Synthesis of the impacts of COVID-19 on India's labor market: looking at people, places and policies

Yiming He, Ambar Narayan, Pedro Olinto, Sutirtha Sinha Roy, Nayantara Sarma

1 Introduction

The coronavirus pandemic has had an unprecedented impact on the Indian labor market. To curb the virus, India implemented nation-wide stringent lockdowns at the onset of the pandemic and subsequently, localized restrictions during the second and third waves. During the first set of lockdowns in April 2020, almost a quarter of the labor force became unemployed as most economic activity was halted. Headline labor market indicators recovered once the lockdowns were relaxed but workers faced many transitions, poorer job quality and reduced earnings.

This paper examines the impact of Covid-19 on a host of labor market outcomes in India using a continuous panel survey of around 170,000 households conducted 3 times a year. The survey is called the Consumer Pyramids Household Survey (CPHS) and is conducted by the Centre for Monitoring the Indian Economy (CMIE). We first look at cross-sectional trends of headline indicators, disaggregate them based on demographic characteristics, and then analyze the nature and determinants of labor market transitions using the panel structure of the data. As a last step, we look at the policy implications of India's vaccination campaign on individual employment outcomes.

For the panel data analysis, we follow two fixed cohorts from the CPHS data – a Covid-affected cohort and a pre-Covid cohort for comparison – over a span of 12-16 months. Keeping each self-contained cohort fixed allows us to track the same individuals at different points in time. Further, the pre-Covid cohort acts as a plausible counterfactual for the Covid-cohort so that we have a baseline reference for "normal" labor market dynamics. The Covid-cohort consists of individuals interviewed between November 2019 – February 2020, right before the pandemic and we track their outcomes every 4 months afterwards till March–June 2021. The pre-Covid cohort consists of individuals interviewed either between November 2017-February 2018 or November 2018- February 2019 as baseline, and then followed for 12-16 months. The outcomes of these two cohorts are then compared with reference to their own baselines using a difference-in-difference regression framework, to assess the impact of the pandemic on labor market dynamics. We further examine whether individual circumstances like education and location mitigated the impacts of pandemic-related labor shocks.

Unemployment peaked at an unprecedented 24.3 percent in April 2020 and recovered quickly to 7.3 percent by July 2020. It rose again in May 2021 to 11.4 percent during India's devastating second wave of Covid but came back to around 7 percent between July and December 2021. The quick recoveries in unemployment however mask an overall decline in labor force participation. Moreover, while Covid-19 was an economy-wide shock, women, youth, and historically disadvantaged castes experienced relatively more adverse effects, partly due to the vulnerable and informal nature of their pre-pandemic occupations. Covid-19 has induced further shifts into insecure forms of employment. In the immediate aftermath of the national lockdown, the Covid-cohort who were employed at baseline were more likely to shift into self-employment from casual-wage and salaried work by 3.6 percentage points relative to the pre-Covid cohort. In the longer run (16 months after baseline), these workers were 3.9 percentage points more likely to be in casual wage work, the most vulnerable form of employment. Transitions into more insecure jobs were also accompanied by downward transitions into lower paying jobs even among salaried workers. Salaried workers in the Covid-cohort shifted into jobs earning a median income of INR 250 less per month than the pre-Covid cohort up to 16 months after the pandemic.

We also find significant transitions from industry into agriculture for the Covid-cohort 4 months after baseline relative to the pre-Covid cohorts. However, the differences between the two cohorts become insignificant when we follow them 16 months afterwards, which suggests that the sectoral shift induced by the pandemic was temporary in nature. The short-term shift into agriculture is accompanied by return-migration, primarily into rural areas. The migrant crisis that was extensively covered by the media saw almost 4 percent of the Indian population (roughly 50 million migrants) move back to their native households. Another potential crisis, albeit less documented, concerns the labor market scarring of youth, which refers to the impacts of longer-duration unemployment spells on later employment and wage outcomes. Young people of age 16-24 years in the Covid-cohort, who were not employed at baseline were 9.5 percentage points more likely to remain out of the labor force even 16 months afterwards relative to their counterparts in the pre-Covid cohort. This abstention from the labor market is not compensated by acquiring more education, as the Covid cohort is also more likely to be out of school by 9.6 percentage points, and consequently face greater learning losses relative to the pre-Covid cohort.

Our study contributes to the emerging literature on the impacts of Covid-19 on India and other emerging economies. Gupta et al. (2021) document findings similar to ours, of downward labor market churn into jobs that yield lower earnings. While casual workers faced higher relative losses in earnings vis-à-vis salaried workers, losses were also relatively higher for individuals from richer households, with mixed implications for overall income inequality. Bussolo et al. (2021) look at short-term effects of Covid-19 indicating a large shift into self-employment. Researchers have also focused on the gendered impacts of the pandemic in India and have found that conditional on being employed, women were more likely to lose their jobs and face greater domestic burdens due to the pandemic (Abraham et al., 2021; Deshpande et al., 2020). Our results confirm early findings on the differential impacts of Covid-19 along caste lines, driven by the over-representation of marginalized castes in informal work and their lower levels of human capital (Deshpande and Ramachandran, 2020).

Our paper also adds to emerging evidence in developing economies on how labor markets fared during the "recovery" period that followed the first wave of Covid-19 and associated lockdowns in developing countries. In the early days of the pandemic between April and June 2020, the recession inflicted by the pandemic caused severe labor market disruptions in developing countries. The World Bank's High-Frequency Phone Survey (HFPS) data collected in a large sample of developing countries show that work stoppage, pay-cuts and income loss were common consequences (Khamis et al., 2021) and occurred at a disproportionately high rate among those with low education, informal jobs in urban areas, women and youth (Bundervoet et al., 2022) Sectors hit hardest by Covid included accommodation and food services, non-food manufacturing, retail and wholesale, and travel and transport (ITC Business Impact Survey 2020).

Evidence on labor market recovery in developing countries since the summer of 2020 is rather sparse. The limited and indicative evidence that exists suggests that even as economic activity started reviving in many countries since May/June 2020, the job market recovery was slow and uneven in most countries. In a sample of 17 developing countries where policies became more conducive to economic activity between May and September 2020, employment among those who suffered larger initial shocks – women, non-college-educated, and urban workers – did not recover enough to close the gaps caused by initial disparities in losses. There are indications that self-employment, which is often lower-quality employment in developing countries, is accounting for a high share of the employment that is coming back (Narayan et al., 2022).

More detailed evidence on labor market dynamics available for a few countries indicates continued signs of distress in nonfarm labor markets even as economies recover, but with important differences across countries. For example, in South Africa, where employment rates were already low before the pandemic, Covid-19 led to a further decline of 13.6 percent in overall employment followed by a slow rebound whereby just 40 percent of the jobs lost were recovered by the end of 2020. Employment losses were four times as large among the bottom quintile of workers than among the top quintile, and strongly concentrated among young workers, workers with lower skills or education, black and colored workers, and workers in the informal sector or in small firms. These gaps remained largely unchanged even as jobs started coming back (World Bank, 2021*b*).

Evidence from Nigeria suggests that labor market impacts of the pandemic can persist even as aggregate employment numbers recover. After a sharp fall during the initial

Covid-19 lockdown in the share of the Nigerian population who were working, employment recovered to exceed pre-pandemic levels by August 2020. Most of the increase was among women and the poor, in a pattern that is consistent with an "added worker effect" whereby households increase their overall labor-market participation in order to cope with economic shocks. Many Nigerians have shifted to retail and trade jobs in non-farm household enterprises, most of which are lower productivity jobs that do not yield secure earnings (Lain et al., 2021). Vietnam offers another example of a country where signs of weaknesses have persisted amidst a robust recovery in aggregate employment. High initial losses in jobs, hours worked and wages – and large gaps by gender, skill level and sector of workers – largely dissipated by the fourth quarter of 2020. However, the highest rate job growth was occurring in more precarious forms of off-farm self-employment rather than in wage work (World Bank, 2021*a*). Job quality, as measured by the probability of having employment with a labor contract, is estimated to have declined as a result of the pandemic in second and third quarters of 2020 (Dang and Nguyen, 2020).

Our paper adds to this body of evidence by deepening the understanding of the short-term as well as longer-term impacts of the shock, such as labor market scarring, for a developing economy. Access to several rounds of panel data with detailed information on labor market outcomes and individual characteristics, spanning several years before and during the pandemic, offers us the unique opportunity to explore causal impacts of the shock on labor market dynamics, after accounting for the effects of confounding factors like seasonality, time trends and worker characteristics to a reasonable degree. To the best of our knowledge, this is the first paper to analyze causal impact of the Covid shock on labor market dynamics in a developing economy, over a fairly long (16 months) time horizon since the end of the initial lockdowns in the summer of 2020. The findings are also likely to have relevance for other developing countries whose labor markets share some similarities with India.

Our paper also relates to the broader literature on the impact of economic crises in general on labor outcomes, the longer-term impacts of which can be particularly harmful for inequality and socioeconomic mobility. There is evidence to suggest that loss of jobs can leave lasting impacts on vulnerable workers, and particularly on young entrants to the labor market, due to the effects of labor market scarring. For example, Guvenen et al. (2017) use data from the Social Security Administration in the United States to show that individuals who go through a long period of non-employment suffer large and long-term earnings losses compared to individuals with similar age and previous earnings histories. Because of this effect, a cohort that enters the labor market during a recession are likely to face long-term disadvantages that lead to lower lifetime earnings. Moreover, employment shocks that are unexpected in nature can be particularly harmful – studies have shown workers who are displaced by unexpected firm closures to experience significant and long-lasting reductions in earnings. A crisis also tends to affect workers unequally because of differences in their socioeconomic background, widening existing inequalities. Youth from disadvantaged backgrounds may be forced to enter the labor market at a time when few economic opportunities are available, compared with youth in households that are more well off or enjoy better access to credit, who are more likely to postpone labor market entry, accumulate more schooling or unpaid work experience, and improve their prospects of upward mobility.

