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ABSTRACT

We use a large, representative panel data set from India with monthly data on household finances to examine the incidence of economic harms during the COVID pandemic. We observe a sharp spike in poverty, peaking during India's sharp but short lockdown. However, there was a striking decrease in income inequality outside the lockdown. There was a smaller decrease in consumption inequality, likely due to consumption smoothing. Evidence supports two mechanisms for the decline in income inequality: the capital income of top-quartile earners covaries more with aggregate income, and demand for labor fell more for higher quartiles.

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Introduction

There is growing evidence that the COVID pandemic was associated with negative impacts on the income and health of the poor within low- and middle-income countries like India (e.g., Miguel and Mobarak, 2021; Egger et al., 2021; Gupta et al., 2021; Malani et al., 2020). A common inference is that this shock was likely therefore also regressive. For example, reports from Oxfam (2021) and Azim Premji University (2021) argue that the pandemic likely hurt the poor more than the rich globally and in India, though these claims are contested (Deaton, 2021).

We contribute by examining poverty and, in particular, inequality in India during the pandemic using a large, representative, panel data set of roughly 197,000 households (990 thousand members) with monthly data from January 2015–July 2021. We explore the mechanisms—some similar to those in the U.S.—responsible for the shifts in inequality in India. Our data have advantages over other data typically used to study poverty and inequality in India or the U.S. We observe individuals over time, not just repeated cross-sections, allowing us to decompose income changes into movements across quantiles of the income distribution and changes in income at particular quantiles. The long time span enables us to contrast outcomes during the pandemic to outcomes during prior shocks, such as India's demonetization in 2016. The data include information on both income and consumption, so that we can observe how income inequality trickles down to consumption inequality. Finally, the breadth of our individual- and community-level covariates and the monthly frequency of our data permits us to explore several mechanisms using a common sample and data.

Our most notable finding is that the pandemic in India was associated with a <u>decline</u> in inequality in two senses. First, Indians from higher percentiles of the income distribution from 2015–2019 had, almost monotonically, larger relative reductions in income during the pandemic. Second, consumption inequality, measured analogously to income inequality, also fell. However, consumption was less unequal to start and consumption inequality contracted less than income inequality, likely due to consumption smoothing.[1]

The only signal that inequality may have increased during the pandemic is that the country's Gini coefficient spiked in April 2020 during India's short, national lockdown. However, the Gini fell to pre-pandemic levels when the lockdown ended in June, well be-

[1]Our findings are aligned with Malani and Ramachandran (2021), which finds that excess deaths during COVID disproportionately affected high incomes. Before COVID, lower income terciles had higher death rates. During the pandemic, however, death rates for the top terciles rose more. As a result, by July 2021, death rates were flat across terciles.

fore cases peaked during India's first COVID wave (September–October 2020). To reconcile our main findings with this non-decline in Gini, note that individual income changes are a combination of (a) the change in income given a person's income percentile, and (b) a change in the income percentile to which a person belongs. The Gini roughly measures the former. However, we find that movement across percentiles, i.e., social mobility, swamped changes in income within percentiles such that changes in overall income during the pandemic were progressive.

We explore several mechanisms for the progressive changes in income during the pandemic, corresponding loosely to capital income and the two determinants of labor income: labor supply and demand. First, we show that the capital incomes of higher-income individuals vary more with aggregate income. This higher "beta" also makes them more susceptible to downturns, such as the pandemic. Second, labor supply cannot explain our findings. Using a Roy model to estimate the monthly reservation wages of individuals from each income quartile, we find that the rich, if anything, were more willing to supply labor than the poor during the pandemic. Third, demand for the type of labor supplied by the rich fell more than for the poor. The rich experienced larger declines in wages and, after India's lockdown, lower employment rates. These equilibrium outcomes are more consistent with a decline in relative labor demand than labor supply. Moreover, we find that income of the rich is more sensitive to demand in categories of consumption where expenditure fell the most during the pandemic.[2]

Our objective in documenting the decline in inequality during the pandemic is not to minimize the burdens experienced by the poorest of Indians. Indeed, we begin our analysis by showing the stark increase in poverty during pandemic. However, separately measuring poverty and inequality can help us understand the relationship between these two phenomena. Our results suggest that increases in poverty are not a sufficient statistic for inequality, especially during supply shocks, such as the pandemic. Conversely, distributional effects may be an incomplete measure of genuine shifts in welfare.

An important caveat to our findings is that we only demonstrate the coincidence of the pandemic and changes in poverty and inequality. There was a stark change in outcomes during the lockdown, consistent with a causal interpretation based on the time series trend. However, there was a decline in income inequality that began in 2018, before the pandemic, suggesting a pre-trend. Nor can we say one way or another whether inequality will rise when the pandemic ends.

[2] We also document that remote-amenable work (Dingel and Neiman, 2020) did not protect income of the rich.

Our analysis also has implications for income dynamics during lockdowns. Poverty and the Gini coefficient peaked during India's lockdown, which well preceded the spikes in cases during India's two main initial COVID waves. The main reductions in income inequality took place outside the lockdowns, when voluntary distancing mediated economic activity.

Our work contributes to three literatures. The first addresses inequality in India in general (Banerjee and Piketty, 2005; Chancel and Piketty, 2019; Anand and Thampi, 2016; Sarkar and Mehta, 2010). Our contribution is employ data that is relatively novel to this literature and that enables a deeper analysis of trends in inequality.

The second literature examines poverty and inequality during the pandemic (Miguel and Mobarak, 2021). Several papers examine economic outcomes (Alstadsæter et al., 2020; Chen et al., 2020) and inequality (Egger et al., 2021) in other countries. Bertrand et al. (2020) and Deshpande (2020) use the same data we do to study inequality and hours worked, respectively, during India's lockdown. Several papers use different Indian data to study income during COVID (Dhingra and Machin, 2020; Lee et al., 2020; Pinto et al., 2020). Most of the papers above suggest COVID had regressive impacts. A notable exception is Deaton (2021), which argues that inequality may fall across countries during the pandemic; we show that within-country inequality may have fallen, at least within India. Another exception is Scheidel (2018), which argues that plagues have historically reduced inequality by disproportionately impacting the rich.

The third literature examines the sensitivity of income to business cycle shocks across the income distribution (Guvenen et al., 2017, 2015; Parker and Vissing-Jorgensen, 2010). These papers focus on high-income countries. Our paper examines this relationship in the context of a developing country.

1 Data and methods

1.1 Background

India is a valuable setting to study the incidence of harms during the pandemic because of India's sizable population and the large magnitude of both the health and economic shock in that country (Appendix Figure A1). India's first COVID case was on 27 January 2020 (Andrews et al., 2020). After several weeks of gradual restrictions on travel, India declared a national lockdown on 24 March 2020, but lifted it by 1 June 2020 (Sheng et al., 2021). The lockdown and the concomitant decline in mobility was one of the most severe observed in the world at the time (Hale et al., 2020; Google LLC, 2021).

Importantly, the lockdown preceded the peak of the health shock. The first wave of cases did not peak until September–October 2020. A second wave, due to the Delta variant (Organization, 2021), peaked in April 2021. While local lockdowns returned and mobility declined during the second wave, the mobility decline was less severe compared to the national lockdown. Although official statistics suggest that 3.1 million were infected and 410,000 died with COVID, serological surveys and measures of excess deaths suggest perhaps 1.1 billion were infected with COVID and 5 million died by mid-July 2021 (Malani and Ramachandran, 2021).

1.2 Data

Our primary data source is the Consumer Pyramids Household Survey (CPHS) conducted by Center for Monitoring Indian Economy. CPHS covers nearly the whole of India and employs stratified sampling to ensure representativeness down to a substate level (details in Appendix C). CPHS surveys each household every four month, and sampling is staggered so that a representative 25% of all households are sampled each month. At each survey, CPHS updates its household roster and asks questions common to the household and about each member present. It asks about income and consumption for each of the previous 4 months. Income is obtained at both the individual (individual wage income) and household level (non-attributed income for the whole household). Consumption expenditure is surveyed at the household level.

CPHS has several coverage advantages relative to comparable surveys in the American context. First, CPHS is very large relative to panels such as the Panel Study of Income Dynamics (PSID) or the Survey of Consumer Finance (SCF), measured either in absolute numbers (197,000 Indian households compared to 6,000 households in the SCF) or in the percentage of the population (0.073% vs. 0.004%). Second, CPHS provides greater ability to conduct subnational analysis relative to the PSID. Third, CPHS is a true 6-year panel data set, not a repeated cross-section, rotating panel like the Consumer Expenditure Survey (CEX) or the Current Population Survey (CPS), or an infrequent panel like the SCF. Fourth, CPHS has data on both income and consumption, unlike credit report data; moreover income is broken down by source, unlike credit report data.

In Appendix C, we address known issues in the CPHS data, such as churn in the sample frame, falling response rate during India's COVID lockdown (Vyas, 2020a), and criticism over whether the sample adequately captures the very poor (Dreze and Somanchi, 2021).

1.3 Methods

Our objective is to examine the changes in income and consumption in both the cross-section of income distribution, as well as time-series changes during the COVID pandemic. To do so, we define our key measures here.

Per capital income and consumption indices. Each sample member's income is obtained by dividing total household income by the household size. Consumption is defined similarly. We use this measure of income (rather than individual wage income plus per member non-attributed household income) to ensure all household members are assigned to the same income percentile in a given month,[3] as we are not investigating intra-family inequality. We use inflation data from the Reserve Bank of India to convert nominal value to real 2012 rupees (Bhoi et al., 2020). We create income indices by dividing monthly income by average 2018 income for the same individual, and comparably define consumption indices. Our choice of 2018 is chosen because it is roughly in the middle of the panel and because it makes it easier to evaluate trends in inequality which may begin prior to the pandemic.

Quantile assignment. To assign individuals to income quantiles, we use their average 2015–2019 per capita incomes. Quantiles are defined as a default at the the state $\times$ urban status level.[4] (We define quantiles at the national $\times$ urban status level in robustness checks reported in the 2.) We calculate weighted average income (in rupees or as an index) in these local income percentiles, using CPHS individual member weights.

Employment and wages. The employment rate is defined as the fraction of persons aged 15–65 reporting they were employed in a month.[5] The number of hours at work is obtained from the CPHS time-use survey for the same persons. Wages are derived by dividing per capita income by hours.

Pandemic-relevant periods. We define the pandemic period as February 2020–July 2021 (the last date which data are currently available), inclusive. We define the lockdown

[3]Technically, it is possible for members to be in different quantiles when averaging income over a time period if members are not in the household all of that period.

[4]When defining quantiles, we weight individuals by their average sampling weight over 2015–2019 using the sampling weights that make individuals nationally representative.

[5]A small fraction of these individuals also report 0 hours. We still count them as employed because some jobs only entail sporadic work. CPHS does not report employment for minors aged <15. Individuals aged above 65 are excluded because their employment rates are very low.

period as March–May 2020, inclusive. The pandemic ex-lockdown period is February 2020 and June 2020–July 2021. India experienced two initial waves of cases during the pandemic. The first wave ranges from February 2020–December 2021, and the second (Delta) wave spans January 2021 to July 2021.

Statistical inference and baselines. We use the following regression of outcomes (relative to some pre-pandemic baseline) on month $\times$ quartile fixed effects to make inferences about how economic outcomes changed during the pandemic:

$$y_{i,t} - \hat{y}_{i,t} = \sum_q \sum_s \gamma_s^q \mathbb{1}(1 \in q) + e_{it} \tag{1}$$

where $y_{i,t}$ is an outcome, such as income at t relative to the average income in 2019; $\hat{y}_{i,t}$ is the same predicted outcome in the absence of the pandemic; q indexes quantiles; γ_s^q are quantile-specific time fixed effects, and e_{it} is a regression error that is clustered at the state $\times$ urban status. This regression can be estimated with data just during the pandemic or also with pre-pandemic data. Observations are weighted to makes them representative at the national level after accounting for non-response (see Appendix C).

We consider multiple baselines, i.e., $\hat{y}_{i,t}$ predictions, when estimating the regression above. Our conservative, default baseline is $\hat{y}_{i,t} = 100$, which implies that the normalized outcome would remain at the average 2019 level. This baseline ensures that the monthly fixed effects are the equivalent of the weighted average of monthly outcomes.

We consider two other alternative baselines estimated from following prediction model with pre-pandemic period data:

$$y_{it} = \sum_q \zeta^q \mathbb{1}(i \in q) + \sum_q \delta^q \cdot t \cdot \mathbb{1}(i \in q) + \sum_{m=1}^{12} \sum_q \phi_m^q \mathbb{1}(t \in m, i \in q) + u_{it} \tag{2}$$

where ζ^q is a quantile fixed effect; δ^q is a quantile-specific time trend; m indexes months; and ϕ_m^q is a month-of-year fixed effect intended to capture seasonality. Our second baseline is the predicted y_{it} when equation (2) includes only a time trend δ^q and no seasonal controls ϕ_m^q in either equation above. A third baseline accounts for both the trend as well as seasonality.

We typically visualize changes in economic outcomes during the pandemic by plotting month $\times$ quartile fixed-effect estimates. We add 100 to fixed effects when plotting them regardless of the baseline for ease of visualization.

2 Incidence of economic shocks

2.1 Poverty

Extreme poverty rose during the pandemic (Figure 1A). We measure poverty by applying the World Bank's $1.90 cutoff to income and consumption. (In Appendix D1, we consider two India-specific measures of poverty.) We find that income poverty spiked from over 40% before the pandemic to nearly 70% in urban areas during India's lockdowns. Income poverty increased from 60% to 80% in urban areas during the lockdown period. This coincided with a sharp drop in mean income and consumption. Poverty fell, and income and consumption rose, after the lockdown, but did not recover to pre-pandemic levels.

2.2 Income inequality

Despite the increase in poverty, our striking key result is that income inequality <u>fell</u> during the pandemic. We highlight this result in Figure 1B which shows, in rural areas, the relative income of individuals from top-quartile households fell more before, fell further during, and remained more depressed after the lockdown compared to incomes of those from lower quartiles. Urban areas show a similar pattern, except that the dip during the lockdown was identical across quartiles.

To directly quantify the reduction in inequality, Figure 1B also plots the difference between the relative incomes of bottom- and top-quartile groups. Note that a higher difference implies lower inequality. In rural areas, inequality fell almost monotonically over time starting the first month of pandemic. In urban areas, inequality dropped almost monotonically except during the lockdown, when it spiked because all quartiles had similar reductions in relative income.

