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Workers at Risk

Panel Data Evidence on the COVID-19 Labor Market Crisis in India

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Abstract

The COVID-19 pandemic is having unequal impacts. Research has highlighted that across race, gender, age, and income groups, the health and economic consequences of this crisis are far from uniform and other preexisting inequalities have been exacerbated. This paper focusses on the differential impact on the formal and informal segments of the labor market in India, using data from a large household panel survey and employing a difference-in-differences event study approach. Within the same industry and district, initially informal wage workers were significantly more vulnerable to the loss of employment than initially formal workers during the early phase of COVID-19 (April 2020). Furthermore, income declined significantly more for households whose head worked as an informal wage worker than for households with a formally employed head. However, the post-COVID employment and income differentials between informal and formal workers narrowed after April 2020. By July 2020, the decline in income (from the pre-COVID baseline of February 2020) was not significantly different across households with informally and formally employed heads, suggesting that while informal workers were affected more severely by the early COVID-19 shock, they also recovered faster from it.

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Workers at Risk: Panel Data Evidence on the COVID-19 Labor Market Crisis in India

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1 Introduction

There is growing concern over the vulnerability of informal workers, who number more than 1.6 billion worldwide, to the adverse labor market impacts of the COVID-19 crisis (World Bank, 2020; ILO 2020 a and b). Informal workers are not covered by formal employment protection laws and social insurance programs, and are concentrated in small and micro-sized firms, which have limited cash reserves for paying employees in the event of insufficient earnings. Informal workers may have limited access to relief measures introduced by governments in response to the COVID-19 crisis. It is also likely that they have a lower capacity to cope with this shock than formal workers do, owing to lower levels of savings and poorer access to credit.

This paper contributes to the knowledge base on the impact of the COVID-19 crisis on informal workers in developing economies by conducting a difference-in-difference event study analysis using a large, nationally representative panel dataset. Our setting is India, where informal employment comprises more than 85 percent of total employment, including those holding informal wage jobs – who are the main focus of this study – and those who are informally self-employed (World Bank, 2020). The Indian economy was hit hard by the onset of the pandemic and the stringent lockdown measures taken to control its spread, with quarterly GDP for the April to June period declining by 23.9 percent year-on-year, and the unemployment rate exceeding 23 percent in early April (Vyas, 2020).

We first document a sharp overall decline in employment by April 2020, following the imposition of a comprehensive national lockdown in late March that lasted until early May. Only 59 percent of those individuals who were employed in December 2019 were still employed as of April 2020. The magnitude of this decline in the employment rate is consistent with estimates reported in other recent studies on the impact of COVID-19 on India (e.g. Dhingra and Machin, 2020; Bertrand et al. 2020; Deshpande 2020; Lee et al., 2020). It is also a stark departure from pre-COVID times: for example, in contrast to the precipitous decline in the employment rate seen between December 2019 and April 2020, about 95 percent of those employed in August 2019 were still employed in December 2019.

Informal workers experienced a more severe shock than formal workers. Only 43 percent of those who were in informal jobs in December 2019 were still employed in April 2020. The corresponding employment retention rate among those initially in the formal sector was 72 percent. Furthermore, households headed by an informal wage worker experienced a significantly higher drop in per capita household income than those headed by formal wage workers.

When interpreting this observed differential labor market shock to informal wage workers, we need to consider the fact that the vulnerability of jobs to the COVID-19 pandemic and associated lockdown measures has varied across industries and occupations. For example, jobs involving tasks that are inherently less amenable to remote work have been more vulnerable during this crisis (Dingle and Neiman, 2020). Could it be that informal wage workers had more adverse outcomes than formal workers during the early COVID-19 period not because of their informal work status, but because they happen to be concentrated in more vulnerable industries or occupations?

To examine this question, we estimate the differential post-COVID shock between formal and informal wage workers in difference-in-difference event study regressions that control for shocks specific to industry, occupation and location (districts). The results indicate that some of the excess vulnerability of informal workers in the early phase of the COVID-19 crisis can be accounted for by the high vulnerability of the industries and occupations in which they are concentrated. Nevertheless, a significant portion of the differential between formal and informal workers persists in spite of the additional controls: for example, between December 2019 and April 2020, controlling for industry-wave and district-wave fixed effects, households headed by an informal wage worker experienced a 10 percentage points larger decline in per capita household income than those headed by a formal worker. This suggests that informal wage employment was inherently more vulnerable during the early COVID-19 shock.

Furthermore, even the self-employed fared better than informal wage workers in the early phase of the COVID-19 crisis. After controlling for industry-wave and district-wave fixed effects, there is no statistically discernible difference in the employment retention rates or incomes of the self-employed as compared to formal workers. Self-employment may also have served as a fallback for wage workers who lost jobs: both among those with formal and informal wage jobs in December 2019, about 18 percent were in self-employment by April 2020.

Strikingly, the differential labor market shock experienced by informal wage workers during the national lockdown did not persist for long. After April-May 2020, the labor market outcomes of informal workers began recovering towards their pre-COVID levels faster than did those of their formal counterparts. By August 2020, there was no longer a significant differential between informal and formal wage workers in terms of the decline in the employment rate or income from pre-COVID levels. In fact, controlling for industry-wave, occupation-wave, and location-wave fixed effects, the gap between the incomes of informal and formal-headed households was significantly *lower* by June 2020 than it used to be in the pre-COVID period. This suggests that informal workers were quick to catch up once the lockdown was lifted.

Our paper adds to the mounting global evidence that the labor market impacts of the COVID-19 crisis have been unequal. The crisis appears to have reduced employment and income disproportionately among less-educated or lower-wage workers (Adams-Prassl et al., 2020; Gulyas and Pytka 2020; Mattana et al 2020; Guven et al 2020; Kikuchi et al 2020), women (Deshpande 2020; Adams-Prassl et al., 2020; Kikuchi et al 2020; Abraham et al., 2020), migrants (Guven et al 2020; Gulyas and Pytka 2020) and more "contingent" workers (Kikuchi et al. 2020). As most of this evidence is from the context of high-income countries, a key contribution of our paper is to address the important dimension of informality in low- and middle-income countries.

In related work in the context of India, Lee et al. (2020) and Abraham et al. (2020) find that the crisis affected daily-wage workers (compared to workers with more permanent job contracts) more severely, and Dhingra and Machin (2020) find that workers with more guaranteed job tenure experienced relatively smaller declines in employment and earnings.[2] However, to our knowledge, our paper is the first to use nationally representative panel data to systemically explore differences in post-COVID outcomes between formal and informal workers.

Because our dataset spans a relatively long post-COVID period (up to December 2020 in the case of employment), we are also able to examine the trajectory of labor markets several months after the onset of the crisis and associated lockdown measures. In this sense, our paper echoes work on the United States by Lee et al. (2021), who find that while the early labor market impact of the

[2] Also in the context of India, Deshpande (2020) examines gender differentials in the impacts of COVID-19.

pandemic differed across gender, age and education, these differentials had disappeared by November 2020.

Our paper also contributes to the broader literature on how informality in the labor market affects the way in which economies respond to shocks. In particular, the more "elastic" response of informal wage employment that we observe could be related to the more contingent or flexible nature of informal employment relationships, as opposed to the more regulated and inflexible nature of formal employment. We are unable to test this hypothesis due to data limitations, but note that there is prior evidence that the employment protection provisions of India's industrial labor laws – which apply to formal ("permanent") workers— constrain employers from adjusting their formal workforce in response to local weather-related shocks (Adhvaryu et al. 2013) and shift the burden of adjustment to the informal ("temporary") workforce (Chaurey, 2015). A similar asymmetry in labor adjustment along formal and informal margins is possible in the face of macro shocks. For example, unemployment in European countries during the global economic crisis of 2007-11 was concentrated among temporary workers, and to a greater extent in countries with a greater stringency of employment protection laws for permanent workers relative to temporary workers (Sharma and Winkler, 2018; Bentolila et al., 2012). Relatedly, Alfaro et al. (2020) model the impact of the COVID crisis in economies with a prevalence of informality and small firms and use that to conduct a counterfactual analysis using pre-COVID data from Colombia and the United States. Their analysis, too, suggests that informal employment was at higher risk in the early stages of the crisis, due to the lack of employment protection and low cash reserves in small firms. But it may recover faster than formal employment because of its greater hiring and firing flexibility, and lower dependence on organizational and physical capital.

The idea that the informal sector can be both vulnerable and a source of resilience due to its greater flexibility is not new (Loayza and Rigolini, 2011). As such, our paper contributes to a long-standing debate on flexibility as a salient characteristic of informality (see, for example, Maloney 2004). Moreover, our finding that self-employment served as a buffer during the COVID-19 crisis adds to the literature on how poor households cope with large, aggregate shocks (e.g., McKenzie 2003; Skoufias, 2003).

We conclude the paper with two additional findings that are worth examining further in future research.

First, we find that the differential response of informal wage employment to the COVID-19 lockdown was primarily an urban occurrence. Both rural and urban areas witnessed a major labor market shock during the lockdown, with their unemployment rates crossing 20 percent in April and May 2020 (Vyas, 2020). But unlike urban areas, rural areas did not experience a statistically significant difference in the post-COVID trajectory of formal and informal workers. We confirm that this difference in how COVID-19 affected rural and urban labor markets is not because of their differing industrial and occupational profile. Unlike their urban counterparts, workers in rural areas have access to a jobs guarantee scheme, the Mahatma Gandhi National Rural Employment Guarantee Program (MGNREGA), which has cushioned rural job losses during the COVID-19 crisis (Afridi et al., 2021).[3] However, there was a lockdown on MGNREGA activities

[3] Azam (2012), Berg et al. (2012), Deininger and Liu (2019), Imbert & Papp (2015), Dutta et al. (2012) and Zimmermann (2015), among others, have examined the impact of the MGNREGA scheme on the labor market outcomes of rural workers, especially those who are unskilled and likely to be in casual wage jobs.

until April 20, 2020.[4] This suggests that the urban-rural difference in the impact of the lockdown shock in April reflects some other, unobserved urban-rural differences in labor market conditions or institutions.

Second, we present an intriguing inconsistency between the relative declines in income and consumption across households headed by informal and formal wage workers. In contrast to income, the percentage decline in per capita household consumption expenditure in the early phase of COVID-19 was significantly larger in households headed by formal workers (who tend to be richer), compared to those headed by informal workers. This inconsistency is puzzling in the light of standard theories of how household consumption responds to temporary income shocks. These theories predict that households will use their savings or borrow to smooth consumption intertemporally when their income drops temporarily. Formal households are expected to have better access to consumption smoothing mechanisms than informal households. Yet, the patterns we uncover suggest that it is the latter who were better able to smooth consumption during the early COVID-19 income shock.

While a full investigation of this issue is beyond the scope of this paper, we discuss some potential explanations. The first one relates to the fact that the lockdown shock did not just affect incomes, but also restricted consumption possibilities directly. Specifically, it could be that the lockdown imposed more restrictions on the consumption possibilities of richer, formal households because they consume disproportionately more "non-essential" items. The second explanation relates to a potential differential mismeasurement of real consumption: it could be that the prices of items consumed more intensively by informal households rose faster in the lockdown period, so that their real consumption fell relatively more than suggested by the drop in their nominal expenditures. A third explanation could be that formal households expected the initial COVID-19 income shock to last longer than informal households did, and consequently adjusted their consumption expenditure by a larger amount. This explanation is consistent with our observation that the incomes of households headed by informal workers have eventually recovered faster than those of households headed by a formal worker.

