INTERNATIONAL MONETARY FUND

Inequality and Poverty in India: Impact of COVID-19 Pandemic and Policy Response

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WP/23/147

2023
JUL

WORKING PAPER

 WP/23/147

IMF Working Paper
Asia Pacific Department

Inequality and Poverty in India: Impact of COVID-19 Pandemic and Policy Response*
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Authorized for distribution by Nada Choueiri and Chris Papageorgiou
July 2023

ABSTRACT: Using microdata from nationally representative household and labor force surveys, we study the impact and drivers of poverty and inequality in India during the pandemic. We have three main findings. First, India has made significant progress in reducing poverty in recent decades, but the economic downturn associated with the COVID-19 pandemic is estimated to have temporarily increased poverty and inequality. Second, education and employment status seem to be the main factors associated with poverty and income/consumption changes. Finally, the government's expansion of food subsidies has likely played a significant role in mitigating the increase in poverty during the pandemic.

JEL Classification Numbers:	D63, E24, H23, I32, I38, O15
Keywords:	COVID-19; poverty; inequality; earnings; India
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* This paper is part of a research project on macroeconomic policy in low-income countries (IATI Identifier: GB-1-202960) supported by the U.K.'s Foreign, Commonwealth and Development Office (FCDO). The views expressed herein are those of the authors and should not be attributed to the IMF, its Executive Board, its management, or the FCDO.

† The authors would like to thank Nada Choueiri, Chris Papageorgiou, Jarkko Turunen, Sinha Roy Sutirtha, Pedro Olinto, Nayantara Sarma, Hamid Davoodi, Dinar Dhamma Prihardini, TengTeng Xu, John Spray, Geetika Dang, and seminar participants from the Reserve Bank of India, the Ministry of Finance of India, and Asia Pacific Department of the IMF for useful comments. All remaining errors are our own.

‡ Mattia Coppo, Nasser Khalil, and D. Filiz Unsal were working at the IMF when much of this work was completed. D. Filiz Unsal is on leave from the IMF.

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Glossary

CMIE	Centre for Monitoring Indian Economy
CPHS	Consumer Pyramids Household Survey
MNREGA	Mahatma Gandhi National Rural Employment Guarantee Act
NFHS	National Family Health Survey
PDS	Public Distribution System
PLFS	Periodic Labor Force Survey
UMPCE	Usual Monthly Consumer Expenditure

I. Introduction

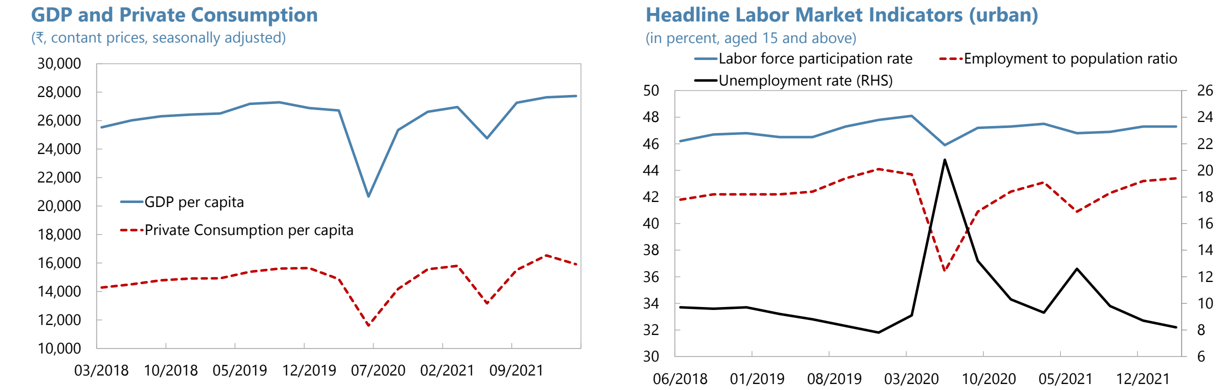
Existing studies suggest that India has made significant progress in reducing poverty during the decades leading up to the pandemic (Bhalla et al. (2022), Edochie et al. (2022), Newhouse and Vyas (2019), and Sinha Roy and van der Weide (2022)). However, the magnitude of the decline in poverty over the past decade is highly uncertain given the lack of official household expenditure data after 2011. While India's robust growth over the past decade likely contributed to such a reduction, the authorities have also expanded social assistance programs, most notably through the 2013 National Food Security Act, whereby the government provided enhanced rations of food to the bottom 50 and 75 percent of the urban and rural populations, respectively. Broader measures of poverty likely declined as well, reflecting the government's development interventions in health and education—for example, a saturation of village electrification and toilets, which was achieved in 2018. Similarly, the Multidimensional Poverty Indicator (MPI) shows a large reduction in poverty in India, where about 275 million people moved out of multidimensional poverty between 2005-06 and 2015-16 and about 140 million people between 2015-16 and 2019-21.

Notwithstanding this considerable improvement in poverty, the large impact of the pandemic shock on economic activity has raised concerns about poverty and inequality. According to the nowcasting analysis by the World Bank (2022), the global poverty rate increased by 11 percent or 70 million people, and the global Gini coefficient increased by over 0.5 points in 2020. As with other countries, India's economy was adversely affected by the pandemic and the associated containment measures. GDP and consumption per capita declined sharply during the first and second waves of the pandemic (Figure 1).[1] Following the first wave, the employment to population ratio decreased by 7.3 percentage points, and unemployment rate spiked to above 20 percent in urban areas (Figure 1). Although both GDP and labor market indicators recovered quickly, the distributional impact of the pandemic could be significant given the heterogenous shocks of the pandemic.

To mitigate the adverse economic impact of the pandemic, the authorities expanded the existing social protection schemes (Figure 2). A key pillar of the authorities' policy response was the expansion of the food transfers provided through the Public Distribution System, which also constituted the largest component of the additional social protection spending during the pandemic (1.4% of GDP in FY20/21). Direct cash transfers provided through the Direct Benefits Transfer (DBT) system and the rural employment guarantee program (MNREGA) were also expanded during COVID (representing 0.3% and 0.4% of GDP, respectively). In terms of coverage, MNREGA's beneficiaries during COVID peaked at about 4 percent of the population.

[1] The first wave of the pandemic started in March 2020 and peaked in September 2020. During the first wave, a strict national lockdown was implemented on 25 March, followed by a gradual reopening from June 2020. The second wave started in urban centers in March 2021 but spread to all states, including rural areas. During the second wave, localized state-wide lockdowns were implemented in most states, followed by Unlock phase from June 2021.

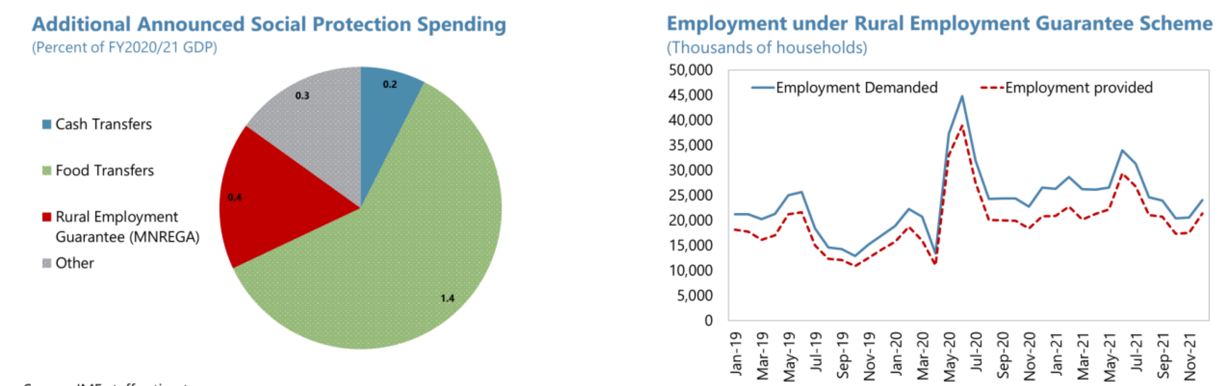
Figure 1: Pandemic Impact on Macro data in India



Sources: MoSPI and IMF staff estimates

Source: MoSPI

Figure 2: Expansion of the social protection program



Source: IMF staff estimates.
Note: Covers measures announced during March 2020 - December 2021.

Source: CMIE Economic Outlook.

Based on this background, this paper aims to address three issues. First, we investigate the evolution of poverty and inequality in India during COVID. For this we rely on two nationally representative household surveys, conducted throughout the pandemic, and study income and consumption dynamics across groups of households from different income percentiles. Second, we examine the factors that are associated with the impact of the pandemic on income and consumption using regression analysis. Various characteristics of households are considered for this empirical analysis, including age, gender, employment, industry, and financial access and savings. Finally, we incorporate into our analysis of poverty and inequality the impact of the government's food subsidy scheme using simulation exercises.

We use unit-level data from two nationally representative surveys for our analysis: the Consumer Pyramids Household Survey (CPHS) collected by a private agency called the Centre for Monitoring the Indian Economy (CMIE) and the Periodic Labor Force Survey (PLFS) conducted by the Ministry of Statistics & Programme Implementation (MoSPI). CPHS tracks the same household over long periods and contains a broad range of household variables, including detailed consumption and income information, employment, and demographic characteristics. Given the previous literature's concern about the CPHS's representativeness, we adjusted the sampling weights of CPHS based on Sinha Roy and van der Weide (2022). It is important to mention that the definition of consumption and income as captured by the CPHS do not necessarily match the relevant variables in India's official household survey, and therefore our main emphasis is on capturing the changes and drivers of poverty and inequality during the pandemic, as opposed to estimates of the level of poverty and inequality consistent with official measures or surveys (i.e., the last official survey from 2011-12).[2] We further develop our analysis of labor income dynamics through the PLFS to benefit from its representativeness and rich labor market variables and to highlight the robustness of our results for income dynamics using an official survey.

Our main findings are as follows. First, the economic downturn associated with the COVID-19 pandemic is estimated to have increased poverty and inequality, but the impact has been temporary with both poverty and inequality returning to their pre-pandemic levels by the end of 2021. Second, demographic and labor market characteristics were the key factors associated with poverty, income, and consumption changes. The analysis broadly suggests that low skill (low education) workers and those working in the informal sector with no formal employment protection were more negatively impacted during the pandemic. Lastly, the government's expansion of food subsidies has likely provided significant mitigation to the rise in poverty during the pandemic. Going forward, ongoing improvements in targeting and portability are critical to improve outcomes with limited fiscal space.

Our study contributes to multiple strands of the literature. First, our analysis is among the few studies that use nationally representative household income and consumption data from the pandemic period to examine the impact of the pandemic. Second, our analysis contributes to an active debate on the evolution of poverty and inequality in India. We examine not only changes in poverty and inequality but also shed light on the household characteristics that were associated with this impact which informs how the pandemic affected different groups of households. Lastly, our work adds to the debate on the impact of the pandemic policy response, using simulation exercises, using actual household data.

The rest of the paper is organized as follows. Section II provides a brief overview of the existing literature regarding the pandemic's impact on income, poverty, and inequality. Section III presents the data used in our analysis. Section IV discusses the dynamics of poverty and inequality during the pandemic. Section V presents the regression results highlighting different channels of impact. Section VI shows our results from simulation exercises to estimate the mitigating role of government's food subsidies. Section VII concludes with some takeaways.

[2] The latter purpose of estimating comparability levels over time was researched by the World Bank. See Annex 1G of World Bank (2022) and Sinha Roy and van der Weide (2022).

II. Literature Review

Our paper contributes to the emerging literature analyzing the distributional impact of the pandemic, featuring insights from India—an emerging market economy which has had one of the most severe economic downturns as a result of the pandemic. The impact of the pandemic on developed and emerging market economies has been studied in different papers, focusing on income and consumption inequality (Stantcheva, 2022), while in developing economies the focus has also been placed on differences across rural and urban regions and impact on extreme poverty (Narayan et al., 2022). Recent studies have suggested uneven impacts on the different segments, disproportionately exacerbating vulnerable groups (Bundervoet et al. (2022) and Galasso et al. (2020)), suggesting a sudden and substantial negative impact on poverty and inequality (Narayan et al. (2022), Sumner et al. (2020), Reddy (2021), and Rönkkö et al. (2022)).