In the next two sections of this paper, we describe the data and methods used for our main analysis. Section 4 presents our main results on labor market impacts looking at transitions across employment status, earning levels, employment types, sector and location. In Section 5, we examine how education and location may have mitigated some of these transitions. Section 6 contains some additional results on the effect of vaccination on individual employment outcomes. The last section concludes.

2 Data and descriptive statistics

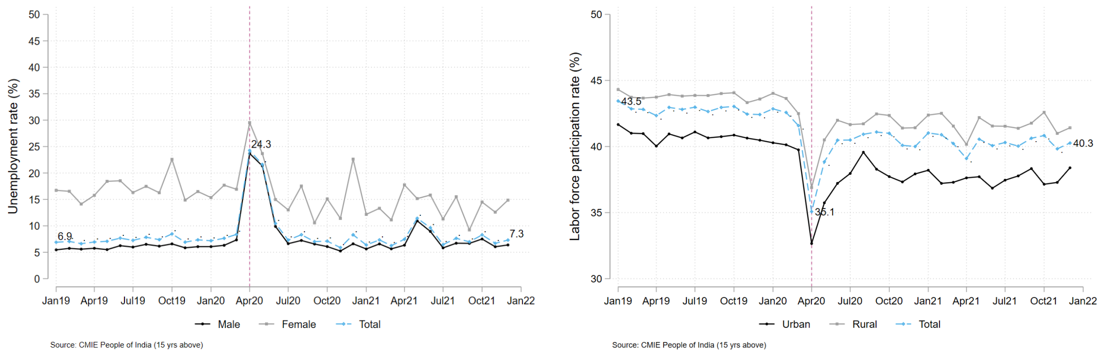
The Consumer Pyramids Household Survey (CPHS) is a continuous panel survey of approximately 170,000 households in each wave. The surveys are conducted by the Centre for Monitoring the Indian Economy (CMIE), a private think tank and data collection agency. Sample households are visited 3 times (3 waves) per year, with each wave taking 4 months to complete. New households are added periodically to the sample to address attrition. While the surveys have been ongoing since 2014, we restrict our attention to years just before and after the onset of the pandemic, November 2017 - December 2021. For this paper, we use only the CPHS modules on household and member incomes, and labor market participation.

Employment outcomes collected by the CPHS refer to the individual's engagement in economic activity either on the day of the survey, the day preceding it, or whether they are generally regularly engaged in any economic activity. This differs from the reference periods used in official labor force indicators by the National Statistical Office in the usual status (1 year) and the current weekly status (1 week). These differences in definitions result in lower employment rates measured by the CPHS relative to the Periodic Labor Force Surveys especially for women, but closely matching trends for both genders (Appendix A).

Given the sparsity of real-time data to assess the impact of the pandemic in India, the CPHS has gained substantial prominence in filling this gap. However, its representativeness of the Indian population has been questioned by several scholars. Roy and Van der Weide (2022) address this issue by proposing adjustments to the survey weights in the CPHS datasets so that the sample more closely represents the national population. We replicate some of our main results using re-weighted data in Appendix B as a robustness check.

India implemented a nationwide lockdown on March 24th, 2020 to curb the spread

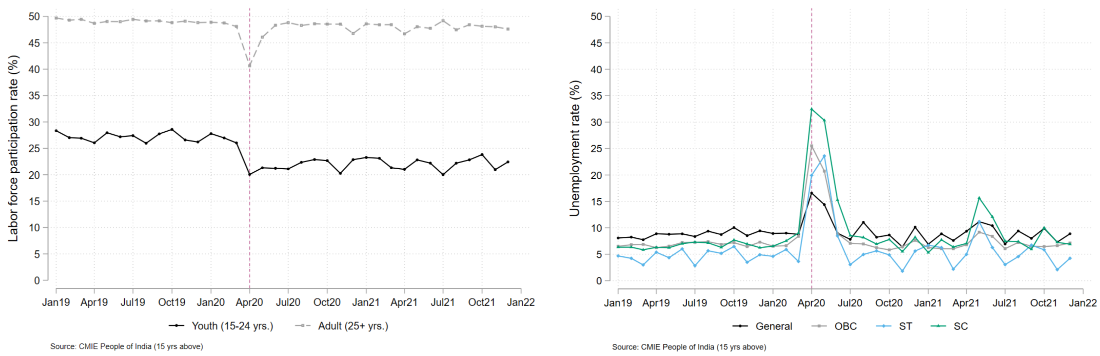
Figure 1: Unemployment rate by gender (left) and labor force participation rates by location (right) - Jan 2019 to Jan 2022



of Covid-19. The lockdown restricted public mobility, temporarily closed educational institutions and brought business operations to a halt, excepting essential services. Unemployment spiked to 24.3 percent in April 2020 and labor force participation fell by 12.5 percent as a result of the lockdown (Figure 1, left). This was the largest labor market shock witnessed since the data series was collected.

The aggregate unemployment rate, however, recovered once the lockdown was relaxed and the economy entered the "Unlock 1.0" phase in June 2020. Barring another spike during the second wave of the pandemic in May 2021 when the unemployment rate reached 11.4 percent, it has largely returned to pre-pandemic levels of 7 percent. For an economy like India, the unemployment rate is not fully informative and its recovery, in fact, masks a decline in labor force participation. The labor force participation rate (LFPR), already low in India relative to other countries, dipped to 35.1 percent in April 2020 and remained 3 percentage points below pre-pandemic levels even 20 months later (Figure 1, right). The decline holds for both urban and rural individuals.

Figure 2: Labor force participation rate by age (left) and unemployment rate by caste (right) - Jan 2019 to Jan 2022



The adverse shock of Covid-19, while felt by the whole economy, was sharper for specific groups. Women had alarmingly low employment rates even before the pandemic, a trend that continued post 2020 and was exacerbated for women with higher household burdens (Abraham et al., 2021). Youth aged between 15-24 years were also more affected. The labor force participation rate for youth dropped by around 20 percent during the lockdowns relative to the same month in 2019 and remains 5 percentage points below pre-pandemic levels (Figure 2, left). Corresponding youth unemployment is averaging above 35 percent since April 2020 but has been on an upward trend even before the pandemic. So not only is the number of youth supplying their labor significantly lower, among them fewer are able to actually find jobs.

Similar to other studies, we find that the effect of the pandemic was not neutral along caste-lines (Deshpande and Ramachandran, 2020). During the nation-wide lockdowns as well as the second wave, Scheduled Castes saw the highest spike in unemployment in levels and relative terms (Figure 2, right). This was, to a large extent, driven by their over-representation in casual-wage work. The share of Scheduled Castes in the overall population is 23 percent while their share in casual labour is 39 percent. Casual-wage workers saw the largest drop in employment in the immediate aftermath of the pandemic. Due to the flexible nature of casual work, they also saw a quick recovery to pre-pandemic shares of employment. Section 4 discusses how transitions between employment types during the pandemic were likely a distress signal in the labor market.

3 Methodology: Fixed cohort analysis: using CMIE panel structure to follow same cohorts over time

In this section, we introduce a fixed-cohort analysis that allows us to study the same cohort of individuals over time. This approach has two advantages. First, it eliminates the concern over different composition of individuals in different snapshots of time from the cross-sectional analysis, which confounds any analysis of trends in labor market outcomes. Second, it allows us to follow the labor market trajectory of individuals up to 16 months afterwards.

We define a Covid-affected cohort as the group of workers employed at the baseline period (Nov 2019-Feb 2020), right before the pandemic. The CPHS revisits households once every 4 months, therefore we can track this group of workers 4 months later (Mar 2020-Jun 2020), 8 months later (Jul 2020-Oct 2020), 12 months later (Nov 2020-Feb 2021), and 16 months later (Mar 2021-Jun 2021). We consider only workers who can be tracked consistently over all four periods so that the composition of workers stays the same for each time period.

We create a pre-Covid cohort for comparison. It consists of workers who are employed in Nov 2017-Feb 2018 and those who are employed in Nov 2018-Feb 2019 period as baseline and follow them for 16 months and 12 months respectively (12 months for the second group to avoid overlap with the Covid period). The goal of having this cohort, for a period that is as close as possible to (and yet distinct from) the Covid period, is to have a comparator group with a likely 'normal' labor market trajectory for workers in India during a time period without Covid. If we observe any difference in terms of labor market trajectory between the Covid cohort and pre-Covid cohort, these differences can reasonably be attributed to the Covid shock.

We formulate the above comparison in a difference-in-difference regression framework, estimating the change in labor market outcomes with respect to baseline for each time period separately for both the Covid and the pre-Covid cohorts. For worker i from cohort k (pre-Covid vs Covid cohort) at time period t , we run the following regression specification:

$$Outcome_{ikt} = \beta_{kt} \times CovidCohort_{ik} \times Period_t + \ Fixed\ Effects\ +\ \epsilon_{ikt}$$

We estimate β_{kt} separately for each of the 4 post-baseline periods. We are particularly interested in the difference in the coefficients between pre-Covid and Covid cohort.