The rest of the paper is organized as follows. A brief timeline of the pandemic and lockdowns is summarized in section 2. Section 3 describes the data, the variables we use, and our sample. Section 4 presents some descriptive statistics. Section 5 introduces our empirical specification and section 6 concludes with the difference-indifferences event-study results.

2 Background: The onset of COVID-19 and the government response

The timeline of COVID-19 in India begins on January 30, 2020, when the first COVID-19 case was confirmed in the state of Kerala (Andrews et al., 2020). The number of daily new confirmed cases reached about 100 by March 30, 1,000 by April 15, 5,000 by May 20 and 10,000 by June 10.[5]

[4] Order No. 40-3/2020-DM-I(A) of the Ministry of Home Affairs, Government of India, allowed the state governments to lift lockdowns in certain types of activities including MNREGA employment.

[5] Johns Hopkins University CSSE COVID-19 Data.

The federal government announced a nationwide lockdown in late March, effective March 25 to April 14.[6] Although a stepwise, limited easing of lockdown conditions commenced in late April, the nationwide lockdown was ultimately extended until May 18. Even after the nationwide lockdown lapsed, many state governments continued to impose lockdowns until late July.

The first phase of the lockdown was among the most stringent in the world (Hall et al, 2020). Only "essential" businesses, such as banks, internet services and shops selling food were allowed to operate. All educational intuitions and non-essential public and private establishments were closed, including non-essential transport and hospitality establishments. Large gatherings were prohibited. In late April, the government announced some easing of restrictions in areas that had not yet experienced COVID-19 cases. For example, agricultural activities, rural public works and some industrial activities were permitted in these areas. By early May, districts were being categorized by the government as green, orange and red zones based on their COVID-19 risk profile, with restrictions on mobility and economic activity being kept the most stringent in red zones. In mid-May, the state governments were given more leeway in tailoring lockdown conditions. By late July, the lockdown restrictions were generally removed everywhere except in "containment" zones.

Indicators of mobility based on tracking smartphones indicate a sharp decline in mobility during the lockdown. For example, when the lockdown was implemented in late March, estimated presence at the workplace declined by 50-70 percent, while presence at residential places increased. Estimated presence at workplaces recovered partially by end-May, but is still a third below pre-COVID levels (Beyer et al. 2020).

3 Data

Our main dataset is the Consumer Pyramids Household Survey (CPHS), which is implemented by the Center for Monitoring the Indian Economy (CMIE). The CPHS is administered on a panel of over 170,000 households across India thrice a year. The survey is typically conducted face-to-face but owing to the COVID lockdown in India after the third week of March, the face-to-face interview format was replaced with a telephonic one, allowing CMIE to continue gathering data. The response rate in comparison to the planned execution during the lockdown was a little over 60 percent, compared to over 95 percent before the lockdown (Vyas 2020).

CMIE maintains that even with this reduced sample, their data is representative of the population across several dimensions. Notably, the rural-urban divide of the CPHS sample is typically about 37:63. In the first week of the lockdown (ending March 31), this shifted to 46:54 but was restored to pre-lockdown levels by week 3.

3.1 Sample selection

The full CPHS sample of over 170,000 households is surveyed over a four-month period, called a "wave", during which the survey team is continuously in the field. Each wave of the survey is representative of the Indian population. A new CPHS wave begins immediately after the previous

[6] MHA order No. 40–3/2020-DM-I(A).

ends, and every household in the panel is potentially re-surveyed at approximately four-month intervals.

Within a wave, the execution of the survey is planned such that the households surveyed during a month are well distributed over the country. In this sense, the set of households covered in one full month of the survey can be considered to be a representative subsample of the full panel. Every such monthly "cohort" reappears in the CPHS panel at four-month intervals.

India imposed its lockdown in the third week of March, which fell in the middle of wave 19 of the survey. To capture the impact of the COVID shock, we therefore focus our sample on the households that were interviewed in the month of April 2020, as part of wave 19. Previously, this set of households – the "April 2020 cohort" – had been interviewed in December 2019 (wave 18), August 2019 (wave 17), April 2019 (wave 16) and December 2018 (wave 15). Furthermore, the April 2020 cohort was re-interviewed in August 2020 (wave 20) and December 2020 (wave 21). Including only those households from the April 2020 cohort that responded to the survey in all these waves, we create a balanced panel of 14,695 individuals of working age (15 years of age or more) from 4,862 households from December 2018 to December 2020 (waves 15 to 21). Note that given the balanced rollout of the survey, this sample spans 28 states of India.

3.2 Variables

We use individual-level data on employment status, employment arrangement, district, industry, and occupation. A person is considered unemployed if she reports her employment status as "Unemployed, willing and looking for a job". She is characterized as out of the labor force if she reports her employment status as "Unemployed, not willing and not looking for a job" or "Unemployed, willing but not looking for a job".

CPHS asks individuals to report their employment status only for the current month. Hence, employment outcomes are observed at four-month intervals. Specifically, for our main panel of individuals, we observe employment outcomes for the pre-COVID months of December 2018 (wave 15), April 2019 (wave 16), August 2019 (wave 17) and December 2019 (wave 18), and the post-COVID months of April 2020 (wave 19), August 2020 (wave 20) and December 2020 (wave 21). Thus, for our analysis of employment, we use an individual-level panel of 14,695 persons which has a frequency of four months. Of these, 7,467 are unemployed or out of the labor force throughout the sample period. Our analysis is based on the remaining 7,182 individuals.

In contrast to the employment data, CPHS provides household income and consumption data at a monthly frequency. For example, households visited in April 2020 report income and consumption not just for April 2020 but also March, February and January 2020. Hence, we observe household income and consumption for each month. Therefore, for our analysis of income and consumption we use a monthly panel of 4,632 households from to October 2019 to August 2020.

CPHS records the employment arrangement of each employed individual which can be (1) permanent salaried, (2) temporary salaried, (3) self-employed, and (4) daily wage or casual. We define an individual to be informal if she is either a daily wage worker or a temporary salaried worker. Permanently salaried individuals are treated as formal workers.

We are interested in how the pandemic affected these different worker types differentially. We therefore focus on an individual's employment status in the last pre-pandemic wave of CPHS, i.e.

December 2019. The employment arrangement of an individual is defined as a time-invariant individual characteristic—fixed at its initial December 2019 level.[7] This allows us to study the differential labor market patterns among workers who were initially employed in the formal sector as opposed to initially self-employed or informal workers using difference-in-differences event study methodology. Similarly, for our income and consumption analysis, we categorize households as formal, informal, or self-employed based on the employment arrangement of the household's head.

Table 1 shows key summary statistics for each worker type in our balanced panel sample in the last pre-pandemic wave, i.e. December 2019.[8] While all worker categories have similar levels of employment, informal workers earn and consume a lot less than their formal and self-employed counterparts. The average per-capita household income of informal workers is less than half that of formal workers and their average per-capita consumption is only 62% that of formal households. Compared to formal workers, a larger share of informal workers (and self-employed counterparts) are rural. The share of females among informal workers is slightly higher than that among formal workers, though nearly twice that among the self-employed. Informal workers are the least educated of the three worker groups, with only 37 percent of them having passed high school as compared to 82 percent of formal workers and 55 percent of the self-employed. Informal workers are also significantly more likely than the other worker types to be employed in a high face-to-face contact intensity industry (80 percent, versus about 50% for the other two types). As such industries were inherently more vulnerable to the early COVID-19 shock, controlling for industry-specific shocks will be important to assess the relevance of informality in isolation from that of industry.

Table 1. Descriptive statics of outcome variables by worker type

	% Persons employed	*Per capita HH income (INR)*	*Per capita HH consumption (INR)*	*% Rural*	*% Women*	*% who have passed high school*	*% in high face-to-face industries*
Formal	79.01	10195	4879	17.2	17.9	82.5	49.3
Informal	72.98	4958	3015	28.8	20.8	36.6	79.1
Self-employed	76.61	7321	3640	30.2	10.5	55.3	50.0

Note: These statistics are based on a balanced sample of 7,467 individuals and 4,632 households in our 7-wave balanced panel. See section 3.1 for details of the sample. Passing high school refers to passing the grade 10 exams. High face-to-face industries are Communication, Post & Courier, Education, Entertainment and Sports, Hotels and Restaurants, Media and Publishing, Personal & Professional Services, Personal Non-Professional Services, Public Administrative Services, Retail Trade, Travel and Tourism, Wholesale Trade.

[7] If an individual was unemployed in December 2019, we do not observe her employment arrangement in wave 18. We then impute this variable according to the (last time in the past ten waves) that this person was employed. If the person is never employed in the past, we impute her December 2019 employment arrangement based on the next time the person becomes employed (i.e. in one of waves 19, 20, 21). If the person is neither employed before or after the wave 18, we treat her as unemployed and drop her from our estimation sample.

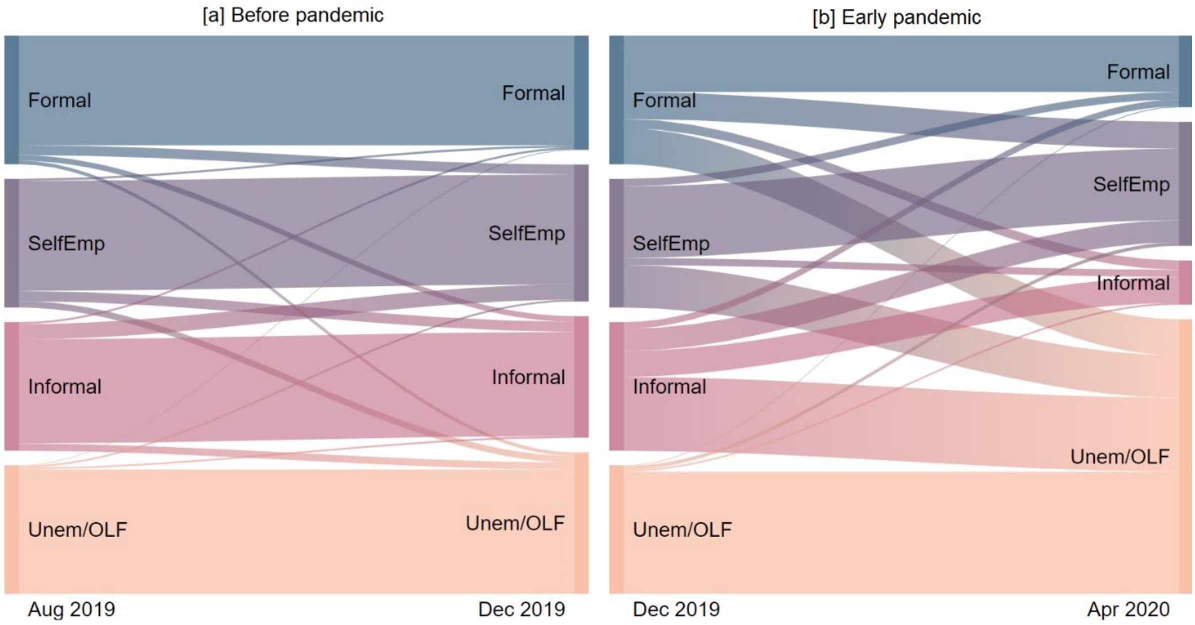
[8] Although the CPHS dataset contains survey weights to adjust for differences in sampling probabilities across the sample, we do not use them as they are designed to be applied to the full CPHS sample and are not appropriate for our balanced panel (which is a subset of the full sample). Hence, the summary statistics presented in this table may not be representative of the Indian population. For example, the unweighted balanced panel has an urban bias, with the share of rural workers being below 30%. This is because the CPHS oversamples urban areas.