The estimated reduction in inequality is robust to different methods of measuring baselines, sample weights, and to concerns about mean reversion. If we use a baseline that accounts for the pre-pandemic trend in income (rather than 2018 levels), we estimate a larger decline in inequality (Figure A4A, Figure A3A), though the difference is not significant. This is because the top quartiles have greater pre-pandemic income growth rates than the bottom quartile. Our findings are also robust to different weighting schemes and to defining quartiles using the national rather than state income distribution (Figure 2B). Finally, our primary measures of inequality are already somewhat robust to mean reversion since we define quartiles based on long-term (2015–2019) income. When we go further and use month fixed effects in our prediction model to allow within-year mean reversion, we estimate similar declines in inequality (see Appendix D2).

Our findings also hold at the extremes of the income distribution, i.e., quantiles above the 75th- and below the 25th-percentiles (Figure A4). Indeed, relative income declines during the pandemic were nearly monotonic in pre-pandemic income levels (Figure 3A). The performance of lower percentiles are particularly remarkable since India—unlike the US—had little fiscal stimulus in the form of income transfers. While government transfers did spike during the lockdown, they were small in absolute value relative to household income (Figure A5A). Income net of government transfers shows the same pattern of declining inequality as income with transfers during the pandemic (Figure A5B). Our results therefore highlight the surprising income progressivity of the pandemic shock in India, even absent substantial public insurance mechanisms.

2.3 Consumption inequality

Inequality in consumer expenditures also fell during the pandemic. The time series of consumption inequality follows patterns similar to income, except that changes are more muted (Figure 1C).[6] One minor difference is that decline in relative consumption is even progressive during the trough of the lockdown in urban areas. The decline of relative consumption is also monotonic in percentile of 2015–2019 income (Figure 3B).

Consumption inequality may be more muted than income inequality because households were able to smooth consumption—even during the pandemic. To estimate the common degree of consumption smoothing across quartiles, we use a regressions of individual consumption on individual income, à la Cochrane (1991) and Townsend (1994):

$$\log c_{ikt} = \mu_i + \alpha \Delta d_{kt} + \gamma \log M_{ikt} + \pi(\log M_{ikt} \times \mathbb{1}(2020)) + \varepsilon_{ikt} \tag{3}$$

where c_{ikt} is consumption by household i in location k, μ_i are household fixed effects, d_{kt} is a measure of the aggregate shock (proxied by location average consumption as in Townsend (1994)); M_{it} is idiosyncratic household income, and $\mathbb{1}(2020)$ is an indicator for 2020. We add aggregate consumption in order to capture aggregate shocks at the homogeneous region $\times$ community-type level. Here γ measures risk smoothing (with $\gamma = 0$ implying full-risk sharing) and π measures whether COVID affected the ability to

[6] Using a baseline that accounts for the pre-pandemic trend in consumption yields virtually the same result (Figure A7A).

smooth consumption.

Pre-pandemic, a 10% income fall in income was associated with a 0.980% decline in consumption (Table A1). This is a somewhat smaller estimate of the marginal propensity to consume than in Townsend (1994), but our sample benefits from a quarter-century of credit-market development and includes cities. During COVID, a 10% fall in income was associated with a 0.869% decline in consumption, suggesting even more smoothing during the pandemic. While this difference between smoothing before and during COVID is statistically significant, it is very small.

The ability to smooth consumption does not vary meaningfully across income quartiles, as some prior literature (e.g., Morduch, 1999) has suggested. We estimate a version of equation (3) interacted with indicators for income quartiles (Table A2). We do not find material differences in pre-COVID marginal propensity to consume (MPC) across the income distribution. The lowest quartile had an MPC of 8.23%, while the highest had an MPC of 9.67%. During COVID these MPCs are 7.96% and 9.22%.

A particular concern about the pandemic is that it led to greater food insecurity amongst the poor (e.g., Egger et al., 2021; Bottan et al., 2020). We check to see if this translates to food inequality, measured by relative changes in food expenditure across different income quartiles. Substituting food expenditures for total expenditures in Figure 1C, we find that inequality in food expenditures did not increase during the pandemic (Figure A8). Households across quartiles were able similarly to smooth food expenditures both before and during the pandemic (Table A3).

2.4 Gini coefficient

Gini coefficients paint a less rosy picture of inequality during the pandemic (Figure 3B). The time series of Gini coefficients for income show a spike during the lockdown, and then a return to pre-pandemic levels of inequality by July 2020. The Gini coefficient for consumption does not even jump during lockdown, remaining constant at pre-pandemic level throughout.[7]

Why do Gini coefficients show a different pattern than our primary measures of income inequality? Income change can be thought of as the sum of two processes: (1) change in income holding relative position or percentile constant and (2) change in rela-

[7]Snapshot Lorenz curves show that inequality spiked during the lockdown (April 2020) and then returned to pre-lockdown levels by July 2020, even before the peak in cases (Figure A9).

tive position. The Gini coefficient loosely tracks the first element.[8] The second element is often called social mobility. Our main measures of inequality track both measures combined.

Comparing the pre-pandemic to pandemic period (aside from the lockdown), Gini coefficients show that there were no large changes in the (share of) income of each percentile. However, there was a large spike in progressive social mobility across all quartiles. The Shorrock's Index, which reports transitions across quartiles, shows the bottom (top) 2 quartiles moved up (down) more from 2019–2020 than from 2018–2019 (Figure 3C, left).[9]

The lockdown period contrasts with the post-lockdown period. Lockdown was associated with a spike in the Gini, but also a jump in progressive social mobility (Figure 3C, left). After the lockdown, Gini returned to pre-pandemic levels, but social mobility did not. This is consistent with voluntarily lower economic activity increasing social mobility throughout the pandemic, but the lockdown's mandatory reduction in activity also making relative income across quartiles more regressive.

3 Mechanisms

We examine the two largest components of income—business and labor—to explain the decline in income inequality during the pandemic in India.

3.1 Capital income

Aggregate income declined during the pandemic, especially during the lockdown. Payments to residual claimants may be the first on the cutting block in a downturn. If the rich are more likely to be residual claimants, their income may suffer more during a downturn.

To explore this, we use the fact that the CPHS disaggregates income into components, including business and labor.[10] Following Guvenen et al. (2017), we regress changes in each component of an individual's income against changes in aggregate income (all com-

[8] We say loosely because Gini is normalized by the population's overall income. A simple change in income does not have to be normalized in that manner.

[9] Comparing Shorrock Index values before and during the pandemic shows progressive social mobility increased by more than 10% in 2019–2020 relative to 2018–2019 (Table A5).

[10] For our analysis, we count (1) non-pension income from dividends, interest, rent and sale of assets as (passive) capital income distinct from pension income and business income, and (2) wage income as labor income. There are other sources like government transfers and gambling that are classified as other. Total income—and aggregate income—includes all components (capital, pension, business, wage and other.

ponents) interacted with quartile indicators:

$$\log y^{c,q}_{i,t+1} - \log y^{c}_{i,t} = \sum_q (\alpha^{c,q} + \beta^{c,q}(\log Y_{t+1} - \log Y_t)\mathbb{I}(i \in q) + e^{c,q}_{i,t+1} \tag{4}$$

where $y^c_{i,t}$ is an income component c a person and Y_{t+1} is aggregate (capital plus labor) income. Because income from a component may be 0, we add one to each component before taking logs. The coefficient $\beta^{c,q}$ gives the sensitivity ("beta") of income component c to aggregate income for individuals from quartile q. We focus on the business income and labor income components because, outside the lockdown (Figure 4A), they are the biggest components of income.

The high beta of business income may explain some of the reduction in income inequality during the pandemic. The business income of the top quartile is more sensitive to aggregate income (Figure 4). The difference is not significant, but it is nominally large. Moreover, business income is a larger share of per-capita income of that quartile than other quartiles.[11]

The beta of labor income is unlikely to offset this effect. Labor is a greater share of the income of lower quartiles. However, the labor income of lower quartiles are not more sensitive to aggregate income.

3.2 Labor supply

Turning to labor income, we first examine labor supply, then demand. We explore the hypothesis that the rich saw income declines because they disproportionately reduced their labor supply during the pandemic. To test this explanation, we measure labor supply by reservation wage and see how that covaries with income quartile.

Specifically, we estimate a Roy model with two sectors, employed and unemployed, to address selection. We assume a wage equation for employment of the form:

$$Y_{ijkt} = \beta_{jt} X_{ijkt} + \gamma_{jt} \mathbb{1}_{ik,t}(j) + e_{ijkt} \tag{5}$$

The controls (X_{ijkt}) are demographics, education, and location (k), and $\mathbb{1}_{ik,t}(j)$ is an indicator for whether the person just switched into the relevant sector. The indicator, which differs in the employed and unemployed wage equations, is our exclusion restriction.

[11] The same is true of passive capital income (not reported), but that is a small share of top-quartile income (Figure 4).

(The coefficient γ_{jt} in the employed equation captures the lower wage that just-hired individuals may earn because they lack experience in employment.) We assume the errors for the two sectors are bivariate normal. Following French and Taber (2011), we estimate a probit first stage, obtain a consistent estimates for the wage equation for the employed sector, and then back out consistent estimates for the coefficients of (unobserved) wage equation for the unemployed wage sector from the combination of the two equations. We then predict each individual's reservation as the value of switching from employment status j to unemployment status j':

$$V_{i,j,j',kt} = \hat{\beta}_{j'k} X_{ij'kt} + \hat{\gamma}_{j'kt} - \hat{\beta}_{jk} X_{ijkt}. \tag{6}$$

To test if the reservation wage of the rich rose more during the pandemic we estimate the following individual-level regression:

$$log\hat{V}_{i,j,j',k,t} = \alpha + \beta \mathbb{1}_k(> \text{median}) + \theta \mathbb{1}_k(t \geq p) + \pi[\mathbb{1}(> \text{median}) \times \mathbb{1}(t \geq p)] + u_{i,t} \tag{7}$$

where $\hat{V}_{i,j,j',k,t}$ log predicted reservation wage, $\mathbb{1}_k(>$ median$)$ is an indicator for above median income in location k, $\mathbb{1}(t \geq p)$ is an indicator for the pandemic period, and $u_{i,t}$ is a individual regression error. We report results using a sample from CPHS round 2 (May–August) in 2019 and 2020.[12]

We find that, while the well-off have higher reservations wages, the average person's reservation wage falls during the pandemic and, importantly, the reservation wages of the well-off fall more than average during the pandemic (Table A6, Column 5). Everyone appears to be willing to work for less during the pandemic, i.e., supply increases. If anything, the rich are more willing than others to supply labor during the pandemic. Thus, it is unlikely that labor supply explains the rise in inequality.

One might still wonder whether factors that affected the relative behavior of the rich in high-income countries, such as COVID risk and access to remote work, also affected those in a lower-income country like India. We explore and rule out these factors in Appendix E1.

[12] Our results are similar if we use quartiles of income and/or a sample that includes all of 2019 and 2020.

3.3 Labor demand

A third possibility is that demand for the services provided by the top quartiles fell more than demand for services from lower quartiles. We review indirect and then direct evidence for this mechanism.

The decline in income inequality is largely driven by suppressed hourly wage and, to a lesser extent, a lower employment rate in the top quartile (Figure 5A). The employment rate fell more for the lowest quartile during the lockdown. However, it recovered almost completely for all quartiles—except the top quartile—after the lockdown. Hours fall somewhat less in the trough of the lockdown for the top quartile in rural areas, but otherwise hours shifts are nearly identical across quartiles in both areas. The biggest gap between the rich and poor emerges for labor wages. Top quartile hourly wage falls earlier, dips lower during the pandemic, and recover less than lower quartiles. Indeed, top quartile wages in rural areas remain below lockdown levels even after it ends. Moreover, the relative decline in wages is almost monotonic in starting wages.

These are changes in equilibrium outcomes, but a relatively larger contraction of demand for higher quartile labor can explain them better than a relatively larger contraction of labor supply from higher quartiles. A supply contraction would be associated with less recovery in in wages but greater recovery in employment rate. Those were the changes in equilibrium outcome we saw during the lockdown, but only in rural communities and not after the lockdown in either type of community. By contrast, a larger reduction of demand for labor from the higher quartiles would be associated with both the relatively lower recovery and employment recovery we observe.

To obtain more direct evidence on the role of labor demand we check if top-quartile incomes are more sensitive to expenditures in consumption categories that fell more during the pandemic. This is difficult to do precisely, as it is difficult to map how much labor from each income quartile is required to produce different consumer products. Our approach is therefore somewhat crude. First, we map each of the 55 categories in which we have disaggregated household expenditure to 3 broad sector: agriculture, manufacturing and services (Table A7). Second, we map 37 occupational categories to those 3 sectors (Table A8).

At the sectoral level, labor demand likely plays a role in the decline in inequality. A larger fraction of top-quartile income is from the service sector (Figure 5B, left) and that sector experienced the largest drop in consumer expenditure during the pandemic (Figure 5B, right). It is true that top-quartile income is less sensitive to manufacturing and manufacturing consumption fell more than agricultural consumption. However, manufacturing is a much smaller share than services of top-quartile income and manufacturing consumption fell half as much as service consumption during the pandemic. The implication is that the source of income of India's rich—deriving disproportionately from services and capital income (defined broadly)—was disproportionately impacted during the pandemic, making the pandemic shock progressive in nature.

4 Discussion

We find that income inequality fell during the pandemic. The results are robust to alternative baselines, definitions of quartiles, and methods of weighting. Consumption inequality also fell, but to a lesser extent due to consumption smoothing. The fact that the Gini coefficient was the same post-lockdown suggests that most of the decline in inequality was due to progressive social mobility. Some of the decline in income among the rich may be explained by higher sensitivity of business income to aggregate fluctuations. It is also likely that labor demand for in the occupations the rich occupy fell more than demand for the services provided by the poor.

To benchmark these changes in inequality, we compare them to what happened in India during demonetization. Demonetization began in November 2016, when the Prime Minister declared that ₹500 and 1000 notes, which accounted for 86% of cash in circulation, would be banned and removed from circulation. They would ultimately be replaced by new ₹500 and 2000 notes. The purpose was to eliminate notes that were used by the black market and corrupt politicians to facilitate trade and store wealth. In the short run, demonetization had the potential to generate a massive transaction cost or liquidity crisis because 78% of transaction in India were in cash (Chodorow-Reich et al., 2020).