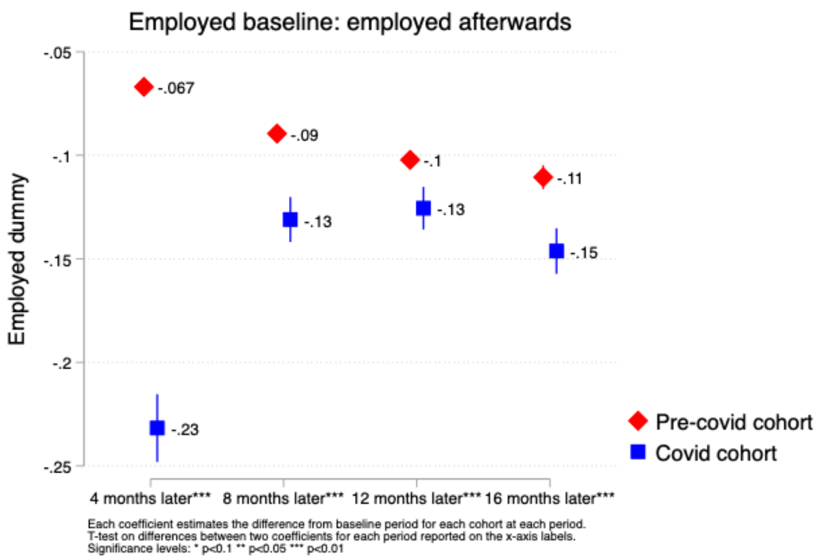
The CPHS cannot track its whole sample over time and naturally experiences attrition. So, although we follow each cohort consistently over 4 periods, the sample of individuals across cohorts varies. As the two cohorts are largely self-contained, the cohort indicators do not vary at the individual level. Hence, we cannot use individual fixed-effects and instead use a rich set of demographic fixed effects (gender, caste, district of residence, age, education group) to absorb any level difference on labor market outcomes between two cohorts.

4 Results

4.1 Key findings on labor market outcomes

We find that the Covid cohort is less likely to be employed post-baseline compared to the pre-Covid cohort, and the gap is persistent over time. Figure 3 below shows that while the share of workers who stayed employed decreased gradually over time for the pre-Covid cohort there is a sudden drop in employment four months after baseline for the Covid cohort. Compared to the pre-Covid cohort, the Covid cohort is 16.3 ppts less likely to be employed four months after the baseline. This finding is in line with the lockdown period (Mar 2020-May 2020) when there was a sudden halt in economic activities in the country. The labor market recovered gradually afterwards but the recovery was not complete. Even 16-months after baseline, the Covid cohort is still 4 ppts less likely to be employed compared to the pre-Covid cohort (statistically significant at 95 percent confidence levels). These results are broadly consistent with the overall employment trends shown in section 2 earlier using quarterly cross-section data, which indicate a steep decline in employment levels during the lockdown period followed by a partial recovery by January 2022.

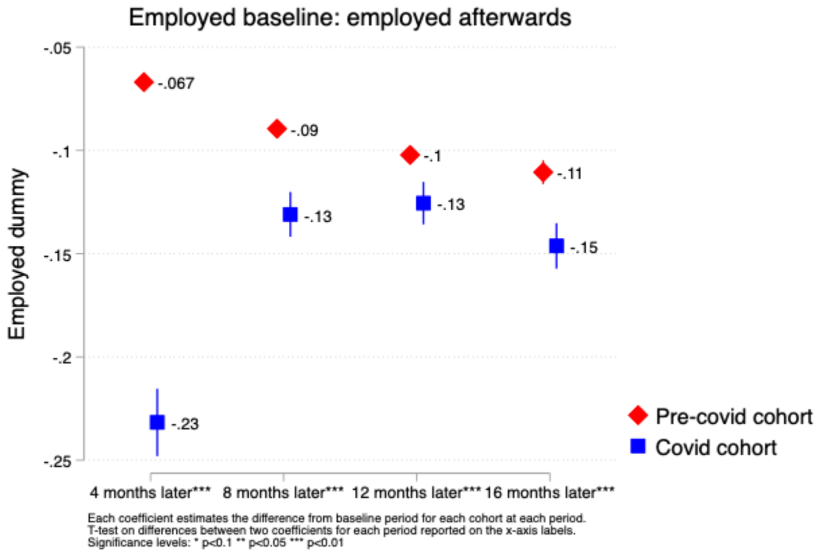
Figure 3: Effect of Covid on likelihood of being employed



We conduct additional analyses using employment dummy as our outcome variable. Our findings are robust with alternative specifications of no weighting on observations (Figure 17) and using only Nov 2017-Feb 2018 baseline as the control cohort (Figure 18). We find that the effect is similar between scheduled caste (SC) workers and non-SC workers (Figure 19). We also find women experienced a larger drop in employment during Covid than men 4 months after baseline (33 ppts vs 15.8 ppts drop), and long-term drop in employment during Covid was also larger for women (Figure 20).

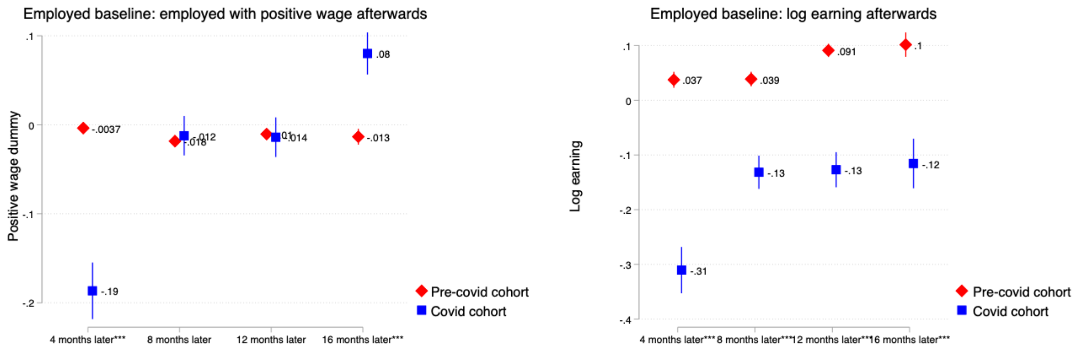
We also find that the Covid cohort is more likely to stay out of the labor force post baseline. Figure 4 below shows that 4 months after baseline the Covid cohort is 8.2 ppts more likely to be out of the labor force, and there is still a 1.2 ppts gap 16 months after baseline (statistically significant at 99 percent confidence levels). The result shows that Covid poses a longer-term shock to workers' labor force participation. We also show later that not only employed workers, but also young workers who are in school at the baseline, are less likely to enter the labor force during the Covid period.

Figure 4: Effect of Covid on likelihood of being out of labor force



We find that conditioning on staying employed, the Covid cohort is also more likely to experience zero earning in the short run. Figure 5 (left) below shows that the Covid cohort is 19 ppts less likely to report having positive earning 4 months after baseline, but the gap disappears in the longer run and even reverses. This may be driven by selection based on employment, i.e., workers who are less likely to have zero-wages do not report to be employed post-Covid. In addition to a short-run decrease in earnings at the extensive margin, we also find that the Covid cohort has consistently lower earnings after baseline. Figure 5 (right) shows that conditional on being employed, the Covid cohort has 34 log points log earnings 4 months after baseline, and the gap stays at 22 log points 16 months later. This is equivalent to a decrease of 34 percent relative to baseline vis-à-vis the pre-Covid cohort.

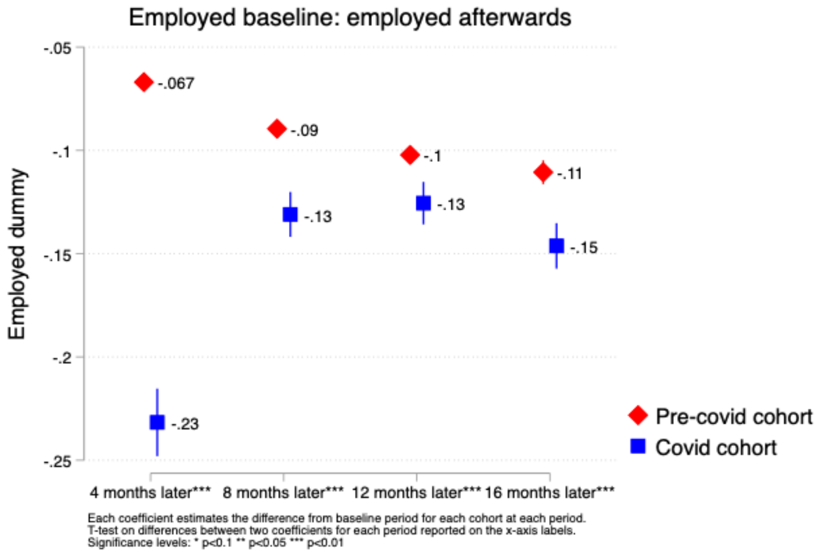
Figure 5: Effect of Covid on likelihood of positive wages (left) and log earnings (right)



Each plotted coefficient estimates the difference from baseline for each cohort for different time periods. T-tests on differences between the Pre-Covid and Covid cohorts for all the periods are reported on the x-axis. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$

We also investigate the type of occupations that salaried workers take after baseline. For each of the 209 occupations for salaried workers in the CMIE data, we calculate the median income for each occupation using the pre-Covid 2018 data. We use this variable as proxy for how desirable an occupation is. We find that the Covid cohort is more likely to transition to low-income occupations post baseline, and the gap in the 'median 2018 income' level of the occupation at around INR 250 per month is qualitatively similar across all 4 periods over time (Figure 6). We also construct an alternative measure of the occupation-score by ranking each of the 209 occupations in our sample. Similarly, we find that the Covid cohort ends up taking low-ranked occupations (aka low-earning occupations) post baseline, and there is no recovery even 16 months after baseline (see Figure 21 in appendix A).

