Azim Premji University

CSE Working Paper

#58

Regressive income shocks during COVID-19: Evidence from India

Amit Basole, Anand Shrivastava, Jay Kulkarni and Akshit Arora

August 2024

Centre for Sustainable Employment

https://azimpremjiuniversity.edu.in/cse

Regressive income shocks during Covid-19: Evidence from India

Amit Basole[*], Anand Shrivastava[†], Jay Kulkarni[‡] and Akshit Arora[§]

22nd August 2024

Abstract

Studies based on the Consumer Pyramids Household Survey (CPHS) in India have shown that the impact of the Covid-19 lockdown on household incomes was progressive in nature - richer households suffered more. But several media reports as well as purposive surveys carried out during the pandemic suggest that the poor suffered more than the rich. We use nationally representative panel data for urban India from the official Periodic Labour Force Survey (PLFS) to show that households that were relatively richer prior to the start of the pandemic suffered relatively less during the lockdown compared to households that were poorer. That is, the shock was regressive in nature. We also confirm that, as per CPHS, richer households did indeed experience higher drops in income than poorer ones. But we show that this progressivity is much less than what prevailed prior to the pandemic. Thus the pandemic either disrupted ongoing progressive income changes or was outright regressive in its impacts.

JEL Codes: D31, D63

Keywords: Covid-19, lockdown, income distribution, India

Word count: 3118

[*]Corresponding author. Email: amit.basole@apu.edu.in. Postal address: Azim Premji University Burugunte Village, Survey No 66, Bikkanahalli Main Rd, Sarjapura, Bengaluru, Karnataka 562125

[†]Azim Premji University

[‡]Bocconi University

[§]Azim Premji University

1 Introduction

The impacts of the Covid-19 pandemic and its associated containment measures on economic growth in India are well understood. But the nature of the impact across the distribution of income is less clear. One study, based on the nationally representative Consumer Pyramids Household Survey (CPHS), has shown that richer households suffered more during the 2020 nationwide lockdown (Gupta, Malani and Woda (2021)).[1] But many other purposive surveys carried out during the pandemic suggest that the poor suffered more than the rich.[2] In this paper, we investigate this question using both the CPHS as well as a different source of nationally representative household-level panel data- the official Periodic Labour Force Survey (PLFS). Both datasets reveal that income changes were progressive in nature prior to the pandemic, in the sense that poorer household were experiencing higher income growth than richer households. As per the CPHS, the pandemic reduced the extent of progressivity while as per the PLFS progressive changes reversed into regressive ones- households that were relatively richer prior to the pandemic suffered relatively less compared to households that were poorer.

Our approach is as follows. We first calculate per capita income in real terms for each quarter in the analysis. We take the October-December 2019 quarter as the base or reference quarter. Each household is assigned to a fixed income percentile or decile based on its position in the distribution of income in that quarter. We then calculate the proportionate change in income in three subsequent quarters (Jan-Mar, Apr-May and Jul-Sep 2020) compared to the reference quarter. We define progressive changes as those where households in lower deciles grow more (or shrink less) as compared to

[1] The authors argue that *income inequality* declined during the pandemic, which contradicts the findings of Centre for Sustainable Employment (2021) showing that the distribution of income worsened during the lockdown, thus increasing inequality. This apparent contradiction stems from a confusion between income inequality and mobility. In its usual definition, the former is a property of the distribution of income at a given point in time. But the availability of panel data allows us to follow households over time and thereby opens up the possibility of examining mobility. We can "fix" the position of a household (or an individual) in a distribution in a baseline period and then measure the change in income of that household or individual relative to the baseline period. In the case of the pandemic, it allows us to ask the question, how did households which were part of the top decile before the shock fare as compared to households that were part of the bottom decile? While Centre for Sustainable Employment (2021) examine inequality in its conventional sense, Gupta, Malani and Woda (2021) explore the mobility implications. The results are not mutually inconsistent.

[2] See for example the reports of the Stranded Workers Action Network. Also see the Azim Premji University Covid Livelihoods Phone Survey and this compilation of a large number of purposive surveys.

households in upper deciles, and vice versa for regressive changes. To quantify the degree of progressivity or regressivity, we regress household level proportionate changes in income on the percentile of the household interacted with period dummies. We perform this analysis for the Covid year (2019-20) as well as the pre-Covid year (2018-19). Finally, we perform several checks including for period of reference (annual or quarterly), type of income (labour versus all sources), and type of panel (balanced or unbalanced), and find that the results are robust to these changes.

Taking this approach and using the CPHS data we find, in agreement with Gupta, Malani and Woda (2021), that richer households did experience higher falls in incomes during the lockdown. For example, compared to their baseline incomes (in October-December 2019) households in the 75th percentile suffered a 49% fall in income during the April-May 2020 (lockdown) quarter. This fall was smaller at 41% for those at the 25th percentile. Interestingly, when we examine the pre-Covid year, we again find evidence for progressive changes. While incomes *grew* by 12% between October-December 2018 and April-June 2019 for households at the 25th percentile, they *shrank* by 9% for those at the 75th percentile. That is, the extent of progressivity during the pandemic was substantially less than over the same period in the previous year. This changes how we interpret the earlier results. Rather than seeing the pandemic as being associated with progressive change, we find that its effect was to reduce the pre-existing progressivity in income changes.

