0.006)	(0.008)	(0.008)
Salaried-government (self-employed)	0.008	-0.009	-0.030***	-0.034***	0.022	0.044***
	(0.014)	(0.008)	(0.008)	(0.008)	(0.014)	(0.012)
Salaried-private (self-employed)	0.007	-0.008**	0.002	0.004	-0.006	-0.003
	(0.009)	(0.003)	(0.006)	(0.005)	(0.008)	(0.004)
others-retired (self-employed)	0.006	0.004	-0.030***	-0.031***	0.016	0.028***
	(0.015)	(0.005)	(0.008)	(0.008)	(0.014)	(0.007)
2nd quartile (1st quartile)	-0.043**	0.018	-0.164***	-0.129***	0.253***	0.245***
	(0.017)	(0.011)	(0.007)	(0.003)	(0.018)	(0.015)
3rd quartile (1st quartile)	-0.139***	-0.030***	-0.164***	-0.129***	0.349***	0.293***
	(0.021)	(0.009)	(0.007)	(0.003)	(0.022)	(0.013)
4th quartile (1st quartile)	-0.199***	-0.047***	-0.164***	-0.129***	0.409***	0.310***
	(0.025)	(0.004)	(0.007)	(0.003)	(0.026)	(0.008)
State Fixed effects	✓	✓	✓	✓	✓	✓
Observations	20,061	20,061	20,061	20,061	20,061	20,061

Source: Estimates from Consumer Household Pyramid Survey.

Notes: Data in columns 1, 3, and 4 refers to households interviewed in both 2019 and 2020, while data in columns 2, 4, and 6 refers to households interviewed in both 2018 and 2019. Standard errors reported in parentheses are clustered at the district level. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

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INSTITUTE OF ECONOMIC GROWTH

University Enclave, University of Delhi
(North Campus) Delhi 110007, India
Tel: 27667288/365/424
Email: system@iegindia.org

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