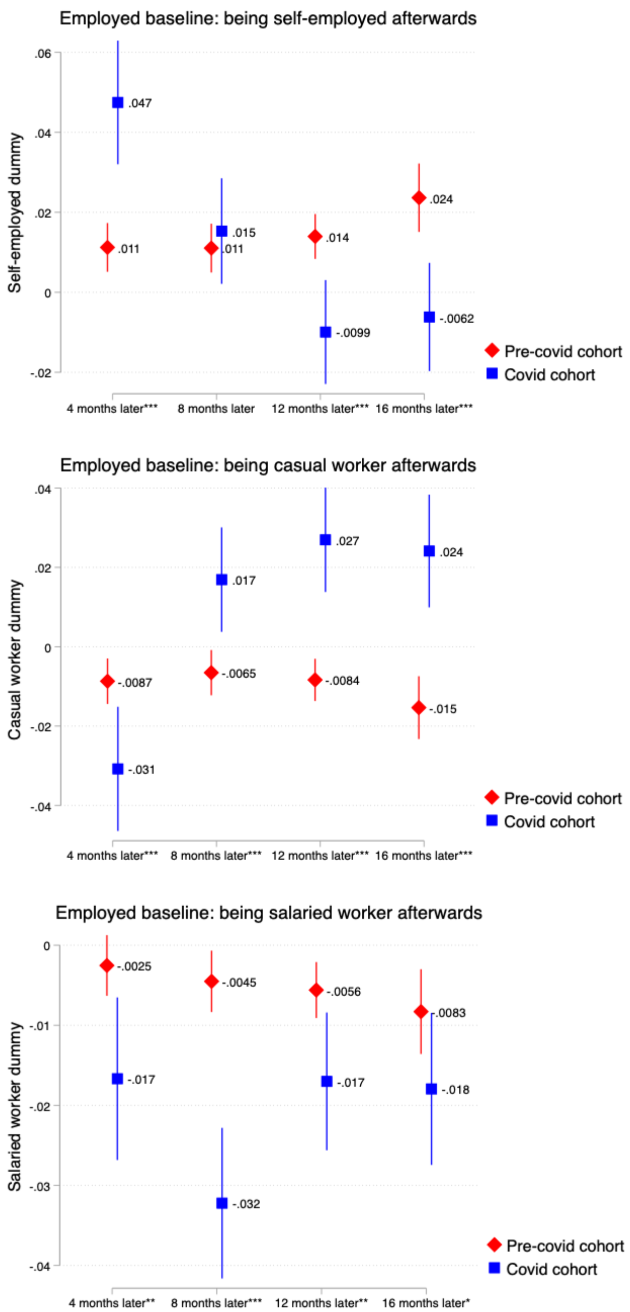
Figure 6: Effect of Covid on occupational rankings



4.2 Change in employment types and industries

We proceed to study whether workers permanently changed into different employment arrangements and different industries after baseline. We categorize three employment arrangements: self-employment, casual-wage jobs, and more stable salaried workers. At baseline 53% of workers are self-employed, 27% are casual workers, and 20% are salaried workers. We restrict the sample to only those workers who stay employed in all post-baseline periods. We find that in the short-run (4 months after baseline) workers are more likely to switch into self-employment at the expense of casual-wage and salaried jobs (Figure 7, top). When we look at longer periods, however, we see an increase in casual employment at the expense of self-employment and salaried workers (Figure 7, middle). Overall, there is a decrease in salaried employment (1 ppt on average), suggesting that for Covid cohort is less likely to have more stable employment which tends to pay more. We also find a non-trivial earning premium for salaried workers, after conditioning for worker characteristics.

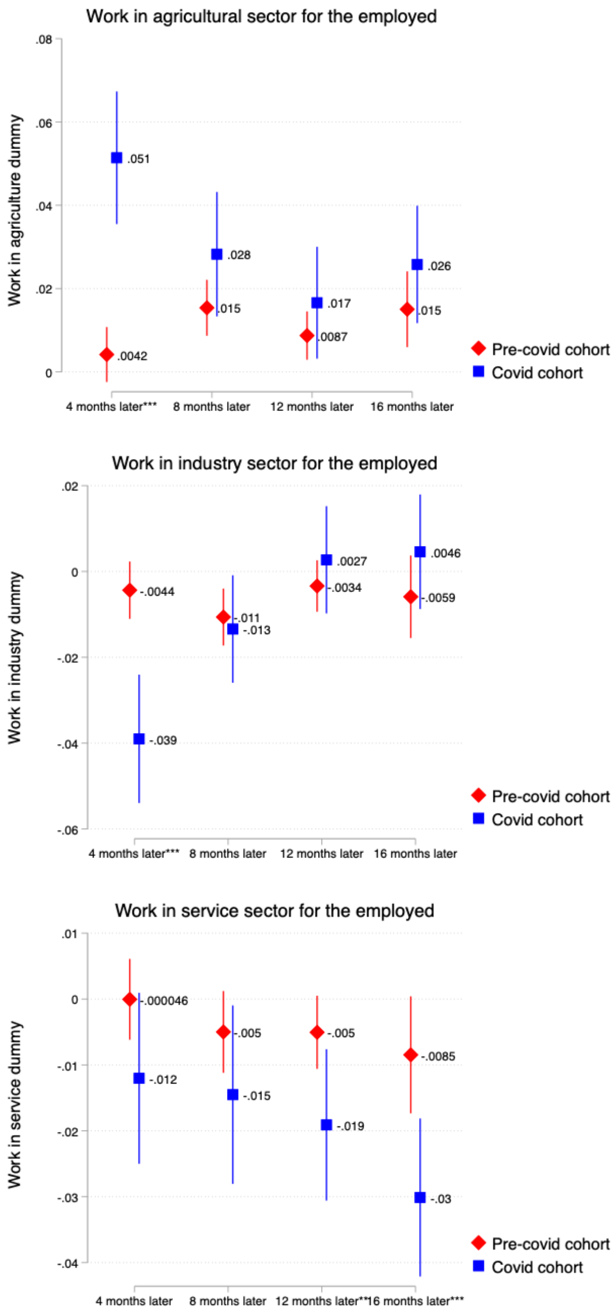
Figure 7: Effect of Covid on transition across employment types



Each plotted coefficient estimates the difference from baseline for each cohort for different time periods. T-tests on differences between the Pre-Covid and Covid cohorts for all the periods are reported on the x-axis. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$

We also look at the employment sectors that workers switch to. We define three industries: agriculture, industry, and services. At baseline, 37% of workers are in agriculture, 26% in industry, and 37% are in services. In the short run, we see a large switch in the agricultural sector (4.7 ppts) at the expense of industry and service (Figure 8, top). In the long run we see a slight but steady decrease in service sector jobs for the Covid cohort (1.8 ppts 12 months later and 2.1 ppts 16 months later). The decrease is statistically significant at 95 percent confidence level only 16-months after baseline (Figure 8, bottom).

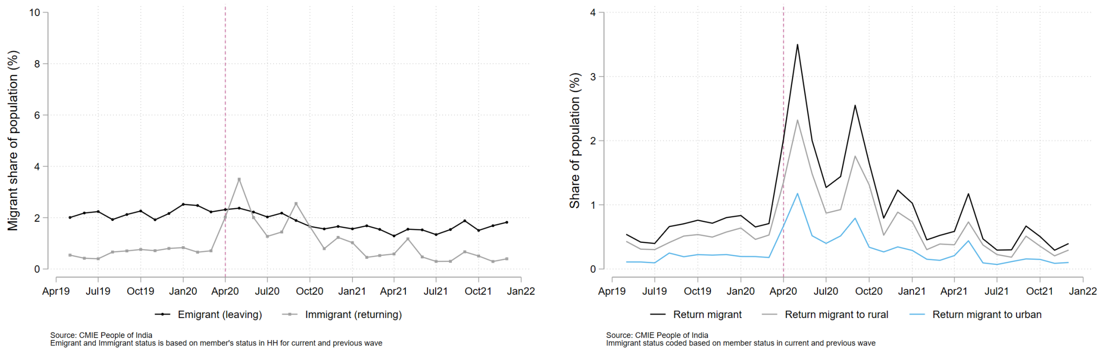
Figure 8: Effect of Effect of Covid on transitions across sectors



Each plotted coefficient estimates the difference from baseline for each cohort for different time periods. T-tests on differences between the Pre-Covid and Covid cohorts for all the periods are reported on the x-axis. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$

The short-term shift into agriculture immediately after the onset of Covid is accompanied by geographic movements– primarily into rural areas. Although the CPHS cannot track households who change their location over time, the survey can track individual migrants from households who move location by looking at changes in the household roster. Changes in member status within the household roster across different waves can be used to identify returning and out-migrants in a particular month or wave.