We find progressive changes in the PLFS data as well for the pre-pandemic year, albeit to a lesser degree than observed in CPHS. Between October-December 2018 and April-June 2019, incomes grew 3% in real terms for those at the 25th percentile but shrank 6% for those at the 75th. But the story is different during the pandemic year. During the lockdown the income changes actually turn regressive i.e. the rich do not suffer more, it is the poor who do. While all incomes shrank significantly during the lockdown, they declined by 44% for those at the 25th percentile but by 34% for those at the 75th. Thus, it seems clear, based on both data sources, that the 2020 Covid-19 lockdown disrupted (either muted or reversed) ongoing progressive income changes in India.

These results contribute to two strands of literature. The first strand examines the distributional consequences of Covid and accompanying containment measures both in terms of inequality and mobility. Adams-Prassl et al. (2020) find that in UK, US and Germany, the effect of Covid exacerbates existing inequalities. Egger et al. (2021) and Bundervoet, Dávalos and Garcia (2022) look at the impact in a selection of developing countries and come up with a mixed story on inequality. While Egger et al. (2021) find no correlation between socio-economic status and the impact of Covid, Bundervoet, Dávalos and Garcia (2022) find that workers in non-agricultural self employment were worse affected than those in agriculture.[3] In the Indian context, there have been a number of studies on the differential impact of Covid along different axes including gender (Deshpande, 2022; Abraham, Basole and Kesar, 2022), caste (Deshpande and Ramachandran, 2020) and informality (Kesar et al., 2021). The second strand is a set of papers on the comparison of two nationally representative household surveys in India that are conducted multiple times a year - PLFS and CPHS. Jha and Basole (2023) compare labour incomes between the two surveys while Abraham and Shrivastava (2022) compare employment outcomes. This study is the first to compare income growth as shown by both these surveys.

The rest of the paper is organised as follows. In the next section we discuss the datasets and the empirical strategy used. Section 3 presents results. In Section 4 we discuss the implications and conclude.

2 Data and empirical strategy

We use two large nationally representative panel datasets for this exercise. Each of them is described below.

2.1 Data sources

The PLFS is India's official employment survey being conducted since 2017. For urban India, the survey is a quarterly one where every household is visited four times over four consecutive quarters before it is rotated out of the panel. We use data for four quarters,

[3] See Miguel and Mobarak (2022) for a detailed survey of these and other studies on Covid-19 impacts in developing countries.

from October 2019 to September 2020, for our analysis as this allows for a good amount of time before and after the first nationwide lockdown, which lasted from 25th March to 31st May 2020. The key variable that we use from the survey is labour income reported for each employed individual in the household. This includes income from regular wage work, casual wage work as well as self-employment. We include self-employment income even though it is not strictly labour income (but rather a mix of labour and capital income) since the vast majority of such incomes come from own-account enterprises and because an argument has been made that business incomes were hurt more than wage incomes (Gupta, Malani and Woda (2021)). The PLFS reports monthly income from self-employment and regular wage work but weekly income from casual wage work. We multiply weekly casual wage income by four to arrive at monthly numbers. Labour incomes are summed at the household level and divided by household size to generate per capita household labour income in each quarter.

The CPHS is a private long running panel survey with households visited three times a year in rural and urban areas. We present results here only for the urban panel to maintain consistency with the PLFS. The rural CPHS results are similar to the urban (Appendix A). Unlike PLFS, the CPHS reports incomes from all sources, not only labour. To ensure comparability with the PLFS, we confine our analysis to household labour incomes (once again the sum of wage incomes and income from self-employment at the household level). However, since previous work on this issue has used household income from all sources, we confirm that our results hold when labour incomes are substituted with total household income (Appendix B). Since CPHS income data is available at a monthly frequency, our analysis is also performed at the monthly level. However we have confirmed that the quarterly level results (comparable to PLFS) are qualitatively similar (Appendix C).

We use the state-level Consumer Price Index (CPI-U, base Jul-Sep 2020 quarter) to convert nominal incomes to real.[4] We present results from an unbalanced panel for both datasets. The results do not change qualitatively if a balance panel is used (Appendix D).

[4]In Appendix A we report results for rural India using CPHS data, where state-level CPI-R is used for inflation adjustment. State level CPI data is not available for the lockdown months of March, April and May 2020. We use all-India values where state-level data is not available.

2.2 Panel construction and regression model

We designate the October to December quarter as the base quarter to assign households into percentiles or deciles of the labour income distribution. We use these to see how the income shocks resulting from the lockdown vary depending on the position of the household in the baseline period. The next three quarters, i.e. January to March, April to June, and July to September, are labelled as Periods 0, 1 and 2 respectively. For the year 2019-20, Period 1 encompasses the national lockdown (Table 1). The comparable quarters from the previous year (2018-19) serve as a reference period to see the nature of the income changes prior to the pandemic.