4 Descriptive analysis

The unprecedented labor market shock from the onset of COVID-19 and the sudden imposition of a national lockdown in late March 2020 is evident in Figure 1, which presents employment transition estimated for two successive 4-month intervals using our panel of individuals.[9] The flows describe transitions of working age individuals across four labor market categories: formal wage employment, self-employment, informal wage employment, and unemployment/ being out of the labor force ("Unemp/OLF"). Panel (a) of Figure 1 corresponds to the pre-COVID August 2019-December 2019 period, while panel (b) presents transitions with a pre-COVID starting point (December 2019) and a post-lockdown ending point (April 2020). We use panel (a) as a benchmark of typical worker transitions against which to compare the post-pandemic churning in India's labor markets.

Overall, about 41 percent of those employed in December 2019 were unemployed or out of the labor force by April 2020. This is far higher than typical, pre-lockdown flows out of employment. For example, only about 5 percent of those employed in August 2019 were out of employment as of December 2019.

Figure 1. Labor market churning: before and during the lockdown



Note: This figure shows percent transition flows between successive survey waves among the four worker categories in the data. Panel (a) shows typical transition patterns before the pandemic-- between August and December 2019. Panel (b) shows transitions during the pandemic—from december 2019 to April 2020. See Table A1 in the appendix for the corresponding transition matrix.

Figure 1 also highlights that there was considerable heterogeneity in the COVID shock, with the likelihood of employment loss being higher among those initially working in the informal sector than those initially in formal jobs. Informal workers are also more vulnerable than the self-employed. Among those in informal jobs in December 2019, over 57 percent were not in employment by April 2020. Those initially self-employed in December 2019 had a 33 percent chance of not being in employment by April 2020, while those initially formally employed in December 2019 had a 28 percent chance of being unemployed/OLF by April 2020.

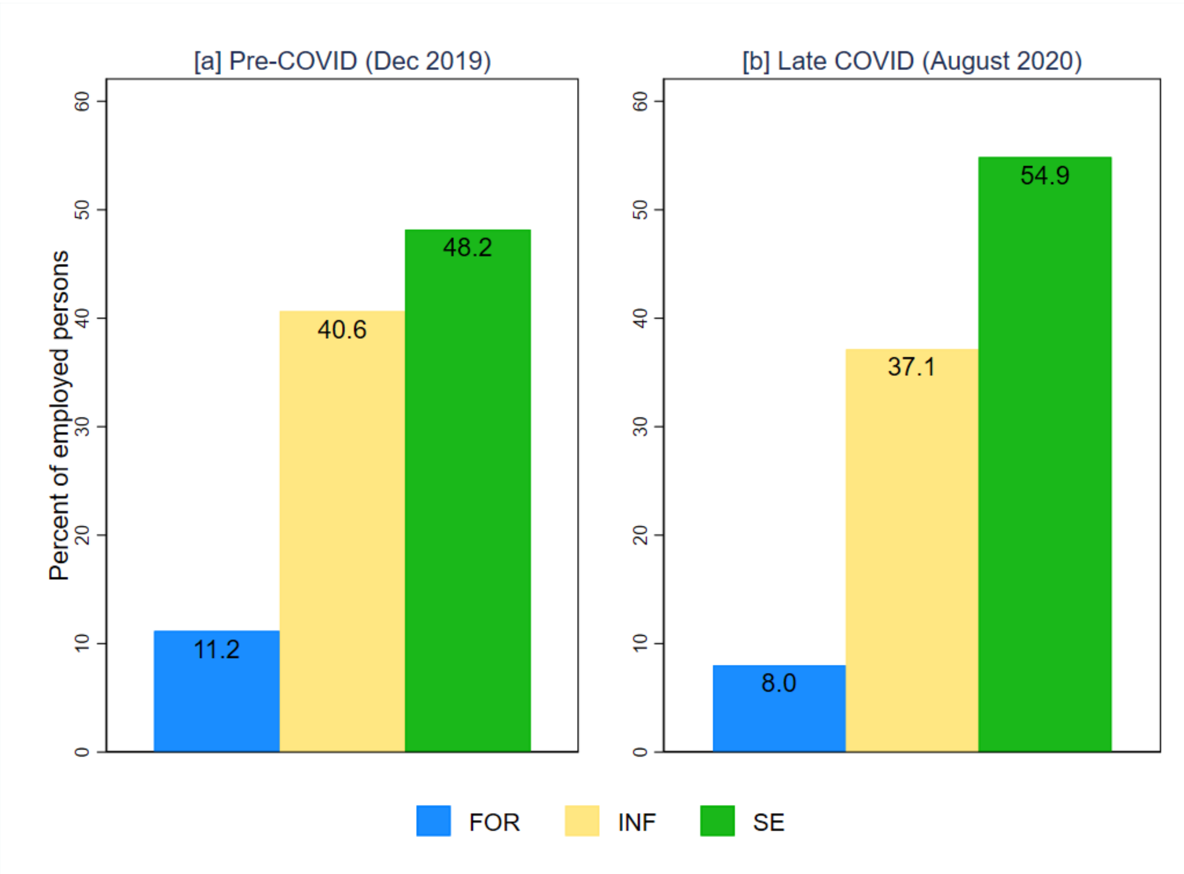
[9] See Table A1 in the appendix for the corresponding transition matrix.

As indicated by the pre-pandemic flows in panel (a) of Figure 1, transitions between formal and informal job categories are rare in normal times. In particular, only 1.6 percent of those in the informal sector move into the formal sector during a typical four-month interval. Thus, in normal times, informality is a persistent state for a worker and upward mobility is rare. This partly justifies treating informality as a pre-determined attribute in our analysis of the COVID shock, as discussed in Section 3.2.

After the lockdown, a strikingly large proportion of those initially working in the formal sector transitioned into the informal and self-employed sectors. In addition, an unusually large proportion of those initially employed in informal wage jobs transitioned into self-employment. Overall, both among those with formal and informal wage jobs in December 2019, about 18 percent were in self-employment by April 2020.

Transition matrices for the April 2020 to December 2020 period– not presented here for the sake of concision– show that there was a recovery in aggregate employment after May 2020. However, this aggregate recovery masks a continued churn across job categories. Individuals continued moving out of formal (or informal) wage jobs into self-employment at unusually high rates compared to pre-COVID times. In addition, an unusually large fraction of those who were either unemployed or out of the labor force in April 2020 but reported being employed by August 2020 had moved into self-employment, not wage jobs.

Figure 2. Cross-sectional breakdown of the labor market



Note: This figure shows the distribution of employed persons in formal jobs (FOR), informal jobs (INF), or self employment (SE). The data pertains to the full CPHS sample from waves 18 (panel [a]) and 20 (panel [b]).

As a result, by August 2020, six months into the COVID crisis in India, employment (as a share of the total working age population) had nearly recovered to its pre-COVID levels but its composition had shifted markedly towards self-employment (Figure 2). Expressed as a share of total employment, formal wage employment shrank by nearly 30 percent between December 2019 and August 2020. Informal wage employment too shrank marginally, while self-employment expanded from 48.2 percent of total employed persons in December 2019 to 55 percent of all employed persons in August 2020.

Post-COVID trends in per capita income largely mirror the trajectory of employment rates. Figure 3 compares the trajectory of per capita income across the formal and informal households in the panel dataset. We categorize households into formal wage, informal wage and self-employed based on the baseline (December 2019) employment status of the household head and estimate the mean per capita income (in logs) for each group in each month between July 2019 and August 2020. To facilitate the visualization of the differential income trends after COVID-19, the log mean per capita income of each group in February 2020– the last pre-COVID month– is normalized to 100. The charts also show the 95 percent confidence intervals for the estimated means.

Figure 3. Average per capita household income across worker groups (relative to February 2020)

Note: This figure shows mean levels of per capita household income (natural logarithm) by worker category. For ease of comparability, all group means are normalized to 100 in February 2020, which is used as a base as it was the last pre-pandemic month. 95% standard errors are reported in shaded areas around the group means.

Figure 3 demonstrates that while all three types of households on average experienced sharp drops in per capita income in April and May 2020, informal wage households were the worst-affected. The log mean per capita income of informal wage households declined by nearly 20 percent between February 2020 and April 2020. In comparison, the log mean per capita income of formal wage households and self-employed households declined by 10 percent between February 2020 and April 2020.

Incomes began to recover to their pre-COVID levels after May 2020. Significantly, mean per capita income rebounded to its pre-COVID level most rapidly for informal wage households. The differential between informal wage households and other types of households in the mean post-COVID income decline did not persist beyond May 2020.

5 Empirical specification: event study analysis

The formal approach we adopt to assess the differential impact of the COVID-19 crisis across groups of workers is that of a difference-in-difference event study panel regression. We use a multi-period specification for the employment regression as follows:

$$\begin{aligned} Employed_{it} &= \alpha\, WorkerCategory_i + \sum\nolimits_t \beta_t\ WAVE_t \\ &+ \sum\nolimits_{t,c} \gamma_{t,c}\, WorkerCategory_i \times\ WAVE_t + \sum\nolimits_{t,j} \lambda_{jt}\, (X_j\ \times\ WAVE_t) +\ \varepsilon_{it} \qquad (1) \end{aligned}$$

where the dependent variable is a dummy variable equal to 1 if the worker is employed and zero otherwise; $WorkerCategory_i$ is variable representing whether a worker is informal or self-employed (formal workers are the omitted category); $WAVE_t$ is dummy variables indicating each survey wave[10]; $\sum_{t,j} X_j\ \times\ WAVE_t$ are time interacted fixed effects: $State\ \times WAVE_t$, $Industry\ \times WAVE_t$, $Occupation\ \times WAVE_t$. These control for district-wave specific shocks like the incidence of COVID-19 and the intensity of lockdown measures in a district over time, and time varying shocks at the industry and occupation levels.

It is important to note that $WorkerCategory_i$ does not have a time subscript. We use a person's worker category as of December 2019 to define this time-invariant attribute. Therefore, the main coefficients of interest, γ's, capture the differential impact of the crisis on workers who were initially informal or self-employed relative to initially formal workers.

This specification is also used for the income and consumption regressions. However, since we observe income and consumption for each month, we use monthly time dummies instead of wave dummies as in equation (1).

The event study approach estimates the heterogenous impact of COVID on different worker categories for each time period. Thus, not only can we estimate the differential impact during the lockdowns, we can also see whether the recovery in later month differs across worker types. For

[10] Since we observe employment at four-month intervals, there is a one $WAVE_t$ dummy for every fourth months starting from December 2018 and ending December 2020.

all regressions, the last observed pre-COVID time period is the omitted time dummy so that all regression coefficients are scaled with reference to this base period. For employment regressions which are at four-monthly wave frequency, the base period is the 18th wave of the survey (ending December2019) and for monthly frequency regressions for income and consumption, the base period is February 2020.

Event study graphs also allow us to examine whether the parallel trends assumption holds for the dependent variable(s) before the shock. This flexible approach exploits the time dimension of the panel. The cost to restricting the sample to individuals who we repeatedly observe is a slightly reduced sample size of households. Our main results regarding the differential impact of COVID-19 are robust to using a two-period panel with a larger sample size.