Regarding the India context, Gupta et al. (2021) employs CPHS data and reports a substantial increase in poverty but a decline in inequality during the lockdown periods, claiming richer people were more impacted than their poorer counterparts. Jha and Lahoti (2022) criticize data handling by Gupta et al. (2021), and using the same dataset, they find a significant temporary increase in inequality during the lockdown, returning to its pre-pandemic levels after the lockdown. The nowcasting analysis by the World Bank (2022) suggests the poverty rate in India has increased by somewhere between 4 to 8 percentage points from FY2019 to FY2020. Acknowledging the difference between the 2011-12 official household survey and GDP, Panagariya and More (2021) employ the PLFS consumption data and report a very marginal rise in poverty and a decline in the Gini coefficient during the pandemic.[3]

Our analysis adds to this body of evidence by providing new insights using the CPHS database while trying to improve its representativeness and investigating the factors associated with poverty and inequality. As in previous studies, we use a nationally representative household survey (CPHS) but adjust the sample weights following Sinha Roy and van der Weide (2022) to reflect the improvement of socio-economic indicators in India based on other nationally representative official surveys. Adjusted sample weights are used throughout our paper. We also examine the changes in poverty and inequality during the recovery phase and the channels affecting poverty and inequality. As recent studies by Edochie et al. (2022), Newhouse and Vyas (2019), Gupta et al. (2021), and Jha and Lahoti (2022) have documented, changes in inequality and poverty during COVID, we further extend the analysis to examine socio-economic factors related to these changes. Availability of a household panel survey allows us to examine income and consumption changes during the pandemic. We also use consumption data prior to and during COVID to examine the likelihood of households falling into poverty and explore the role of demographics, education, labor status, and industry of employment in understanding income and consumption dynamics during the pandemic.

[3] Basole and Jha (2023) question the appropriateness of using PLFS consumption data for the poverty analysis, arguing that the PLFS is designed to capture employment but not consumption.

Our paper also provides insights regarding the policy responses during the pandemic. Evidence from other countries suggests that policy interventions were important in mitigating the adverse impact of the pandemic (e.g., Carta and Philippis (2021) and Chetty et al. (2020)). In India's context, Bhattacharya and Roy (2021) find that the expansion of social protection schemes that were already in place prior to the pandemic helped provide needed relief for many poor households. Bhalla et al. (2022) highlight that including food subsidies in measures of consumption estimates is important in understanding the extent to which India may have helped mitigate extreme poverty during the pandemic. In this paper, we use actual household data to simulate the impact of food subsidies on poverty under different scenarios and assumptions.

III. Data

For the analysis we conduct in this paper we mainly utilize two household surveys: Consumer Pyramids Household Survey (CPHS) and Period Labor Force Survey (PLFS). CPHS is conducted by a private agency called the Centre for Monitoring the Indian Economy (CMIE). It is a nationally representative survey, available at the monthly frequency and covers the COVID period. It is also used by many researchers in academia (e.g., Chodorow-Reich et al. (2020)). The survey collects information about detailed consumption, income (from labor, pension, investment, and others), asset ownership, employment, and demographic characteristics. Another benefit is the fact that it is a panel (longitudinal) survey, allowing us to track developments for the same household over long periods (some for the whole period of analysis). The households are visited three times (wave) per year, and each wave takes four months to complete. Approximately 170,000 households were interviewed in each wave.

While the CPHS has many benefits for studying the distributional effects of the pandemic shock, there have been several concerns raised related to its representativeness. In particular, some studies have highlighted differences relative to other nationally representative but official surveys in terms of certain demographic and economic characteristics. These concerns include missing the very poor sampling (Somanchi, 2021), inadequately capturing female employment (Abraham and Shrivastava, 2022), and bias toward higher income distribution (Jha and Basole, 2022).[4] Another concern is related to the large decline in the response rate during COVID. The sample of households that responded during the pandemic declined by about 36 percent relative to the pre-pandemic level in April 2020 due to the transition to a telephone survey. The available sample size recovered as the initial lockdown was gradually lifted but dropped again during the second wave. As of the last wave of 2021, the responded sample size was still about 91 percent of the pre-pandemic level.

[4] Singh and Subramanian (forthcoming) argues that CMIE data is not reliable in capturing employment developments and finds that employment in India has registered a robust V-shaped recovery after being severely impacted during the first and second waves of the pandemic.

To address these concerns, we modified household weights monthly so that the weighted average of household characteristics (e.g., age, education, and asset ownership) are broadly consistent with the official nationally representative survey. We follow the approach of Sinha Roy and van der Weide (2022) to adjust the CPHS weights, where the National Family Health Survey (NFHS) 2015-2016 and 2019-2021 are used as the benchmark national survey. Information on household statistics from NFHS, including household ownership of assets, household size, educational attainment, age composition, and religion and caste, are used as the target variables in the reweighting scheme (Table 1). We interpolate target variables linearly for periods between the release of the two surveys (i.e., years 2016 through 2020) to reflect the changes in these targeted socio-economic indicators. The adjusted weights are used throughout the paper. See Appendix 1 for details of the reweighting procedure.

Table 1: Targeted Characteristics

Asset Ownership	Household count of assets owned. Assets include air conditioning units, vehicles, four and two-wheeler vehicles, refrigerators, computers, televisions, and washing machines.
Size Count	Household size counts of 1, 2, 3, and 5.
Educational Attainment	Proportion of household members with below primary education, primary education, and secondary education.
Age Composition	Proportion of household members above 60 and below 10 years of age.
Religion and Caste	Based on the head of household. Caste categories of SC, ST, and OBC. Religions include Hindu and Muslim groups.

One of the potential drawbacks of the reweighting, however, is that the method does not take into account the panel structure of CPHS and optimizes the weights for each household every month as if we had a new sample of households.[5] This leads to higher weight volatility for the same household over time (for an extended discussion of the CMIE weights, see Bhalla and Das (2022)). The higher weight volatility is less of a concern for the descriptive analysis, where we treat the data as a cross-section. Since we exploit the panel structure of the database for the regression analysis (in section V), we use the household's average weights over certain months to remedy the potential volatility over time due to the reweighting procedure.

We construct income (consumption) per capita measures by dividing aggregate household income (consumption) by household size to measure poverty and inequality. We define aggregate household income as the sum of 1) Earnings from wages, pension, business, and self-production profits, 2) Earnings from dividends, rent, and interest, and 3) Earnings from transfer and insurance. For occupations with sources of income stemming from agriculture-related industries, income is reported periodically rather than consistently through the survey. We correct this seasonality by

[5] Other potential concerns of the reweighing method are also raised by Drèze and Somanchi (2023), including the unknown and possibly wide margin of error and insufficient correction of the underrepresentation of poor households.

creating a 6-month moving average of business income. For aggregate household consumption, we simply sum all available consumption variables of CPHS.[6]

The second data source we rely on is PLFS or the official labor force survey. PLFS has an advantage in terms of national representativeness and rich labor market information, and this paper uses the survey for 2018-19, 2019-20, 2020-21, and 2021-22. The survey period of PLFS is from July to June. In urban areas only, PLFS visits the same household four times (four consecutive quarters), which makes the longitudinal analysis (but not exceeding one year) possible for urban households (e.g., Bhattacharya, 2021). For every quarter, about 60,000 individual data are available in rural households and about 44,000 data in urban households. PLFS covers a wide range of labor market characteristics, including activity status, industries, and earnings.

The analysis using PLFS covers inequality changes based on earned income per capita. The survey asks for the wage or gross earnings by activity status[7], but the dataset does not contain other income sources, such as financial income, pension, and remittance. This non-inclusion of all income sources may be an issue, but since labor income is the major income source for most households, analyzing labor income trends will be another valuable aspect of examining the distributional impact. As with the case of CPHS, the total labor income for each household is divided by the household size to drive the per capita measure.

Although PLFS also collects consumption data called usual monthly consumer expenditure (UMPCE), we do not use this variable for our inequality and poverty analysis, as PLFS is not designed to capture consumption (Basole and Jha, 2023). As highlighted by the annual report of PLFS, the "UMPCE was collected in PLFS only to classify the households in different UMPCE classes and it cannot be used to estimate the household consumer expenditure which is generally estimated based on detailed survey" (National Statistical Office (2022), page 7). In addition, PLFS measured UMPCE based on a single question until 2Q of 2020, which can raise the concern of the rounding issue for analyzing inequality and poverty.[8] From 3Q of 2020, PLFS started to ask five separate questions (instead of one question) to collect the UMPCE, and this discontinuity in questionnaire can make comparisons over time challenging.

[6] Note that this consumption definition is different from the World Bank (WB) and the official household survey. The WB's poverty estimates are based on the Uniform Recall Period (URP) method. URP asks for the expenditure of all items for the previous 30 days. The Indian government uses the Modified Mixed Recall Period (MMRP), where the recall period varies depending on the items' purchasing frequency. The WB has continued to use URP to maintain comparability with historical estimates (WB, 2018). On the other hand, CPHS collects consumption data based on the past four calendar months. We use CPHS's data since our research aims not to construct comparable poverty and inequality estimates with the previous official survey but to capture their changes and drivers during the pandemic.

[7] The employment or activity status is based on the current weekly status. The following earned income is used by employment type. Casual workers: the total wage earnings for 7 days preceding the survey date. Regular workers: monthly earnings for the last calendar month. Self-employed: gross earnings (gross output – total expenses) during the last 30 days. We divide the earnings of regular workers and self-employed by four to make them comparable with the earnings of casual workers.

[8] The UMPCE was a single expenditure variable until PLFS 2019-20 or 2Q of 2020, and the respondents were highly likely to round off their consumption values, which would make the poverty and inequality estimate biased. The analysis by Sinha Roy and van der Weide (2022) indicates that the rounded downward or upward can affect the poverty headcount rate by 4.6 pp or 9.6 pp, respectively.

IV. Impact of COVID-19 on Inequality and Poverty

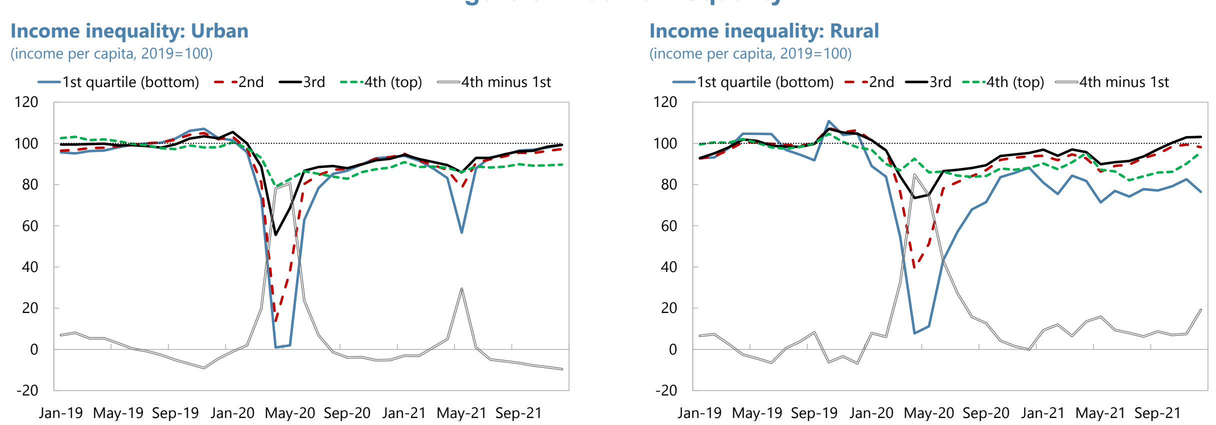
We construct estimates of inequality (in terms of both income and consumption) over the course of the pandemic using two measures, namely the difference between the bottom and top quartiles and the Gini coefficient. While inequality is often measured by consumption in South Asia, we assess inequality based on both income and consumption. Given the pandemic's unprecedented rapid and extensive impact, considering inequality from income, earnings, and consumption perspectives facilitates a more comprehensive assessment. For the poverty line definition, we use the World Bank's $1.9 PPP and $3.2 PPP daily consumption metric.

Impact of COVID on Inequality

We construct measures of inequality based on quartiles by dividing the household samples into quartiles based on per capita income by region (urban or rural) for every month during 2019-2021. For each quartile, we calculate the weighted average income and consumption levels and then rebase these series using 2019 as the base year.