Plotting income and consumption by quartiles defined in 2015, we see that income inequality did not decline as much during demonetization as during the pandemic (Figures A12 and A13). The yellow line marks the beginning of demonetization in November 2016 and the orange line indicates its resolution by July 2017 with the substantial introduction of new notes. Remarkably, income grew during demonetization. However, income grew *relatively* slower for the rich: the top quartile had a higher income to start and the change in percentage points was the same or lower in that quartile than lower quartiles. Consumption inequality seems stable during demonetization.

The experience in India during the pandemic also contrasts with the experience of the

United States. Higher income persons saw smaller reductions in income excluding government transfer than did lower income persons (Chetty et al., 2020). This was partly the result of better access to remote work (Adams-Prassl et al., 2020). Relative consumption by lower-income persons was protected by transfers from the government rather than earned or capital income (Han et al., 2020). Our results therefore highlight the importance of considering technological shifts and public insurance in considering the incidence of economic shocks across countries.

Our work has important caveats and limitations. First and foremost, we do not show that the pandemic *caused* a decline in inequality. We only show that inequality declined during the pandemic. Indeed, Figure 1B suggests that the decline in income inequality started in late 2018. India's lockdown interrupted that decline, but it resumed afterwards during the bulk of the pandemic.

Second, while the CPHS panel data set has some valuable features, it also has important flaws. Dreze and Somanchi (2021) have criticized it for undersampling the poor. We partly address this by showing declining inequality across percentiles, even at the bottom 10% or even 5% of the sample. However, more work is required to compare CPHS to overlapping government data sets (Somanchi, 2021).

Third, much of the literature on inequality focuses on top earners, i.e., the top 5 or 1%, because they appear to be pulling ahead of even the remainder of the top quartile. We show inequality for the top 5% and 10% of the CPHS sample, but it is surely the case that CPHS does not capture the top 0.1% of the actual income distribution. Those individuals are unlikely to respond to the CPHS.

Fourth, analysis of mechanisms provides incomplete explanations for the decline in inequality. The evidence for labor demand is indirect. Moreover, we have not demonstrated what percent of the decline in inequality occurs through each mechanism.

Fifth, we only provide evidence on inequality through July 2021. It does appear that the decline in inequality began before the pandemic. However, the pandemic is not yet passed. There is no guarantee that, when the pandemic is truly over, inequality will not return to at least its December 2019 levels.

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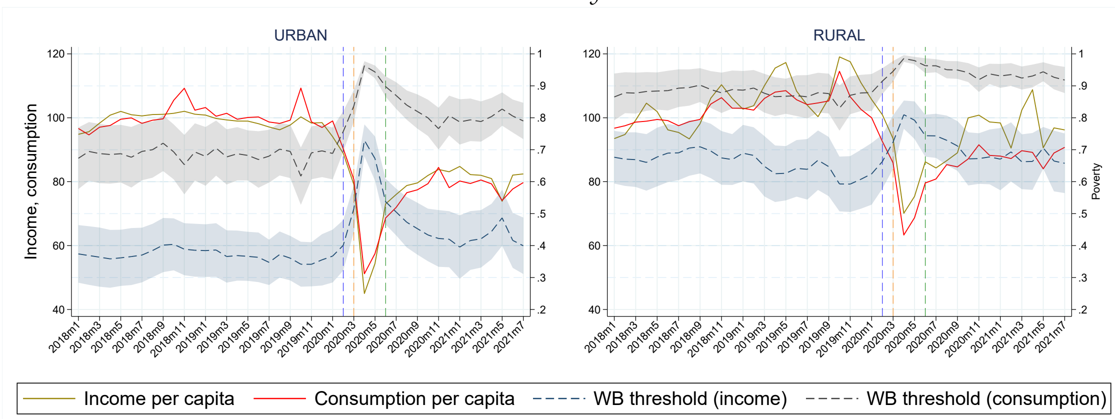
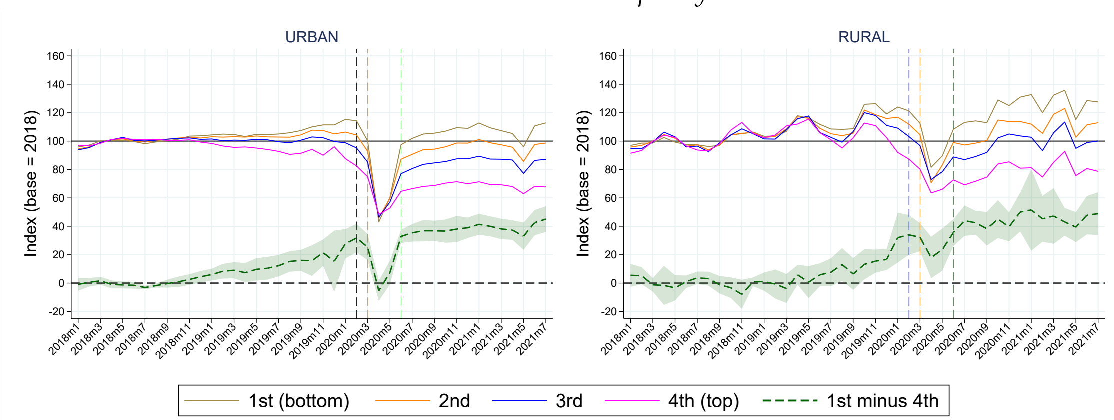
Exhibits

Figure 1: Time-series of poverty and income and consumption inequality

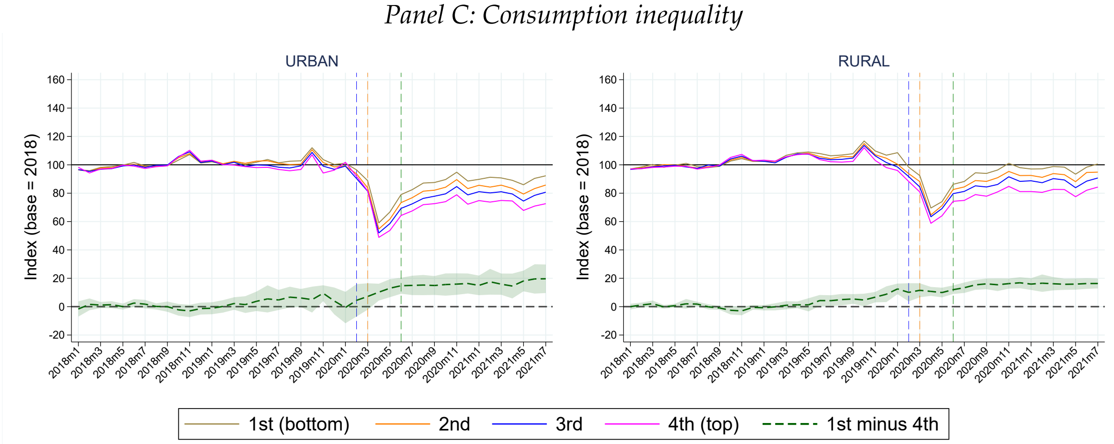
Panel A: Poverty measures



Panel B: Income inequality



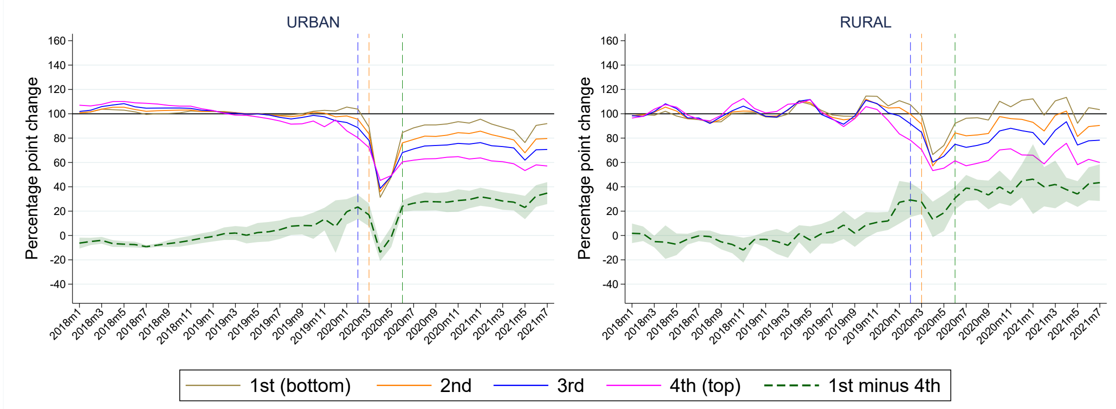
Panel C: Consumption inequality



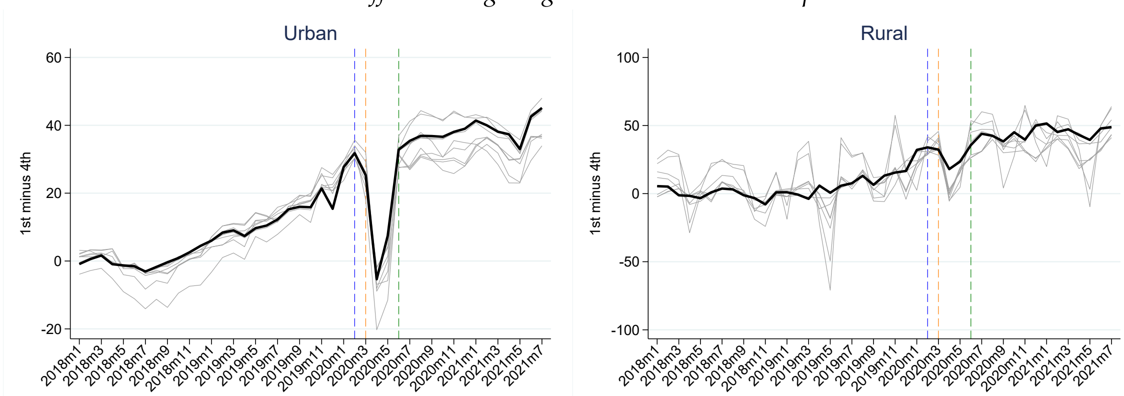
Note. Panel A: Mean per-capita income and consumption are each reported an index, relative to average 2018 values. We report shares of the population below the World Bank's $1.90 extreme poverty thresholds applied to income and consumption. Rupee conversions use the average exchange rate for each month from the IMF's International Financial Statistics. Panel B (C): The figure plots the fixed effects (lines) and 95% confidence intervals (shaded areas) for quartile x month fixed effects estimated using equation (1) with $\hat{y}_{i,t} = 100$. The lines are the equivalent of the weighted average of per-capita income (consumption) within income quartiles in each state $\times$ urban status location, using individual member weights. The units are an index where 100 is average 2018 income (consumption) of a person. The dashed line at the bottom indicates the difference between the first- and fourth-quartile index for income (consumption), measuring the decline in inequality in percentage points. All: Shaded area is the 95% confidence interval around a statistic. Dashed vertical lines in February 2020, March 2020 and June 2020 indicate the first month of the pandemic (blue), the month the national lockdown started (orange) and the month the national lockdown ended (green).

Figure 2: Robustness of trends in income inequality

Panel A: Linear trend baseline



Panel B: Different weighting schemes and national quartiles

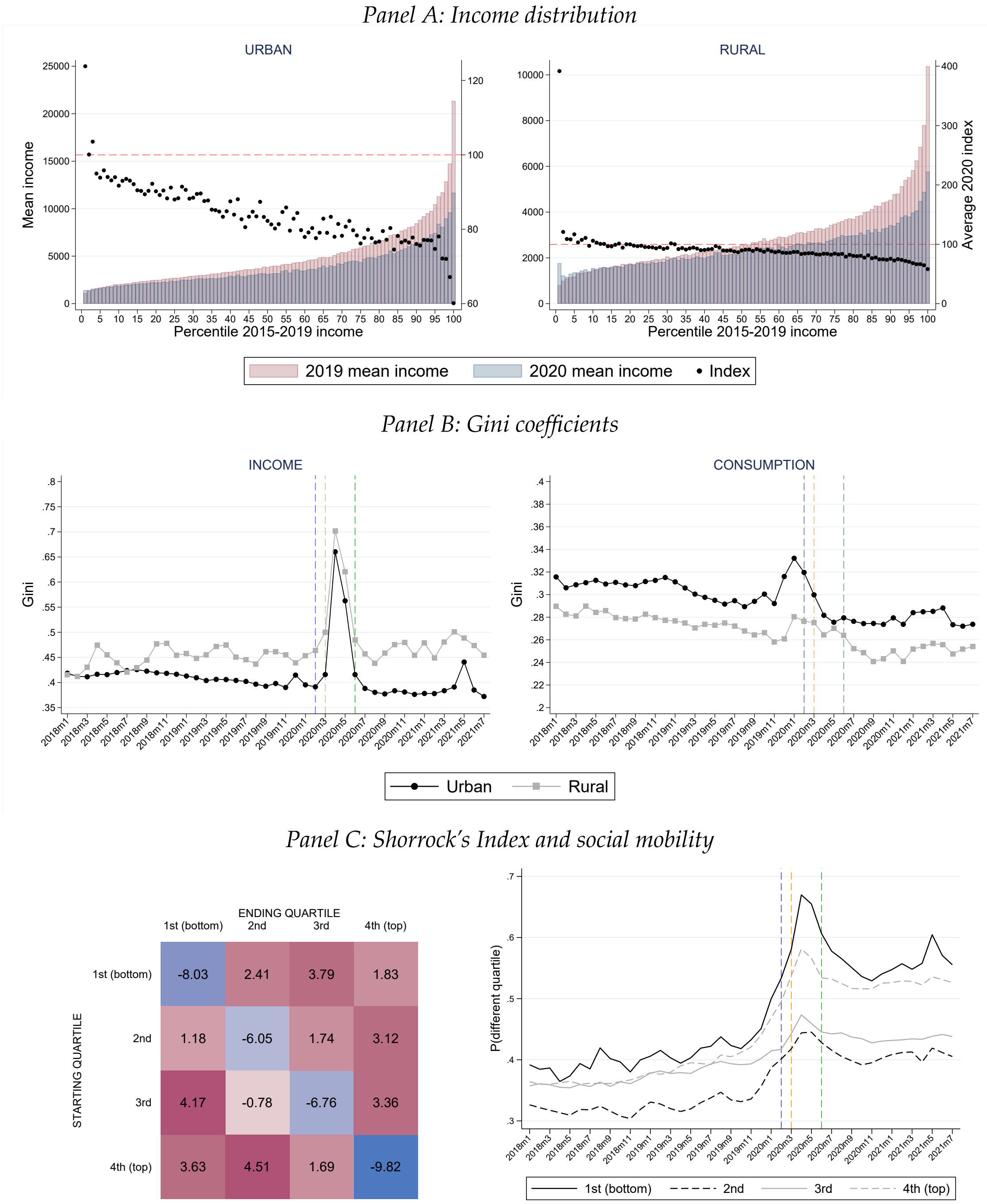


Note. Panel A: The units are an index where 100 is average 2018 income of that person. A trend was obtained from a regression of pre-pandemic income on time, separately for each income quartile, per equation (2). Deviations from the trend (plus 100) were then regressed on month × quartile dummies, per equation (1). Panel B: The figure was constructed by calculating the (weighted) average of per capita income within indicated income quantiles in each jurisdiction × urban status location and taking the difference between the 1st quartile values and the 4th quartile values. This difference measures the decline in inequality, i.e., positive values indicate a decline in inequality. The (weighted) means are obtained from the time fixed effects estimates in (1) using the default baseline (100, corresponding to a person's average 2018 income). The units are an index where 100 is average 2018 income of a person. The black line using individual weights that ensure the sample is nationally representative even after accounting for non-response, assuming that response is random. The grey lines present measures of inequality using the following, alternative weighting and quartile calculations:

> [noitemsep]using the last weight observed, instead of mean weight, using no weights at all, using a national base value instead of state x community specific with mean weights, and using a national base value instead of state x community specific with no weights.