Our outcome variable is the proportionate change in household per capita labour income between the base quarter (Oct-Dec) and the three subsequent quarters. We discard the top 1% of values for this variable to exclude large outliers resulting from a base effect. Our regression specification is as follows. We only include households who had non-zero labour incomes in the base quarter.

$$\delta y/y = \alpha + \beta_1\ Period\ 1 + \beta_2\ Period\ 2 + \beta_3\ Period\ 0 * percentile + \beta_4\ Period\ 1 * percentile + \beta_5\ Period\ 2 * percentile + \epsilon$$

The variable *percentile* has range (-49,50) which allows us to interpret the base coefficient as the impact on the median household. The coefficients are interpreted as follows. The constant term α captures the proportionate change in household per capita labour income between the base quarter and Period 0 (Jan-Feb) for the median household. Adding the constant term and the coefficients for the Period 1 or Period 2 dummies, i.e. $\alpha + \beta_1$ and $\alpha + \beta_2$, give the impact on the median household for Periods 1 and 2 respectively. The differential impact across the income distribution is captured by the coefficients of the interaction terms i.e. β_3, β_4 and β_5. Note that for ease of interpretation we have chosen to interact each of the three period dummies with percentile rather than interact only two of them and have a stand alone percentile term. If the proportionate decline in income during the lockdown was progressive (regressive) in nature, the coefficient β_4 should be negative (positive) for Period 1 showing larger (smaller) decline for higher percentiles in the lockdown quarter.

3 Results

3.1 Descriptive statistics

Table 2 shows the average change in labour incomes in urban India in both datasets relative to the base quarter in both the pandemic and the pre-pandemic years. As expected, small changes are observed in 2018-19 (a 1 to 2% decline in real terms), though as we show later, this average hides significant differences across the income distribution.[5] But the lockdown quarter (Period 1) as well as the subsequent quarter (Period 2) saw substantial declines in labour incomes in both surveys. The PLFS recorded a 38% drop on average during the lockdown while the CPHS recorded a 43% drop relative to the base quarter. In the subsequent quarter after the lockdown, real incomes remained around 16 to 17% lower as compared to the base quarter.

Figures 1a and 1b shows the decile-wise Growth Incidence Curves (GIC) for the pre-Covid as well as the Covid year calculated from the PLFS. Note that each decile is composed of households assigned to that decile based on their income level in the base quarter. We see that households in lower deciles experienced higher income gains in 2018-19. However, the picture is the opposite in the Covid year. In the lockdown quarter households in the lower deciles experienced larger falls in labour incomes. While the fall is the largest for the lockdown quarter of Apr-Jun 2020, the subsequent quarter also shows a reduction with respect to the base quarter, i.e. an incomplete recovery of income levels from the lockdown. Though it is worth noting that recovery is faster for households in lower deciles.

Figure 2a and 2b show the corresponding GICs based on CPHS. They presents a similar picture to PLFS when it comes to the reference year of 2018-19 i.e. a progressive change. Households in lower deciles experienced higher growth rates while incomes actually shrank in real terms for households in upper deciles. Where the CPHS estimates diverge clearly from PLFS is for the Covid year. The extent of income decline is larger as one moves up the distribution. But, a visual inspection of the two graphs also suggests

[5] Usually incomes should register a rise in real terms alongside economic growth, however GDP growth was slowing down significantly during 2018-19. It seems that the impact of this growth recession was a contraction in average household labour incomes, particularly for households above the median (see Figure 1a).

that the extent to which income growth is observed to be progressive in CPHS actually reduces in the pandemic year. We provide more precise estimates of this difference later in the paper.

3.2 Regression results

We now turn to the regressions. Here the analysis is at the percentile level. Before presenting the results, we show the basic result using percentile-based GICs. Figure 3a shows the GICs estimated from PLFS data and Figure 3b does the same for CPHS (only the Covid year GICs are shown). Note that the PLFS GICs slope downwards for Period 0 and Period 2 but upward for Period 1, i.e. a flip from progressive to regressive income changes during the lockdown. While all three GICs estimated from the CPHS are downward sloping. But, as expected from the decile GICs shown earlier, the lockdown GIC has a much shallower slope as compared to the other two quarters - i.e. income changes are weakly progressive during the lockdown, as compared to both before and after.

Tables 3 and 4 show the regression results for PLFS and CPHS respectively. Looking at the PLFS results first, the Period 1 and 2 dummies for the year 2019-20 capture the impact of the Covid lockdown and the recovery from the lockdown for the median percentile. The differential impact across the distribution is captured by the interaction terms. Note that the coefficient for the Period 1*percentile interaction is negative for the pre-Covid year but positive for the Covid year. The coefficient estimate of -0.0018 indicates that, in the pre-Covid year, the rise in income during this period is smaller (or the fall in income is larger) by 0.18 percentage points for every percentile increase - in other words the income of the rich increased by less (fell by more) in percentage terms than that of the poor. For the Covid year the situation is the opposite- the fall is income is lower as one moves up the income distribution (in this case all incomes fall, so there is no rise to be considered). There is a 0.2 percentage point drop in the extent to which incomes decline with each percentile.

In contrast to what we see in the PLFS panel, the CPHS panel shows progressive changes for both years. Table 4 shows the results. Here we show only the urban results for comparison with PLFS. The rural results from CPHS are shown in Appendix A. Once again, the Period 1 and 2 dummies by themselves capture the impact of the lockdown and recovery from the lockdown for the median percentile. The interaction terms are negative in both years showing that households in higher percentiles experience higher income losses (or lower income gains) in both the pre-Covid and Covid years. However, the extent of progressivity given by size of the coefficient is significantly smaller in the Covid year indicating that the impact of the pandemic was to make income changes *less* progressive. Directionally, this is in line with the PLFS result.[6]

We present these results in summary form in Table 5. The PLFS results are in the top row and the CPHS in the bottom. The base quarter (Oct-Dec) income is indexed at 100 for each percentile. We then calculate the income level for three points in the distribution - the 25th, the 50th and the 75th percentile, for each period for both years using the regression coefficients.[7] Our focus is on the Covid year. The baseline year is given for reference only. Note that, as per the PLFS estimates, during the lockdown (Period 1) incomes fell further for households in lower percentiles - to 56% of the base income for the 25th percentile and 66% for the 75th. The picture is reversed if we consider the CPHS estimates, with households in upper percentiles experiencing higher losses. But the post-lockdown recovery is similar in both datasets - households in lower percentiles recover faster than those in upper ones.