Figure 3 shows the evolution of income per capital for different quartiles and our measure of income inequality based on the difference between the 4th (top) and 1st (bottom) quartiles for urban and rural areas separately. Following the first wave of the pandemic, those in the bottom quartile reached almost zero income. However, the income reduction of those in the top quartile was about 20 percent. As a result, income inequality spiked significantly during this period. The impact of the second wave was much milder, but the rise of inequality is also observed during this period, especially in urban areas. Even though inequality is estimated to have returned to its pre-pandemic level, the pandemic has had a persistent impact on the level of income for some quartile groups, including the top quartile in urban areas and the bottom quartile in rural areas, with incomes still lower than their pre-pandemic levels at the end of 2021.

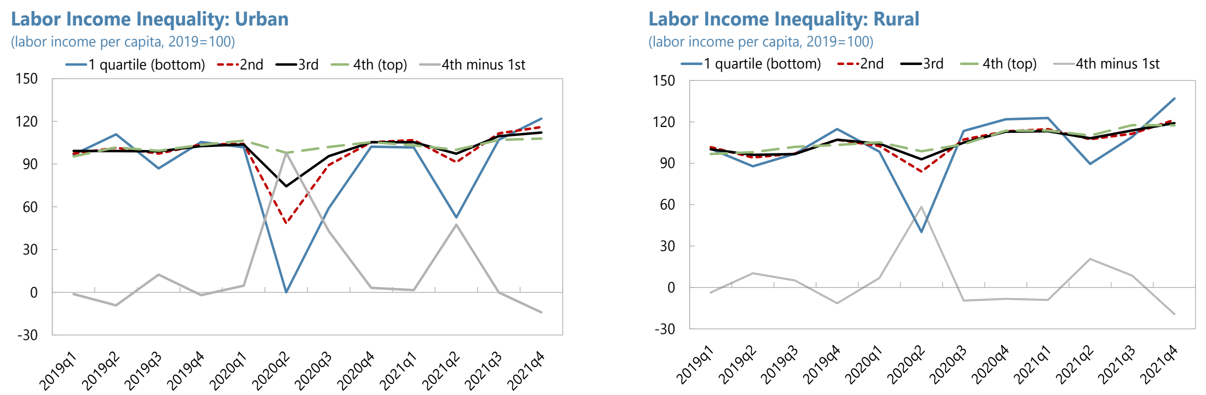
Figure 3: Income inequality



Sources: CMIE-CPHS and IMF staff estimation.

The inequality dynamics using earned income from PLFS suggests a similar picture, but the distributional impact of the pandemic in urban areas is estimated to be somewhat larger, while the impact is relatively muted for rural areas (Figure 4).[9] For the bottom quartiles, the decline of labor income in 2Q of 2020 was almost 100% in urban areas, while the decrease was about 60 percent in rural areas. On the other hand, for the top quartiles, the labor income decreased by about 8 percent and 1 percent in urban and rural areas, respectively. Although the labor income recovered quickly after the first lockdown period, the second wave largely impacted the bottom labor income group, albeit the magnitude is smaller than the first wave. Contrary to the first wave, an apparent decline was observed only for the bottom groups, and again a larger adverse impact on urban households.

Figure 4: Earnings inequality



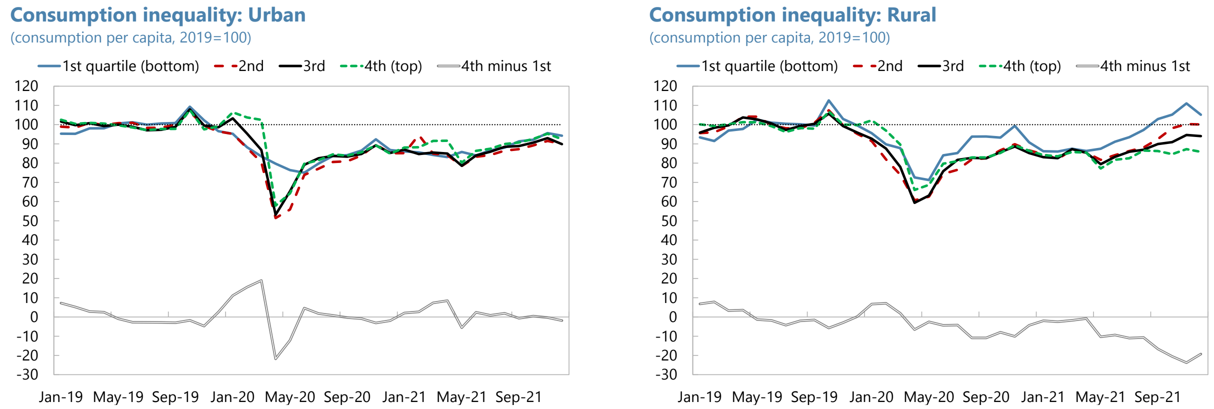
Sources: PLFS and IMF staff estimation.

Compared to income, the dynamics of inequality in terms of consumption are more muted (Figure 5). In urban areas, the decline in consumption for the bottom quartile of households is smaller than the decline for the other quartiles, and there is a slight improvement in inequality during the lockdown. In rural areas, all quartiles saw a similar decline in consumption, so the data suggests that there is no material change in inequality. Toward the end of 2021, the consumption recovery is slower for the top quartile in rural areas, which implies some improvement in inequality.

The Gini coefficient implies a rise in inequality in terms of income but a fall in terms of consumption. The Gini coefficient using income increased drastically in 2Q of 2020, especially in urban areas (Figure 6). We can also observe the increase in the Gini coefficient for urban areas during the second wave. However, after both lockdowns, the Gini coefficient declined back rapidly. Contrary to income, the Gini coefficient using consumption dropped in 2Q of 2020 (Figure 6). This is because the top earners cut consumption more than the bottom earners, as Figure 5 suggests. Although there are no drastic changes in inequality in terms of consumption, the decline in consumption occurred across all percentiles. This suggests that the lockdown period may have exacerbated poverty.

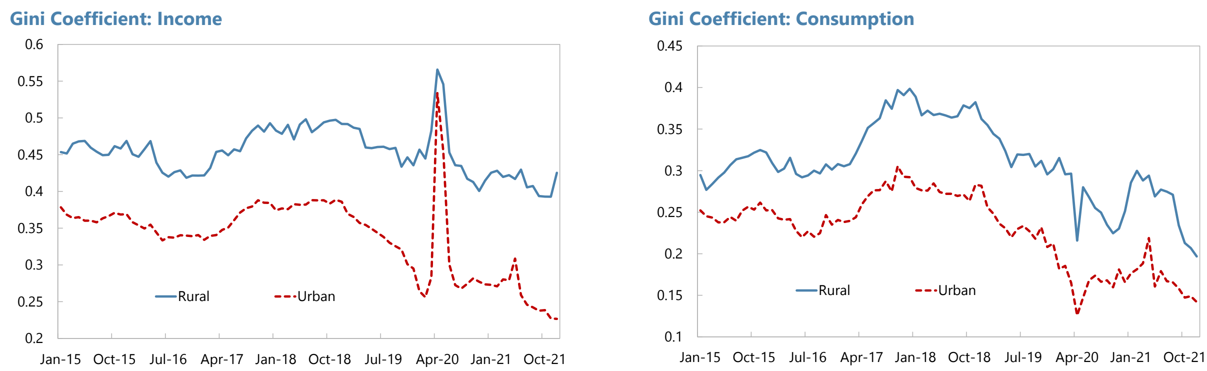
[9] For the inequality analysis using PLFS, we included revisit samples for urban areas.

Figure 5: Consumption inequality



Sources: CMIE-CPHS and IMF staff estimation.

Figure 6: Gini Coefficient



Sources: CMIE-CPHS and IMF staff estimation.

Impact of COVID on Poverty

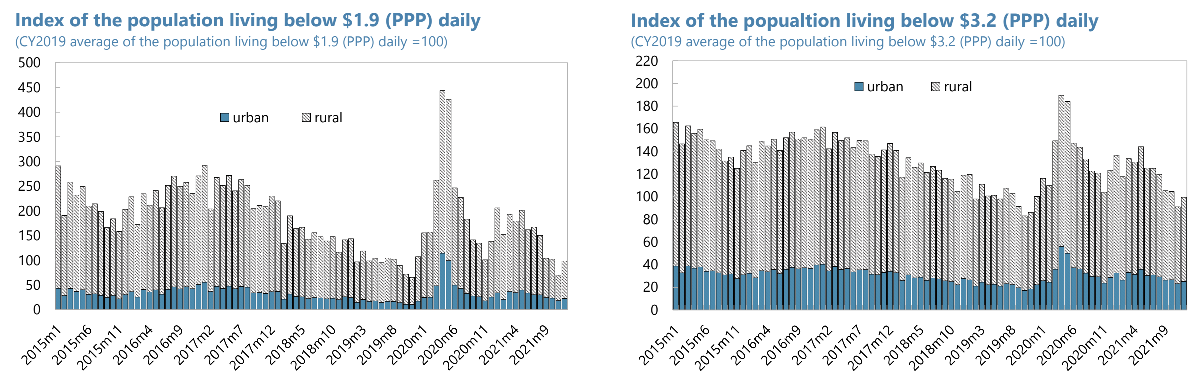
We construct estimates of poverty over the course of the pandemic using the World Bank $1.9 PPP and $3.2 PPP daily consumption metrics. Figure 7 shows the indexes for the population living below $1.9 and $3.2 PPP daily consumption by setting CY2019 monthly average as 100. Although poverty seems to improve over time, it increased drastically during the lockdown period, reaching more than four times of the CY2019 average level based on the $1.9 line.[10] Poverty also increased during the second wave of the pandemic, but the situation improved toward the end of 2021, and as of 4Q of 2021, the number of people both under the $1.9 and $3.2 line was practically back to the pre-pandemic level.

As mentioned earlier, our definition and estimate of poverty is not directly comparable to estimates based on the official household survey from 2011-12 and it importantly does not take into account the food subsidies provided through the Public Distribution System. We therefore emphasize the

[10] Based on the $3.2 line, poverty reached about 1.9 times higher than the CY2019 average in April-May 2020.

change in poverty as opposed to its level and later in Section VI try to account for the potential impact of the food subsidy scheme on poverty.

Figure 7: Poverty



Sources: CMIE-CPHS and IMF staff estimation.

V. Channels of Impact

To capture the characteristics associated with poverty, income, and consumption during the pandemic, we conducted two types of regression analysis, using data for households that responded to the survey both before and after the pandemic. The first regression analysis investigates who has a greater chance of becoming poor after the pandemic, and the second is to examine the income and consumption changes during the pandemic.

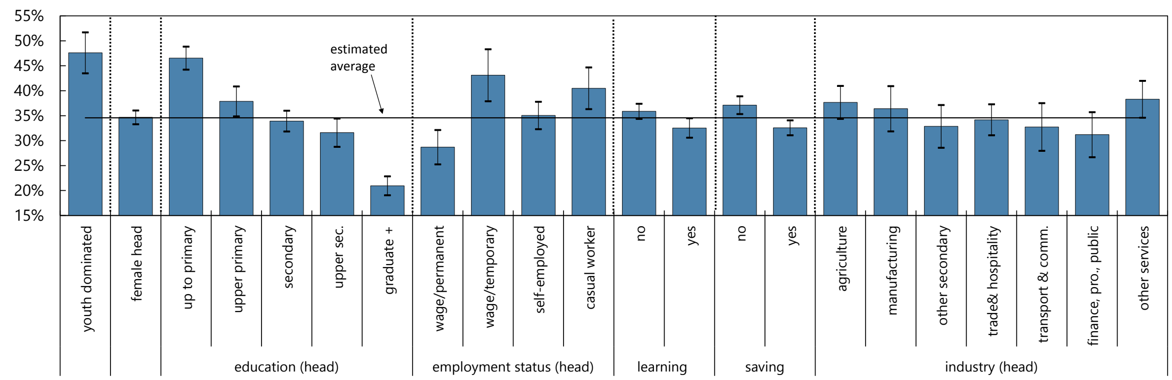
Differently from the above descriptive income and poverty analysis, which uses data as a cross-section, we exploit the panel structure of the database for this regression analysis. As we discussed in the data section, the reweighing procedure for CPHS data may increase the volatility of a given household's weight in the sample. To remedy this potential volatility, we use the household's average adjusted weight during Apr-Dec 2020 for the first regression analysis and during the year 2020 for the second one.

For the first regression analysis, we use households that were not below the $3.2 PPP poverty line through 2019. The dependent variable is binary and takes the value of one if the household's consumption level falls below the poverty line for at least one month during April-December 2020 and zero otherwise. As the dependent variable is binary, a logistic regression is used. The independent variables include characteristics of households and household head, such as family structure, the share of employed persons, location (state and rural or urban areas), the household head's education level, and the household head's employment status and industry. All the independent variables are as of 2019.[11] See Appendix III for the statistical tables.