Figure 9: Trends in return-migration and out-migration (left) and return-migration by rural-urban (right



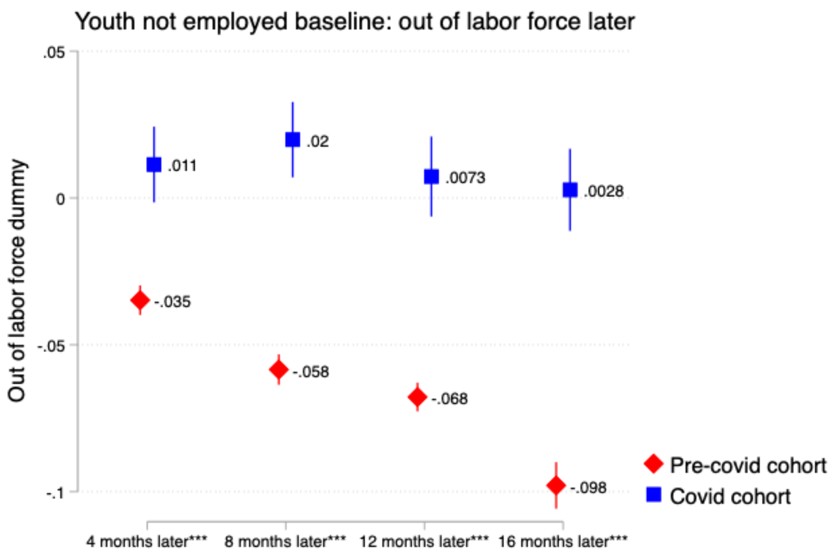
In Figure 9 above (left), during the months following the nation-wide lockdown we find a large spike in return-migration of almost 4 percent of the population (50 million people). A smaller spike shortly after that occurs in September 2020 as lockdowns were eased. There is an yet another small spike in May 2021 during India's second wave, but the monthly rate of return-migration goes back to pre-pandemic levels after that. However, the trend of out-migration, i.e., individuals who are recorded as "members of the household" in previous surveys but are recorded as "emigrated", sees a steady decline. Decomposing the trend of return-migration in Figure 9 (right) shows that, as expected, most migrants returned to rural areas, suggesting greater pressures on agriculture and rural labor markets.

4.3 Youth scarring effect

Next, we proceed to investigate the 'scarring' effect of Covid among a particular demographic group – youth. More specifically, we investigate whether Covid changed the labor market trajectory of young individuals in the short-run and in the long-run, i.e., whether they were less likely to be employed, less likely to enter the labor force, and less likely to be in school. We construct a new sample of young individuals between the ages of 16 and 24 years who were not employed at baseline. We use the same regression specification and track these individuals up to 16 months afterwards. The final sample consists of 17,984 individuals (5,928 of them are from the Covid cohort) that can be tracked consistently for all 4 subsequent periods. At baseline, 72% of them were in school and 90.1% of them were out of the labor force.

We find that our Covid cohort were significantly more likely to stay out of the labor force post baseline compared to the pre-Covid cohort, and the gap reached 9.5 ppts 16 months later. Figure 10 shows that while the pre-Covid cohort gradually entered the labor force after baseline (less likely to be out of labor force), the Covid cohort were almost equally likely to be out of labor force up until 16 months later. The gap increases from 4.6 ppts four months after baseline to 9.5 ppts at 16 months after baseline.

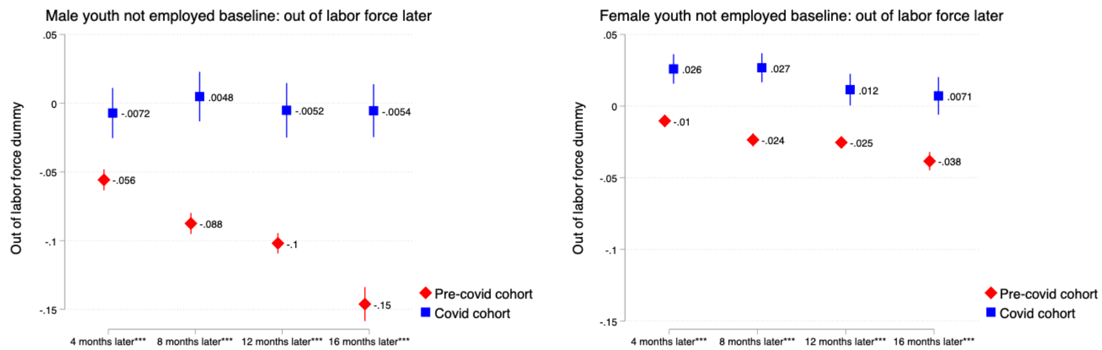
Figure 10: Effect of Covid on likelihood of being out of labor force for youths



Each plotted coefficient estimates the difference from baseline for each cohort for different time periods. T-tests on differences between the Pre-Covid and Covid cohorts for all the periods are reported on the x-axis. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$

We investigate whether female and male youth behaved differently during Covid. In the pre-Covid cohort, women were on average 12 ppts more likely to be out of the labor force post-baseline, relative to males. We find that, using the same linear regression framework, male youth experienced a larger negative shock on labor force participation during Covid compared to female youth. The male Covid cohort of age 15-24 was 6.3 ppts more likely to be out of labor force four months after baseline compared to the pre-Covid cohort, and the gap increases to 15.5 ppts 16 months after the baseline (Figure 11, left). For female youth, the gaps between Covid- and pre-Covid cohorts are 3.6 ppts 4 months after baseline and 3.9 ppts 16 months after baseline (Figure 11, right). The smaller gap can be explained by the fact that women were less likely than men to enter the labor force during the pre-Covid period, so that the extent to which Covid can affect labor force participation is smaller for women.

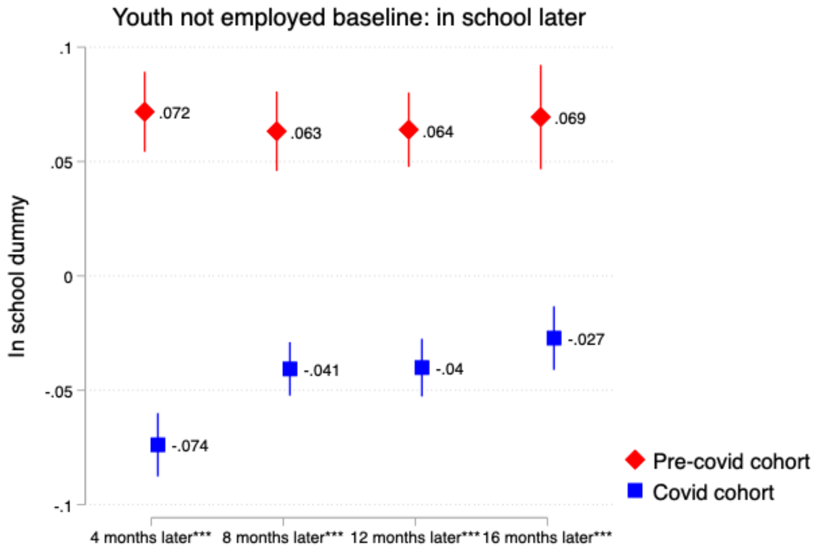
Figure 11: Effects of Covid on likelihood of being out of labor force for youth - by gender



Each plotted coefficient estimates the difference from baseline for each cohort for different time periods. T-tests on differences between the Pre-Covid and Covid cohorts for all the periods are reported on the x-axis. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$

Compared to youth in the pre-Covid cohort, those in the Covid-cohort were less likely to enter the labor force but not more likely to continue their education. Figure 12 below plots the estimated coefficients using an indicator for whether the youth is in school as the outcome variable. It shows a persistent gap between the pre-Covid cohort and the Covid cohort (from 14.6 ppts 4 months later to 9.6 ppts 16 months later).

Figure 12: Effect of Covid on likelihood of being in school for youth

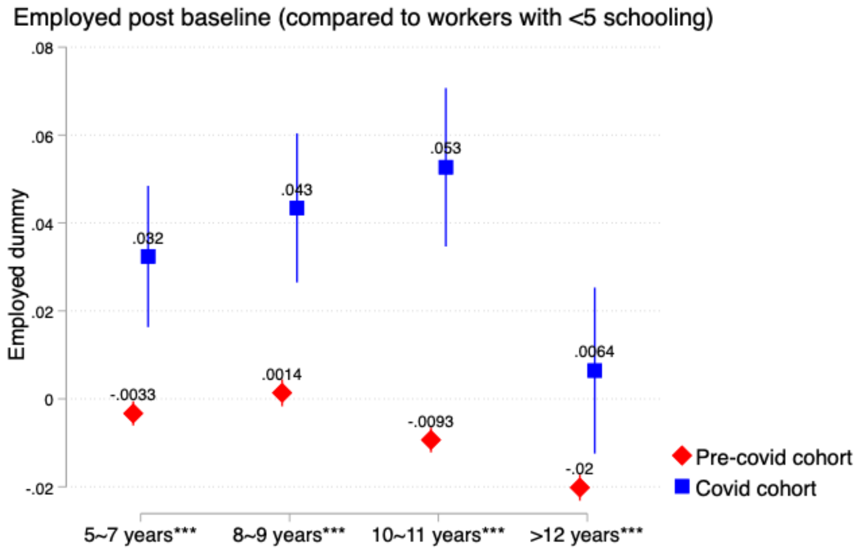


Each plotted coefficient estimates the difference from baseline for each cohort for different time periods. T-tests on differences between the Pre-Covid and Covid cohorts for all the periods are reported on the x-axis. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$

4.4 Mediating factors: education and location

We find that Covid has significant negative labor market impacts for both workers employed at baseline and young workers who were about to enter the labor force. We proceed to investigate two potential mediating factors, education and location. First, we investigate whether Covid causes different extents of labor market disruptions among workers of different education groups. We classify years of education in five categories: $0-4$ years, $5-7$ years, $8-9$ years, 10 11 years, and ≥ 12 years. Using workers with the lowest education group $(0-4)$ as the baseline group, the estimated coefficients β are interpretable as the differences between the lowest education group and higher education groups. First, we find that at the extensive margin, workers with higher years of education were more likely to stay employed for the Covid cohort compared to the pre-Covid cohort (Figure 13). The gap is statistically significant across all education groups (3.5 ppts for $5-7$ years,4.1 ppts for $8-10$ years, 6.2 ppts for $10-11$ years, and 2.6 ppts for ≥ 12 years).