4 Discussion and Conclusion

The aggregate impact of the Covid-19 pandemic on growth as well as the pace of recovery from the pandemic are well understood based on national income data. But the distributional impact is also important to understand. If the impact was more severe for those who were already worse off, this would worsen existing social and economic inequalities. This has indeed been observed for social identities such as gender and caste

[6]Note that Gupta, Malani and Woda (2021) follow a slightly different approach to address the same question. They consider total household incomes from all sources and take the entire calendar year, 2019, as the base year to calculate Covid year changes. We have replicated this approach and results in qualitative terms (see Appendix B).

[7]The estimates are calculated as follows: For the median percentile the change in income corresponding to base period is given by α for period 0. Adding β_1 to the former give estimates for subsequent periods. For any percentile other than the median, say x, the final estimates can be arrived by adding (x - 50)$\times\beta_3$ to the median estimate for a given period.

(Deshpande, 2022; Deshpande and Ramachandran, 2020; Abraham, Basole and Kesar, 2022; Kesar et al., 2021). The post-pandemic recovery measures would then need to take this into account.

In the foregoing analysis we have estimated the impact of India's nationwide lockdown across the income distribution. Both the data sources used here reveal that the pandemic disrupted progressive changes that were underway prior to it. As per the PLFS, in the preceding year (2018-19) relatively richer households had experienced a decline in income in real terms while the relatively poorer ones (the bottom two deciles) experienced growth. This picture was reversed during the pandemic and households in lower deciles experienced larger losses than those in upper ones. As per the CPHS, once gain, the pre-pandemic year was one where incomes grew in real terms for households in the bottom three or four deciles, but shrank for those in the upper deciles. During the pandemic, changes remained progressive in the sense that poorer households experienced smaller losses as compared to richer ones, but the degree of progressivity was much smaller.

In sum, using nationally representative household panel data we have demonstrated that the impact of the Covid-19 lockdown in India was felt differently across the income distribution. As per the PLFS, poorer households suffered larger proportionate decreases in their incomes as compared to richer households. We have also shown that the progressive changes observed in the CPHS data are not specific to the pandemic, but rather is a pre-existing feature that needs to be explained on its own terms. Thus the conclusion that the pandemic reduced "inequality" seems unjustified. We hope that this study will spur future work on the impacts of the Covid-19 lockdown.

Acknowledgements: The content and opinions expressed are that of the author(s), and do not necessarily reflect the views of Azim Premji University. We thank Arjun Jayadev for helpful comments and suggestions. All errors and omissions are authors' responsibility.

References

Abraham, R., A. Basole, and S. Kesar (2022). Down and out? the gendered impact of the covid-19 pandemic on india's labour market. *Economia Politica 39*(1), 101–128.

Abraham, R. and A. Shrivastava (2022). How comparable are india's labour market surveys? *The Indian Journal of Labour Economics 65*(2), 321–346.

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public economics 189*, 104245.

Bundervoet, T., M. E. Dávalos, and N. Garcia (2022). The short-term impacts of covid-19 on households in developing countries: An overview based on a harmonized dataset of high-frequency surveys. *World development 153*, 105844.

Centre for Sustainable Employment (2021). State of Working India 2021: One year of covid-19. Technical report, Azim Premji University.

Deshpande, A. (2022). The covid-19 pandemic and gendered division of paid work, domestic chores and leisure: evidence from india's first wave. *Economia Politica 39*, 75–100.

Deshpande, A. and R. Ramachandran (2020). Is Covid-19 "the great leveler"? the critical role of social identity in lockdown-induced job losses. *GLO Discussion Paper, No. 622*.

Egger, D., E. Miguel, S. S. Warren, A. Shenoy, E. Collins, D. Karlan, D. Parkerson, A. M. Mobarak, G. Fink, C. Udry, et al. (2021). Falling living standards during the covid-19 crisis: Quantitative evidence from nine developing countries. *Science advances 7*(6), eabe0997.

Gupta, A., A. Malani, and B. Woda (2021). Inequality in india declined during covid. *National Bureau of Economic Research Working Paper 29597*.

Jha, M. and A. Basole (2023). Labour incomes in India: A comparison of two national household surveys. *The Indian Journal of Labour Economics 66*, 181–201.

Kesar, S., R. Abraham, R. Lahoti, P. Nath, and A. Basole (2021). Pandemic, informality, and vulnerability: impact of Covid-19 on livelihoods in india. *Canadian Journal of Development Studies / Revue canadienne d'études du développement 42*(1-2), 145–164.

Miguel, E. and A. M. Mobarak (2022). The economics of the Covid-19 pandemic in poor countries. *Annual Review of Economics 14*, 253–285.