Figure 8 shows the estimated probability of falling below the $3.2 line after the pandemic based on this logistic regression.[12] The probability is estimated by setting all other variables at their respective averages except for the variables of interest. The estimated probability suggests that households with many youths or children face a higher chance of falling into poverty (higher by 13 percentage points (pp) than the average). From the labor market perspective, low skill (education) or unprotected employment status (temporarily salaried and casual workers) are the main factors that are associated with falling into poverty (with an impact of 12 pp for people with up to primary, 9 pp for temporarily salaried, and 6 pp for causal workers compared with the average).[13]

Figure 8: Estimated probabilities of becoming poor after the pandemic

(Probabilities of becoming below $3.2 at least one month during Apr-Dec 2020)



Note: Error bars indicate the 95 % confidence interval.
Sources: CMIE-CPHS and IMF staff estimation.

Industry-wise results are not necessarily evident, as shown on the right side of the chart, but household heads employed in "other services" appear to have a slightly higher chance of falling below the poverty line. This category mainly captures "Personal Non-Professional Services", which generally refer to physical or manual jobs, for example, barbers, gardeners, decorators, and watchmen. The results also imply that conducting learning activities is associated with a lower probability of becoming poor, highlighting the importance of upgrading skills and strengthening

[11] The last available data in 2019 is used.

[12] For this regression analysis, we did not include the 2019 income decile. Since variables such as employment status and savings are correlated with income levels, adding income level makes these variables less or not significant. Including the 2019 income decile simply suggests that households with lower income levels were more likely to fall into poverty.

[13] To confirm this point, we also run a machine learning analysis, called random forest, to analyze the importance of different variables. The result suggests that the variables with the highest importance are: 1) household size; 2) state; 3) employment status; 4) education; and 5) share of members aged under 15.

vocational training.[14] Finally, having outstanding savings helps cushion the income reduction, and prevent falling below the poverty line.[15]

The second part of the analysis uses all available households and examines the dynamics of income and consumption using a linear regression model (see Appendix III for statistical tables). In addition to CPHS, we use PLFS to capture the labor income changes in urban areas, as the PLFS only has a panel structure in urban areas. Although the PLFS analysis in this section does not capture rural India, the regression analysis can still be insightful, as the pandemic impact was particularly large in urban areas.[16] For the analysis using CPHS, the dependent variable is income and consumption changes from 2019 to 2020.[17] The independent variables are broadly the same as above. We also conduct the CPHS regression analysis by dividing samples into three income levels (see Appendix IV). For the analysis using PLFS, the dependent variable is percent change in labor income from 1Q of 2020 to 2Q of 2020.[18] All independent variables are as of 2019 (CPHS) or 1Q of 2020 (PLFS).

Figure 9 shows the estimated income changes by setting other variables at their respective averages. The results are standardized, with the bar chart above (below) zero showing that income reduction is higher (lower) than the average. Generally, characteristics discussed earlier for the poverty analysis also affected income dynamics during the pandemic.[19] Households headed by low-skilled (education) experienced higher negative income growth (by about 4 pp lower than the average), while the income reduction was less for households headed by permanent wage workers (by about 5 pp higher than the average). Households with a higher share of female youth tend to have a lower income growth. Although the sector-wise result is not very clear, working at other services is associated with lower income growth, and working in the agriculture sector mitigates the adverse impact. The analysis with different income groups suggests that the mitigation role of agriculture is more evident for the lower income group (Appendix IV).

The regression analysis using the PLFS, capturing changes in labor income in urban areas also suggest a similar picture as the CPHS analysis above, but the impact of employment status and industry (Figure 10) is even more evident. The analysis shows that the decline in income is substantially lower for casual workers (by about 17 pp lower than the average). The panel analysis using PLFS shows that more than 50 percent of casual workers lost their job in 2Q of 2020 (see Appendix II). Although the rate of job loss was significantly lower for regular wage and self-

[14] The learning variable takes one if the household head have conducted learning activities for at least one hour and zero otherwise. Learning activities include school, self-learning, tuition, etc.

[15] The saving variable takes one if the household had outstanding savings in either bank fixed deposits or Post Office savings scheme and zero otherwise.

[16] We need longitudinal data to calculate the income changes and estimate factors associated with the changes. PLFS visits the same household four times in urban areas but only once in rural areas, which limits our analysis to the urban areas.

[17] We omit observations if the percent change in consumption or income is more (less) than 90 (-90) percent as outliers.

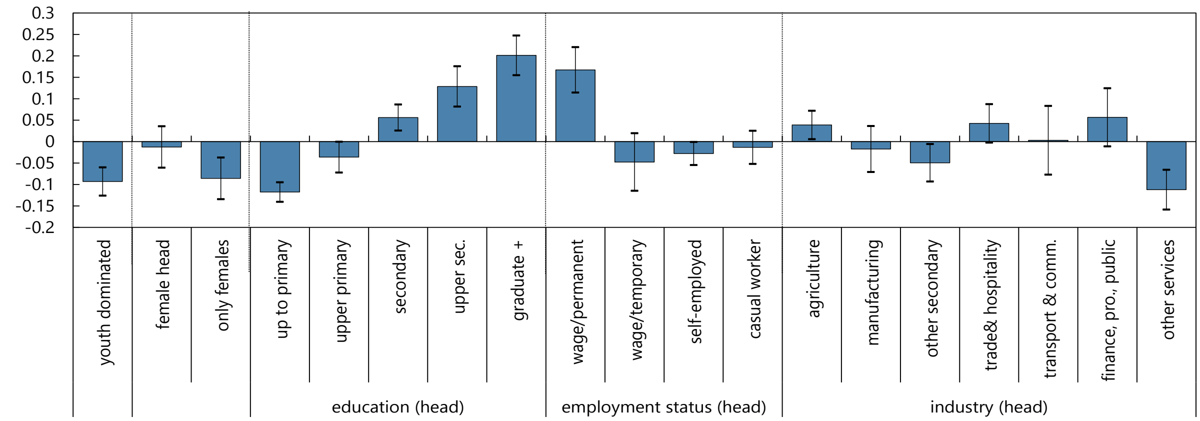
[18] We do not use samples if the labor income per capita is zero in 1Q 2020. We also omitted samples as outliers if the labor income percent changes are more than 100 percent.

[19] We examine the importance of variables again using a machine learning analysis (see footnote 7). The result suggests that the variables with the highest importance are: 1) 2019 income level; 2) state; 3) employment status; 4) industry; and 5) education.

employed, many people did not work in 2Q of 2020. Regular wage workers were more protected because some could continue to receive wages despite their absence from work, but that was not the case for self-employed and casual workers. With regards to industry, the adverse impact on income was higher for contact-intensive services such as hotels & restaurants and other services (e.g., personal services activity). Real estate was also affected, possibly because of a halt in activity in this sector (e.g., lower transaction volumes). On the other hand, the impact was much milder for agriculture, utility, public, and health/social sectors. Although this analysis only captures urban areas, the result suggests that agriculture jobs in rural areas might have mitigated the income reduction during the pandemic.

Figure 9: Estimated Income Changes (standardized)

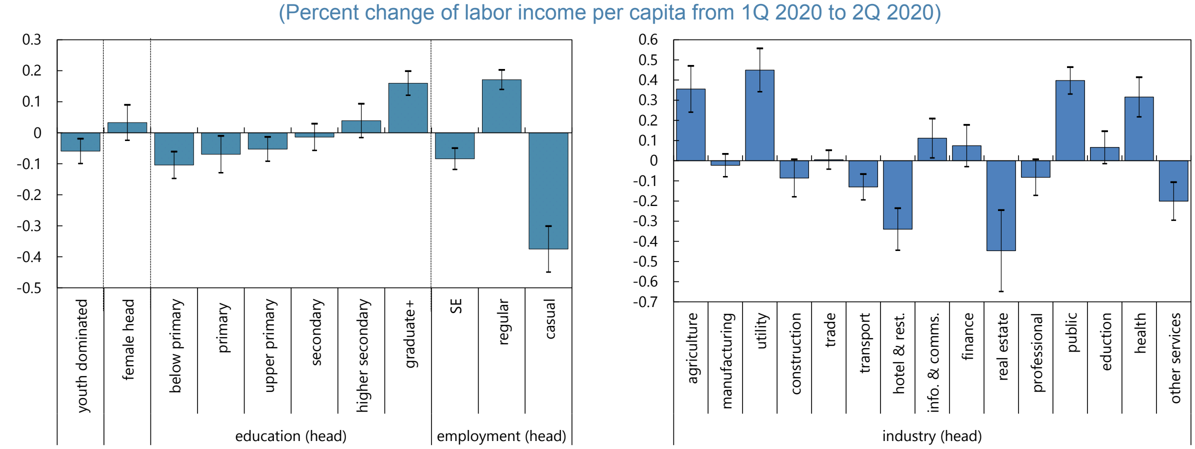
(Percent change of income per capita from 2019 to 2020)



Note: Error bars indicate the 95 % confidence interval.
Sources: CMIE-CPHS and IMF staff estimation.

Figure 10: Estimated Labor Income Changes (urban areas, standardized)

(Percent change of labor income per capita from 1Q 2020 to 2Q 2020)

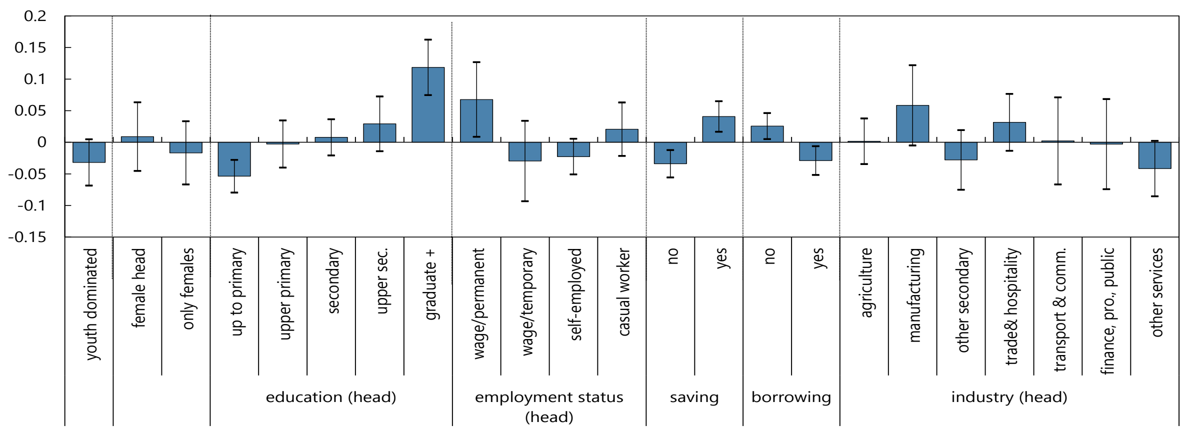


Note: Error bars indicate the 95 % confidence interval.
Sources: PLFS and IMF staff estimation.

The results for changes in consumption have higher standard errors due to the more volatile nature of consumption across households, but the overall picture is broadly in line with the income analysis (Figure 11), with education level and employment status playing an important role. The consumption decline is significantly lower if households have outstanding savings, and higher if households have some outstanding debt. The impact of savings is much higher for households in the lower income (Appendix IV). These results suggest that there was a role for consumption smoothing and liquidity constraints in explaining consumption dynamics during the pandemic.

Figure 11: Estimated Consumption Changes (standardized)

(Percent change of consumption per capita from 2019 to 2020)



Note: Error bars indicate the 95 % confidence interval.
Sources: CMIE-CPHS and IMF staff estimation.

The regression analysis broadly suggests that education status and employment protection were the main drivers of poverty and inequality during the pandemic and controlling for these factors, we found no significant impact related to the sex of the household head. This contrasts with some of the previous papers (e.g., Basole et al., 2021), which find a larger impact related to female head status. To shed some light on this, Table 2 shows the distribution of education and employment status by sex, suggesting that female heads tend to have lower education levels than male heads, while in terms of employment status the differences are not as large—a higher proportion of female heads work in regular wage jobs, and casual jobs, and a lower proportion are self-employed.[20] The distributional characteristics of education and employment status are also different among industries. Regarding education level, agriculture, construction, hotel & restaurant, and other services tend to have workers with lower education levels. Casual workers are especially clustered in the construction sector, while the ratio of regular workers is more than 80% for the public, education, information & communication, and health & social sectors.