6 Results

6.1 Impact of COVID on employment and income

The regressions confirm the descriptive analysis of section 4: the peak of the crisis in April 2020, coincides with the most stringent phase of India's lockdown. It caused a large loss of jobs and, most importantly, the probability of job loss was higher for the informal than the formal workers.

The regression estimates of equation (1) are presented in Table A2 of the appendix. Column 1 corresponds to a specification with only individual fixed effects. Columns 2, 3, and 4 successively add district-time, industry-time, and occupation-time fixed effects. Column (3), with individual, district-wave, and industry-wave fixed effects is our preferred specification.

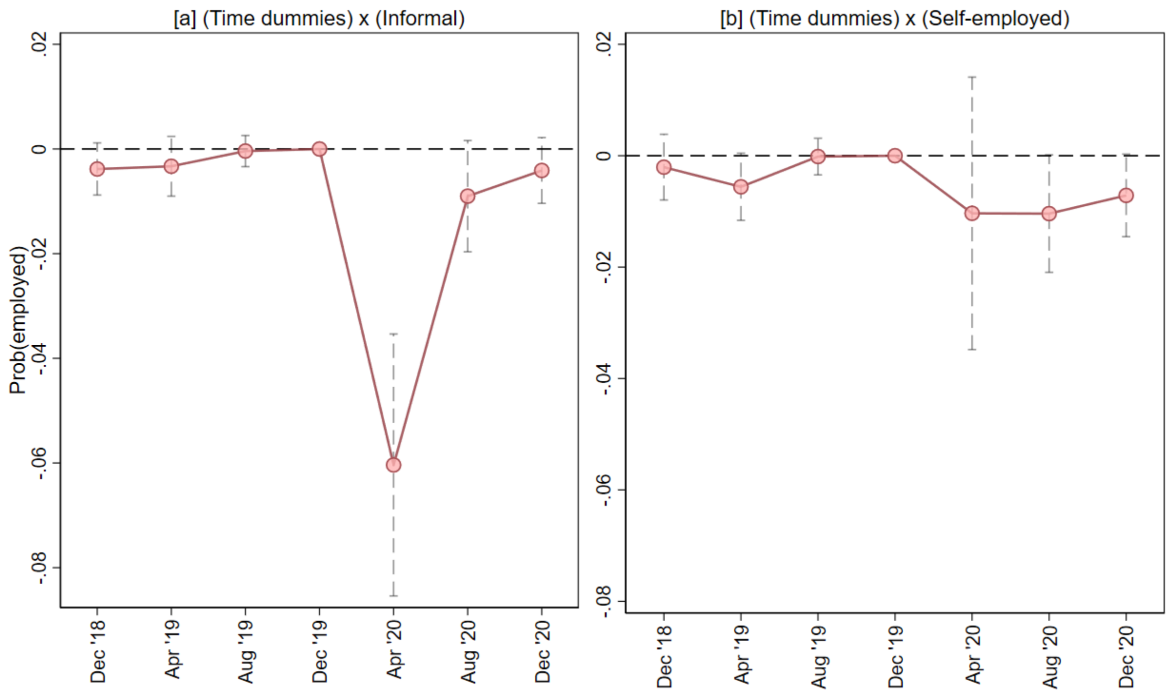
In the regression specification without any time-specific fixed effects (column 1), we can calculate that in April 2020 there is a sharp increase in the probability of job loss (and correspondingly a large reduction of the employment rate) for each employment group relative to December 2019. Since formal workers are the reference group, the decline for the formal workers corresponds to value of the $\beta_{Apr\ 2020}$ coefficient, which is 15 percentage points. The additional penalty for the informal (the value of the coefficient $\gamma_{Apr\ 2020}$) is of 21 percentage points which, when summed to the 15 percentage points, means that the total loss of employment for the informal workers is 36 percentage points.

The magnitude of the differential impact of the pandemic falls as we add more fixed effects in columns 2, 3, and 4 of Table A2 but remains statistically significant and economically large: informal workers are more vulnerable even after controlling for a variety of fixed effects. The initial difference of 21 pp is reduced to 19 pp when wave-district fixed effects are added as controls (column 2 in Table A2). These fixed effects control for factors such as the time-varying intensity of COVID-19 or the lockdown across Indian districts and also control for any district-time variation in the ability of local governments to contain the virus. A mere 2pp reduction indicates that these factors do not play a major role in explaining the vulnerability of informal jobs during the pandemic. The magnitude of the differential impact of the pandemic falls by over two-thirds, to 6 pp, when both industry-time and district-time fixed effects are controlled for (Table A2, column 3, also plotted in Figure 4 below), and to 3.4 pp when occupation-time and district-time fixed effects are controlled for (Table A2, column 4). This means that the COVID shock and informality are somewhat more intense in certain vulnerable industries and occupations. Controlling for these characteristics explains a significant but not all of the difference between informal and formal job vulnerability during the pandemic. Even within industries or occupations, being an informal worker is a significant disadvantage vis-à-vis a formal worker.

The insights from the regression analysis go beyond reproducing the patterns observed in the raw data. Figure 4 shows the values of the estimated $Inf \times \gamma_t$ and $SelfEmp \times \gamma_t$ coefficients (the differential impacts across employment categories) from our preferred specification (column (3), Table A2). Panel A of Figure 4 shows the differential impact of the pandemic on informal wage workers and an easy inspection of pre-trends in the outcome variable across informal and formal workers. The identifying assumption is that formal and informal workers were on parallel trends in employment outcomes prior to the pandemic in India and did not experience systematically different idiosyncratic shocks after the pandemic. The lack of pre-trends in Figure 4 confirm that this is a reasonable assumption.

Figure 4. Impact of the pandemic on the probability of being employed:

difference-in-differences event study



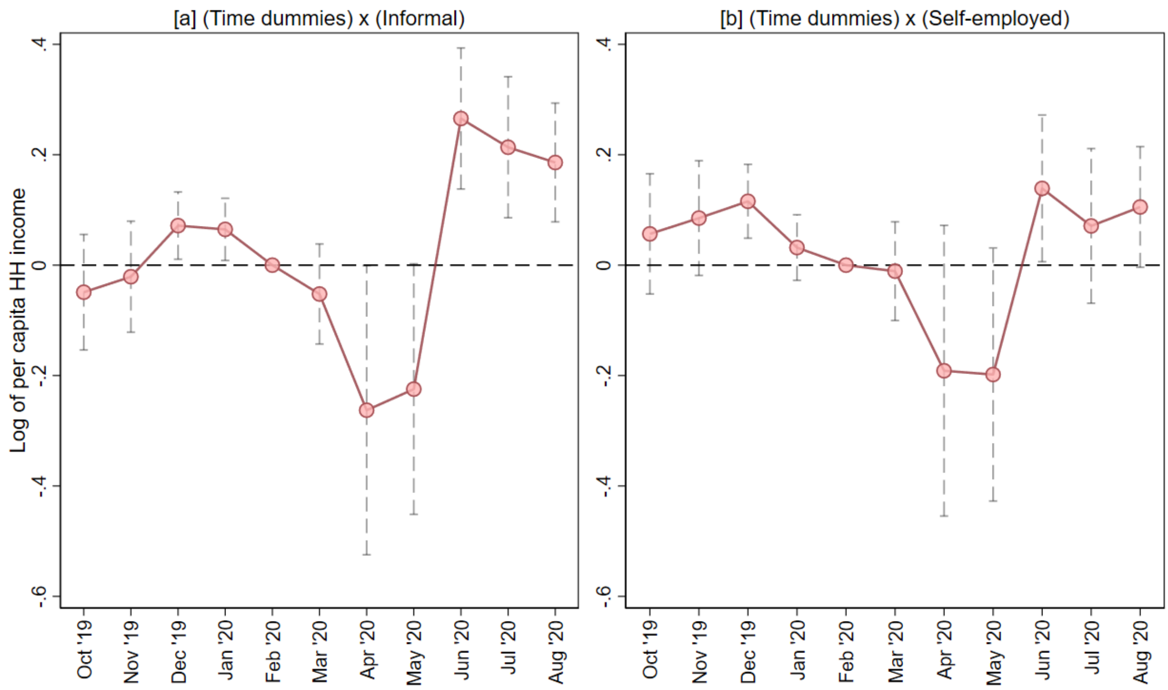
Note: Difference-in-difference estimates that include individual, district × wave, and industry × wave fixed effects. Informal and self-employed denotes employment status as of December2019. Standard errors are clustered at the individual level. N = 7,182 individuals.

Figure 4 also shows that the differential is eliminated almost completely during the recovery period—the point estimates for Augustand December2020 cannot be distinguished from zero. In other words, an informal worker, in comparison to a formal one, was exposed to a larger probability of losing employment during the peak of the crisis, but she was also able to return to employment during the recovery. By December 2020, her probability of employment was no less than her formal counterpart. This analysis cannot capture whether a worker regains the same job that she lost in April 2020. Indeed, a large part of the employment gain from June to December 2020 seems to be coming from new, self-employed jobs, as discussed in Section 4. So even though employment rates are close to their pre-COVID levels, the quality of this employment recovery may not be the same.

Panel B of Figure 4 displays the estimated differential impacts of the pandemic for self-employed individuals. The difference in the probability of job loss is much smaller, and in fact not statistically different from zero for the self-employed.

Estimates of equation (1) with per capita household income as the dependent variable are presented in Table A3 in the appendix. Figure 5 displays the estimated differential impacts for informal (Panel A) and self-employed (Panel B) households. As with the previous figure, the point estimates plotted in Figure 5 correspond to the regression specification with household, district-wave and industry-wave fixed effects (Table A3, column 3).

Figure 5. Impact of the pandemic on per-capita household income: difference-in-differences event study



Note: Difference-in-difference estimates that include household, district × month, and industry × month fixed effects. Informal and self-employed denotes employment status of the household head as of December2019. Standard errors are clustered at the household level. N = 4,623 households. The dependent variable is the log of total per capita household income.

Consider first the early COVID-19 period (until May 2020). Like employment, there is a large overall negative impact on per-capita household income, with an additional penalty for informal workers. Incomes of formal and informal workers fall by 59 percent and 78 percent in April 2020 as compared to their February 2020 levels (see column 1 of Table A3, which only controls for household fixed effects). This larger loss for informal households, as in the case of employment, is partly because informal workers are concentrated in industries and occupations that are more affected by the COVID crisis: the magnitude of the coefficient on Informal × April 2020 in column

3 of Table A3, which controls for industry-month and district-month fixed effects, is 40 percent as compared to its magnitude in column 1.

Largely, Figure 5 highlights the same set of points discussed for the case of employment[11]: relative to February 2020, the informal-formal income gap was zero before the crisis but rises dramatically in April and May 2020. Controlling for industry and occupation reduces the magnitude of this difference. Like employment, there is an equally sharp recovery in household incomes. In fact, informal households recovered faster than formal workers: controlling for district-wave and industry-wave fixed effects, the estimated informal-formal income difference in June, July and August 2020 (relative to February 2020) is *positive* and statistically significant. In other words, their income level relative to formal workers had improved from its pre-COVID baseline.

6.2 Rural-urban differences in the impact of COVID on formal and informal workers

Although rural and urban areas both experienced unprecedented employment loss in the early COVID-19 period, there is limited evidence on the differential incidence of the shock in rural versus urban areas. Regression analysis conducted separately on the rural and urban subsamples indicates that the observed differential impact of the COVID-19 shock on the informal sector was driven by urban areas.