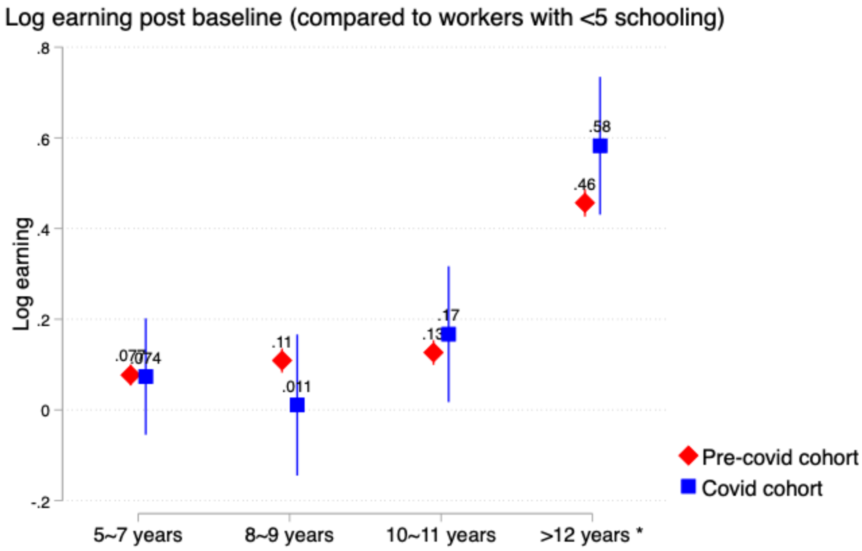
Figure 13: Effects of Covid on the likelihood of being employed - by education groups



Each plotted coefficient estimates the difference from baseline for each cohort for different time periods. T-tests on differences between the Pre-Covid and Covid cohorts for all the periods are reported on the x-axis. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$

Second, we find that while earning increases with respect to education, the premium is even larger for the upper tail of the education distribution ($>= 12$ years of education) during Covid. Figure 14 shows that for the pre-Covid cohort, workers with $>= 12$ years of education have on average 46 log points higher earnings compared to the lowest education group, the premium increases to 58 log points for the Covid cohort. The 12-log point difference in premium between two cohorts is equivalent to 10 percent higher wages and is weakly significant at the 90 percent confidence level. The gap between Covid vs non-Covid cohort is small and statistically insignificant for other education groups.

Figure 14: Effect of Covid on earnings premium by education



Each plotted coefficient estimates the difference from baseline for each cohort for different time periods. T-tests on differences between the Pre-Covid and Covid cohorts for all the periods are reported on the x-axis. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$

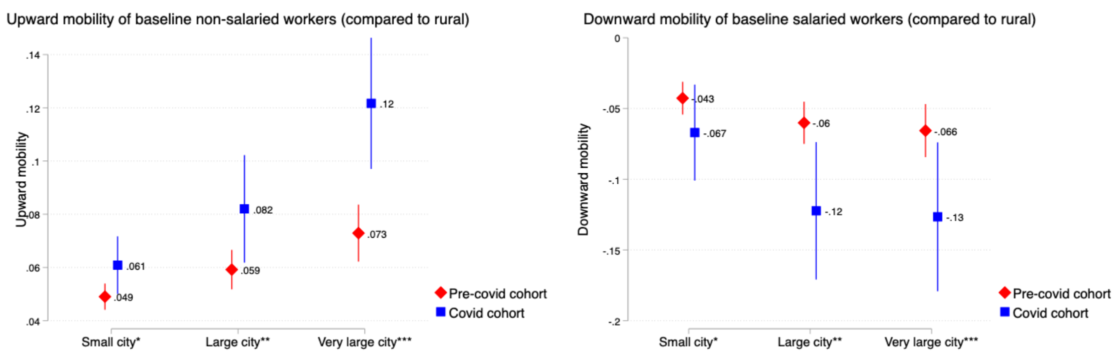
Another potential mediating factor that could have cushioned or exacerbated the Covid-shock is location. Next, we investigate whether living in big cities impacted the possibility of upward or downward mobility. We define upward mobility as workers who were not salaried workers at baseline but transitioned to salaried workers afterwards. Location of individuals is classified into four categories: rural, small cities, large cities, and very large cities. Pre-Covid, workers in the rural areas have a 3.9 ppts chance of upward mobility in the sample. For worker i in location j , we use the following regression model:

$$Mobility_{ijt} = \beta_j \times CovidCohort_{ij} \times UrbanType_{ij} + \ Fixed\ Effects\ +\ \epsilon_{ijt}$$

Workers from rural locations are used as the baseline group and the estimated coefficients β are interpretable as the differences between urban locations vs rural locations for each cohort on upward mobility. As we do not estimate the difference for each post-baseline period separately for a simpler interpretation of results, we can interpret β as the average difference between the pre-Covid and Covid cohort. Like earlier specifications, we use a rich set of demographic fixed effects to account for any difference between cohorts at baseline.

We find that, compared to workers in rural areas, urban workers have a higher chance of upward mobility in general, and the difference is even larger for the Covid cohort. Figure 15 (left) below shows that for pre-Covid cohort, workers in urban areas have higher upward mobility compared to rural areas. Larger cities have higher mobility, workers in small cities are 4.9 ppts more likely to have upward mobility, and the difference increases to 7.3 ppts for workers in very large cities. For Covid cohort the gap is even larger. Workers in small cities are 6.1 ppts more likely to have higher mobility, and the difference increases to 12 ppts for workers in very large cities. Additional t-tests show the differences between the Covid cohort and the pre-Covid are statistically significant. To check the robustness of our robustness, we look at downward mobility, defining downward mobility as workers who were salaried workers at baseline but moved to non-salaried jobs afterwards (rural workers have a 44 ppts chance of downward mobility). We run the same specification with the downward mobility dummy as outcome variables. Figure 15 (right) below shows that, similarly workers in bigger urban areas are less likely to experience downward mobility, and even less likely to experience downward mobility during Covid times. Both results suggest that living in urban areas that have dense labor markets of salaried jobs allow workers to switch to more desirable jobs more easily or stay in more desirable jobs, especially during difficult times.

Figure 15: Effects of Covid on upward and downward occupational mobility; by location



Each plotted coefficient estimates the difference from baseline for each cohort for different time periods. T-tests on differences between the Pre-Covid and Covid cohorts for all the periods are reported on the x-axis. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$

4.5 Labor market impacts of vaccination policy measures

In the early stages of the pandemic, vaccines against Covid-19 were much awaited for a return to normalcy. A recent study by Oliu-Barton et al. (2022) in the context of three European countries (France, Germany, and Italy) has found that vaccine certificates might have spurred economic recovery in the short run by allowing people to resume economic activity and governments to stop relying on mobility restrictions to curb the spread. The authors model vaccine uptake with and without the Covid-19 vaccine certificate and identify the impact of the certificate on high-frequency GDP figures provided by the OECD Weekly Tracker. They find that a 1pp increase in the share of people vaccinated would increase weekly GDP by between 0.042- 0.061 pp one month later. The economic impact of vaccination has not yet been measured in a developing country, and no study has examined impacts on micro-level outcomes in a developing country either.

Using CPHS data, we can examine the relationship between vaccination and individual labor market outcomes. In a Covid Special Module fielded by the World Bank, individuals were asked about their vaccination status and the number of doses they have taken. This information was collected during the 24th Wave of CPHS between September - December 2021 when all adults were eligible for vaccination. India's vaccination campaign took place in a phased manner. Vaccination of frontline workers started on January 16th, 2021; individuals above 60 years and above 45 years with comorbidities on March 1st, 2021; for all individuals above 45 years on April 1st, 2021; and finally, for all adults on May 1st, 2021. However, survey data on individual vaccination status was not collected until September 2021. Due to the panel structure of CPHS, we are able to observe outcomes for the 18-45 years age-group both before they were eligible for vaccines (January – April 2021) and after (September – December 2021). Hence, the results in this section exploiting the panel structure of the data restrict the sample to adults aged between 18-45 years.