As an additional robustness check, all of the above are calculated using a constant sample of individuals who are observed in each month from January 2015 to July 2021. All: Dashed vertical lines in February 2020, March 2020 and June 2020 indicate the first month of the pandemic (blue), the month the national lockdown started (orange) and the month the national lockdown ended (green).

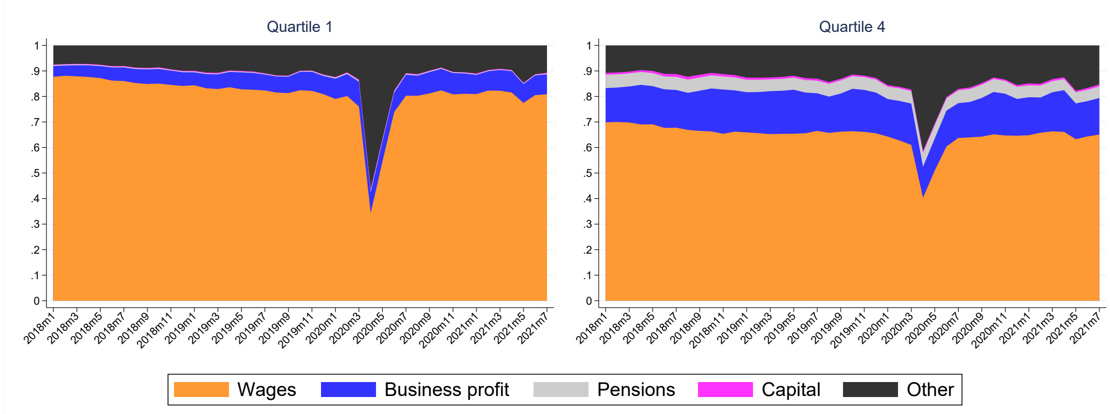
Figure 3: Aspects of income inequality



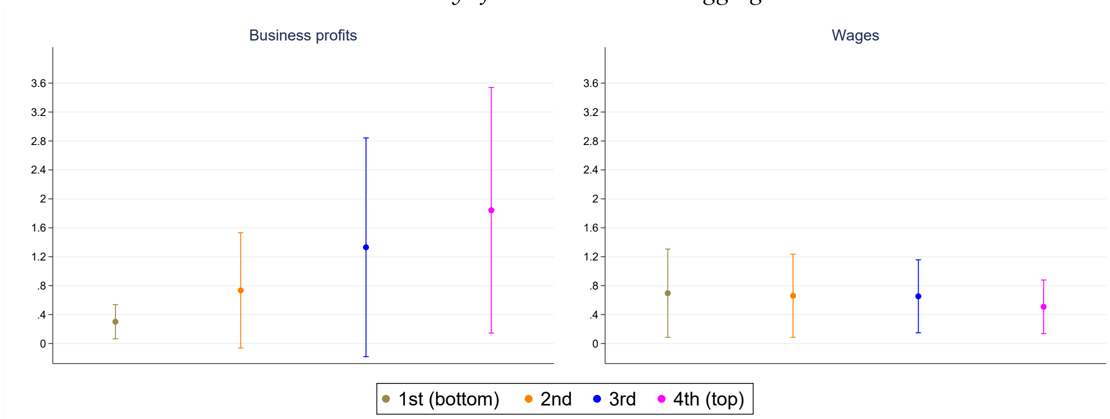
Note. Panel A: The red (blue) bars show the mean 2019 (2020) income in each percentile. Note that mean 2020 income divided by 2019 mean income is not equal to the exact value of the index because the base value is specific to each person's state × urban status. The dashed red line demarcates 100%. Panel B: Gini coefficients were obtained by sorting individuals on income, separately for urban and rural areas, and assigning each individual a place in the income distribution, based on their survey weight. We then calculated the individual's share of the population based on their survey weight, as well as their share of the total national income. We multiplied the population share by the cumulative share of income and summed across individuals in a given month to obtain the Gini coefficient for that month. Panel C Left: The matrix is equal to the 2019-2020 income quartile transition matrix minus the 2018-2019 income quartile transition matrix. The 2018-2019 income transition matrix is the probability (× 100) that a person in the (row) income quartile in 2018 was in the (column) quartile in 2019. The 2019-2020 income transition matrix is calculated analogously. 2018, 2019 and 2020 income quartiles are defined separately for each year based on the distribution of average per-capita monthly income across all months. Panel C Right: The subplot reports the fraction in the 1st and 4th quartile during 2015-2019 who are in a different quartile the reported month. The 2nd and 3rd quartile line report the fraction of persons in those quartiles during 2015-2019 that are in a higher and lower quartile, respectively, in the reported month.

Figure 4: Role of business income

Panel A: Sources of income by quartile



Panel B: Sensitivity of income sources to aggregate income

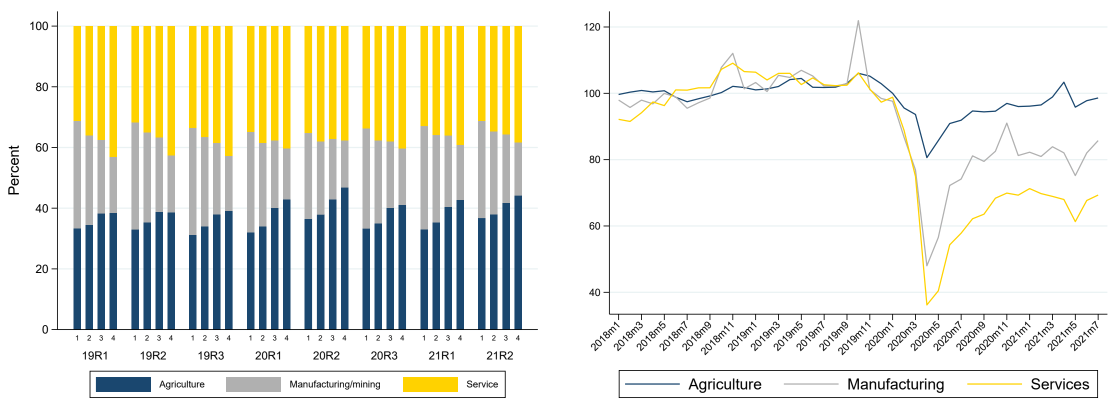


Note. Panel A: Share of income from different income sources. Capital income includes dividends, interest, rent, sale of assets outside of pension accounts. Other income includes government transfers, private transfers, value of agricultural goods produced for self-consumption, lottery winnings, insurance payouts. Panel B: The subplots report coefficients from regressions of monthly differences in the log of (one plus) an individual's business (left plot) or wage (right plot) income against changes in aggregate income (all components) interacted with 2015-2019 quartile indicators (see (4)). The specific coefficient reported is the coefficient on aggregate income interacted with each quartile.

Figure 5: Role of labor demand

Panel A: Margins of income

Panel B: Consumption and income by sector



Note. Panel A: We use the same income quartile categorization as before but only include individuals aged 15–65 for whom we have employment status. Average 2019 employment rates are the baseline for employment rate. For hours and wage, we include individuals who report being employed but working 0 hours. Average September-December 2019 hours and wage income per hour are the baseline for hours and wages because CPHS does not measure hours before September 2019. Panel B, left: Each bar reports the share of population in each quartile with occupations in each of 3 sector (agriculture, manufacturing and services) in each month. Table A8 reports the mapping of occupations to sectors. Panel B, right: This plot shows aggregate consumption of goods in 3 sectors by month relative to aggregate consumption in that sector in 2018. Table A7 reports the mapping of CPHS consumption categories to sectors.

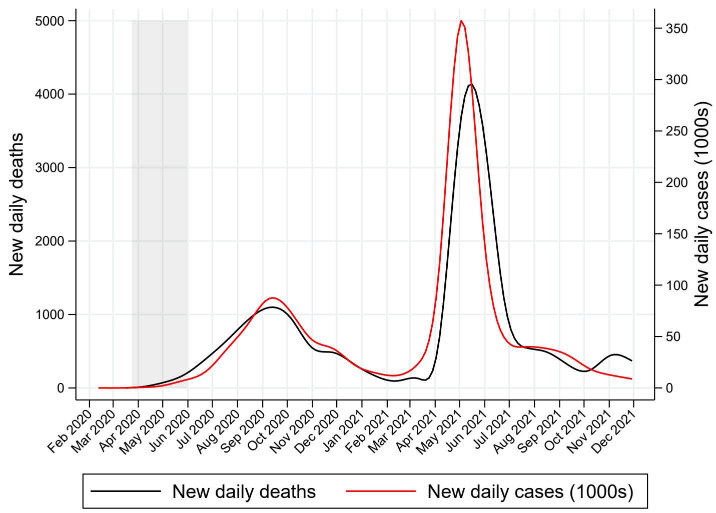
Appendix

A Figures

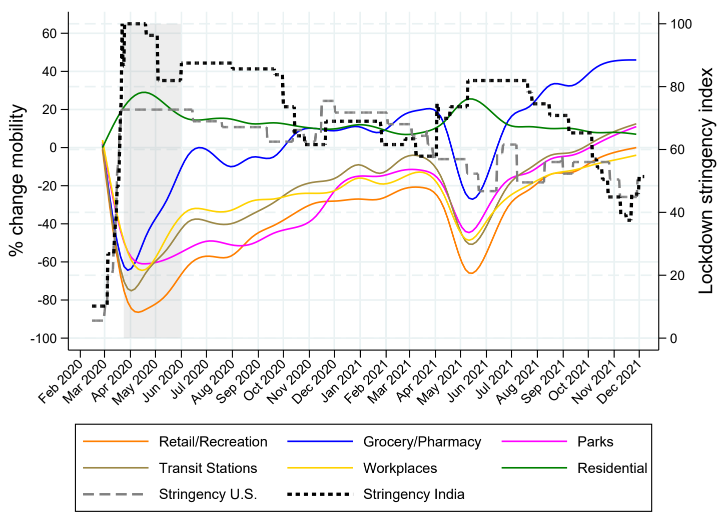
A1 Background

Figure A1: COVID Trajectory, Severity of Lockdown, and Mobility Changes

Panel A: Cases and deaths



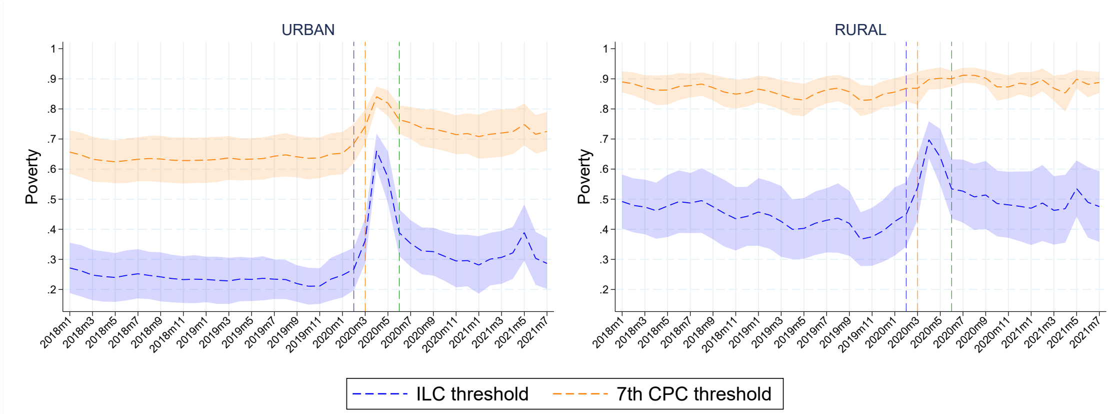
Panel B: Lockdown severity and mobility



Note. Case and death data are from `www.covid19India.org`. We show aggregated daily reported cases and deaths from the government. Shaded period marks the national lockdown. Lockdown severity data are from Oxford Hale et al. (2020). Mobility data are from Google mobility reports Google LLC (2021). Shaded period marks the national lockdown. Time periods cover February 2020–January 2021.