First, consider how the estimated differential employment impact in urban areas mirrors that in the overall sample (Table A4 in the appendix). The regression specification without any wave-specific fixed effects (column 1) establishes a sharp increase in the probability of job loss in urban areas in April for each employment group relative to December 2019. The estimated decline for formal workers (the reference group) is 13 percentage points, with an additional decline of 26 percentage points for informal wage workers. This differential is no longer significant by August and December 2020. This is robust to including wave-specific industry, occupation and district effects.

The income impact in urban areas too is similar to that observed in the overall sample (Table A5 in the appendix). Relative to February 2020, the estimated difference in the per capita income of

[11] An important caveat must be mentioned here. Since we do not have individual level data on incomes, we need to use household level per capita income levels and use the household head informality or formality status to classify the household per capita income as informal or formal. In this way, we ignore the composition of the household. This could lead to an underestimation of the differential. Imagine for simplicity that each household has exactly 2 working age members, whose baseline formal (F) or informal (NF) status is observed. So, there are 4 types of households based on the baseline status of the head and the non-head. Let's denote each type by a "pair" dummy where the first term denotes the head's status and the second term the non-head's: (NF,NF), (NF,F), (F,NF) and (F,F). One then could run a household level regression of income where the regressors include interactions of time with all four of these dummies. We know from the individual regression on employment that households with the greatest number of informal members were hit hardest in the crisis, so we expect the coefficient on Time X (NF, NF) to be the most negative, and that on Time X (F,F) to be the least negative. The other two are in between as they are "mixed households". In our current specification, where we ignore the non-head, our coefficient on Post X NF is actual a mixture of Time X (NF,NF) and Time X (NF, F). In this sense we might be "underestimating" the impact of informality, if we claim that Post X NF is equivalent to Post X (NF, NF). To the extent that there are some mixed households, in ignoring the non-head, we likely bias the estimated differential between formal and informal workers down (only in the sense that we do not measure the difference between the two polar cases of NF,NF and F,F). Estimations with this more elaborate regression are available upon request.

households headed by informal and formal wage workers is significantly negative in April and May 2020, and significantly positive in June-August 2020.

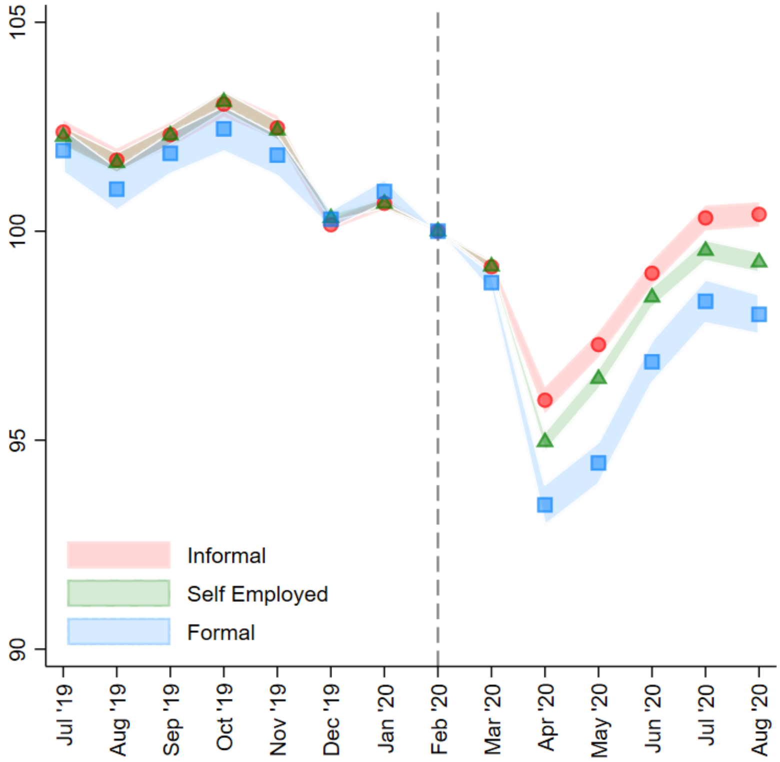
In rural areas, too, there was a sharp increase in the probability of job loss in April 2020: the decline for the reference group is estimated to be 26 percentage points (Table A6, column 1). But in this case, the differential between informal and formal wage workers (as well as the self-employed) is statistically not significant. Moreover, relative to February 2020, the estimated difference in the per capita income of households headed by informal and formal wage workers is significantly positive in April 2020 and insignificant in May 2020 (Table A7). These regressions suggest that in rural areas, formal and informal workers were equally vulnerable to the early COVID-19 shock.

There is evidence that India's flagship rural jobs guarantee program (MNREGA) has cushioned the impact of COVID-19 in rural areas (Afridi et al. 2021). But given that there was a lockdown on MGNREGA activities until at least 20th April 2020, it is unlikely that MNREGA alone explains why there was no differential job loss between formal and informal workers in rural areas in April 2020. Future research should look into why formal jobs were just as vulnerable as informal jobs to the early COVID-19 shock in rural areas.

6.3 Impact of COVID on consumption

The CMIE survey also collects panel data on consumption, which we use to estimate the impact of the COVID crisis on welfare. Figure 6 shows the evolution of consumption per capita before, during and after the COVID crisis, using the same approach as that adopted for income in

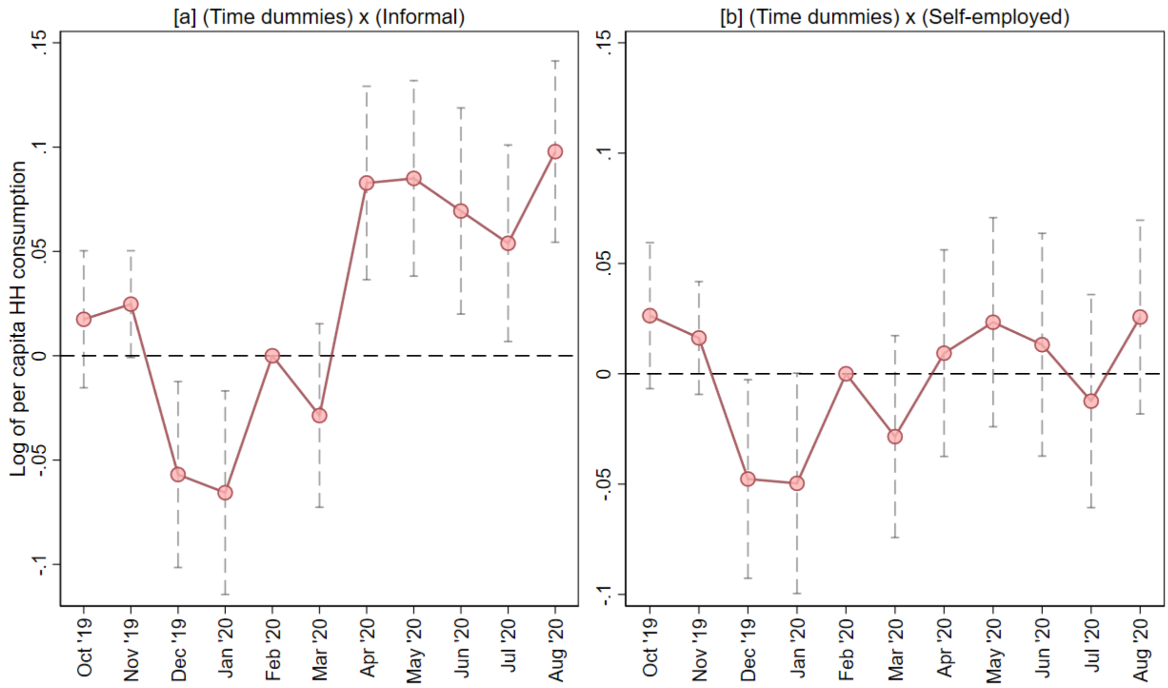
Figure 6. Average per capita household consumption across worker groups (relative to February 2020)



Note: This figure shows mean levels of per capita household consumption (natural logarithm) by worker category. For ease of comparability, all group means are normalized to 100 in February 2020, which is used as a base as it was the last pre-pandemic month. 95% standard errors are reported in shaded areas around the group means.

Figure 3. Specifically, total households' consumption is divided by household size to calculate per capita individual consumption and households are classified into the three worker categories based on the employment status of the household head in December2019. The log per capita consumption of each group in February 2020 is normalized to 100 and the 95 percent confidence intervals for the log per capita consumption are represented in the figure by the shaded bands.

Figure 7. Impact of the pandemic on per-capita household consumption: difference-in-differences event study



Note: Difference-in-difference estimates that include household, district × wave, and industry × wave fixed effects. Informal and self-employed denotes employment status of the household head as of December2019. Standard errors are clustered at the household level. N = 4,623 individuals. The dependent variable is the log of total per capita household consumption.

As in the case of income per capita, for all categories of workers, consumption is severely reduced in the months of maximum restrictions linked to the COVID pandemic. However, this graph also uncovers an interesting puzzle: why do informal workers, who were exposed to larger job and income losses vis-à-vis formal ones, reduce their consumption to a lesser extent? This lower reduction is also confirmed by estimating equation (1) with log of per capita consumption as the dependent variable. The results are presented in Table A8 in the appendix and in Figure 7, which plots the interaction of time dummies with worker category indicators from column 3 of Table A8.

The key message of Figure 7 is that there is a positive, statistically significant consumption differential for the informal workers after March 2020 and a similar effect (although not statistically significant) for the self-employed. In percentage terms, and without controlling for time-specific fixed effects, the reduction in consumption in April 2020 with respect to Feb 2020 is about 64 percent for formal workers but only 45 percent for informal workers. Some of this differential is accounted for by industry-month and district-month fixed effects: the magnitude of the coefficient on Informal × April 2020 in Table A8, column 3 is 40 percent its magnitude in column 1.

However, even within the same industry, occupation and district, and despite larger income losses, informal workers are affected by a smaller reduction of their consumption relative to that of their formal counterparts. Three possible mechanisms can explain this puzzle: a) "forced" savings; b) differential price changes; c) differential adjustment to the crisis. Let's consider them in turn.

First, the COVID economic crisis is not just an employment/income shock to households but also a goods and services supply shock. Some people, even if their income has not decreased much, may be prevented from consuming certain items because some shops and services are either closed or people wish to maintain voluntary social distance. The data shows that not only are formal incomes higher than informal incomes, but also the composition of the consumption of formal workers is quite different from that of their informal counterparts. Formal workers devote a much higher share of total consumption to non-food items and, specifically, to services such as restaurants and other recreational services which were not available during the lockdown. The unavailability of these services may have forced formal households to save a larger part of their income than they typically do.

In fact, preliminary evidence of this forced saving effect can be seen in Figure A-1 in the appendix. The figure plots log of per capita income and consumption between July 2019 and August2020 for households in different transition groups. The transition groups are defined according to the employment status (formal, informal, self-employed and unemployed/OLF) in December2019 and August2020. So, for instance, the top left corner plots consumption income for households who were formal in December2019 and remain in formal employment even in August 2020. This graph shows that for this specific formal-formal group, income is quite smooth while its consumption contracts during the peak of the crisis (April-May 2020), forcing these households to save a large part of their monthly income. On the other hand, the informal-informal group shows the more common case of consumption smoothing (dissaving) where income is falling but consumption does not.