[20] See Appendix II for a more detailed discussion.

Table 2: Distribution of household heads' education and employment status in 2019

household head	education				employment		
	below primary	primary	secondary	graduate+	self-employed	regular wage	casual
male	33%	34%	21%	13%	52%	22%	23%
female	60%	23%	11%	6%	41%	26%	29%
agriculture	47%	34%	15%	4%	75%	1%	24%
manufacturing	22%	39%	24%	15%	38%	49%	14%
utility	22%	28%	24%	25%	17%	78%	5%
construction	43%	40%	14%	3%	13%	5%	82%
trade	19%	37%	29%	14%	76%	21%	3%
transport	22%	44%	26%	8%	49%	40%	11%
hotel/rest	27%	42%	23%	8%	56%	35%	9%
I&C	2%	8%	16%	74%	16%	83%	0%
finance	3%	12%	26%	59%	21%	79%	0%
real estate	7%	20%	31%	42%	85%	15%	0%
professional	10%	23%	27%	40%	33%	63%	4%
public	6%	20%	38%	36%	0%	100%	0%
eduction	5%	10%	21%	64%	6%	94%	0%
health	6%	19%	28%	47%	19%	80%	0%
other services	27%	40%	23%	11%	71%	20%	9%

Note: Industries with the top four highest ratios are highlighted for each education and employment category.
Sources: PLFS and IMF staff estimation

VI. Impact of social assistance schemes

As mentioned earlier, the authorities responded to the pandemic through increasing and expanding existing social assistance schemes, which are important to incorporate in the analysis of poverty during the pandemic. While our measure of income includes cash and labor income from government programs and schemes, it does not capture in-kind subsidies of food and other goods. Similarly, our measure of consumption is based on consumption expenditures and therefore does not include subsidies. To estimate the impact of food subsidies, we follow Bhalla et al. (2022) and construct estimates of consumption which also include the value of food subsidies provided by the Public Distribution System (PDS). Under this system, a certain percentage of the population covering the bottom 50 percent in urban and the bottom 75 percent in rural areas is eligible to receive the subsidy in each state. We assign eligibility for different households [21] and the current month's income. Using the current month's income assumes that eligibility is determined perfectly. This is clearly a big assumption, as in reality, eligibility is not updated frequently. However, we make this assumption as we do not have the information to reflect the process of determining eligibility more accurately

We estimate the amount of subsidy (wheat and rice) per recipient as follows (Figure 12).

$$q * (p_m - p_s) * l$$

[21] See the Department of Food and Public Distribution for state-wise coverage (https://dfpd.gov.in/Introduction.htm) of food subsidies.

where q is quantities distributed per recipient calculated from PDS-Offtake data, p_m is a market price, p_s is a subsided price, and l is an assumption on the extent of leakage. The difference between the market price and subsided price is the estimate of the price subsidy $(p_m - p_s)$. We consider leakage to capture the fact that only a part of subsidy reaches the intended recipients. Based on the previous official household expenditure surveys, leakage was estimated at more than two-thirds in 2004. Prior to the Food Security Act 2013 data showed that leakage has improved to about 45%. As we do not have any data to estimate the recent leakage, we consider two scenarios. For scenario 1, leakage is assumed to decline from about 45% in 2015 to 14% in early 2020, as in Bhalla et al. (2022). For scenario 2, we use a more conservative assumption where leakage declines by 0.2% each month and reaches about 30% at the end of 2021.

Figure 12: Estimated monthly subsidy per recipient

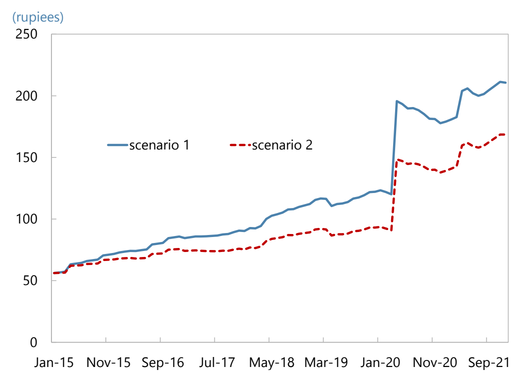
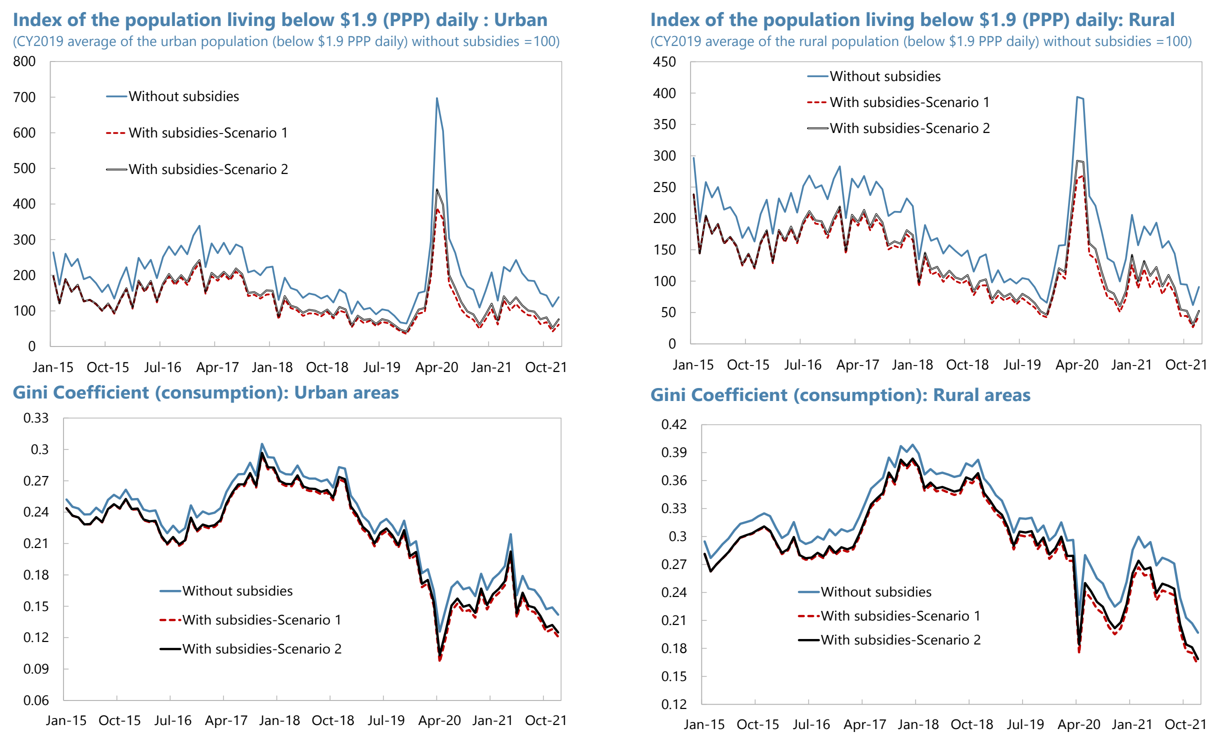


Figure 13 shows the impact of food subsidies on poverty (the indexes for the population below the \$1.9 PPP poverty line) and inequality for urban and rural areas with and without food subsidies. During 2015-2019, the food subsidies lower the poverty ratio by about 5 percentage points in rural areas and by about 2 percentage points in urban areas, using the monthly average. During 2Q of 2020, we estimate that the number of people below the poverty line was reduced by about 27 to 34 percent in rural areas and about 35 to 43 percent in urban areas, depending on the leakage assumption. In total, estimates suggest that food subsidies lowered the number of people living below the poverty line by about 30 to 40 percent during Apr-Dec 2020. Not surprisingly, food subsidies can also lower the inequalities in both urban and rural areas. With food subsidies, the results indicate that Gini coefficient was lower by about 0.03 in rural areas and by about 0.02 in urban areas between Apr 2020 and Dec 2021. This simulation exercise suggests that the expansion of social protection helped mitigate the impact of the pandemic shock on poverty.

Figure 13: Impact of Food subsidies



Sources: CMIE-CPHS and IMF staff estimation.

If the subsidies were more targeted, reallocating subsidies towards lower income groups, holding the total budget for the subsidy constant, the number of people below the $1.9 PPP poverty line could be reduced even further. We consider two hypothetical scenarios, using monthly income and consumption percentiles to redistribute subsidies. The government still provides food subsidies, as described above, but reallocates resources based on the following criteria (Figure 14).

- Redistribution based on income: Subsidies are taken from households that fall above the 25th percentile in urban areas and the 37th percentile in rural areas in terms of income, and equally redistributed to households in the bottom 20th income percentiles.
- Redistribution based on consumption: Subsidies are taken from households whose consumption level is above the 50th percentile in rural and urban areas, and equally redistributed to households in the bottom 20th consumption percentiles.[22]

The simulation results show that both redistribution cases are effective in reducing poverty (Figure 15).[23] Since poverty is measured based on consumption, in the case where redistribution is based on consumption, targeting is a highly effective way to alleviate poverty. Especially in rural areas, poverty could seemingly reduce to zero outside the lockdown period. Targeting those that are in

[22] Since subsidies are distributed based on income, some households could receive subsidies even if they have higher consumption levels.

[23] With subsidies case in Figure 15 is the same as Scenario 1 in Figure 13.

lower income percentiles is effective during normal times, but the impact on poverty is unchanged or even worse than in the baseline during 2Q of 2020. Our interpretation is that since the first wave of the pandemic led to a very sharp decline in income and consumption for most households, narrowing the support through income-based redistribution led to some households falling into poverty. This highlights the fact that when faced with large shocks it is beneficial to provide support using schemes with broad coverage and the authorities' response to the pandemic through increasing support through the food subsidy was important in reducing poverty. Finally, although the redistribution scenario based on consumption is unrealistic, as using consumption level for targeting is difficult in practice, ongoing efforts to improve targeting should continue. Improving targeting can improve outcomes in terms of poverty reduction and enhance the effectiveness of public expenditure, which is crucial when fiscal space is limited.

Figure 14: Hypothetical reallocation scenarios

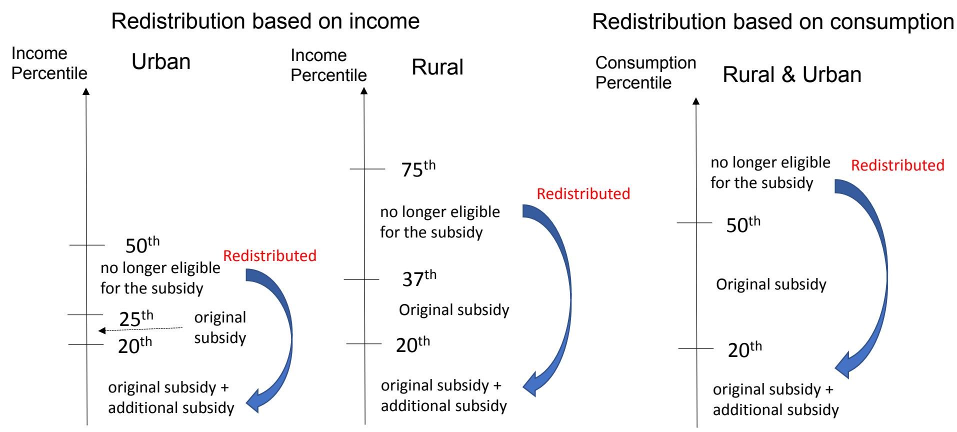
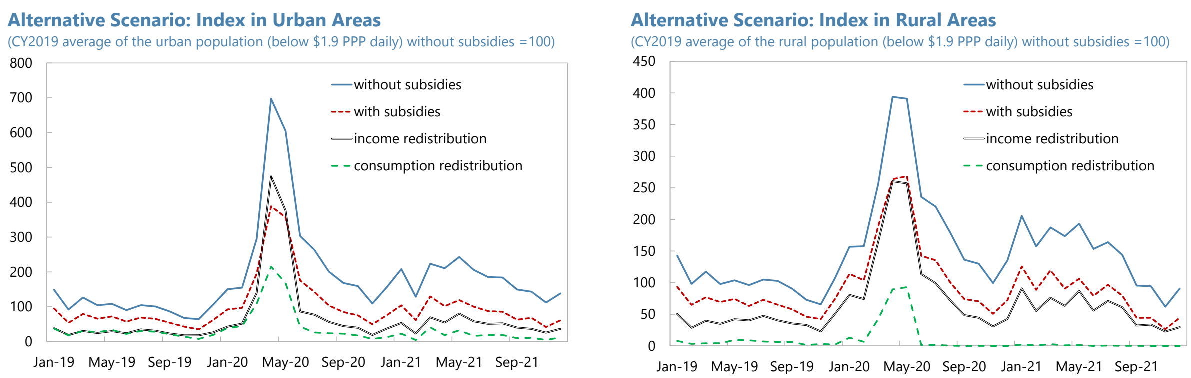


Figure 15: Reallocation Scenario of food subsidy



Sources: CMIE-CPHS and IMF staff estimation.

