Covid-19, Employment and the Role of Social Protection Programs

Farzana Afridi *
ISI

Kanika Mahajan †
Ashoka University

Nikita Sangwan ‡
ISI

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Abstract

The Covid-19 pandemic has highlighted the potential of social protection programs in addressing labor market shocks. We examine the role of two nation-wide employment guarantee programs in cushioning job losses in one of the worst affected economies due to the pandemic - India. While the MG-NREGA is an existing public employment program in rural areas, which was bolstered following the pandemic, PM-GKRA program was initiated specifically targeting migrant workers who lost their livelihoods due to the pandemic. Our findings show that an increase in provision of work days under MG-NREGA reduced job losses in rural areas, more so for women and older individuals aged 30 years and above, as the restrictions eased. The districts with PM-GKRA program witnessed a lower reduction in the employment rate, but only for urban women and older workforce. These findings indicate that employment guarantee programs can benefit certain demographic groups relatively more than others depending on the wage and skill level of work offered.

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*Indian Statistical Institute, Delhi. Email: fafridi@isid.ac.in
†Ashoka University. Email: kanika.mahajan@ashoka.edu.in
‡Indian Statistical Institute, Delhi. Email: nikita18r@isid.ac.in

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1. Introduction

The Covid-19 pandemic is an unprecedented health and economic shock to the world economy. Most major economies in the world are in recession and unemployment has peaked, demanding a response from policy makers that ensures sustainable economic recovery. Social safety nets - a somewhat neglected policy tool - such as employment guarantees, unemployment insurance, Universal Basic Income (UBI) guarantees - are once again being debated.[1] Furthermore, ongoing research on the pandemic suggests that economic impacts differ across demographic groups. But there is limited evidence on both the role played by social safety nets on stemming labor market disruptions as well as their impacts across demographic groups, which may well vary depending on the design of programs. For instance, unlike a UBI that would not distinguish between working and dependent populations, employment guarantees provide support during labor market shocks to the workforce, potentially impacting productivity and bolstering demand by enhancing incomes (Devereux (2002)).[2]

In this paper we measure the impact of negative labor market shock in one of the worst affected economies due to the pandemic - India. We first assess the dynamic effects on individuals' employment status by region, gender and age over three phases of restrictions - a nationwide lockdown during April-May, with easing from June and full easing by August 2020. We then examine the role of two nation-wide employment guarantee programs in cushioning job losses for each demographic group across as the stringency of the lockdown eased. While the Mahatma Gandhi National Rural Employment Guarantee Act (MG-NREGA) is an existing public employment program in rural areas since 2006, which was bolstered following the pandemic, Prime Minister's Gramin Kalyan Rozgar Abhiyan (PM-GKRA) program was initiated specifically targeting migrant workers who lost their livelihoods due to the pandemic. These two programs vary in terms of the wages offered and the skill level of the labor required for public infrastructure projects.

Using nation-wide individual panel data and employing a difference-in-differences estimation strategy that compares changes in employment status pre (2019) and post (2020) pandemic, during

[1] A report by ILO discusses the various schemes implemented in the Asia-Pacific region. Rees-Jones *et al.* (2020) review various social safety nets in Europe and the United States.

[2] Pissarides (1992) shows that a short negative employment shock can lengthen unemployment durations leading to potential loss of skills and further "thinning" of the labor market as human capital of the labor force erodes. Hence there can be long-term implications of even short episodes of economic downturn.

the months January-March (control months) and April-August (treated months), we find that employment fell precipitously during the lockdown phase - April-May 2020 relative to Jan-March 2020, compared to the change for the same period in 2019. In terms of overall employment, urban and males suffered greater job losses. While individuals above 30 years of age suffered higher job losses initially, the youth suffered a larger fall in employment as the restrictions eased. However, allowing for differential effect of the pandemic across occupations (since different demographic groups may be concentrated in different types of occupations) shows that within the same occupation the fall in employment was higher for urban, women and younger workers. Employment shows a V-shaped recovery post the lockdown (April-May) with easing of mobility restrictions (June-July) but tapers off and continues to remain below the pre-pandemic level as the economy was fully opened (August). Our results suggest that the recovery was somewhat aided by the MG-NREGA program in rural areas, more so amongst women and the older working population as the restrictions eased. Perhaps not surprisingly the urban, young and men, who are likely to be more skilled, did not benefit significantly from this safety net. The PM-GKRA program, on the other hand, appears to have cushioned job losses in urban areas but again more so for women and older individuals.