Tables

Table 1: Periods of analysis in the baseline and Covid years

Baseline periods		Pandemic periods	
Period	Months	Period	Months
base	Oct 2018-Dec 2018	base	Oct 2019-Dec 2019
0	Jan 2019-Mar 2019	0	Jan 2020-Mar 2020
1	Apr 2019-Jun 2019	1	Apr 2020-Jun 2020
2	Jul 2019-Sep 2019	2	Jul 2020-Sep 2020

Table 2: Proportionate change in per capita labour incomes in comparison to base quarter

PLFS			CPHS		
Period	2018-19	2019-20	Period	2018-19	2019-20
0	0.00	-0.01	0	0.01	-0.10
1	-0.01	-0.38	1	0.02	-0.43
2	-0.02	-0.17	2	0.02	-0.16

Table 3: Regression results for PLFS 2018-19 & 2019-20

Dependent Variable:	Proportionate change in labour income	
Model:	2018-19	2019-20
Variables		
Constant	-0.0005	-0.0123**
	(0.0044)	(0.0055)
Period 1	-0.0101**	-0.3729***
	(0.0046)	(0.0080)
Period 2	-0.0203***	-0.1566***
	(0.0061)	(0.0066)
Period 0 × percentile.m	-0.0017***	-0.0012***
	(0.0002)	(0.0002)
Period 1 × percentile.m	-0.0018***	0.0020***
	(0.0002)	(0.0003)
Period 2 × percentile.m	-0.0024***	-0.0009***
	(0.0002)	(0.0003)
Fit statistics		
Observations	28,304	27,800
R^2	0.0276	0.1356
Adjusted R^2	0.0274	0.1355

Standard errors clustered at household level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Regression results for CPHS 2018-19 & 2019-20

Dependent Variable:	Proportionate change in labour income	
Model:	2018-19	2019-20
Variables		
Constant	0.0044***	-0.0957***
	(0.0015)	(0.0036)
Period 1	0.0098***	-0.3528***
	(0.0017)	(0.0046)
Period 2	0.0074***	-0.0578***
	(0.0021)	(0.0045)
Period 0 × percentile.m	-0.0024***	-0.0027***
	(5.22×10^{-5})	(0.0001)
Period 1 × percentile.m	-0.0042***	-0.0015***
	(6.38×10^{-5})	(0.0001)
Period 2 × percentile.m	-0.0052***	-0.0055***
	(7.05×10^{-5})	(8.93×10^{-5})
Fit statistics		
Observations	726,065	321,042
R^2	0.07723	0.10859
Adjusted R^2	0.07722	0.10858

Standard errors clustered at household level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Changes in income for selected percentiles based on regression coefficients (base quarter = 100)

	2018-19				2019-20			
	Period	**00**	**01**	**02**	Period	**00**	**01**	**02**
PLFS	25th	104	103	104	25th	102	56	85
	50th	100	99	98	50th	99	61	83
	75th	96	94	92	75th	96	66	81

	2018-19				2019-20			
	Period	**00**	**01**	**02**	Period	**00**	**01**	**02**
CPHS	25th	106	112	114	25th	97	59	98
	50th	100	101	101	50th	90	55	85
	75th	94	91	88	75th	84	51	71