A2 Poverty

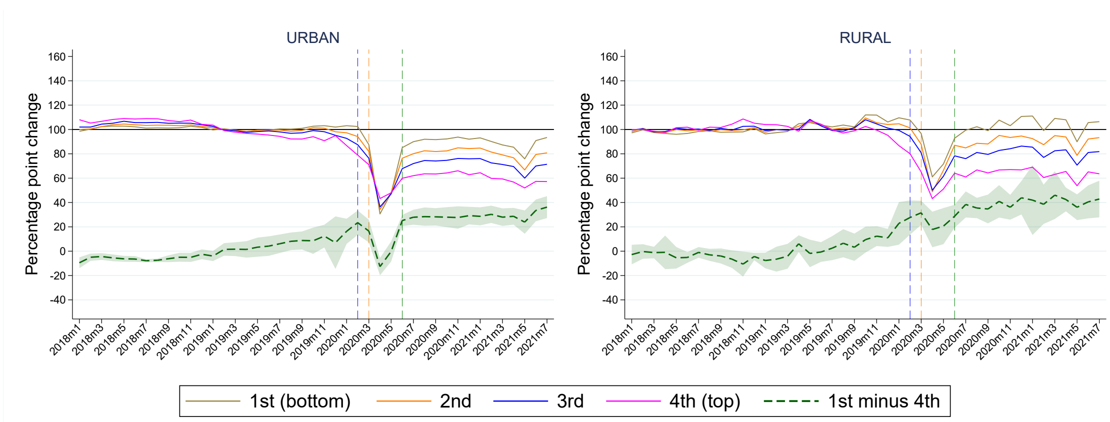
Figure A2: Time-series of India-specific poverty measures



Note. The figure plots shares of the population below 1) the National Minimum Wage, equal to ₹1909 (in 2012 terms) for rural areas and ₹2256 for urban areas per month and 2) the minimum wage recommended by the 7th Central Pay Commission, equal to ₹4660 per month. Shaded area is the 95% confidence interval around a statistic. Dashed vertical lines in February 2020, March 2020 and June 2020 indicate the first month of the pandemic (blue), the month the national lockdown started (orange) and the month the national lockdown ended (green).

A3 Income inequality

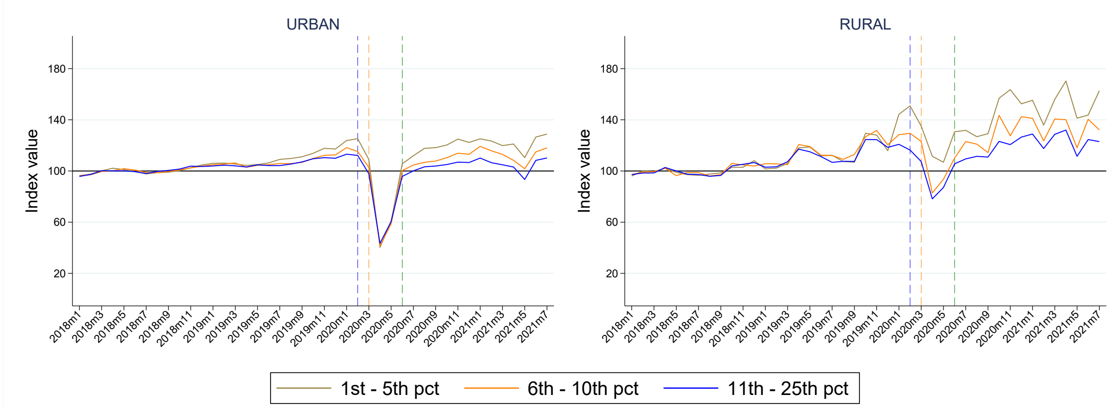
Figure A3: Income inequality with linear trends and seasonal adjustment.



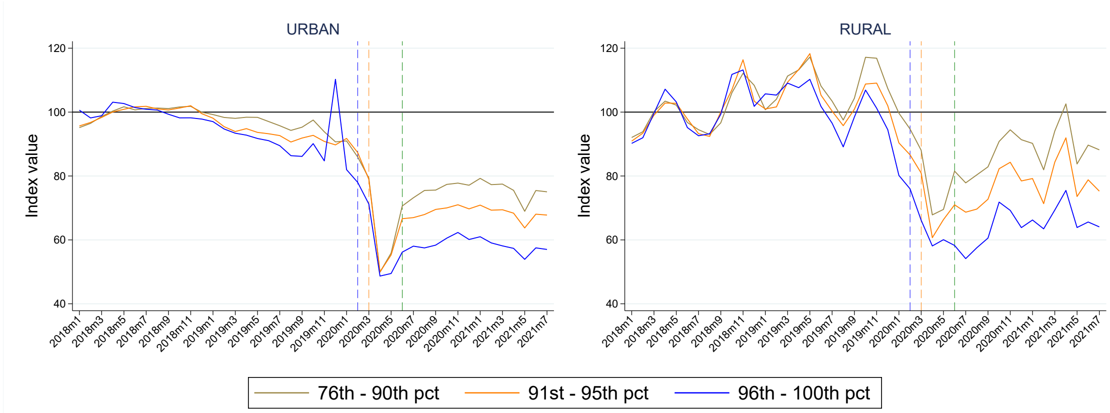
Note. The units are an index where 100 is average 2018 income of that person. This figure is constructed in 2 steps. First, a trend with seasonal adjustment was obtained from a regression of pre-pandemic income on a linear time trend and month fixed effects, separately for each income quartile, per equation (2). Second, deviations from the trend (plus 100) were then regressed on month-by-year $\times$ quartile fixed effects, per equation (1). The figure plots the coefficients on the month-by-year fixed effects separately for each quartile from the last regression.

Figure A4: Top and bottom earners.

Panel A: Bottom earners



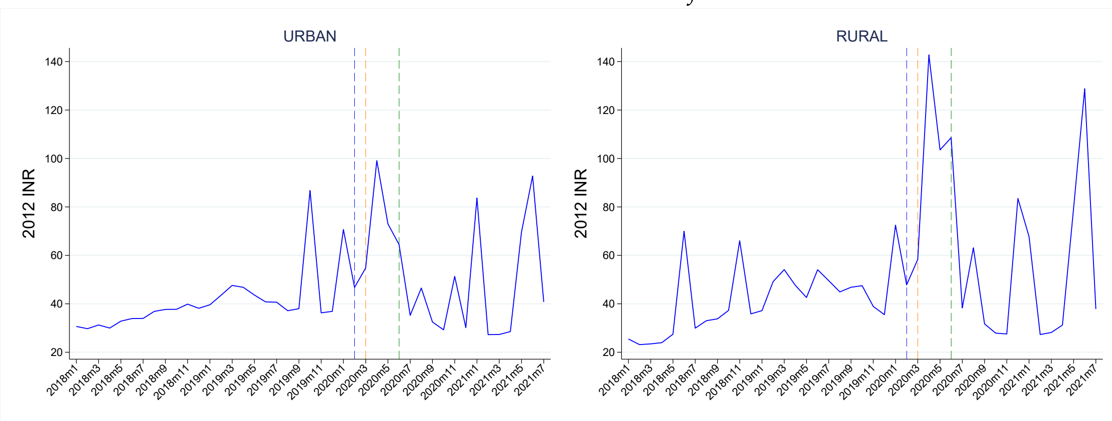
Panel B: Top earners



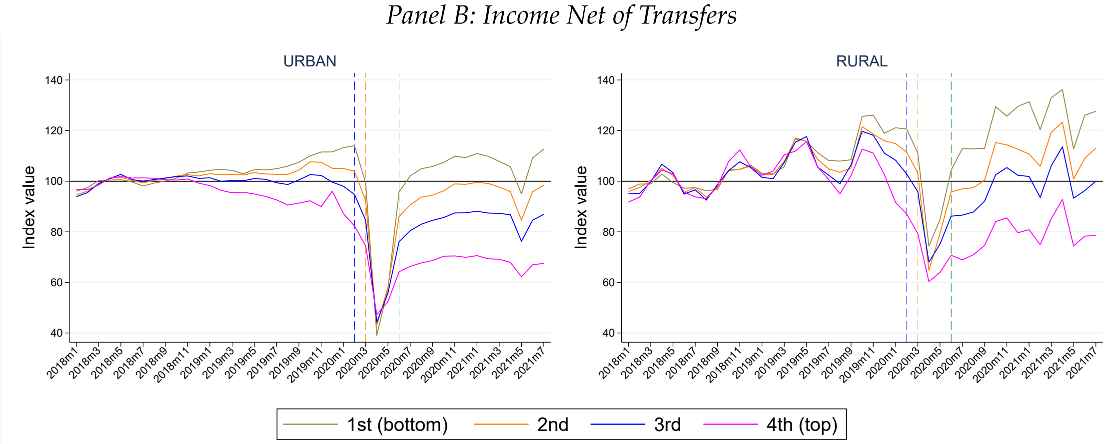
Note. The figure was constructed by calculating the weighted average of per capita income within indicated income quantiles in each state × urban status location, using individual member weights. These weighted means are obtained from the time fixed effects estimates in (1) using the default baseline. The units are an index where 100 is average 2018 income of a person. Dashed vertical lines in February 2020, March 2020 and June 2020 indicate the first month of the pandemic (blue), the month the national lockdown started (red) and the month the national lockdown ended (green).

Figure A5: Role of Government Transfers in Income Inequality, 2019-2021

Panel A: Government transfers



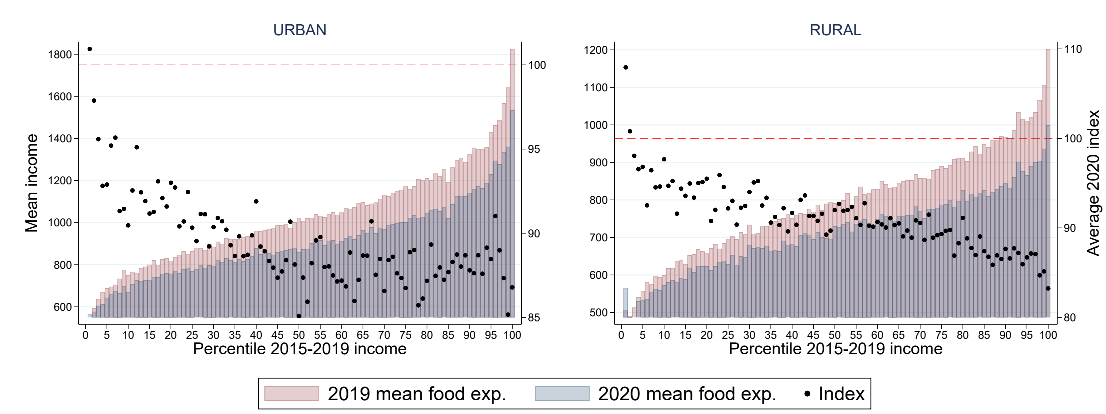
Panel B: Income Net of Transfers



Note. Panel A presents the monthly average of government transfers per household in 2012 INR. Panel B presents a version of Figure 1B but with income excluding government transfers.

A4 Consumption inequality

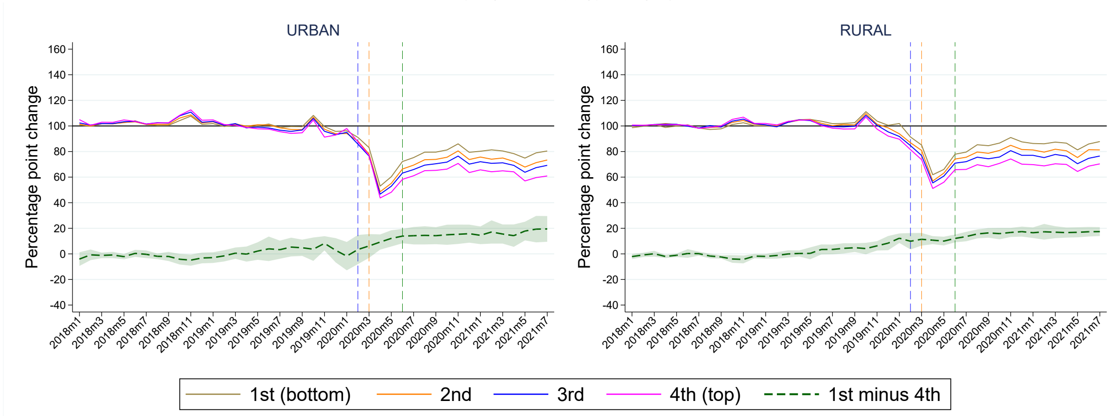
Figure A6: Cross-sectional shifts in consumption



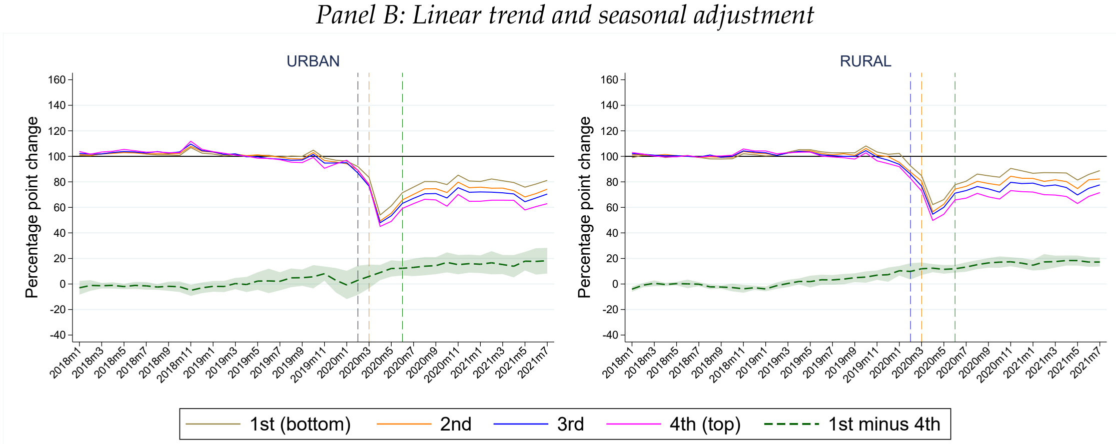
Note. First (second) column shows values for urban (rural) areas. The red (blue) bars show the mean 2019 (2020) consumption in each percentile. Note that mean 2020 consumption divided by 2019 mean consumption is not equal to the exact value of the index because the base value is specific to each person's state × urban status. The dashed red line demarcates 100%.

Figure A7: Consumption inequality with linear trends and seasonal adjustment.