VII. Conclusion

Notwithstanding the significant uncertainty, the economic downturn associated with the pandemic is estimated to have at least temporarily increased poverty and inequality in India. Our analysis using two household surveys suggests that the number of people with daily consumption expenditures below the standard poverty lines increased sharply in 2020, but the impact was short-lived, declining toward the end of 2021, close to its pre-pandemic levels. While all income groups experienced a decline in income during the pandemic, the impact on lower income groups was larger, especially in urban areas, suggesting a temporary increase in income inequality. Contrary to income inequality, inequality in terms of consumption temporarily declined because the top earners cut consumption by a larger percentage than the bottom earners.

Demographic, education, and labor market characteristics are linked to developments in poverty and changes in income and consumption during the pandemic. Estimates suggest that households with more youth or children and households headed by less educated individuals faced a higher incidence of becoming poor and experienced a higher reduction in income during the pandemic. Labor market characteristics also mattered, as households headed by informal workers (such as casual workers and temporary wage workers) and workers in contact intensive or non-professional personal services were associated with a higher probability of falling into poverty and experienced a higher decline in income. In addition, the analyses imply that conducting learning activities and having savings helped mitigate the negative impact on consumption.

Policy simulations suggest that the government’s expansion of food subsidies has likely contributed to a considerable reduction in poverty during the pandemic. The simulation exercises also imply that the expanded support targeting a broad group of households was appropriate, at least initially, given the broad-based and large impact of the pandemic during the initial phase with strict lockdowns. As the economy recovers from the pandemic, efforts to improve the targeting should continue to enhance the effectiveness of fiscal expenditure.

Annex I. Reweighting CPHS data

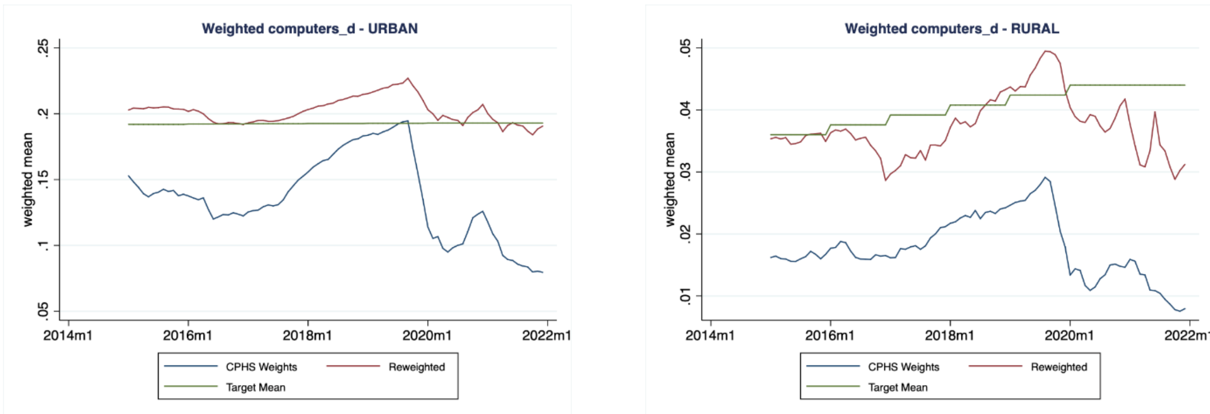
We implement a reweighting procedure suggested by Sinha Roy and van der Weide (2022), using NFHS 2015-2106 and 2020-2021 national estimates. Socio-economic indicators and demographics are used as benchmark estimates in matching similar indicators found in CPHS (see Table 1 of Section II). The matching procedure is conducted using the max entropy procedure described in Hainmueller and Xu (2013). With this technique, characteristics taken from CPHS can be broadly consistent with the national estimates from NFHS.

The max entropy procedure minimizes the distance between national estimates and rebalanced survey weights. First, we use asset ownership, household size, religion and caste, educational attainment, and age composition as the main target variables in the reweighting procedure. All indicators are jointly added in the max entropy procedure as well as the initial base weights from CPHS to ensure that the reweighting considers original estimates of survey weights. We rebalance weights monthly. Since NFHS releases periodic national estimates, we interpolate target variables for periods between 2015 and 2021. Second, rebalanced weights are winsorized at the 1.5th and 98.5th percentiles to address outliers. Finally, we adjust weights based on population estimates separately for rural and urban areas, and for each month in the survey.

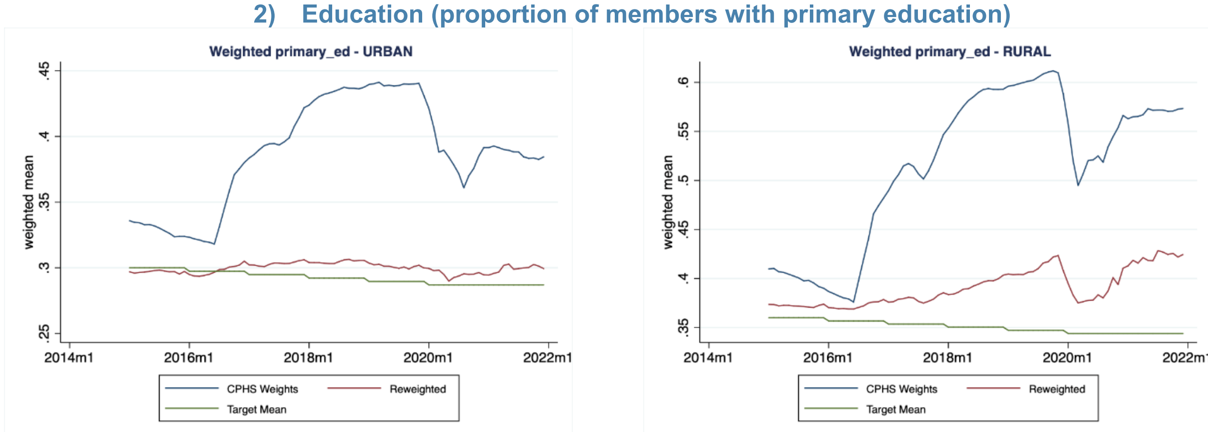
Figure A-1 show some indicators from the benchmark survey and CPHS (original and adjusted), suggesting that the originally observed biases in CPHS are corrected. The green line in Figures A-1 is the interpolated NFHS estimates used as a benchmark. The original CPHS values (blue lines) are adjusted to the red lines, which are broadly in line with the benchmark values. Convergence between the target mean and newly adjusted weights shows the effectiveness of the max entropy procedure when applied to the dataset.

Figure A-1 Benchmark Survey and CPHS

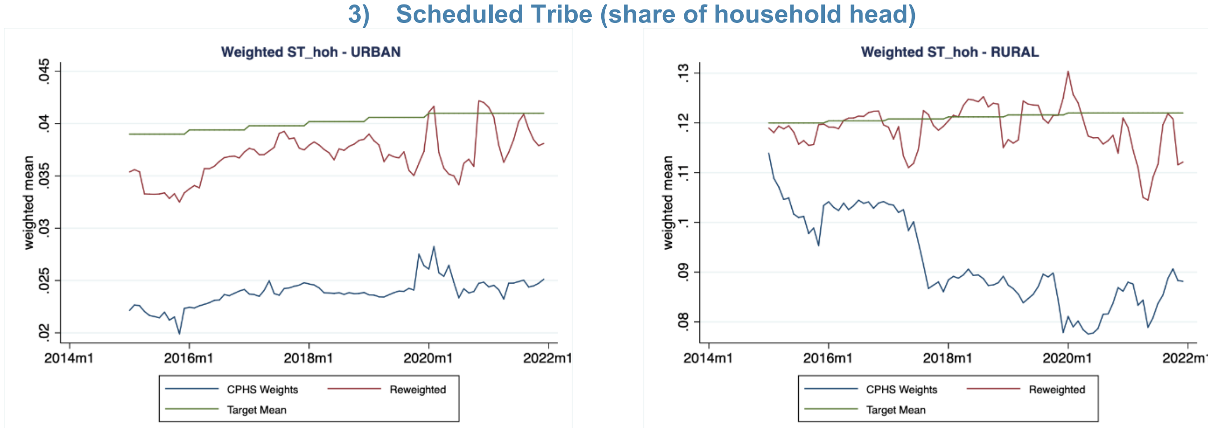
1) Computer Ownership (share of household)



2) Education (proportion of members with primary education)



3) Scheduled Tribe (share of household head)

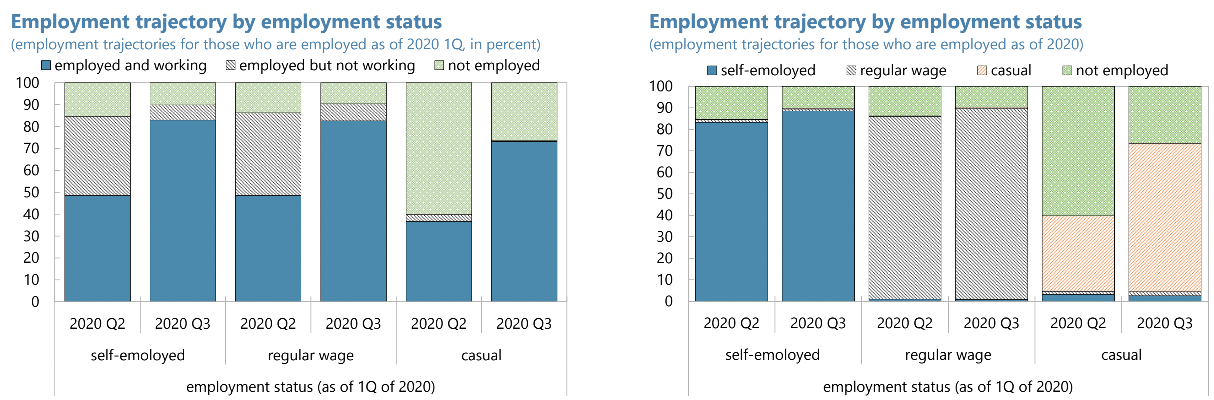


Annex II. Urban Employment Trajectories

To understand the employment changes during the pandemic, this appendix briefly looks at urban individuals who were employed before the shock and follow their status during the first and second lockdowns using PLFS. Although this longitudinal study covers only urban areas, the analysis here will give some flavor of the pandemic's impact on the employment trajectory.

Figure B-1 follows the activity status in 2Q and 3Q of 2020 for those who were employed as of 1Q of 2020. During the first lockdown (2Q of 2020), about 37 percent of casual workers and 49 percent of self-employed and regular wage workers continued working. While more than half of casual workers lost their employment during this time, about 37 percent of self-employed and regular wage workers were employed but did not (could not) work. The regular wage workers might still get some payment even if they did not work, but the self-employed would not have earnings during this time, making the impact for the self-employed larger. Most people re-start working with the same employment status in 3Q of 2020, which implies vulnerable workers remained unprotected. About 26 percent of casual workers still had no jobs in 3Q of 2020, which is more than two times higher than self-employed and regular wage workers.