Second, our analysis has been carried out in current prices. Suppose that the prices of food items have been affected by the crisis and increased more than prices for other goods and services. To the extent that informal households, who tend to be poorer, spend a greater portion of their income on food items, the decline in real consumption would be greater among them. If the analysis were carried out in constant prices, then with higher food inflation, and a larger food consumption shares, informal workers may indeed be worse off than formal workers. In fact, there is also evidence for this mechanism being at work as food prices did indeed increase more rapidly than non-food prices during the crisis (see figure A2).

Finally, formal workers may have adjusted their expected permanent income more than informal workers in the aftermath of the lockdown shock. Since consumption adjustment should be driven by changes in expected permanent income, this could solve the puzzle. A larger adjustment to the permanent income for formal workers can be explained by the difficulty of getting a job in the formal sector. Thus, losing such a job may be considered a more permanent loss than losing an informal job. Our finding that the incomes of informal workers have recovered faster than those of formal workers since May 2020 are in line with this hypothesis.

The dichotomy in the differential trajectories of consumption and income has significant policy relevance because of what it may imply for the welfare impacts of the early COVID-19 crisis. For example, to the extent that this inconsistency is explained by a differential price increase for poorer, informal individuals, the welfare impact on those individuals may have been worse than that suggested by the decline in their nominal incomes. The dichotomy may also have a bearing on the expected economic recovery from the COVID-19 crisis. For example, we would expect a relatively rapid recovery in consumption demand among richer households if the differential decline in their consumption during the lockdown was due to forced saving. In comparison, consumption demand might recover slowly if the differential decline in consumption among richer households was due to a larger downward revision in their expected lifetime income. A more in-depth analysis of these mechanisms and their policy implications is planned for future research

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Appendix

Figure A1: Per capita total household income and consumption by transition category

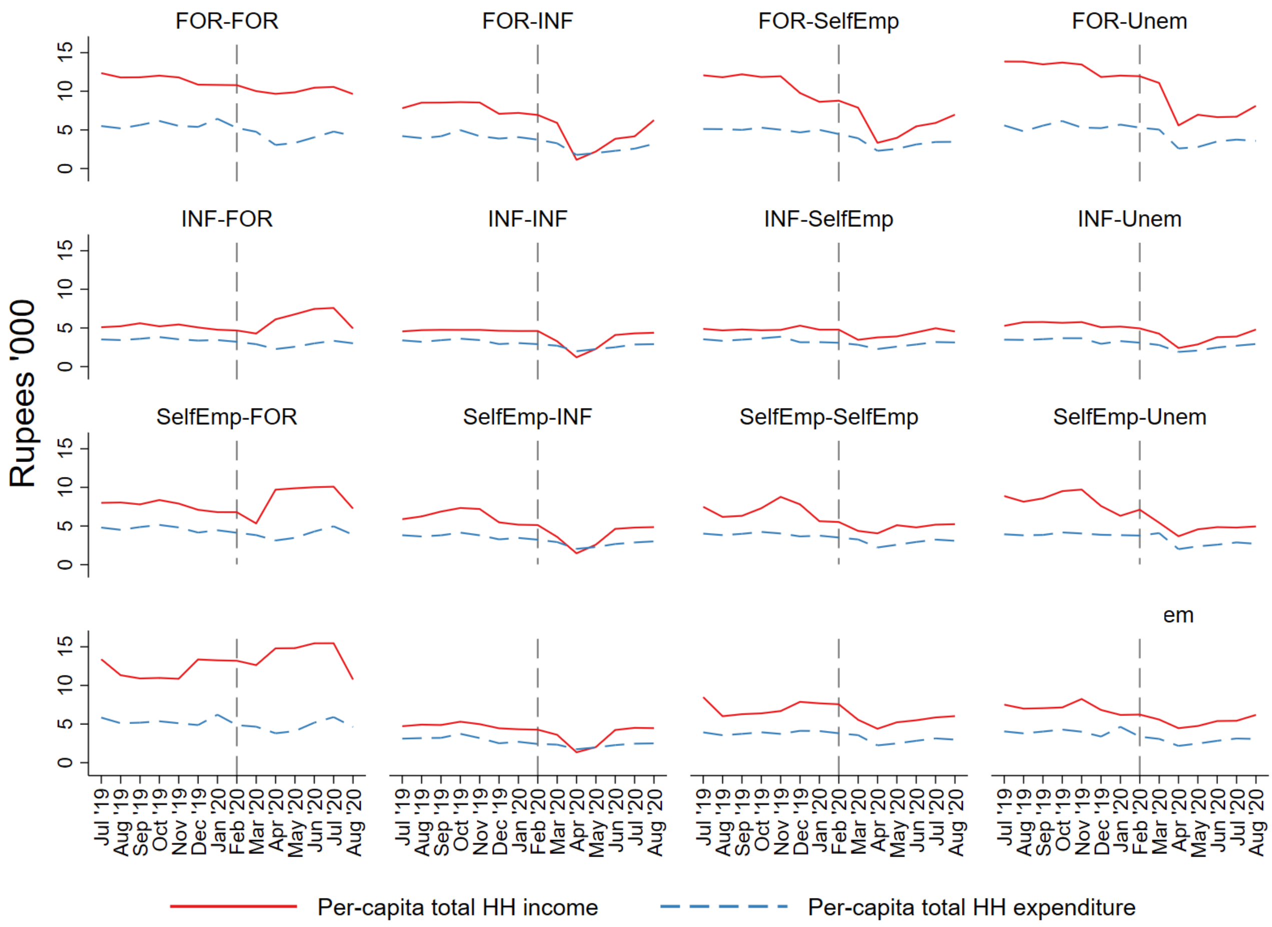

Figure A2: CPI Inflation for various categories

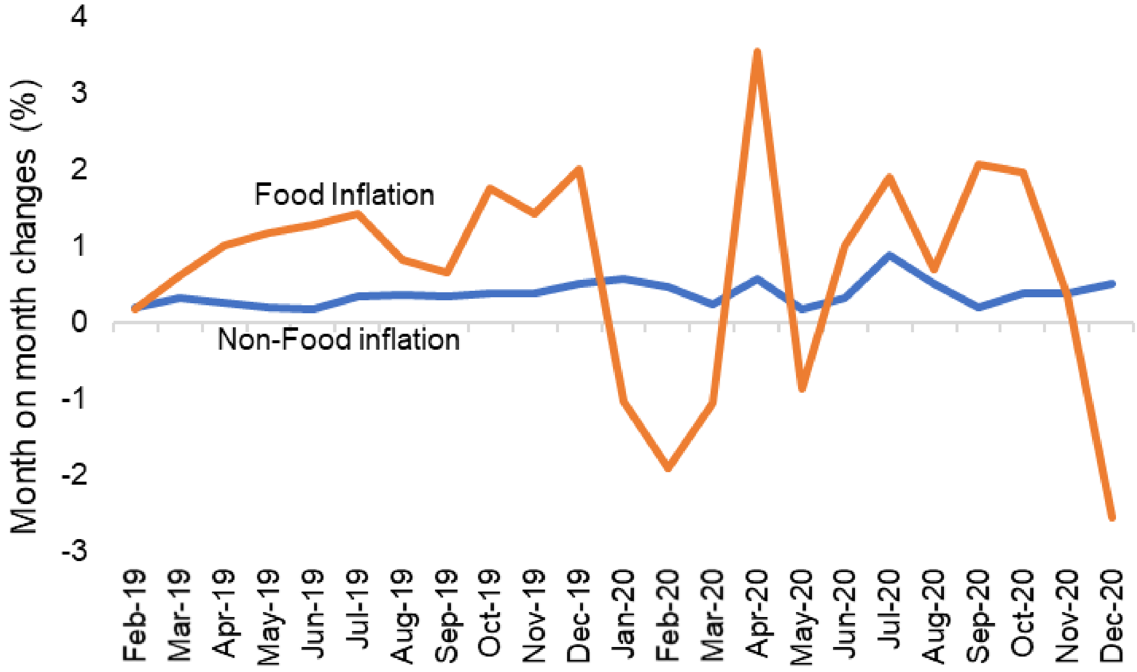

Table A1: Transition matrices for labor market churning before and after the pandemic

	Dec 2019 - Apr 2020				Dec 2019 - Apr 2020			
	FOR	SE	INF	Unem	FOR	SE	INF	Unem
FOR	85.14	7.67	4.38	2.8	43.79	20.91	7.26	28.04
SE	1.63	85.49	7.81	5.08	5.89	55.58	5.5	33.03
INF	1.63	11.89	80.91	5.57	5.23	17.19	20.18	57.4
Unem	0.43	1.49	1.44	96.64	0.7	2.78	1.44	95.07

Table A2: Impact of COVID-19 on Employment: DID estimates (All India)

	(1)	(2)	(3)	(4)
Dec'18	-0.0058			
	(0.011)			
Apr 19	0.00066			
	(0.0096)			
Aug'19	-0.017**			
	(0.0077)			
Apr 20	-0.15***			
	(0.016)			
Aug'20	-0.055***			
	(0.012)			
Dec'20	-0.063***			
	(0.013)			
Inf × Dec'18	-0.027*	-0.021	-0.0038	-0.0014
	(0.014)	(0.014)	(0.0025)	(0.0031)
Inf × Apr 19	-0.014	-0.015	-0.0033	-0.00084
	(0.012)	(0.012)	(0.0029)	(0.0033)
Inf × Aug'19	0.0091	0.0052	-0.00040	0.00027
	(0.0096)	(0.010)	(0.0015)	(0.0023)
Inf × Apr 20	-0.21***	-0.19***	-0.060***	-0.034***
	(0.020)	(0.021)	(0.013)	(0.012)
Inf × Aug'20	0.011	0.012	-0.0090*	-0.0084
	(0.015)	(0.016)	(0.0054)	(0.0056)
Inf × Dec'20	0.0035	0.014	-0.0041	-0.0036
	(0.015)	(0.016)	(0.0032)	(0.0037)
SelfEmp × Dec'18	0.0031	0.0053	-0.0021	-0.0015
	(0.013)	(0.013)	(0.0030)	(0.0046)
SelfEmp × Apr 19	-0.0056	-0.0091	-0.0056*	-0.0052
	(0.011)	(0.011)	(0.0031)	(0.0044)
SelfEmp × Aug'19	0.013	0.0071	-0.00015	-0.0027
	(0.0091)	(0.0092)	(0.0017)	(0.0029)
SelfEmp × Apr 20	-0.032*	-0.046**	-0.010	-0.027**
	(0.019)	(0.019)	(0.012)	(0.012)
SelfEmp × Aug'20	0.034**	0.026*	-0.010*	-0.015**
	(0.014)	(0.015)	(0.0054)	(0.0061)
SelfEmp × Dec'20	0.037**	0.042***	-0.0071*	-0.0090*
	(0.014)	(0.015)	(0.0038)	(0.0049)
Individual FE	Yes	Yes	Yes	Yes
District × Wave FE	No	Yes	Yes	Yes
Industry × Wave FE	No	No	Yes	No
Occupation × Wave FE	No	No	No	Yes
Observations	50165	50151	50148	50151

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis are clustered at the individual level. The dependent variable is an indicator variable that takes value 1 if the individual is employed and zero otherwise. Inf and SelfEmp denoteemployment status as of Dec 2019. This regression is run on All India sample.