Figures

Figure 1a: Growth Incidence Curve for 2018-19 - PLFS

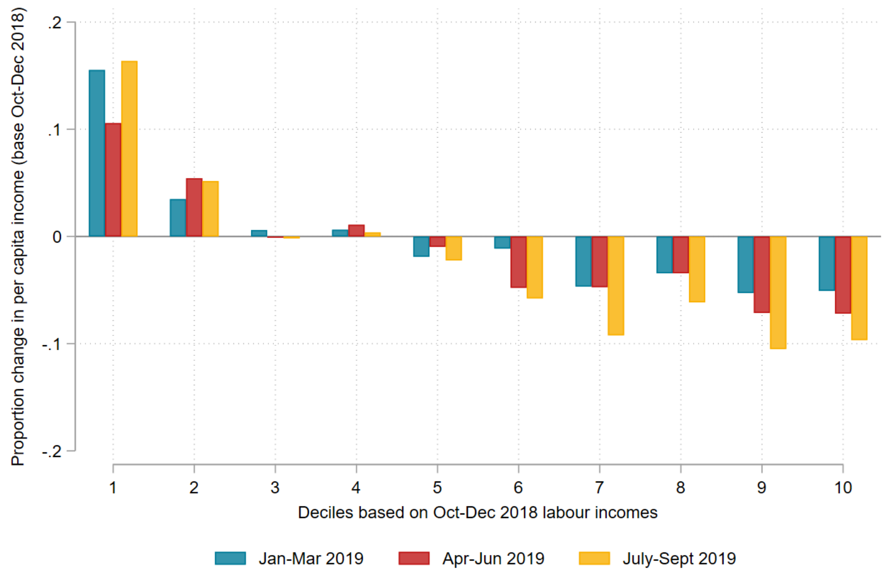


Figure 1b: Growth Incidence Curve for 2019-20 - PLFS

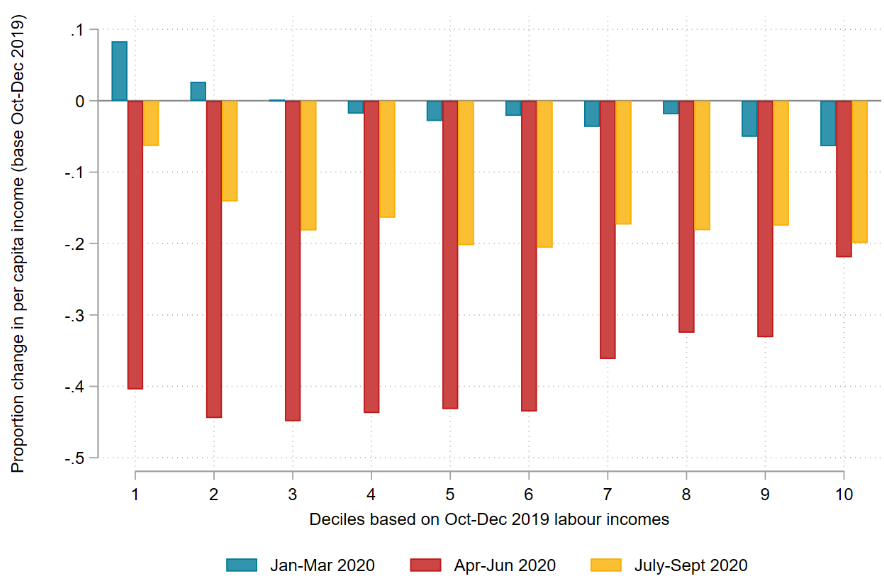


Figure 2a: Growth Incidence Curve for 2018-19 - CPHS

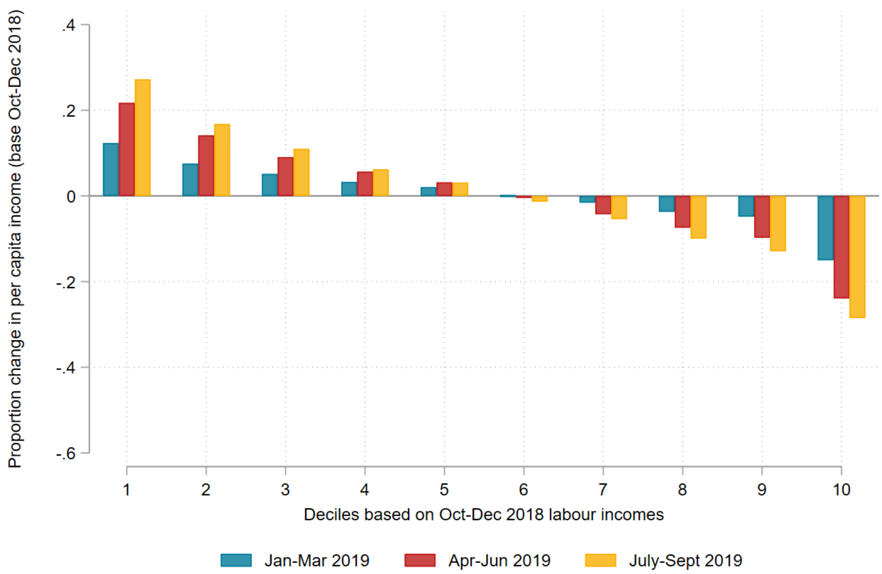


Figure 2b: Growth Incidence Curve for 2019-20 - CPHS

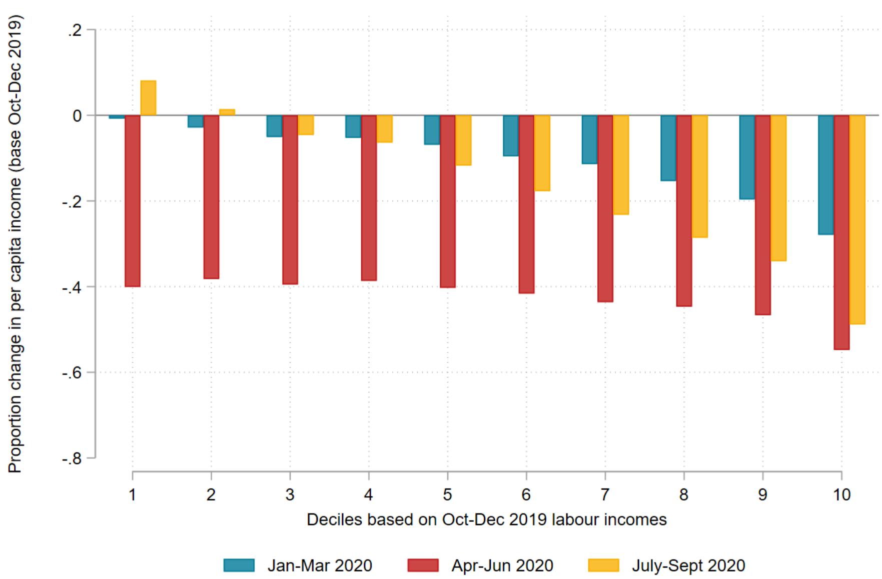


Figure 3a: Percentile Growth Incidence Curves for PLFS 2019-20

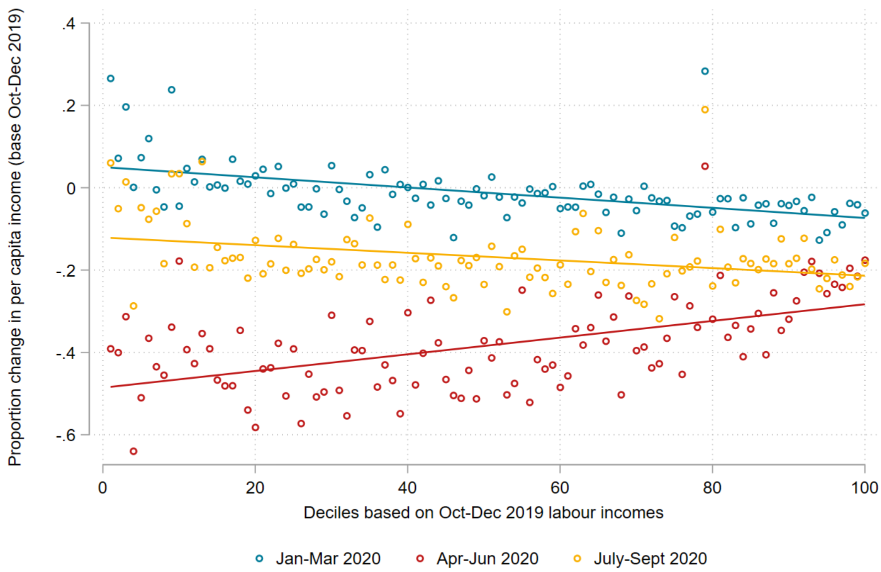
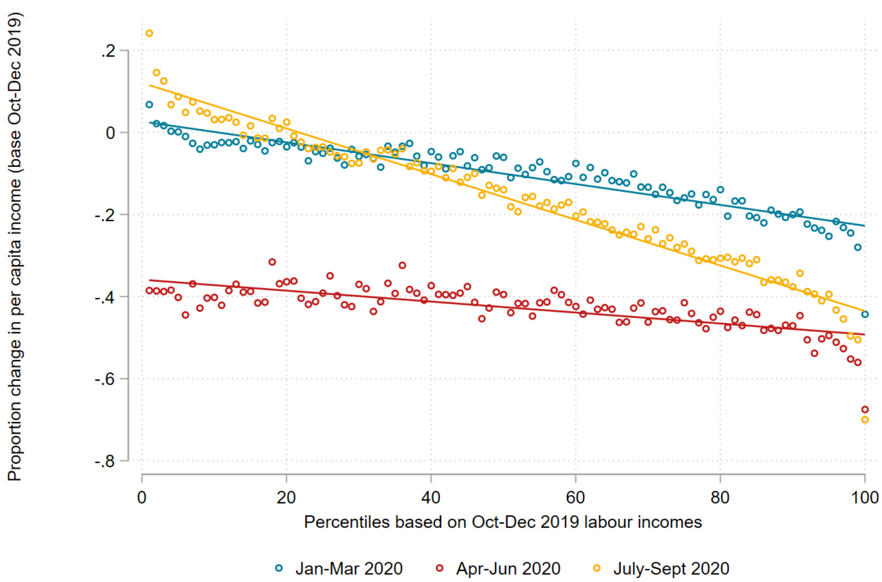


Figure 3b: Percentile Growth Incidence Curves for CPHS Urban 2019-20



Appendix A - Results from CPHS for Rural and Urban India

Table 1: Regression results for CPHS 2018-19 - Rural and Urban

Dependent Variable:	Proportionate change in labour income	
Model:	Rural	Urban
Variables		
Constant	-0.0621***	0.0044***
	(0.0019)	(0.0015)
Period 1	0.0536***	0.0098***
	(0.0020)	(0.0017)
Period 2	0.0236***	0.0074***
	(0.0026)	(0.0021)
Period 0 × percentile.m	-0.0050***	-0.0024***
	(6.75×10^{-5})	(5.22×10^{-5})
Period 1 × percentile.m	-0.0063***	-0.0042***
	(7.93×10^{-5})	(6.38×10^{-5})
Period 2 × percentile.m	-0.0075***	-0.0052***
	(9.5×10^{-5})	(7.05×10^{-5})