Figure B-1: Employment trajectory by status (urban)

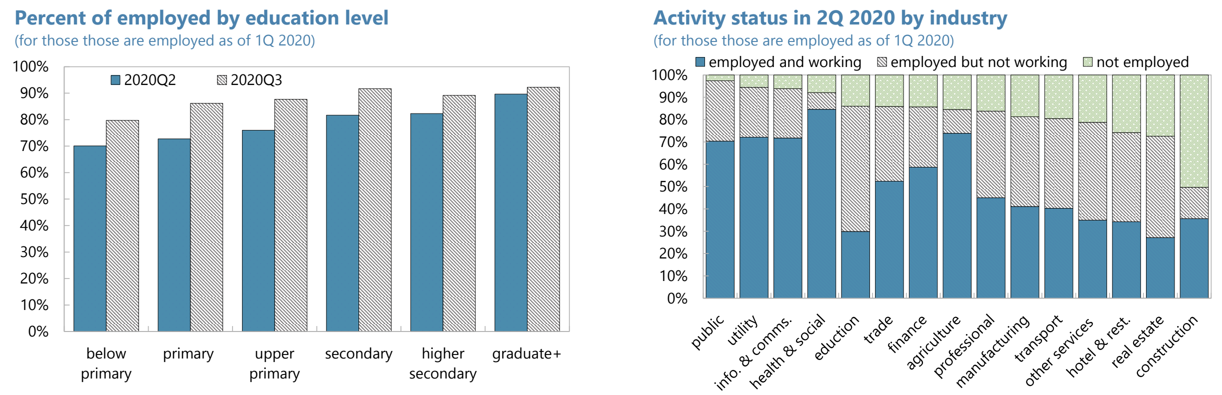


Sources: PLFS and IMF staff estimation

Sources: PLFS and IMF staff estimation

We conduct the same exercise as above by education and industry (Figure B-2). As we saw in the regression results in Section V, more educated workers were more protected. About 30 percent of those with below primary education lost their job, while the ratio is about 10 percent for those with a university degree or above. The recovery in 3Q of 2020 was also slower for the lower educated. At the industry level, sectors such as public administration, utility, and information and communication were more protected. Many people in the health and social sector remained working during the lockdown. Workers in the education sector were also protected, though most did not work in 2Q of 2020. On the other hand, about 50% of construction workers lost their job in 2Q of 2020, as most construction workers are casual workers. Other affected industries include real estate, hotel/restaurant, and other services (e.g., personal service activities).

Figure B-2: Employment trajectory by education and industry (urban)

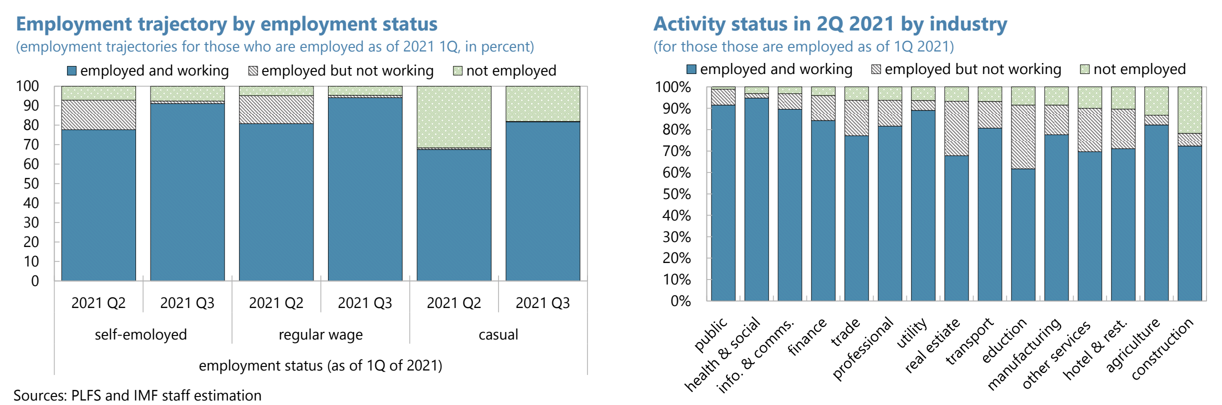


Sources: PLFS and IMF staff estimation

Sources: PLFS and IMF staff estimation

The impact of the second wave is also examined. Figure B-3 follows the activity status in 2Q and 3Q of 2021 for those who were employed as of 1Q of 2021. We can see similar patterns observed during the first lockdown, although the magnitude of the impact was much milder than the first lockdown. Again, while casual workers tended to lose their job, self-employed and regular wage workers remained employed, but some were absent from work. By industry, more construction workers tended to lose their job. The ratio of workers who kept working was lower for some sectors such as education, real estate, and other services.

Figure B-3: Employment trajectory by status and industry (urban)



Sources: PLFS and IMF staff estimation

Sources: PLFS and IMF staff estimation

Annex III. Descriptive Statistics and Regression Tables

CMIE-CPHS (2019, all-India, household)

rural ratio (%)		66.3
ratio of female headed household (%)		14.2
family structure (share, %)	youth dominated	24.3
	grown-up dominated	50.6
	balanced household	25.1
household size (persons, avg.)		4.0
% of househould with SC or ST headed		31.4
% of female per household (avg.)		48.4
% of under aged 15 per household (avg.)		19.0
% of aged above 60 per household (avg.)		13.2
% of employment per household (avg.)		40.3
head's education (share, %)	up to primary	41.6
	upper primary	14.3
	secondary	19.1
	upper sec.	9.6
	graduate +	15.5
head's status (share, %)	Not working	28.4
	Salaried-permanent	9.2
	Salaried-temporary	4.8
	self-employed	38.5
	casual worker	19.2
head's industry (share, %)	agriculture	36.5
(excl. not employed)	manufacturing	7.7
	other secondary	17.5
	trade, hotel, restaurants	15.8
	transport, comms.	5.0
	financial, prof., public	5.3
	other services	12.3
% of household with saving		45.4
% of household with borrowing		47.0
income changes (from 2019 to 2020, %, avg.)		-15.3
consumption changes (from 2019 to 2020, % avg.)		-11.4

State (share, %)	Andhra Pradesh	2.9
	Assam	0.9
	Bihar	9.0
	Chandigarh	0.3
	Chhattisgarh	2.1
	Delhi	1.6
	Goa	0.2
	Gujarat	6.3
	Haryana	2.1
	Himachal Pradesh	0.5
	Jammu & Kashmir	0.6
	Jharkhand	2.6
	Karnataka	2.4
	Kerala	2.1
	Madhya Pradesh	5.1
	Maharashtra	8.6
	Meghalaya	1.8
	Odisha	3.7
	Puducherry	0.6
	Punjab	2.8
	Rajasthan	3.7
	Sikkim	0.4
	Tamil Nadu	2.9
	Telangana	2.5
	Tripura	1.2
	Uttar Pradesh	23.7
	Uttarakhand	1.7
	West Bengal	7.9

Regression results using CPHS

		(1)		(2)		(3)	
Dependent variable		Poverty		Income		Consumption	
Regression		logit		liner		liner	
family structure	grown-up dominated	-0.65	***	4.78	***	1.38	***
(base: youth dominated)		(0.09)		(0.72)		(2.21)	
	balanced household	-0.52	***	2.70	***	0.75	
		(0.11)		(0.92)		(0.75)	
share of female members		-0.13		-5.51	***	-0.84	
		(0.16)		(1.53)		(1.22)	
share of members under aged 15		1.16	***	-16.86	***	-7.49	***
		(0.15)		(1.44)		(1.19)	
share of members above aged 60		0.18		-4.55	***	0.69	
		(0.15)		(1.44)		(1.29)	
rural dummy		0.60	***	-4.42	***	-1.12	***
		(0.05)		(0.55)		(0.41)	
caste dummy (ST/SC)		0.38	***	-3.21	***	-1.68	***
		(0.06)		(0.53)		(0.45)	
male head dummy		0.03		0.48		-0.27	
		(0.10)		(0.93)		(0.80)	
head's education	upper primary	-0.36	***	2.70	***	1.32	**
(base: up to primary)		(0.08)		(0.71)		(0.60)	
	secondary	-0.53	***	5.76	***	1.59	***
		(0.07)		(0.64)		(0.51)	
	upper sec.	-0.63	***	8.17	***	2.15	***
		(0.08)		(0.91)		(0.69)	
	graduate +	-1.19	***	10.57	***	4.46	***
		(0.08)		(0.95)		(0.74)	
share of employed members		-0.164		0.87		2.594	**
		(0.16)		(1.53)		(1.21)	
head's status	Salaried-permanent	-0.21		10.68	***	4.39	***
(base: not working)		(0.16)		(1.45)		(1.26)	
	Salaried-temporary	0.43	**	3.63	**	1.91	
		(0.17)		(1.57)		(1.29)	
	self-employed	0.09		4.28	***	2.09	*
		(0.15)		(1.24)		(1.07)	
	casual worker	0.32	**	4.75	***	3.19	***
		(0.16)		(1.31)		(1.14)	
head's industry	agriculture	0.24		-6.60	***	-4.21	***
(base: none)		(0.15)		(1.35)		(1.20)	
	manufacturing	0.19		-8.43	***	-2.77	**
		(0.17)		(1.48)		(1.34)	
	other secondary	0.03		-9.48	***	-4.97	***
		(0.17)		(1.35)		(1.22)	
	trade, hotel, restaurants	0.09		-6.48	***	-3.45	***
		(0.15)		(1.38)		(1.20)	
	transport, comms.	0.02		-7.77	***	-4.20	***
		(0.18)		(1.79)		(1.40)	
	financial, prof., public	-0.05		-6.02	***	-4.33	***
		(0.18)		(1.63)		(1.43)	
	other services	0.27	*	-11.53	***	-5.31	***
		(0.16)		(1.37)		(1.19)	
saving dummy		-0.20	***	-		1.93	***
		(0.05)				(0.47)	
borrowing dummy		0.06		-		-1.41	***
		(0.05)				(0.43)	
learning dummy		-0.15	**	-		-	
		(0.06)					
constant		-2.17	***	32.47	***	11.15	***
		(0.33)		(3.01)		(2.36)	
household size (dummy)		yes		yes		yes	
state (dummy)		yes		yes		yes	
2019 income decile (dummy)		no		yes		yes	
# of answered in 2020 (dummy)		yes		yes		yes	
Pseudo R2 / R-squared		0.27		0.17		0.11	
Number of obs		91,474		120,155		123,001	

Note: The dependent variables are 1) poverty: binary variable which takes one if samples moved to below the poverty lie of $3.2 PPP after March 2020, 2) income: average monthly income (per capita) changes from 2019 to 2020, and 3) consumption: average monthly real consumption (per capita) changes from 2019 to 2020. Robust standard errors are reported in the blackest. *** p<0.01, ** p<0.05, * p<0.1

PLFS (1Q 2020, urban areas, household)

household member average age	below 24	23.8
(share, %)	24-29	23.2
	30-39	30.7
	40+	22.3
% of female headed household		12.0
household size (persons, avg.)		4.1
social group (share, %)	ST	3.5
	SC	15.2
	other backward	42.0
	others	39.3
head's education	below primary	21.8
(share, %)	primary	10.9
	upper primary	18.9
	secondary	15.1
	higher sec.	9.2
	graduate+	24.2
head's status	not working	17.4
(share, %)	regular wage	33.8
	self-emoloyed	38.7
	casual worker	10.1
head's industry	agriculture	5.6
(excl. not employed, share, %)	manufacturing	22.1
	utility	1.6
	construction	10.8
	trade	19.9
	transport	9.8
	hotel & rest.	4.1
	info. & comms.	2.2
	finance	2.3
	real estiate	0.6
	professional	4.5
	public	3.8
	eduction	4.1
	health & scoail	2.5
	other services	3.8
	others	2.3
% of employment (agriculture) per household (avg.)		2.1
% of employment (industries) per household (avg.)		14.1
% of employment (services) per household (avg.)		26.8

State (share, %)	Jammu & Kashmir	0.6
	Himachal Pradesh	0.3
	Punjab	2.7
	Chandigarh	0.3
	Uttrakhand	0.7
	Haryana	2.8
	Delhi	4.5
	Rajasthan	4.5
	Uttar Pradesh	10.5
	Bihar	2.5
	Sikkim	0.1
	Arunachal Pradesh	0.1
	Nagaland	0.2
	Manipur	0.2
	Mizoram	0.1
	Tripura	0.2
	Meghalaya	0.1
	Assam	1.2
	West Bengal	8.4
	Jharkhand	1.6
	Odisha	1.8
	Chhattisgarh	1.4
	Madhya Pradesh	5.2
	Gujarat	7.4
	Daman & Diu	0.1
	D & N Haveli	0.1
	Maharashtra	11.3
	Andhra Pradesh	4.6
	Karnataka	6.8
	Goa	0.3
	Kerala	4.3
	Tamil Nadu	11.2
	Puducherry	0.2
	A & N Island	0.1
	Telangana	4.1

Regression results using PLFS (urban)

Dependent variable: labor income change (from 1Q 2020 to 2Q of 2020)