Panel A: Linear trend

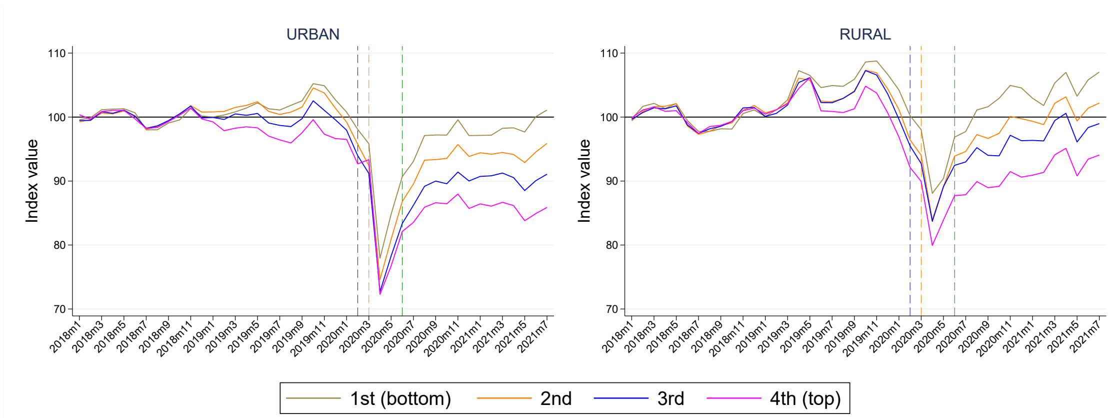


Panel B: Linear trend and seasonal adjustment



Note. Panel A shows a consumption time series relative to a linear trend. The units are an index where 100 is average 2018 consumption of that person. A trend was obtained from a regression of pre-pandemic consumption on time, separately for each income quartile, per equation (2). Deviations from the trend (plus 100) were then regressed on month $\times$ quartile dummies, per equation (1). In Panel B, we add calendar month dummies to the trend regression to adjust for seasonal fluctuations.

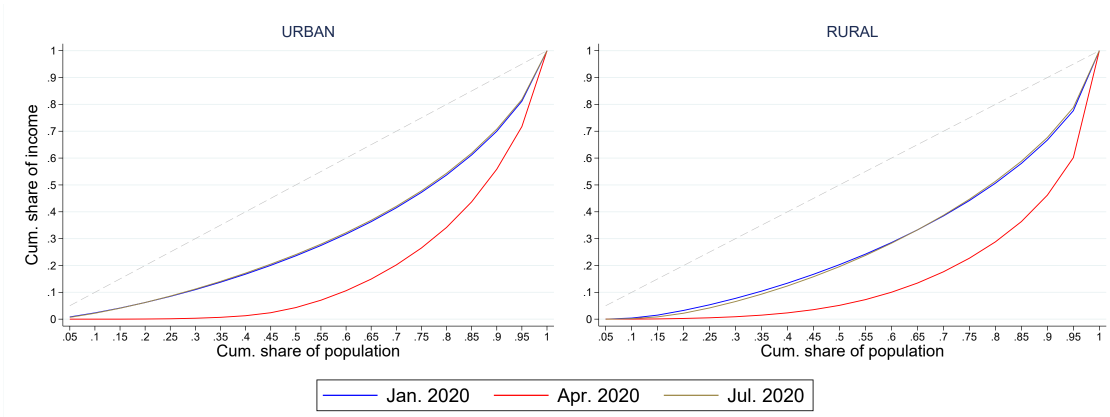
Figure A8: Relative Change in Food Expenditure by Income Quartiles



Note. Individuals were assigned to income quartiles at the state × community-type level calculated using individual's average 2015-2019 per capita incomes. This figure was constructed by first dividing the household food expenditure by the household size to calculate per capita food expenditure, then calculating the mean per capita food expenditure within income quartiles in their state × urban status locations, using individual member weights, and finally dividing by mean per capita local food expenditure in 2018 to create an index. Dashed vertical lines in February 2020, March 2020 and June 2020 indicate the first month of the pandemic (blue), the month the national lockdown started (red) and the month the national lockdown ended (green).

A5 Gini coefficient

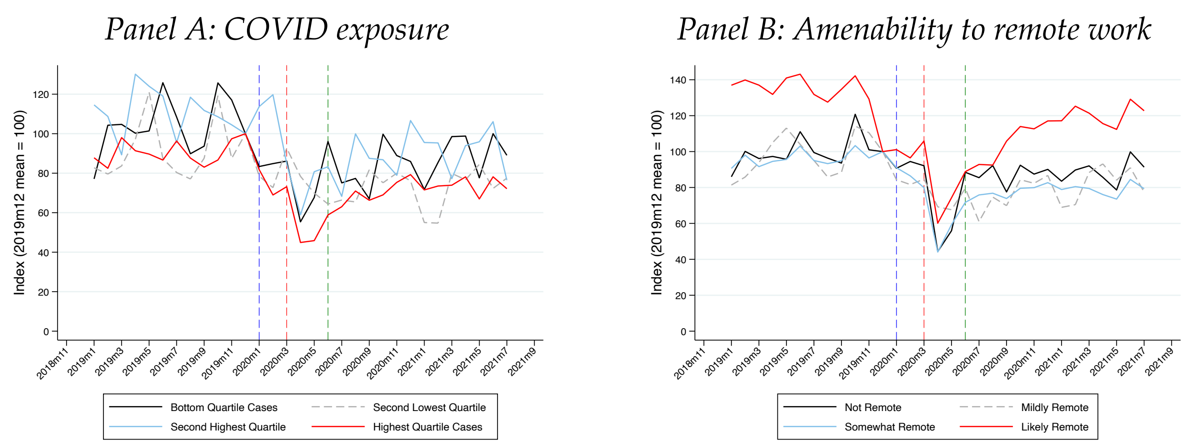
Figure A9: Lorenz curves before and after the lockdown



Note. Lorenz curves are obtained by sorting individuals on income, separately for rural and urban areas, and assigning each individual a place in the national income distribution, based on their survey weight. We then calculated the individual's share of the population based on their survey weight, as well as their share of the total national income. This is done separately for each reported month.

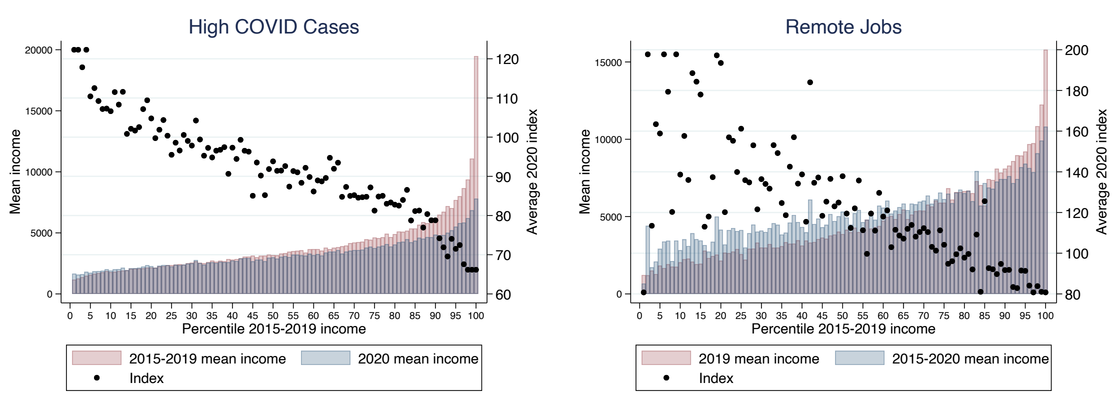
A6 Labor supply

Figure A10: Change in Income by Case Exposure and Ability to Work Remotely



Note. The left figure shows changes in labor income, normalized to the level in December 2019, for individuals divided into quartiles based on cumulative COVID case exposure, at the district level. The right figure divides occupations into four categories of exposure into remote work using the Dingel and Neiman (2020) measure of remote work, also normalized to December 2019. The lowest category has a Dingel and Neiman (2020) remote score of zero; the next category lies between zero and six percent; the next category is between six and 37 percent; and the highest category of remote work consists of occupations above 37 percent.

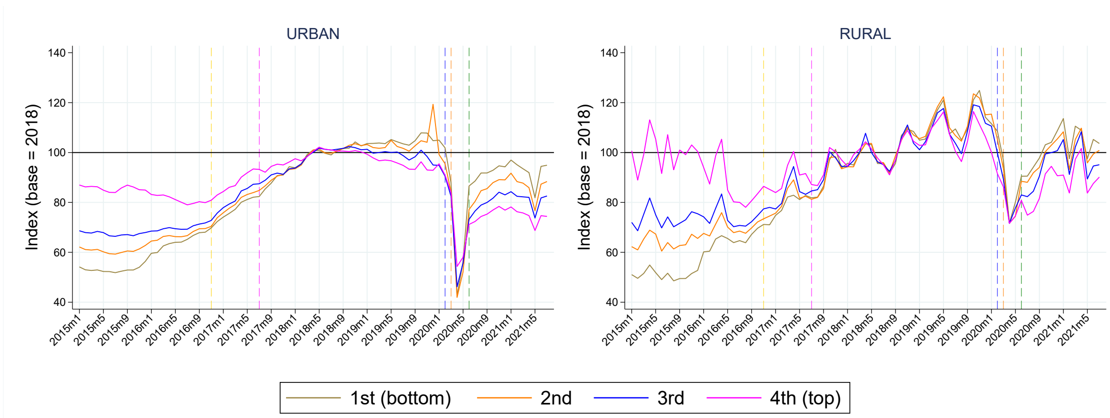
Figure A11: Distributional Consequences of Case Exposure and Remote Work



Note. The right y-axis shows the index value and the left y-axis shows average income. The black dots represent the index, the red bars show the mean 2015–2019 income in each percentile, the blue bars show the mean 2020 income in that percentile. Note that mean 2020 income divided by 2015–2019 mean income is not equal to the exact value of the index because the base value is specific to each person's state $\times$ urban status. The left panel restricts to individuals in the highest quantile of COVID confirmed case exposure; the right panel restricts to individuals in the highest category of possible remote work status.

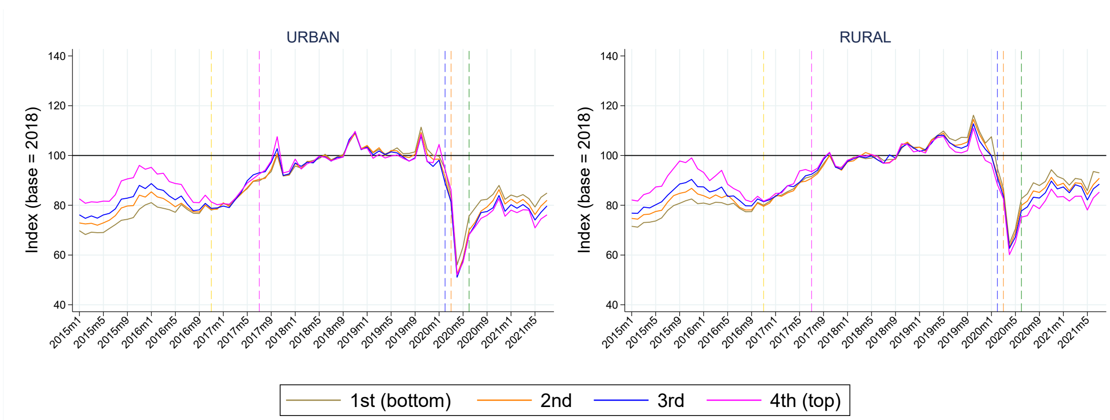
A7 Discussion

Figure A12: Relative Change in Income by 2015 Income Quartiles



Note. Individuals were assigned to income quartiles calculated using average 2015 per capita incomes. The figure was constructed by first dividing the household income by the household size to calculate per capita income, then calculating the mean within income quartiles in their state × urban status locations, using individual member weights, and finally dividing by mean per capita income in 2018 to create an index. Dashed vertical lines in November 2016, July 2017, February 2020, March 2020 and June 2020 indicate the month demonetization was announced (yellow), the month substantial amounts of new currency was introduced (magenta), the first month of the pandemic (blue), the month the national lockdown started (orange) and the month the national lockdown ended (green).

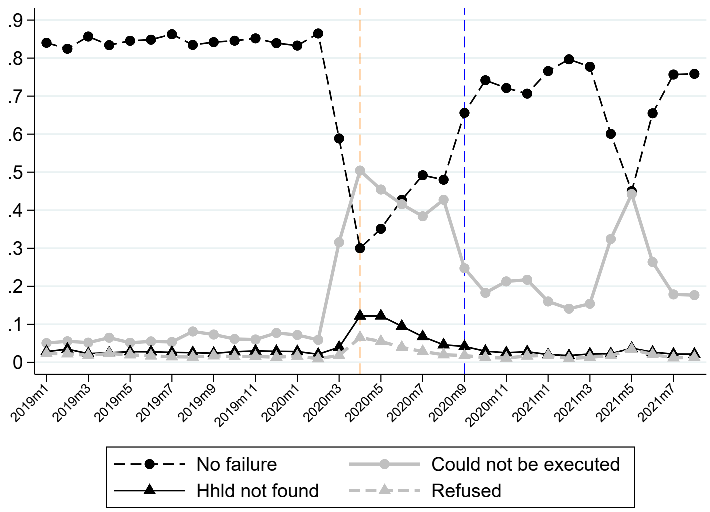
Figure A13: Relative Change in Consumption by 2015 Income Quartiles



Note. Individuals were assigned to income quartiles calculated using average 2015 per capita incomes. The figure was constructed by first dividing the household consumption by the household size to calculate per capita consumption, then calculating the mean per capita consumption within income quartiles in their state × urban status locations, using individual member weights, and finally dividing by mean per capita local consumption in 2018 to create an index. Dashed vertical lines in November 2016, July 2017, February 2020, March 2020 and June 2020 indicate the month demonetization was announced (yellow), the month substantial amounts of new currency was introduced (magenta), the first month of the pandemic (blue), the month the national lockdown started (orange) and the month the national lockdown ended (green).

A8 Appendix: Data

Figure A14: CPHS non-execution and non-response rates during 2020.