Fit statistics		
Observations	396,345	726,065
R^2	0.10703	0.07723
Adjusted R^2	0.10702	0.07722

Standard errors clustered at household level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Regression results for CPHS 2019-20: Rural and Urban

Dependent Variable:	Proportionate change in labour income	
Model:	Rural	Urban
Variables		
Constant	-0.2017***	-0.0957***
	(0.0029)	(0.0036)
Period 1	-0.2637***	-0.3528***
	(0.0039)	(0.0046)
Period 2	-0.0561***	-0.0578***
	(0.0037)	(0.0045)
Period 0 × percentile.m	-0.0051***	-0.0027***
	(0.0001)	(0.0001)
Period 1 × percentile.m	-0.0036***	-0.0015***
	(0.0001)	(0.0001)
Period 2 × percentile.m	-0.0073***	-0.0055***
	(9.63×10^{-5})	(8.93×10^{-5})
Fit statistics		
Observations	237,072	498,042
R^2	0.11923	0.13685
Adjusted R^2	0.11921	0.13684

Standard errors clustered at household level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix B - Results with total household income and annual reference period

Table 1

Baseline periods

Period	Months
base	Jan 2018-Dec 2018
0	Jan 2019-Mar 2019
1	Apr 2019-Jun 2019
2	Jul 2019-Dec2019

Pandemic periods

Period	Months
base	Jan 2019-Dec 2019
0	Jan 2020-Mar 2020
1	Apr 2020-Jun 2020
2	Jul 2020-Dec 2020