Linear Regression

household average age	24-29	2.24 *	head's industry	agriculture	20.79 ***
(base:below 24)		(1.24)	(base:others)		(4.42)
	30-39	3.93 ***		manufacturing	3.92
		(1.15)			(3.74)
	40+	4.08 ***		utility	24.97 ***
		(1.37)			(4.22)
social group	SC	0.37		construction	1.13
(base: ST)		(2.49)			(4.16)
	other backwarc	1.78		trade	5.17
		(2.36)			(3.56)
	others	-0.89		transport	-0.84
		(2.36)			(3.64)
female head dummy		1.67		hotel & rest.	-10.18 **
		(1.42)			(4.08)
head's education	primary	1.54		info. & comms.	9.92 **
(base: below primary)		(1.63)			(3.99)
	upper primary	2.30 *		finance	8.26 **
		(1.32)			(4.06)
	secondary	4.02 ***		real estiate	-14.94 ***
		(1.41)			(5.72)
	higher sec.	6.38 ***		professional	1.28
		(1.63)			(3.88)
	graduate+	11.77 ***		public	22.65 ***
		(1.44)			(3.62)
head's status	regular wage	1.77		eduction	7.90 **
(base: not employed)		(3.44)			(3.76)
	self-emoloyed	-9.59 ***		health & scoail	19.01 ***
		(3.60)			(3.96)
	casual	-22.56 ***		other services	-3.99
		(3.99)			(3.95)
share of agriculture workers		6.56	constant		-26.58
		(6.40)			(4.48)
share of secondary workers		-10.09 ***	household size (dummy)		yes
		(3.51)	state (dummy)		yes
share of service workers		4.22	labor income quintiles (1Q 2020) (dummy)		yes
		(2.73)	pannel identifier (dummy)		yes

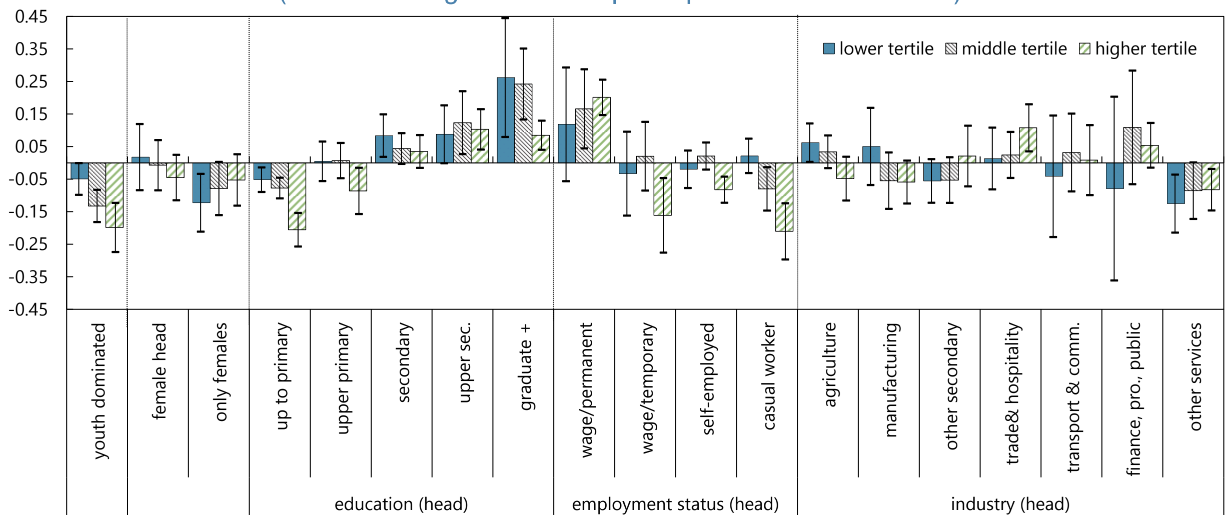
Number of obs = 26,748

R-squared = 0.1375

Note: The dependent variable is earned income (per capita) changes from 1Q of 2020 to 2Q of 2020.
Robust standard errors are reported in the blackest. *** p<0.01, ** p<0.05, * p<0.1

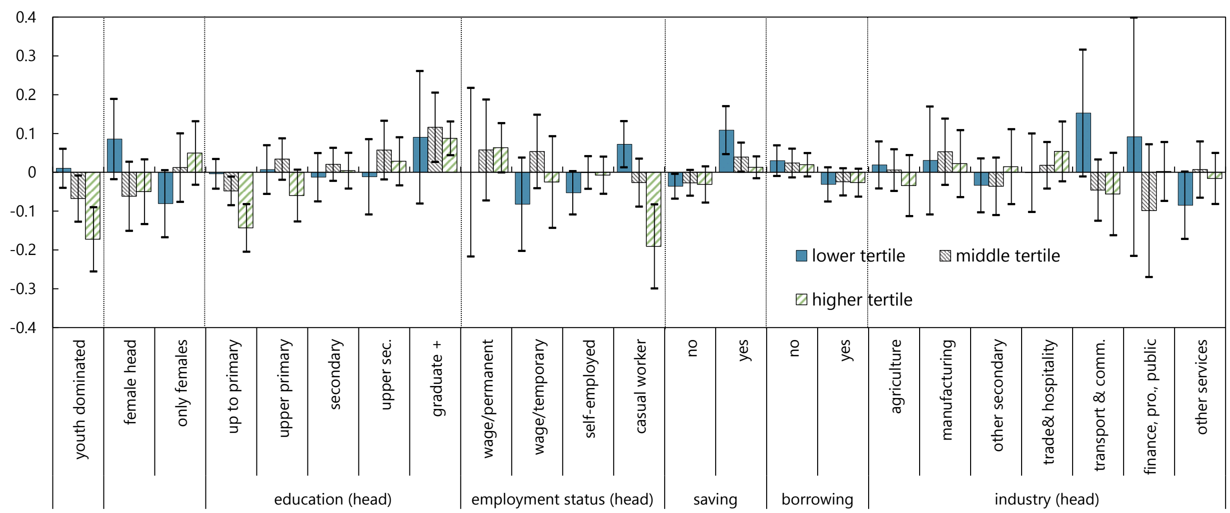
Annex IV. Regression Analysis with Different Income Groups

Figure C-1: Estimated Income Changes (standardized)
(Percent change on income per capita from 2019 to 2020)



Note: Samples are divided into tertile based on the 2019 average income. Error bars indicate the 95% confidence interval.
Sources: CMIE-CPHS and IMF staff estimates.

Figure C-2: Estimated Consumption Changes (standardized)
(Percent change on consumption per capita from 2019 to 2020)



Note: Samples are divided into tertile based on the 2019 average income. Error bars indicate the 95% confidence interval.
Sources: CMIE-CPHS and IMF staff estimates.

Regression results using CPHS

		(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Income			consumption	
Group (tertile)		lower	middle	higher	lower	middle	higher
Regression		liner	liner	liner	liner	liner	liner
family structure	grown-up dominated	3.97***	6.03***	7.72***	-0.32	2.00**	4.99***
(base: youth dominated)		(1.45)	(0.98)	(1.35)	(1.23)	(0.92)	(1.15)
	balanced household	1.80	4.13***	5.17***	-0.70	2.43**	3.82***
		(1.67)	(1.28)	(1.74)	(1.27)	(1.17)	(1.37)
share of female members		-8.01***	-4.82*	-3.27	-4.30*	0.60	2.36
		(2.83)	(2.48)	(2.41)	(2.20)	(2.06)	(1.90)
share of members under aged 15		-17.85***	-23.12***	-14.83***	-1.40	-15.44***	-9.85***
		(2.58)	(2.14)	(2.54)	(2.15)	(1.76)	(2.03)
share of members aged above 60		-14.26***	-7.02***	-1.86	0.22	1.31	0.16
		(4.61)	(2.51)	(1.77)	(3.68)	(2.24)	(1.61)
rural dummy		0.27	-4.62***	-5.87***	0.40	-1.70***	-1.84**
		(0.85)	(0.84)	(1.07)	(0.68)	(0.58)	(0.82)
caste dummy (ST/SC)		-2.97***	-4.01***	-1.84*	-0.76	-1.97***	-2.07***
		(0.93)	(0.79)	(0.99)	(0.76)	(0.71)	(0.79)
male head dummy		-0.66	0.27	1.75	-2.60*	1.83	1.47
		(1.87)	(1.40)	(1.37)	(1.55)	(1.27)	(1.20)
head's education	upper primary	1.81	2.69***	3.96***	0.29	2.07**	2.11*
(base: up to primary)		(1.19)	(1.01)	(1.39)	(1.00)	(0.84)	(1.11)
	secondary	4.35***	3.87***	7.98***	-0.22	1.73**	3.74***
		(1.24)	(0.95)	(1.17)	(0.99)	(0.72)	(0.97)
	upper sec.	4.49***	6.39***	10.24***	-0.20	2.65**	4.35***
		(1.60)	(1.68)	(1.43)	(1.42)	(1.11)	(1.18)
	graduate +	10.09***	10.18***	9.64***	2.48	4.14***	5.85***
		(3.07)	(1.86)	(1.34)	(2.36)	(1.26)	(1.10)
share of employed members		1.46	9.00***	1.63	-2.08	8.20***	3.79**
		(3.24)	(2.54)	(2.24)	(2.65)	(1.91)	(1.69)
head's status	Salaried-permanent	9.49***	8.00***	12.98***	3.56	1.93	5.14**
(base: not working)		(3.36)	(2.76)	(2.21)	(3.17)	(2.30)	(2.05)
	Salaried-temporary	4.72*	3.37	1.10	1.43	1.83	2.91
		(2.80)	(2.48)	(2.75)	(2.18)	(2.07)	(2.33)
	self-employed	5.14**	3.38	3.68*	2.19	0.50	3.36*
		(2.11)	(2.16)	(2.08)	(1.70)	(1.86)	(1.89)
	casual worker	6.44***	0.17	-0.51	5.42***	-0.15	-1.26
		(2.08)	(2.25)	(2.56)	(1.67)	(1.93)	(2.25)
head's industry	agriculture	-5.22**	-2.51	-12.84***	-2.92	-2.72	-7.36***
(base: none)		(2.33)	(2.29)	(2.35)	(1.91)	(2.05)	(2.15)
	manufacturing	-5.58**	-5.33**	-13.19***	-2.63	-1.56	-5.93***
		(2.81)	(2.42)	(2.27)	(2.48)	(2.09)	(2.15)
	other secondary	-8.90***	-5.27**	-10.57***	-4.27**	-3.76*	-6.13***
		(2.27)	(2.27)	(2.54)	(1.92)	(2.03)	(2.19)
	trade, hotel, restaurants	-6.74***	-2.82	-7.73***	-3.44	-2.42	-5.14**
		(2.61)	(2.34)	(2.25)	(2.18)	(2.01)	(2.05)
	transport, comms.	-8.46**	-2.58	-10.98***	0.51	-4.00*	-7.90***
		(3.64)	(2.84)	(2.69)	(2.75)	(2.14)	(2.33)
	financial, prof., public	-9.64*	-0.13	-9.49***	-1.06	-5.31*	-6.44***
		(4.97)	(3.49)	(2.33)	(4.38)	(2.84)	(2.18)
	other services	-11.08***	-6.30***	-13.95***	-5.59***	-2.69	-6.90***
		(2.42)	(2.40)	(2.23)	(1.97)	(2.00)	(2.07)
saving dummy		-	-	-	3.79***	1.67**	1.12
					(0.96)	(0.67)	(0.77)
borrowing dummy		-	-	-	-1.61*	-1.22*	-1.17*
					(0.85)	(0.69)	(0.64)
constant		21.99***	8.83*	-6.03	2.47	-5.34	-6.46**
		(7.78)	(4.56)	(4.36)	(5.98)	(3.75)	(3.29)
household size (dummy)		yes	yes	yes	yes	yes	yes
state (dummy)		yes	yes	yes	yes	yes	yes
2019 income decile (dummy)		yes	yes	yes	yes	yes	yes
# of answered in 2020 (dummy)		yes	yes	yes	yes	yes	yes
Pseudo R2 / R-squared		0.15	0.15	0.16	0.13	0.10	0.11
Number of obs		20,932	44,197	55,026	22,087	45,380	55,534

Note: The dependent variables are 1) income: average monthly income (per capita) changes from 2019 to 2020, and 2) consumption: average monthly real consumption (per capita) changes from 2019 to 2020. Robust standard errors are reported in the blackest.
*** p<0.01, ** p<0.05, * p<0.1

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Working Paper No. WP/2023/147