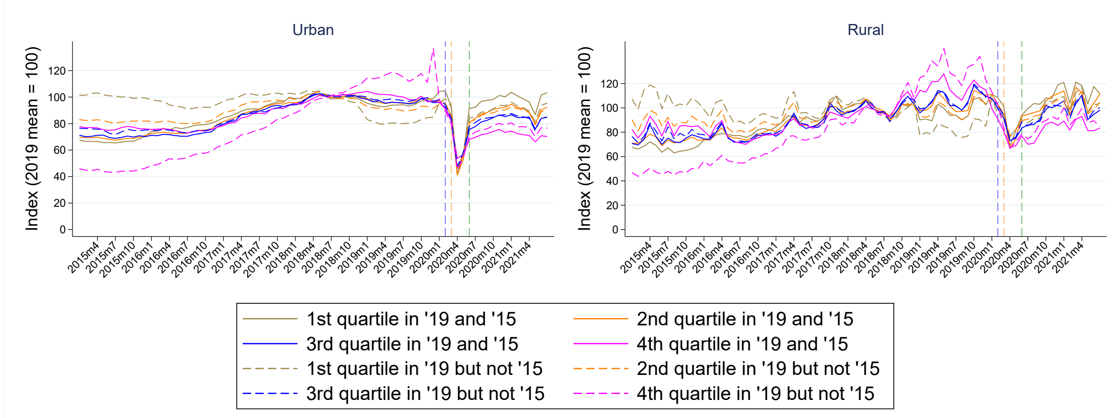


Note. Orange line indicates first month of phone surveys. Blue line indicates month that in-person surveys resumed. The sample includes all households. “Could not be executed” (non-execution) includes both CMIE’s decision not to contact a household and its inability to speak to a household member because, e.g., no one answered the door (“door-lock”). “Household not found” means CMIE attempted to contact the household but surveyors were unable to locate the household.

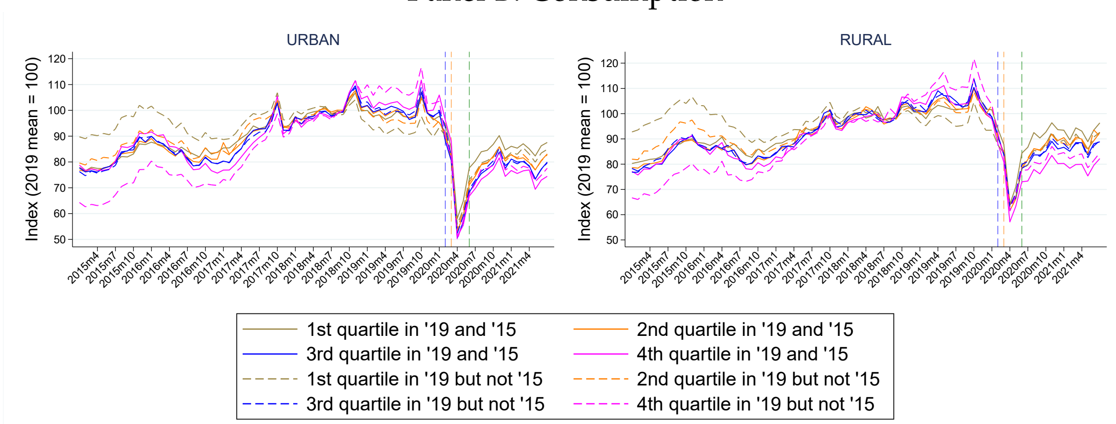
A9 Appendix: Mean reversion

Figure A15: Change in Relative Income and Consumption among Persistent and Transient Members of Each 2019 Income Quartile, 2015-2021

Panel A: Income



Panel B: Consumption



Note. The income figures were constructed in five steps. First, we divide household monthly income by the household size to calculate per capita income for each member of the household. Second, we take the monthly average of a person's per capita income over 12 months (for 2015 and for 2019). Third, we weight individuals to be representative and then we sort weighted individuals into quartiles of average monthly per capita income for that person's state $\times$ community type (rural or urban) and that year. Fourth, we separate the set of all (weighted) individuals in a quartile in 2019 into two groups. One is individuals who were in that same quartile in 2015, using quartile definitions from that year. The other is people who were not in that same quartile in 2015. Fifth, to create an index, we divide (a) the average, weighted monthly income of all members of a quartile $\times$ persistence status group by (b) the average, weighted monthly income of all members of that quartile $\times$ persistence status group in 2018. For the consumption figures, we do the same thing except at the last step, we divide monthly consumption of the average member of a quartile $\times$ persistence status group by the average monthly consumption of that group in 2018. Dashed vertical lines in February 2020, March 2020 and June 2020 indicate the first month of the pandemic (blue), the month the national lockdown started (orange) and the month the national lockdown ended (green).

B Tables

B1 Consumption inequality

Table A1: Test of consumption smoothing (of total expenditure).

	(1)	(2)	(3)	(4)
Ln(aggregate consumption)	0.6533***		0.8790***	0.5302***
	(0.0578)		(0.0254)	(0.0560)
Ln(income)	0.0980***	0.1297***	0.0506***	0.1585***
	(0.0146)	(0.0163)	(0.0081)	(0.0170)
Ln(income) × Pandemic	-0.0052***	-0.0233***	-0.0012	-0.0069***
	(0.0014)	(0.0016)	(0.0009)	(0.0017)
N	3773651	3773651	1237376	2536275
R^2	0.715	0.691	0.700	0.721

Notes. The regressions covers 2019-July 2021. Aggregate consumption is equal to mean household consumption at the state × community type level. Household fixed effects included. Standard errors clustered at the state × urban level. Significance levels: * 10% ** 5% *** 1%.

Table A2: Test of smoothing (of total expenditure), by income quartiles.

	(1)	(2)	(3) Rural	(4) Urban
Ln(aggregate consumption)	0.5576***		0.8621***	0.4436***
	(0.0748)		(0.0218)	(0.0572)
2nd quartile	0.0921***		0.0229	0.0843***
	(0.0253)		(0.0148)	(0.0198)
3rd quartile	0.1653***		0.0205	0.1660***
	(0.0476)		(0.0233)	(0.0386)
4th quartile	0.2520***		0.0037	0.2591***
	(0.0789)		(0.0302)	(0.0690)
Ln(income)	0.0953***	0.1345***	0.0497***	0.1317***
	(0.0122)	(0.0132)	(0.0077)	(0.0095)
2nd quartile	-0.0025	-0.0032	-0.0009	0.0058
	(0.0039)	(0.0050)	(0.0032)	(0.0072)
3rd quartile	-0.0052	-0.0110	-0.0022	0.0145
	(0.0063)	(0.0085)	(0.0049)	(0.0110)
4th quartile	0.0056	-0.0045	0.0054	0.0664***
	(0.0090)	(0.0116)	(0.0055)	(0.0118)
Ln(income) $\times$ Pandemic	-0.0047***	-0.0218***	0.0014	-0.0068***
	(0.0013)	(0.0013)	(0.0010)	(0.0014)
2nd quartile	0.0003	-0.0017***	-0.0017**	0.0005
	(0.0005)	(0.0005)	(0.0007)	(0.0006)
3rd quartile	0.0007	-0.0030***	-0.0029***	0.0015
	(0.0009)	(0.0008)	(0.0010)	(0.0011)
4th quartile	0.0005	-0.0051***	-0.0058***	0.0031*
	(0.0016)	(0.0012)	(0.0018)	(0.0017)
N	2937692	2937692	977542	1960150
R^2	0.725	0.700	0.713	0.730

Notes: The regressions covers 2019-July 2021. Aggregate consumption is equal to mean household consumption at the state $\times$ community type level. Household fixed effects included. Standard errors clustered at the state $\times$ urban level. Specification (1) drops our measure of aggregate consumption, (3) only includes observations on rural households, and (4) only includes observations on urban households. Significance levels: * 10% ** 5% *** 1%.

Table A3: Test of consumption smoothing (of food expenditure), by income quartiles.

	(1)	(2)	(3) Rural	(4) Urban
Ln(aggregate consumption)	0.2674***		0.4274***	0.2038***
	(0.0404)		(0.0294)	(0.0323)
2nd quartile	0.0543**		0.0318*	0.0447*
	(0.0210)		(0.0174)	(0.0219)
3rd quartile	0.0763**		0.0066	0.0715**
	(0.0353)		(0.0213)	(0.0337)
4th quartile	0.1124*		-0.0180	0.1176*
	(0.0573)		(0.0330)	(0.0588)
Ln(income)	0.0703***	0.0891***	0.0430***	0.0923***
	(0.0078)	(0.0078)	(0.0085)	(0.0067)
2nd quartile	-0.0038	-0.0036	-0.0038	0.0021
	(0.0034)	(0.0038)	(0.0037)	(0.0044)
3rd quartile	-0.0090	-0.0119*	-0.0086	0.0048
	(0.0056)	(0.0066)	(0.0056)	(0.0074)
4th quartile	-0.0082	-0.0133	-0.0063	0.0247**
	(0.0070)	(0.0084)	(0.0069)	(0.0092)
Ln(income) $\times$ 2020	-0.0018	-0.0100***	0.0015	-0.0031*
	(0.0015)	(0.0013)	(0.0017)	(0.0018)
2nd quartile	0.0003	-0.0009*	-0.0007	0.0005
	(0.0006)	(0.0005)	(0.0010)	(0.0007)
3rd quartile	0.0008	-0.0009	-0.0012	0.0012
	(0.0009)	(0.0007)	(0.0017)	(0.0009)
4th quartile	0.0013	-0.0012	-0.0036	0.0035**
	(0.0014)	(0.0011)	(0.0023)	(0.0014)
N	2937654	2937654	977536	1960118
R^2	0.705	0.695	0.691	0.709

Notes: The regressions cover 2019-July 2021. Aggregate consumption is equal to mean household consumption at the state $\times$ community type level. Household fixed effects included. Standard errors clustered at the state $\times$ urban level. Specification (1) drops our measure of aggregate consumption, (3) only includes observations on rural households, and (4) only includes observations on urban households. Significance levels: * 10% ** 5% *** 1%.

Table A4: Annualised death rates by 2018 income tercile

	Annualised death rates (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Pandemic	0.113		0.237		0.0823	
	(0.0689)		(0.122)		(0.0801)	
Pandemic × 2nd tercile	0.132		-0.0223		0.177	
	(0.0867)		(0.121)		(0.109)	
Pandemic × 3rd tercile	0.357***		0.235		0.387**	
	(0.0986)		(0.129)		(0.146)	
Wave 1		-0.0247		0.0416		-0.0411
		(0.0767)		(0.135)		(0.0893)
Wave 1 × 2nd tercile		0.239*		-0.00842		0.338**
		(0.102)		(0.141)		(0.129)
Wave 1 × 3rd tercile		0.367**		0.154		0.569**
		(0.114)		(0.149)		(0.181)
Wave 2		0.371***		0.591**		0.315**
		(0.102)		(0.190)		(0.118)
Wave 2 × 2nd tercile		-0.0682		-0.0459		-0.124
		(0.122)		(0.174)		(0.151)
Wave 2 × 3rd tercile		0.328*		0.372		0.0501
		(0.147)		(0.194)		(0.193)
2019 mean	1.160***	1.160***	1.170***	1.170***	1.158***	1.158***
	(0.0463)	(0.0463)	(0.0746)	(0.0746)	(0.0541)	(0.0541)
2nd tercile	-0.172**	-0.172**	-0.150*	-0.150*	-0.184**	-0.184**
	(0.0540)	(0.0540)	(0.0715)	(0.0715)	(0.0671)	(0.0671)
3rd tercile	-0.232***	-0.232***	-0.232**	-0.232**	-0.242**	-0.242**
	(0.0567)	(0.0567)	(0.0726)	(0.0726)	(0.0795)	(0.0795)
Sample	All	All	Urban	Urban	Rural	Rural
N	2816368	2816368	1852668	1852668	963700	963700

Note. Estimates are from a regression model based on equation (1) in Malani and Ramachandran (2021), with the addition of a income tercile indicator and income tercile indicator interacted with the pandemic or wave indicator. For each individual we calculate the income per capita in 2018. We compute the household's income percentile in their homogeneous region and region type (urban/rural). Households between 33 and 67 percentile are in income tercile 2 and households between 67 and 100 percentile are in income tercile 3. Columns 1 and 2 includes all data, columns 3 and 4 include only urban regions and columns 5 and 6 include only rural regions. Sample includes only consecutive observations and is weighted to be nationally representative. Standard errors clustered at the village/ward × month level are reported in parentheses. $p < 0.05/0.01/0.001$.

B2 Gini coefficient

Table A5: Income quartile transition matrix from 2018 to 2019

2018 quartile	2019 quartile 1st quartile	2nd quartile	3rd quartile	4th quartile
1st quartile	62.62	26.57	8.31	2.50
2nd quartile	24.58	43.28	24.73	7.41
3rd quartile	8.15	24.81	43.79	23.25
4th quartile	2.46	6.64	23.06	67.84

Note. This table presents the probability ($\times$ 100) that a person in the (row) income quartile in 2018 was in the (column) quartile in 2019. 2018 and 2019 income quartiles are defined separately for each year based on the distribution of average per capita monthly income across all months.

B3 Labor supply

Table A6: Household Labor Supply over the Pandemic

	(1)	(2)	(3)	(4)	(5)	(6)
New Confirmed Cases	4.9434***		5.2860***	4.9434***		5.2860***
	(1.8088)		(1.8894)	(1.8086)		(1.8892)
Top Half 2019 Income		0.0824***	0.0828***		0.1668***	0.1668***
		(0.0094)	(0.0096)		(0.0136)	(0.0136)
Cases × High Income			-1.4191			-1.4191
			(1.6933)			(1.6931)
Pandemic Period				-0.4638***	-0.4173***	-0.4193***
				(0.0097)	(0.0086)	(0.0087)
Pandemic × High Income					-0.0844***	-0.0840***
					(0.0127)	(0.0128)
N	176130	176130	176130	1011099	1011099	1011099
R^2	0.000	0.003	0.003	0.014	0.017	0.017

Notes: This table regresses log reservation wages, drawn from a Roy Model, against income percentiles and confirmed COVID cases. Columns (1)–(3) focus on the pandemic period (2020 Q2) and regress reservation wages against confirmed cases, the income, and an interaction of cases and income. Columns (4)–(6) include both the pre-pandemic period of 2019 Q2 as well as 2020 Q2, with an interaction with the pandemic period. Reservation wages are measured as rupee income, and confirmed cases are divided by 1×10^6 for ease of interpretation. Significance levels: * 10% ** 5% *** 1%.

B4 Labor demand

Table A7: Mapping expenditure categories to agriculture, manufacturing and service sectors.

Sector	Expenditure category
Agriculture	Whole-grain cereal, pulses, edible oils, dry spices, dry fruit, noodles and flakes, sugar, vegetables and fruit, potatoes and onions, milk and milk products, bread, biscuits, salty snacks, jam, ketchup, pickles, meat, eggs, fish, ghee, mithai, cigarettes and tobacco.
Manufacturing	Processed cereal, health supplements, tea and coffee, beverages and bottled water, chocolate, cakes, ice-cream, ready-to-eat food, baby food, other food, liquor, clothes and footwear, cosmetics and toiletries, appliances, electronic storage, toys, power and fuel, lighting, furniture, utensils.
Services	Restaurants, entertainment, bills and rent, transport, communication and information, education, health expenses, loan installments, domestic help, car repair, remittances, social obligations, religious obligations, general insurance, vacation, pocket money, pets, professional services, renovations.