Table A3: Impact of COVID-19 on Total HH income: DID estimates (All India)

	(1)	(2)	(3)	(4)	(5)
Oct’19	0.29***				
	(0.033)				
Nov’19	0.29***				
	(0.032)				
Dec’19	0.048***				
	(0.017)				
Jan’20	-0.0021				
	(0.021)				
Mar’20	-0.19***				
	(0.031)				
Apr’20	-0.90***				
	(0.075)				
May’20	-0.61***				
	(0.062)				
Jun’20	-0.28***				
	(0.042)				
Jul’20	-0.19***				
	(0.040)				
Aug’20	-0.14***				
	(0.037)				
Inf × Oct’19	-0.20***	-0.17***	-0.049	-0.062	-0.090*
	(0.038)	(0.040)	(0.053)	(0.054)	(0.051)
Inf × Nov’19	-0.18***	-0.21***	-0.021	-0.043	-0.080
	(0.036)	(0.039)	(0.051)	(0.051)	(0.049)
Inf × Dec’19	0.0096	0.010	0.072**	0.052**	0.035
	(0.021)	(0.024)	(0.031)	(0.023)	(0.029)
Inf × Jan’20	0.0065	0.030	0.065**	0.017	0.024
	(0.024)	(0.024)	(0.029)	(0.035)	(0.026)
Inf × Mar’20	-0.18***	-0.21***	-0.052	-0.063	-0.055
	(0.036)	(0.035)	(0.046)	(0.050)	(0.046)
Inf × Apr’20	-0.63***	-0.48***	-0.26**	-0.33**	-0.42***
	(0.093)	(0.095)	(0.13)	(0.14)	(0.14)
Inf × May’20	-0.31***	-0.40***	-0.22*	-0.28**	-0.14
	(0.078)	(0.082)	(0.12)	(0.12)	(0.12)
Inf × Jun’20	0.18***	0.20***	0.27***	0.18***	0.23***
	(0.048)	(0.049)	(0.065)	(0.067)	(0.066)
Inf × Jul’20	0.17***	0.16***	0.21***	0.13**	0.20***
	(0.046)	(0.048)	(0.065)	(0.058)	(0.063)
Inf × Aug’20	0.100**	0.17***	0.19***	0.15**	0.083
	(0.042)	(0.046)	(0.055)	(0.062)	(0.056)
SelfEmp × Oct’19	-0.076*	-0.077*	0.057	0.18**	0.055
	(0.041)	(0.041)	(0.056)	(0.076)	(0.053)
SelfEmp × Nov’19	0.013	-0.036	0.085	0.18**	0.090*
	(0.040)	(0.039)	(0.053)	(0.076)	(0.053)
SelfEmp × Dec’19	0.13***	0.091***	0.12***	0.15***	0.11***
	(0.025)	(0.024)	(0.034)	(0.041)	(0.034)
SelfEmp × Jan’20	-0.019	0.016	0.032	0.020	-0.013
	(0.026)	(0.026)	(0.030)	(0.043)	(0.028)
SelfEmp × Mar’20	-0.11***	-0.12***	-0.011	0.016	-0.014
	(0.037)	(0.034)	(0.046)	(0.060)	(0.047)
SelfEmp × Apr’20	-0.12	-0.12	-0.19	-0.092	-0.19
	(0.088)	(0.088)	(0.13)	(0.17)	(0.14)
SelfEmp × May’20	-0.029	-0.13*	-0.20*	-0.22	-0.14
	(0.075)	(0.076)	(0.12)	(0.15)	(0.13)
SelfEmp × Jun’20	0.16***	0.16***	0.14**	0.11	0.15**
	(0.048)	(0.048)	(0.068)	(0.092)	(0.069)
SelfEmp × Jul’20	0.12***	0.11**	0.071	0.070	0.085
	(0.047)	(0.048)	(0.071)	(0.086)	(0.069)

Table A3 (cont.): Impact of COVID-19 on Total HH income: DID estimates (All India)

	(1)	(2)	(3)	(4)	(5)
SelfEmp × Aug'20	0.072	0.11**	0.11*	0.15*	0.041
	(0.044)	(0.045)	(0.056)	(0.081)	(0.057)
HH FE	Yes	Yes	Yes	Yes	Yes
District × Month FE	No	Yes	Yes	Yes	No
Industry × Month FE	No	No	Yes	No	Yes
Occupation × Month FE	No	No	No	Yes	No
Observations	43810	43744	43742	43744	43808

Standard errors clustered at the HH level. Dependent variable: log of total HH income. Also see notes of Table A2

Table A4: Impact of COVID-19 on Employment: DID estimates (Urban)

	(1)	(2)	(3)	(4)
Dec'18	-0.0047			
	(0.012)			
Apr 19	-0.0015			
	(0.011)			
Aug'19	-0.013			
	(0.0084)			
Apr 20	-0.13***			
	(0.018)			
Aug'20	-0.048***			
	(0.014)			
Dec'20	-0.061***			
	(0.014)			
Inf × Dec'18	-0.031**	-0.029*	-0.0032	0.00014
	(0.015)	(0.016)	(0.0028)	(0.0036)
Inf × Apr 19	-0.019	-0.022	-0.0017	0.00069
	(0.013)	(0.014)	(0.0028)	(0.0034)
Inf × Aug'19	-0.00089	-0.0055	0.00062	0.0012
	(0.011)	(0.012)	(0.0017)	(0.0027)
Inf × Apr 20	-0.26***	-0.24***	-0.070***	-0.048***
	(0.022)	(0.023)	(0.014)	(0.013)
Inf × Aug'20	-0.0011	-0.0088	-0.0066	-0.0057
	(0.017)	(0.018)	(0.0064)	(0.0066)
Inf × Dec'20	-0.0020	-0.00100	-0.0028	-0.0015
	(0.017)	(0.018)	(0.0037)	(0.0044)
SelfEmp × Dec'18	0.0052	0.0066	-0.0031	-0.0016
	(0.014)	(0.015)	(0.0037)	(0.0056)
SelfEmp × Apr 19	-0.0034	-0.0076	-0.0056*	-0.0056
	(0.012)	(0.013)	(0.0034)	(0.0053)
SelfEmp × Aug'19	0.010	0.0045	0.000039	-0.0032
	(0.010)	(0.010)	(0.0019)	(0.0035)
SelfEmp × Apr 20	-0.083***	-0.083***	-0.022	-0.028**
	(0.021)	(0.021)	(0.014)	(0.013)
SelfEmp × Aug'20	0.030*	0.023	-0.013**	-0.017**
	(0.016)	(0.017)	(0.0064)	(0.0074)
SelfEmp × Dec'20	0.032*	0.037**	-0.0090**	-0.011*
	(0.017)	(0.017)	(0.0043)	(0.0060)
Individual FE	Yes	Yes	Yes	Yes
District × Wave FE	No	Yes	Yes	Yes
Industry × Wave FE	No	No	Yes	No
Occupation × Wave FE	No	No	No	Yes
Observations	36242	36242	36237	36242

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis are clustered at the individual level. The dependent variable is an indicator variable that takes value 1 if the individual is employed and zero otherwise. Inf and SelfEmp denoteemployment status as of Dec 2019. This regression is run on Urban sample.

Table A5: Impact of COVID-19 on Total HH income: DID estimates (Urban)

	(1)	(2)	(3)	(4)	(5)
Oct'19	0.24***				
	(0.034)				
Nov'19	0.25***				
	(0.032)				
Dec'19	0.0097*				
	(0.0059)				
Jan'20	0.014				
	(0.014)				
Mar'20	-0.16***				
	(0.028)				
Apr'20	-0.96***				
	(0.082)				
May'20	-0.65***				
	(0.068)				
Jun'20	-0.28***				
	(0.043)				
Jul'20	-0.19***				
	(0.042)				
Aug'20	-0.16***				
	(0.037)				
Inf × Oct'19	-0.18***	-0.17***	-0.054	-0.066	-0.087
	(0.040)	(0.042)	(0.059)	(0.060)	(0.057)
Inf × Nov'19	-0.16***	-0.20***	-0.056	-0.068	-0.071
	(0.037)	(0.039)	(0.056)	(0.054)	(0.055)
Inf × Dec'19	0.020*	0.0081	0.037	0.015	0.036
	(0.010)	(0.012)	(0.027)	(0.016)	(0.026)
Inf × Jan'20	0.020	0.013	0.036	0.014	0.030
	(0.016)	(0.019)	(0.024)	(0.016)	(0.020)
Inf × Mar'20	-0.22***	-0.26***	-0.12**	-0.12**	-0.092*
	(0.035)	(0.035)	(0.050)	(0.047)	(0.049)
Inf × Apr'20	-0.75***	-0.65***	-0.46***	-0.50***	-0.52***
	(0.11)	(0.11)	(0.15)	(0.15)	(0.16)
Inf × May'20	-0.45***	-0.47***	-0.30**	-0.35**	-0.18
	(0.090)	(0.091)	(0.13)	(0.14)	(0.14)
Inf × Jun'20	0.21***	0.21***	0.26***	0.20***	0.25***
	(0.049)	(0.051)	(0.068)	(0.068)	(0.068)
Inf × Jul'20	0.17***	0.15***	0.19***	0.13**	0.19***
	(0.048)	(0.049)	(0.068)	(0.058)	(0.067)
Inf ×Aug'20	0.16***	0.16***	0.17***	0.11*	0.15***
	(0.043)	(0.044)	(0.057)	(0.058)	(0.055)
SelfEmp × Oct'19	-0.051	-0.065	0.085	0.19**	0.095
	(0.041)	(0.042)	(0.060)	(0.083)	(0.059)
SelfEmp × Nov'19	-0.010	-0.035	0.089	0.14*	0.086
	(0.039)	(0.038)	(0.058)	(0.081)	(0.058)
SelfEmp × Dec'19	0.053***	0.041***	0.049	0.033	0.059*
	(0.016)	(0.014)	(0.032)	(0.030)	(0.033)
SelfEmp × Jan'20	0.020	0.023	0.042	0.027	0.027
	(0.018)	(0.022)	(0.026)	(0.029)	(0.023)
SelfEmp × Mar'20	-0.17***	-0.20***	-0.065	-0.077	-0.045
	(0.034)	(0.033)	(0.049)	(0.057)	(0.050)
SelfEmp × Apr'20	-0.23**	-0.24**	-0.34**	-0.36*	-0.28*
	(0.099)	(0.098)	(0.15)	(0.19)	(0.16)
SelfEmp ×May'20	-0.27***	-0.26***	-0.32**	-0.40**	-0.29**
	(0.084)	(0.084)	(0.13)	(0.17)	(0.15)
SelfEmp ×Jun'20	0.19***	0.19***	0.16**	0.14	0.16**
	(0.050)	(0.049)	(0.071)	(0.093)	(0.071)
SelfEmp × Jul'20	0.15***	0.13***	0.077	0.070	0.083
	(0.049)	(0.049)	(0.075)	(0.087)	(0.075)

Table A5 (cont): Impact of COVID-19 on Total HH income: DID estimates (Urban)

	(1)	(2)	(3)	(4)	(5)
SelfEmp × Aug'20	0.12***	0.12***	0.10*	0.17**	0.081
	(0.044)	(0.044)	(0.058)	(0.081)	(0.057)
HH FE	Yes	Yes	Yes	Yes	Yes
District × Month FE	No	Yes	Yes	Yes	No
Industry × Month FE	No	No	Yes	No	Yes
Occupation × Month FE	No	No	No	Yes	No
Observations	32057	32035	32030	32035	32052

Standard errors clustered at the HH level. Dependent variable: log of total HH income. Also see notes of Table A4.