Table 2: Regression results for CPHS 2018-19: Rural and Urban

Dependent Variable:	Proportionate change in total income	
Model:	Rural	Urban
Variables		
Constant	0.1362***	0.0616***
	(0.0040)	(0.0047)
Period 1	0.1055***	0.0154***
	(0.0041)	(0.0037)
Period 2	0.0846***	0.0312***
	(0.0042)	(0.0044)
Period 0 × percentile.m	-0.0039***	-0.0032***
	(0.0002)	(0.0003)
Period 1 × percentile.m	-0.0054***	-0.0045***
	(0.0002)	(0.0002)
Period 2 × percentile.m	-0.0075***	-0.0062***
	(0.0002)	(0.0002)
Fit statistics		
Observations	589,887	1,109,806
R^2	0.01582	0.00746
Adjusted R^2	0.01581	0.00746

Standard errors clustered at household level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Regression results for CPHS 2019-20: Rural and Urban

Dependent Variable:	Proportionate change in total income	
Model:	Rural	Urban
Variables		
Constant	0.1988**	0.0219***
	(0.0833)	(0.0051)
Period 1	-0.2680***	-0.1827***
	(0.0806)	(0.0100)
Period 2	-0.1820**	-0.1170***
	(0.0789)	(0.0070)
Period 0 × percentile.m	-0.0143***	-0.0032***
	(0.0047)	(0.0002)
Period 1 × percentile.m	-0.0091***	-0.0053***
	(0.0016)	(0.0005)
Period 2 × percentile.m	-0.0104***	-0.0057***
	(0.0013)	(0.0003)
Fit statistics		
Observations	301,071	644,778
R^2	0.00128	0.01748
Adjusted R^2	0.00127	0.01747

Standard errors clustered at household level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix C - Quarterly results for CPHS

Table 1: Regression results for CPHS 2018-19: Rural and Urban

Dependent Variable:	Proportionate change in labour income	
Model:	Rural	Urban
Variables		
Constant	0.0374***	0.0226***
	(0.0024)	(0.0016)
Period 1	0.0832***	0.0135***
	(0.0029)	(0.0019)
Period 2	0.0143***	0.0101***
	(0.0033)	(0.0023)
Period 0 × percentile.m	-0.0047***	-0.0025***
	(9.13×10^{-5})	(6.19×10^{-5})
Period 1 × percentile.m	-0.0059***	-0.0044***
	(9.98×10^{-5})	(6.99×10^{-5})
Period 2 × percentile.m	-0.0069***	-0.0053***
	(0.0001)	(7.49×10^{-5})
Fit statistics		
Observations	139,517	252,721
R^2	0.09783	0.08345
Adjusted R^2	0.09779	0.08343

Standard errors clustered at household level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Regression results for CPHS 2019-20: Rural and Urban

Dependent Variable:	Proportionate change in labour income	
Model:	Rural	Urban
Variables		
Constant	-0.0877***	-0.0604***
	(0.0033)	(0.0115)
Period 1	-0.2472***	-0.2980***
	(0.0049)	(0.0120)
Period 2	-0.0869***	-0.0259**
	(0.0044)	(0.0121)
Period 0 × percentile.m	-0.0041***	-0.0027***
	(0.0001)	(0.0003)
Period 1 × percentile.m	-0.0045***	-0.0025***
	(0.0001)	(0.0001)
Period 2 × percentile.m	-0.0069***	-0.0057***
	(0.0001)	(0.0001)
Fit statistics		
Observations	95,246	195,258
R^2	0.11341	0.12943
Adjusted R^2	0.11336	0.12940

Standard errors clustered at household level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix D - Balanced panel results

Table 1: Regression results for PLFS 2018-19 & 2019-20

Dependent Variable:	Proportionate change in labour income	
Model:	2018-19	2019-20
Variables		
Constant	0.0016	-0.0135**
	(0.0044)	(0.0058)
Period 1	-0.0106**	-0.3727***
	(0.0047)	(0.0081)
Period 2	-0.0216***	-0.1547***
	(0.0060)	(0.0067)
Period 0 × percentile.m	-0.0017***	-0.0012***
	(0.0002)	(0.0002)
Period 1 × percentile.m	-0.0017***	0.0020***
	(0.0002)	(0.0003)
Period 2 × percentile.m	-0.0024***	-0.0009***
	(0.0002)	(0.0003)
Fit statistics		
Observations	27,655	26,787
R^2	0.0272	0.1335
Adjusted R^2	0.0270	0.1334

Standard errors clustered at household level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Regression results for CPHS 2018-19 2019-20

Dependent Variable:	Proportionate change in labour income	
Model:	2018-19	2019-20
Variables		
Constant	0.0056***	-0.1097***
	(0.0016)	(0.0036)
Period 1	0.0119***	-0.3449***
	(0.0017)	(0.0045)
Period 2	0.0132***	-0.0385***
	(0.0022)	(0.0053)
Period 0 × percentile.m	-0.0025***	-0.0034***
	(5.58×10^{-5})	(0.0001)
Period 1 × percentile.m	-0.0042***	-0.0010***
	(6.7×10^{-5})	(0.0001)
Period 2 × percentile.m	-0.0053***	-0.0056***
	(7.43×10^{-5})	(0.0001)
Fit statistics		
Observations	665,003	333,132
R^2	0.07758	0.13481
Adjusted R^2	0.07757	0.13480

Standard errors clustered at household level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*