Table 1: Individual vaccination status and employment outcomes

	OLS y_i		First-Differenced Δy_{it}		Within y_{it}				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Wave 24		Wave 23-24		Wave 22, 24			Waves 16-24	
	All ages				18-45 years				
At least 1 dose	0.096***		0.006***		0.009***	0.004***			
	(0.006)		(0.002)		(0.001)	(0.002)			
doses=1		0.068***		0.006***			0.004**		
		(0.006)		(0.002)			(0.002)		
doses=2		0.130***		0.006***			0.004***		
		(0.008)		(0.002)			(0.002)		
At least 1 dose * WAVE24								0.022***	
								(0.002)	
Fully vaccinated * WAVE24									0.028***
									(0.002)
Controls	Age, gender, religion, caste, education							wave#vacinnation status	
Individual fixed effects					yes	yes	yes	yes	yes
District fixed effect	yes	yes	yes	yes					
Month fixed effects	yes	yes	yes	yes					
Wave fixed effects						yes	yes	yes	yes
Observations	394088	394088	234121	234121	363864	363864	363864	1719948	1719948
R-squared	0.422	0.424	0.016	0.016	0.953	0.953	0.953	0.853	0.853
Dependent var. mean	0.386	0.386	0.010	0.010	0.387	0.387	0.387	0.378	0.378

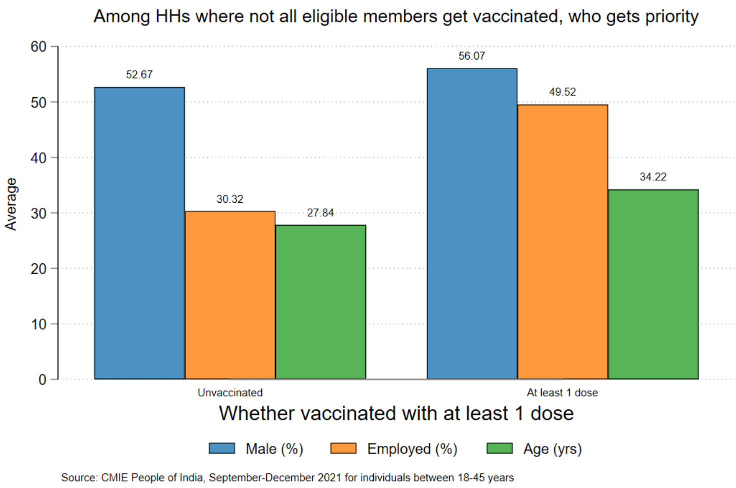
Note: $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$. Standard errors in parentheses are clustered at the district level for Columns 1-4 and at the individual level for Columns 5-9. Columns 1 and 2 estimate the specification $Employed_i = \alpha + \beta Vaccination_i + \varphi Controls_i + Month\ FE +\ District\ FE + \varepsilon_i$ where Vaccination refers to either the individual being vaccinated with at least 1 dose or the number of doses, and the dependent variable is a dummy variable indicating whether the person is employed or not. In Columns 3 and 4, the dependent variable is first-differenced, so that β estimates the effect of vaccination on changes in employment status; $\Delta Employed_{it} = \alpha + \beta Vaccination_i + \varphi Controls_i + Month\ FE +\ District\ FE + \varepsilon_i$. In Columns 5-7 we allow both employment and vaccination to vary over time to partial out individual fixed effects and estimate $Employed_{it} = \alpha + \beta Vaccination_{it} + Individual\ FE_i + Wave\ FE_t + \varepsilon_{it}$. Finally, in Columns 8- 9 we take individual vaccination status as fixed over time and interact with all survey-waves: $Employed_{it} = \alpha + \beta Vaccination_i {*} Wave_t + \varphi Control_{it} + Individual\ FE_i + Wave\ FE_t + \varepsilon_{it}$.

Columns 1 and 2 of Table 1 present the OLS estimates of the correlation between individual vaccination and employment status using cross-sectional data between September-December 2021 (wave 24). Getting vaccinated with at least 1 dose is associated with 9.6 pp increase in a person's likelihood of being employed (Column 1). In Column 2, when we compare the marginal effects of 1 dose (6.8 pp) and 2 doses (13 pp), the 6.2 pp difference is significant at 99% confidence levels suggesting that completing the full vaccination course has stronger effects on employment outcomes. In Columns 3 and 4, we estimate the same specification, but use the first-differenced employment status instead. This allows the coefficient on vaccination status to measure the effect on changes in employment status in wave 24 from employment status in the previous wave. Coefficient estimates reduce substantially to a 0.6 pp increase in the likelihood of being employed and the differences in marginal effects between 1 and 2 doses are not significant.

In the previous estimations, although we control for individual characteristics like age, education, caste, religion, gender and household size, individuals who get vaccinated may have systematically different unobservable characteristics from those who do not, and these factors may be driving the differences between their employment status. To address the endogeneity arising from unobserved and time-invariant individual characteristics, Columns 5-9 use the within (or fixed effects) estimator. Column 5 finds that getting vaccinated with at least 1 dose increases the likelihood of being employed by 0.9 pp which reduces to 0.4 pp once we include survey wave fixed effects (Column 6), which controls for the seasonal nature of employment. These estimations use data from wave 22 (Jan – Apr 2021) where vaccination status of all individuals is 0 due to non-eligibility and wave 24 when all adults were eligible but only some are vaccinated (Sep-De 2021).

Finally, in Columns 8- 9, we take the individuals vaccination status as fixed, i.e., invariant across waves, and interact it with all previous waves. This allows us to distinguish the effect of getting vaccinated once it is available (vaccination*wave 24) from the effect of underlying drivers of vaccination (e.g., risk aversion) that may change across waves, captured by the interactions between vaccination and earlier waves. Marginal effects of partial and full vaccination on the likelihood of being employed range between 2.2 and 2.8 pp, respectively. From all the specifications used in Table 1, we find a statistically significant and positive effect of vaccination on individual employment status. The magnitude of the effect ranges between 0.4pp to 3pp after taking account of individual fixed effects. A back-of-the-envelope calculation suggests that a 100 percent vaccination rate would have the effect of increasing economy-wide employment by 173,000 to 1.3 million people.

Figure 16: Trends in return-migration and out-migration (left) and return-migration by rural-urban (right



The positive relationship between vaccination and individual employment can be due to supply-side or demand-side factors (or both). With vaccination being more widely available, individuals' safety and health concerns might be assuaged and therefore, they are more willing to supply their labor. Alternatively, vaccination can lead to increases in labor demand as the economy recovers and particularly, for those workers who are vaccinated to mitigate spread of the virus at the workplace. While it is not possible to quantitatively distinguish whether supply- or demand-side drivers are behind the findings in Table 1, the supporting evidence seems to be in favor of the latter. Firstly, labor force participation has been declining consistently and has not shown signs of an uptick since India's vaccine campaign was launched. Unemployment, however, has recovered. This suggests that instead of additional workers joining the labor force, vaccination may have allowed existing job seekers to match with employers. Secondly, there are anecdotal reports that employers are requesting new hires to be vaccinated and are prominently displaying signs stating that all staff are vaccinated. This is corroborated by survey data when we look at the individuals who get prioritized for vaccination in households where not all, but only some eligible adults are vaccinated. In Figure 16, we see that male, employed and prime-working age adults are more likely to get priority for vaccinated. This may be due to costs or behavioral constraints in accessing vaccination despite it being freely provided at government health centers. The priority of 'prime-working' members over others in the household suggests that they have greater returns from vaccination, likely through the labor market.

5 Discussion

The impact of COVID-19 on Indian labor markets has been in the form of multiple downward transitions. Individuals affected by COVID-19 transitioned out of employment or the labor force altogether. People who remained employed moved into more vulnerable employment arrangements like casual-wage work or self-employment. This is also accompanied by greater volatility in the probability of positive wages and reduced earnings for the COVID cohort. The reduction in median wages holds even for salaried workers, who transitioned into lower-paying jobs. There was a short-term shift into agriculture at the expense of industry, which coincided with India's migrant crisis. The large movement of people to rural areas was not compensated by a return to cities in the same magnitude, and in fact rates of out-migration steadily decreased since the pandemic.

Women, marginalized castes, and the youth have fared worse due to the pandemic. The former two groups faced greater likelihoods of unemployment conditional on being employed before the pandemic, partly due to characteristics of their pre-pandemic jobs. Youths (aged 15-24 years) were more likely to withdraw or abstain from entering the labor force, and were also less likely to be enrolled in an educational institution relative to their pre-COVID counterparts. The possibility of longer term scarring is worrying because higher education helped mitigate adverse effects of the pandemic. Individuals with tertiary education retained their earnings premium vis-a-vis those with no education even after COVID-19, while lower education groups did not. Since schools and universities in India were closed for almost 2 years, the ability of young people to recover their losses and cope with future shocks may be at risk. Being located in denser urban areas offered more opportunities for informal workers (self-employed and casual-wage) to transition into salaried jobs, but this channel for upward mobility may also be at risk if people choose not to migrate in future.

This paper further looks at the relationship between India's extensive vaccination campaign and labor market outcomes. Vaccinations allowed a return to normalcy in the Indian economy and we find positive and statistically significant effects on individual employment status. However, the magnitudes are small and based on findings in other sections of the paper, unlikely to compensate for the losses in job quality during the pandemic.

References

Abraham, R., Basole, A. and Kesar, S. (2021), 'Down and out? the gendered impact of the covid-19 pandemic on india's labour market', *Economia Politica* pp. 1–28.

Bundervoet, T., Dávalos, M. E. and Garcia, N. (2022), 'The short-term impacts of covid-19 on households in developing countries: an overview based on a harmonized dataset of high-frequency surveys', *World Development* p. 105844.

Bussolo, M., Kotia, A. and Sharma, S. (2021), 'Workers at risk'.

Dang, H.-A. and Nguyen, C. V. (2020), 'Did a successful fight against the covid-19 pandemic come at a cost? impacts of the outbreak on employment outcomes in vietnam', *Impacts of the Outbreak on Employment Outcomes in Vietnam* .

Deshpande, A. and Ramachandran, R. (2020), Is covid-19" the great leveler"? the critical role of social identity in lockdown-induced job losses, Technical report, GLO discussion paper.

Deshpande, A. et al. (2020), The covid-19 pandemic and lockdown: First effects on gender gaps in employment and domestic work in india, Technical report.

Gupta, A., Malani, A. and Woda, B. (2021), Explaining the income and consumption effects of covid in india, Technical report, National Bureau of Economic Research.

Guvenen, F., Karahan, F., Ozkan, S. and Song, J. (2017), 'Heterogeneous scarring effects of full-year nonemployment', *American Economic Review* **107**(5), 369–73.

Khamis, M., Prinz, D., Newhouse, D., Palacios-Lopez, A., Pape, U. and Weber, M. (2021), 'The early labor market impacts of covid-19 in developing countries'.