Table A8: Mapping employment categories to SIC codes and agriculture, manufacturing and service sectors.

Sector	SIC code	Employment category
Agriculture.	Agriculture, forestry and fishing.	Agriculture-allied activities; crop cultivation; fishing; forestry, including wood cutting; fruits and vegetable farming; plantation crop cultivation; poultry farming, animal husbandry and vermiculture.
Manufacturing.	Mining and quarrying.	Mines.
	Manufacturing.	Automobiles and other transport equipment manufacturers; cement, tiles, bricks, ceramics, glass and other construction materials; chemical industries; food industries; footwear and other leather industries; gems and jewelry; handicraft industries; machinery manufacturers; metal industries; pharmaceutical manufacturers; soaps, detergents, cosmetics, toiletries; textile industries.
	Construction and real estate.	Real estate and construction.
Services.	Utilities.	Utilities.
	Retail and wholesale trade.	Retail trade; wholesale trade.
	Transportation and storage.	Communication, post and courier.
	Accomodation and food services.	Hotels and restaurants.
	Information and communication.	IT and ITES; media and publishing.
	Financial services.	Financial services.
	Professional services.	Personal professional services.
	Non-professional services.	Personal non-professional services.
	Public administration and defense.	Defense services, public administrative services.
	Education.	Education.
	Health care.	Health care.
	Entertainment, sports, tourism.	Entertainment and sports; travel and tourism.

C Data

C1 Detailed description of CPHS

The CPHS sample covers nearly all states in India except for a few states in the north-east (e.g., Nagaland, Mizoram, Arunchal Pradesh) that are difficult to sample because of instability (Vyas, 2020d).

CPHS divides each state into homogeneous regions, clusters of districts with similar features.[13] Each region is divided into rural and urban strata, where rural regions are villages as defined by the Indian Census. The urban strata is further subdivided into four sub-strata defined by town size. The primary sampling units are villages and towns. Thirty villages were randomly selected from rural strata of each region. For urban strata, a random subsample of towns in each sub-strata are selected. The ultimate sampling units are households. In each selected village 16 households were selected by systematic random sampling (every n^{th} household on a street, where n is a random number between 5 and 15). In cities, 21 Census Enumeration Blocks (CEB) were randomly selected. In each CEB, 16 households were selected via systematic random sampling. Sample households were selected to be representative at the level of urban and rural areas of regions.

The CPHS started surveying in January 2014. We use the data starting January 2015, the point CPHS suggests that they had stabilized their survey quality.

C2 Issues with CPHS data

Sample churn and non-response

The sample in the CMIE data churns somewhat over time Vyas (2020c). On average 2.1% of households are lost in each four month wave and 2.4% are added in each wave to replace lost households and to grow the sample over time. Weights are included to ensure that the sample remains representative of its region. Prior to the COVID epidemic, response rates were roughly 84%. Non-response was due more to inability to reach all households in the allotted 4 months for each sampling wave more than refusal to be surveyed. Separate weights are included in an attempt to correct for non-response.

During the pandemic, response rates fell (Vyas, 2020a). CPHS is ordinarily an in-person survey. The household response rate (responding households/sample house-

[13] The features are similar agro-climactic conditions, urbanization levels, female literacy, and average household size.

holds) prior to the pandemic was typically around 85%. When India declared a national lockdown on March 24, 2020, in person surveys had to cease. CPHS switched temporarily to a phone survey. Moreover, survey managers, rather than surveyors, conducted phone surveys to keep up the quality of those surveys. Because there are fewer managers than surveyors, CPHS decided to call only half the households in each strata (defined as homogeneous region $\times$ community type). As a result, overall response rates fell. Figure A14 shows that the response rate of the subset of households that were contacted fell to roughly 60% and responding households constituted roughly 35% of the full sample at the height of the lockdown in April and May 2020. When CPHS finished its second round in August 202, it returned to in-person surveys. However, the response rate only rose to 75%.[14]

Despite the drop in response rates, CMIE was able to maintain the distribution of surveys across two dimensions the same as prior to the pandemic. First, the ratio of rural to urban households was roughly 35:65 pre- and post-lockdown, with only a two week deviation to 43:57 when lockdown was declared. The distribution of households across states shifted a bit in favor of rural states, but was roughly the same as pre-pandemic. Second, the distribution across income also remained roughly the same. The fraction earning between ₹150,000–300,000 per annum was 45% before and after lockdown. However, sampling at the extremes of the distribution did change. The share earning $\geq$ ₹500,000 fell from 12.9% to 9%; the share earning $\leq$ ₹150,000 increased from 23% to 29.1%. Of course, some of this change may be a reduction in income due to COVID[15]

The low response rates during round 2 in 2020 are partly addressed by using the responding sample as the denominator in our estimate of rates of various economic outcomes. We address non-random response that makes the same differently representative of the population by using CMIE-supplied weights intended to ensure the responding population has the same demographics as the population in each strata.

Representativeness of sample

Dreze and Somanchi (2021) argues that CPHS undersamples the poor based on evidence that it yields both higher levels of literacy and faster improvement in literacy than government surveys. Of course, the fact of difference between CPHS and government surveys of literacy is not dispositive of whether CPHS is biased since it is possible that the gov-

[14]There was also a drop in response rates during wave 2, but there was no switch to telephone interviews and the dip was not as severe as during the lockdown.

[15]CMIE also reports a shift in the fraction of households across occupational groups.

ernment surveys are the ones that are off. After all, the government has taken steps to suppress data (e.g., the 2017-18 consumption survey by the National Statistical Survey Office) that it finds unflattering. Moreover, government surveys are known to give different estimates of items like slums populations, with the differences driven by the policy aim of the survey.[16]

Dreze and Somanchi suggest that CPHS is the one likely to be wrong because its frame samples more from the main streets of villages than from outskirts, where the poor tend to live. CMIE has responded that its sampling does get to outskirts and that the bias has not changed over time because that sampling frame is largely fixed and that it method for selection (of new households) has been constant (Vyas, 2021).

We address the problem of representativenes by conditioning on where in the income distribution a person falls in 2019. If bias is due to where the individual resides, this approach even addresses the problem that social mobility may cause a change in a person's income percentile over time. To the extent that Dreze and Somanchi's argument suggests that our calculation of 25th percentile is wrong (i.e., too high) because CPHS undersamples the very poor, we provide evidence that lower percentiles in CPHS do relatively better than even the 25th percentile in CPHS (Figure A4).

Survey content and comparisons

The survey is conducted at the household level but measures both individual and household level variables. It measures employment status, time use, and occupation for each member of the household once every four months. It measures income for each household member and the overall household and consumption for the household every month by asking members to recall income and consumption each of the last four months. The survey is conducted on a smart device and gathers data on up to 12 members of each household.

The CPHS has analogues in Indian NSSO surveys on labor statistics and on consumer expenditures. It is difficult to compare the CPHS to the consumer expenditure survey because the NSSO's 2017–2018 consumer expenditure survey was rejected by the government and thus not released (Vyas, 2020b). The previous one was from 2011–2012. Nonwithshanding Dreze and Somanchi (2021), Abraham and Shrivastava (2019) show that the CPHS and NSSO produce similar results for male workers.

[16]For example, public health officials in Mumbai in private conversations have noted that surveys of slum populations by the public health department tend to generate higher estimates of slum population because higher numbers in slums are more likely to generate large appropriations for the department.

C3 RBI inflation data

We obtain data on overall and constituents[17] of inflation from the Reserve Bank of India (Reserve Bank of India, 2020). The data are available at the monthly level for rural and urban areas of each state; the base year is 2012. We obtain relative prices from constituents price indices using the rural and urban constituent weights reported by the RBI (Bhoi et al., 2020).[18]

C4 COVID cases, lockdown rules and mobility

We obtain data on COVID cases and deaths from `www.covid19India.org`, which compiles reports from government sources across the country. We obtain data on national lockdown severity from the Oxford Covid-19 Government Response Tracker (Hale et al., 2020) and district-level mobility from Google Mobility Reports (Google LLC, 2021).

D Incidence

D1 Poverty

Here we consider two other measure of poverty from Azim Premji University (2021) that show slightly different degrees of poverty increases (Figure A2). Using India's National Minimum Wage (income of ₹1909 and ₹2256 per capita month in rural and urban areas, in 2012 terms), poverty spiked sharply from 40% to 70% in rural areas and 25% to 65% in urban areas during the lockdown. It only partly recovered, hovering at 50 and 30%, respectively, by the end of the year. By contrast, the poverty line defined by the Indian government's 7$^{\text{th}}$ Central Pay Commission (income of ₹4,660 per capita per month) only increased gradually in rural areas and more moderately (and $< 10\%$) than the Minimum Wage poverty measure in urban areas (from 65 to 85%) during the lockdown.

D2 Mean reversion

We have documented that the income of top quartiles fell relatively more than those of lower quartiles. One might wonder whether this is actual evidence of a reduction in

[17] Food, clothing, fuel and light, transport and communication, intoxicants, housing, household goods and services, health and education, and others.

[18] CPI for items other than constituent g ($\neg g$) calculated as $\text{CPI}_{\neg g} = (\sum_{k \neq g} w_k \text{CPI}_k)/(\sum_{k \neq g} w_k)$, where k indexes constituents.

inequality or mistaking mean reversion for a reduction in inequality. Mean reversion might be expected to yield similar patterns as reduced inequality if incomes of the rich, which were rising prior to 2020, see mean reversals downward in 2020, while incomes of the poor experienced opposite changes.

To some extent our base results are robust to mean reversions. Critically, our default definition of quartiles is based on average 2015-2019 income rather than just 2019 income. This means our top quartiles persons are not *recently* top quartile person. The latter will be more subject to reversion than people who are consistently top quartile.

It is possible, however, that among those individually who on average in a quartile, especially a middle quartile, there are those who have experienced mean reversion during the 2015-2019 period. To address that concern, we compare the performance of (a) those who are in, say, the top quartile of 2019 incomes but not in the top quartile of 2015 income to (b) those in the top quartile of both 2015 and 2019 income (Figure A15).[19] The latter group tends to net out mean reversion because quartile members do not move around the distribution; the former group highlights mean reversion for the opposite reason. We validate this by looking at the period before 2019, when new arrivals grow faster (slower) than persistent members of the top quartile (bottom).

Consistent with mean reversion, recent arrivals to the top (bottom) quartile experience the sharpest declines (recoveries) in income during the pandemic. However, persistent members of these groups experience similar changes in relative income. The decline in regressivity is somewhat smaller when we adjust for mean reversion in this way, but the differences across transient and persistent quartile members are not stark. The pattern for consumption is the same, except that the differences between persistent quartile members and transient ones is even smaller during COVID.

An alternative approach to measuring changes to inequality after filtering out mean reversion is to compare relative income during the pandemic against a baseline that attempts to account for mean reversion. We do this by comparing actual income to a baseline that accounts for mean reversion with the periodicity of seasons, i.e., we include both trend and seasonality in our model for predicted income. We find (Figure A3B) a significant decline in inequality even against this benchmark.

A limitation of all these approaches is that, with only data from January 2015 - July 2021, we cannot measure mean reversion that has a cycle longer than half our covered time period, i.e., 3.25 years. Any reversion longer than that would occur outside our

[19]For this exercise, we define quartiles cutoffs for each year so that, e.g., a person was in the top quartile in 2015 if she was in the top 25% of the income distribution in 2015.

sample period. That said, mean reversion with a cycle that long would not alter our conclusion that inequality fell during the pandemic because the pattern we observe is during the short 1.5 years of the pandemic.

E Mechanisms

E1 Labor supply: COVID and remote work

One might still wonder whether factors that affected the relative behavior of the rich in high-income countries—COVID risk and access to remote work—also affected those in a lower-income country like India. Labor supply, particularly of the rich, may have been especially sensitive to disease risk to the extent that the rich have higher risk aversion, and hence greater interest in avoiding disease exposure (Oster, 2012). Moreover, greater ability to engage in remote work may have made the rich more willing and able to supply labor despite pandemic risk Adams-Prassl et al. (2020).

We investigate the plausibility of these two channels in Figure A10, which plots relative income over the course of the pandemic for households divided into exposure quantiles of confirmed COVID cases, based on district-level exposure, as well as different categories of remote work based on the Dingel and Neiman (2020) measure of remote work applied to the occupations in our sample.

While areas exposed to the highest level of COVID cases (Panel A) see lower income in the post-lockdown period, income subsequently recovers towards the end of 2020 and does not see a monotonic relationship between case exposure and income changes. We explore further the role that COVID exposure may have had on reservation wages by regressing log reservations wages on the average of daily new COVID cases at the month $\times$ district level, an indicator for above median income, and the interaction of the two (Table A6, column (3)). This regression only include data from the pandemic period, specifically, the second quarter of 2020. We do not find that the reservation wages of the rich were unusually sensitive to COVID case exposure.

We also see scant evidence that remote work (Figure A10B) is protective of incomes in India. While workers in our highest level of remote work classification see their incomes recover more by the end of our sample; these workers still see quite large decreases in income during the lockdown period, when remote work might be expected to shelter the employment of individuals. Additionally, workers in this highest remote work classification see large pre-trends in income declining even prior to the beginning of the pandemic, and never recover the level of income they saw in the beginning of 2019. Additional caveats around this measure include the fact that we do not measure whether an individual actually worked remotely; we only impute, based on their occupational status, whether a comparable occupation in the United States would have had the potential to work remotely. It seems likely that many workers, who have latent ability to work remotely in the United States, face much stronger barriers to doing so in India due to reasons of organizational capacity, broadband access, etc. As a result, we are limited in our ability to draw strong inferences in this sample, but overall see little reason to think that remote work was protective for labor supply in India, in ways that it might have been in other countries.

Finally, we explore the distributional consequences COVID case exposure and amenability to remote work in Figure A11. Even areas with high COVID case counts see income protected more among the rich than the poor. By contrast, we observe substantial income decreases, even among the rich, among occupations that have the highest latent ability to work remotely in our sample. Overall, we see little evidence that labor supply is changing differentially for the risk as a function of these two cross-sectional predictors.