Table A6: Impact of COVID-19 on Employment: DID estimates (Rural)

	(1)	(2)	(3)	(4)
Dec'18	-0.011			
	(0.028)			
Apr 19	0.011			
	(0.024)			
Aug'19	-0.034*			
	(0.019)			
Apr 20	-0.26***			
	(0.040)			
Aug'20	-0.085***			
	(0.028)			
Dec'20	-0.073***			
	(0.025)			
Inf × Dec'18	-0.013	-0.0052	-0.0073	-0.010*
	(0.031)	(0.033)	(0.0060)	(0.0062)
Inf × Apr 19	-0.0084	-0.0023	-0.011	-0.0063
	(0.027)	(0.028)	(0.010)	(0.0084)
Inf × Aug'19	0.042**	0.038	-0.0046	-0.0040
	(0.021)	(0.024)	(0.0039)	(0.0032)
Inf × Apr 20	-0.035	0.0013	-0.012	0.020
	(0.045)	(0.045)	(0.026)	(0.025)
Inf × Aug'20	0.056*	0.064*	-0.018**	-0.019**
	(0.032)	(0.036)	(0.0087)	(0.0083)
Inf × Dec'20	0.022	0.051	-0.011	-0.010*
	(0.030)	(0.034)	(0.0081)	(0.0059)
SelfEmp × Dec'18	0.0011	0.014	0.00022	-0.0056
	(0.030)	(0.032)	(0.0053)	(0.0065)
SelfEmp × Apr 19	-0.016	-0.0068	-0.0083	-0.0055
	(0.026)	(0.027)	(0.0086)	(0.0076)
SelfEmp × Aug'19	0.030	0.024	-0.0030	-0.0037
	(0.021)	(0.023)	(0.0044)	(0.0047)
SelfEmp × Apr 20	0.14***	0.10**	0.034	-0.011
	(0.043)	(0.044)	(0.025)	(0.024)
SelfEmp × Aug'20	0.060*	0.062*	-0.0049	-0.0085
	(0.031)	(0.034)	(0.0076)	(0.0076)
SelfEmp × Dec'20	0.055*	0.072**	-0.0051	-0.0032
	(0.028)	(0.032)	(0.0095)	(0.0071)
Individual FE	Yes	Yes	Yes	Yes
District × Wave FE	No	Yes	Yes	Yes
Industry × Wave FE	No	No	Yes	No
Occupation × Wave FE	No	No	No	Yes
Observations	13923	13902	13889	13897

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis are clustered at the individual level. The dependent variable is an indicator variable that takes value 1 if the individual is employed and zero otherwise. Inf and SelfEmp denoteemployment status as of Dec 2019. This regression is run on Rural sample.

Table A7: Impact of COVID-19 on Total HH income: DID estimates (Rural)

	(1)	(2)	(3)	(4)	(5)
Oct’19	0.54***				
	(0.10)				
Nov’19	0.53***				
	(0.10)				
Dec’19	0.25**				
	(0.10)				
Jan’20	-0.093				
	(0.11)				
Mar’20	-0.35***				
	(0.12)				
Apr’20	-0.61***				
	(0.19)				
May’20	-0.42***				
	(0.15)				
Jun’20	-0.27**				
	(0.13)				
Jul’20	-0.20				
	(0.12)				
Aug’20	-0.045				
	(0.12)				
Inf × Oct’19	-0.36***	-0.20	0.048	0.035	-0.14
	(0.11)	(0.13)	(0.14)	(0.16)	(0.11)
Inf × Nov’19	-0.34***	-0.24*	0.16	0.24	-0.096
	(0.11)	(0.14)	(0.14)	(0.19)	(0.11)
Inf × Dec’19	-0.11	0.025	0.24*	0.30**	0.025
	(0.11)	(0.11)	(0.13)	(0.13)	(0.11)
Inf × Jan’20	0.018	0.11	0.10	-0.17	-0.040
	(0.11)	(0.10)	(0.14)	(0.23)	(0.12)
Inf × Mar’20	-0.0090	0.084	0.28**	0.26	0.14
	(0.13)	(0.13)	(0.14)	(0.23)	(0.13)
Inf × Apr’20	-0.48**	0.20	0.70***	0.65**	-0.034
	(0.21)	(0.20)	(0.27)	(0.32)	(0.26)
Inf × May’20	-0.054	-0.091	0.048	0.095	0.17
	(0.17)	(0.18)	(0.26)	(0.33)	(0.24)
Inf × Jun’20	0.12	0.19	0.34	0.13	0.21
	(0.14)	(0.15)	(0.21)	(0.27)	(0.21)
Inf × Jul’20	0.19	0.26*	0.37**	0.23	0.28
	(0.13)	(0.16)	(0.19)	(0.24)	(0.18)
Inf × Aug’20	-0.10	0.26	0.33*	0.45	-0.16
	(0.13)	(0.16)	(0.18)	(0.28)	(0.19)
SelfEmp × Oct’19	-0.26**	-0.12	0.073	0.17	-0.093
	(0.12)	(0.13)	(0.15)	(0.20)	(0.12)
SelfEmp × Nov’19	-0.054	-0.057	0.11	0.38*	0.11
	(0.12)	(0.14)	(0.15)	(0.22)	(0.12)
SelfEmp × Dec’19	0.20*	0.25**	0.39***	0.44***	0.27**
	(0.11)	(0.11)	(0.13)	(0.16)	(0.12)
SelfEmp × Jan’20	-0.066	0.019	-0.086	-0.31	-0.19
	(0.12)	(0.10)	(0.16)	(0.25)	(0.13)
SelfEmp × Mar’20	0.13	0.17	0.23	0.44*	0.19
	(0.13)	(0.13)	(0.15)	(0.24)	(0.14)
SelfEmp × Apr’20	-0.040	0.44**	0.74***	1.03***	0.17
	(0.20)	(0.20)	(0.27)	(0.37)	(0.26)
SelfEmp × May’20	0.41**	0.25	0.21	0.13	0.51**
	(0.17)	(0.17)	(0.27)	(0.39)	(0.25)
SelfEmp × Jun’20	0.085	0.059	0.085	-0.13	0.14
	(0.14)	(0.15)	(0.22)	(0.33)	(0.23)
SelfEmp × Jul’20	0.077	0.091	0.11	-0.015	0.14
	(0.13)	(0.16)	(0.20)	(0.31)	(0.20)

Table A7: Impact of COVID-19 on Total HH income: DID estimates (Rural)

	(1)	(2)	(3)	(4)	(5)
SelfEmp × Aug’20	-0.088	0.17	0.19	0.15	-0.12
	(0.13)	(0.16)	(0.19)	(0.30)	(0.19)
HH FE	Yes	Yes	Yes	Yes	Yes
District × Month FE	No	Yes	Yes	Yes	No
Industry × Month FE	No	No	Yes	No	Yes
Occupation × Month FE	No	No	No	Yes	No
Observations	11753	11686	11643	11676	11714

Standard errors clustered at the HH level. Dependent variable: log of total HH income. Also see notes of Table A6.

Table A8: Impact of COVID-19 on total consumption: DID estimates (All India)

	(1)	(2)	(3)	(4)	(5)
Oct'19	0.097***				
	(0.012)				
Nov'19	0.045***				
	(0.0084)				
Dec'19	-0.063***				
	(0.016)				
Jan'20	-0.0046				
	(0.019)				
Mar'20	-0.19***				
	(0.016)				
Apr'20	-0.64***				
	(0.016)				
May'20	-0.56***				
	(0.016)				
Jun'20	-0.36***				
	(0.017)				
Jul'20	-0.24***				
	(0.017)				
Aug'20	-0.27***				
	(0.014)				
Inf × Oct'19	0.011	-0.0086	0.017	0.025	0.051***
	(0.013)	(0.012)	(0.017)	(0.017)	(0.017)
Inf × Nov'19	0.020**	0.030***	0.025*	0.021	-0.0076
	(0.010)	(0.0094)	(0.013)	(0.013)	(0.015)
Inf × Dec'19	-0.042**	-0.059***	-0.057**	-0.031	-0.011
	(0.018)	(0.018)	(0.023)	(0.024)	(0.023)
Inf × Jan'20	-0.061***	-0.099***	-0.066***	-0.048**	0.0013
	(0.021)	(0.019)	(0.025)	(0.025)	(0.026)
Inf × Mar'20	0.0026	-0.023	-0.029	-0.0052	0.030
	(0.018)	(0.016)	(0.022)	(0.023)	(0.025)
Inf × Apr'20	0.20***	0.13***	0.083***	0.038	0.16***
	(0.019)	(0.017)	(0.024)	(0.025)	(0.026)
Inf × May'20	0.22***	0.13***	0.085***	0.054**	0.21***
	(0.019)	(0.017)	(0.024)	(0.025)	(0.029)
Inf × Jun'20	0.15***	0.10***	0.069***	0.037	0.14***
	(0.019)	(0.017)	(0.025)	(0.027)	(0.028)
Inf × Jul'20	0.14***	0.093***	0.054**	0.019	0.13***
	(0.019)	(0.017)	(0.024)	(0.025)	(0.028)
Inf × Aug'20	0.17***	0.13***	0.098***	0.081***	0.14***
	(0.016)	(0.016)	(0.022)	(0.024)	(0.023)
SelfEmp × Oct'19	0.020	0.0049	0.026	0.042*	0.044**
	(0.013)	(0.012)	(0.017)	(0.022)	(0.017)
SelfEmp × Nov'19	0.019**	0.022**	0.016	0.035**	-0.0057
	(0.0095)	(0.0089)	(0.013)	(0.017)	(0.015)
SelfEmp × Dec'19	-0.025	-0.041**	-0.048**	-0.045	-0.0083
	(0.018)	(0.017)	(0.023)	(0.031)	(0.023)
SelfEmp × Jan'20	-0.055***	-0.065***	-0.050*	-0.043	-0.0053
	(0.021)	(0.019)	(0.025)	(0.034)	(0.027)
SelfEmp × Mar'20	0.0065	-0.0099	-0.028	-0.045	0.018
	(0.018)	(0.016)	(0.023)	(0.030)	(0.026)
SelfEmp × Apr'20	0.12***	0.064***	0.0093	-0.011	0.062**
	(0.018)	(0.016)	(0.024)	(0.033)	(0.026)
SelfEmp × May'20	0.15***	0.076***	0.023	0.012	0.13***
	(0.019)	(0.016)	(0.024)	(0.033)	(0.029)
SelfEmp × Jun'20	0.11***	0.058***	0.013	0.020	0.072**
	(0.019)	(0.016)	(0.026)	(0.035)	(0.028)
SelfEmp × Jul'20	0.078***	0.037**	-0.012	-0.018	0.062**
	(0.019)	(0.016)	(0.025)	(0.033)	(0.028)

Table A8 (cont.): Impact of COVID-19 on total consumption: DID estimates (All India)

	(1)	(2)	(3)	(4)	(5)
SelfEmp × Aug'20	0.077***	0.051***	0.026	0.050*	0.057**
	(0.016)	(0.015)	(0.022)	(0.030)	(0.023)
HH FE	Yes	Yes	Yes	Yes	Yes
District × Month FE	No	Yes	Yes	Yes	No
Industry × Month FE	No	No	Yes	No	Yes
Occupation × Month FE	No	No	No	Yes	No
Observations	57652	57568	57568	57568	57652

Standard errors clustered at the HH level. Dependent variable: log of total HH consumption. Also see notes of Table A2.