Lain, J. W., Vishwanath, T., Alik-Lagrange, A., Amankwah, A., Contreras-Gonzalez, I., Jenq, C., Mcgee, K., Oseni, G., Palacios-Lopez, A. and Sagesaka, A. (2021), *COVID-19 in Nigeria: Frontline Data and Pathways for Policy*, World Bank.

Narayan, A., Cojocaru, A., Agrawal, S., Bundervoet, T., Davalos, M., Garcia, N., Lakner, C., Mahler, D. G., Montalva Talledo, V., Ten, A. et al. (2022), 'Covid-19 and economic inequality'.

World Bank (2021*a*), *The Labor Market and the COVID-19 Outbreak in Vietnam: Impacts and Lessons Learned for Social Protection*, World Bank.

World Bank (2021*b*), *South Africa Economic Update, Edition 13: Building Back Better from COVID-19 with a Special Focus on Jobs*, World Bank.

A Additional graphs

Figure 17: Effect of Covid on likelihood of being employed: no weighting

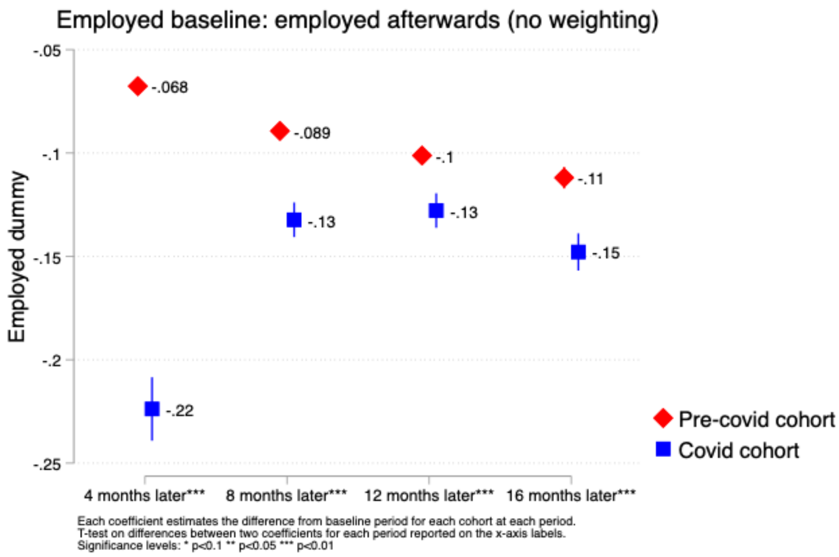


Figure 18: Effect of Covid on likelihood of being employed: using 2017 cohort as control

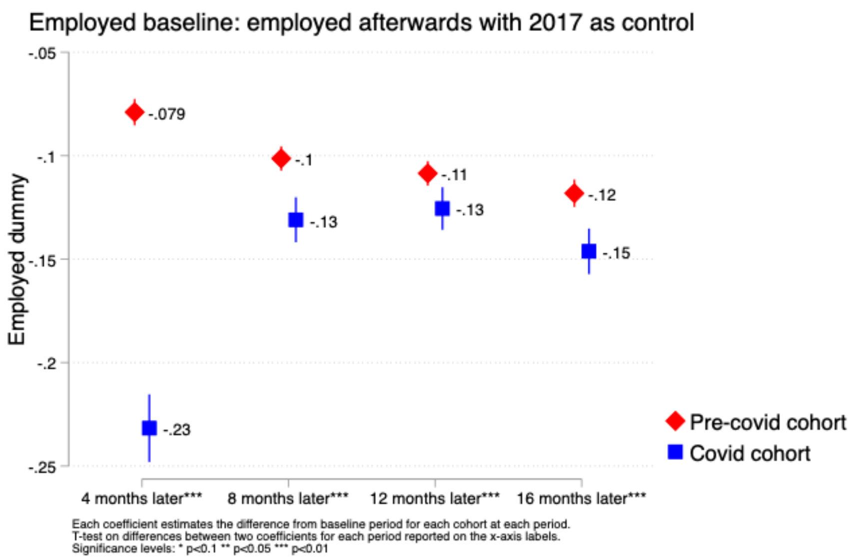


Figure 19: Effect of Covid on likelihood of being employed SC (left) and non-SC (right)

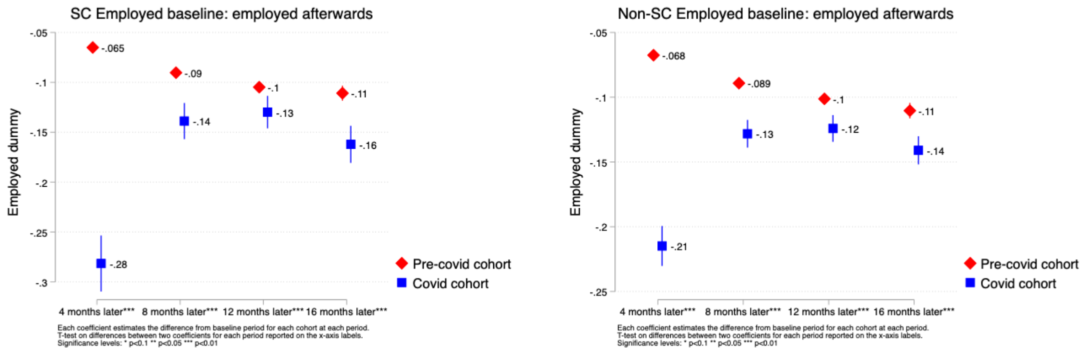


Figure 20: Effect of Covid on likelihood of being employed male (left) and female (right)

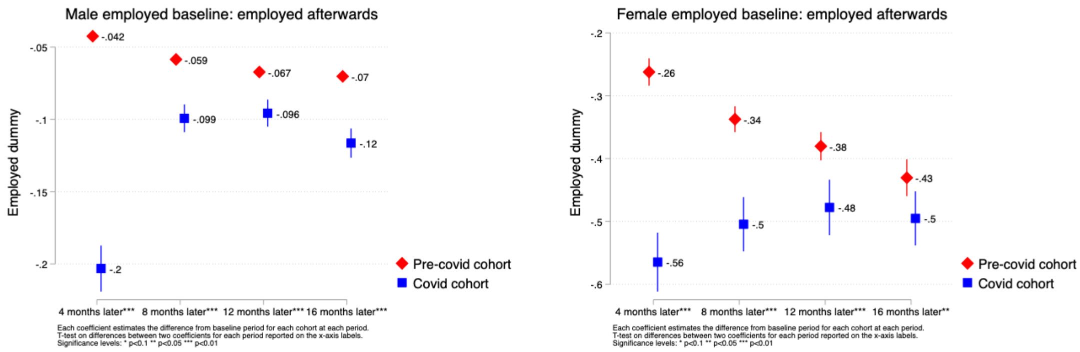
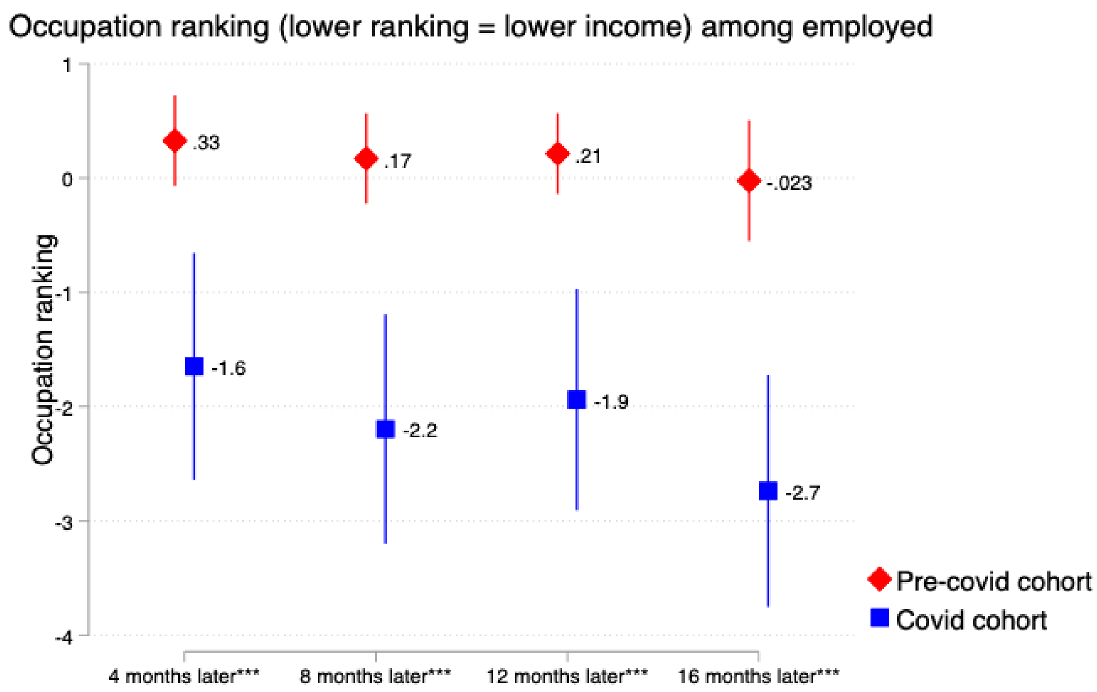


Figure 21: Effect of Covid on occupational rankings



Each plotted coefficient estimates the difference from baseline for each cohort for different time periods. T-tests on differences between the Pre-Covid and Covid cohorts for all the periods are reported on the x-axis. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$