The role of the two programs appears to have been dynamic as well. The person-days generated under MG-NREGA increased many fold between Jan-March 2020 and April-May 2020 (by 19.7%), June-July 2020 (94%) and August 2020 (21%), and more sharply (in absolute workdays per person) in districts which have exhibited historically higher levels of work generation. However, the past higher person-day generation capacity positively impacted employment levels in these districts only during June-July (on an average by 2.5 percentage point or 5.5% in rural areas over the baseline mean) and August 2020 (on an average by 7.5 percentage point or 17% in rural areas over the baseline mean). Moreover, in August 2020, the marginal effect on employment was higher for rural women (an additional effect of 13 percentage point in August or almost 100% over the baseline mean) and rural older individuals (an additional effect of 7 percentage point in August or 11% over the baseline mean). Similarly, the significantly positive impact of the PM-GKRA program in urban areas is observed only by August 2020. Heterogeneous impacts on urban women (by an additional 7 percentage point or 100% over baseline) and older individuals' employment (by an additional 4.5 percentage point or 9%) is observed in August 2020. These results suggest that there was a lag in any impact of the safety nets.

Our findings have important policy implications. First, we show that employment guarantees can play a role in aiding recovery from a negative economic shock and this may differ across demographic groups. Second, the results highlight the relevance of design of the employment guarantees in their effectiveness. While the low-skilled benefitted from the low-wage, unskilled employment under MG-NREGA, the urban poor either did not have access to this safety net or chose not to take up low-wage work.[3] The PM-GKRA program with its focus on higher wage labor, in contrast, may have been effective in urban areas. Thus a 'one-size fits all' employment guarantee program is unlikely to support a diverse labor force.[4] Finally, the findings indicate that state capacity to utilise public funds might be a critical determinant of governments' ability to respond quickly to economic crises.

The remainder of the paper is organised as follows. Section 2 discusses the time of the crisis in India and the two job guarantee programs. We provide details of the data in Section 3. The methodology and results are in Section 4 and Section 5, respectively. Section 6 concludes.

2. Background

2.1. Timeline

The Indian government ordered a stringent national lockdown to deal with the COVID-19 pandemic, on 24 March 2020 until April 14, which was later extended to May 30. In fact, India imposed one of the strictest lockdowns, restricting all economic activity except those deemed essential (Balajee *et al.*, 2020), with just 500 reported and confirmed COVID cases at the time of the lockdown announcement. Phased reopening was initiated from June 8. This was followed by gradual easing of restrictions on mobility in June and further easing in night curfew and domestic air travel from July. From August 1, Phase 3 of 'unlockdown' with removal of night curfew saw further relaxations of restrictions on economic activity and mobility.[5]

We use daily, district-level mobility data from Facebook (FB) to document movements between

[3] Dhingra & Machin (2020) conduct a choice experiment in urban India to find that low-wage workers are willing to work at 25% lower wage if their job can be guaranteed.

[4] See recent debate on providing an urban MG-NREGA: https://www.ideasforindia.in/topics/poverty-inequality/duet-a-proposal-for-an-urban-work-programme.html

[5] https://indianexpress.com/article/india/coronavirus-covid-19-pandemic-india-timeline-6596832/

March 20, 2020 to August 31, 2020 in Figure A.1.[6] Analysing these data show that the mobility fell precipitously post the national lockdown relative to baseline (the first week of February 2020), as has been documented by researchers using google mobility data. We further classify the movements into within state and across state in Figure A.1. During the lockdown, both inter-state and intra-state movements fell. With the re-opening phase in June, within state movements picked up faster and by August the inter-state movements had caught up. The mobility data, thus, indicate that movements have recovered relative to the pre-lockdown period with the gradual easing of restrictions, but not fully. As a consequence of the lockdown, the impact on economic activity across the country was catastrophic and the country entered a recession. India's GDP contracted by 23.9% during April-June and 7.5% in the second quarter (July-September) of the 2020-21 fiscal year as opposed to 5% growth in the GDP in 2019-20.[7]

2.2. MG-NREGA

The Mahatma Gandhi National Rural Employment Guarantee Act (MG-NREGA) mandates provision of 100 days of manual work on publicly funded projects (e.g. rural infrastructure such as irrigation canals and roads) to rural households in India. The Act envisions a rights based approach - rural adults can demand work at a mandated minimum wage. The program was initially implemented in the country's poorest 200 districts in February 2006, with 130 additional districts added in the next stage (2007) and national coverage thereafter (2008). In 2018, the Act provided employment to almost 76 million individuals at an annual expenditure of more than Rs. 60,000 crores (or USD 9 billion), making it one of the most ambitious employment generation programs in the world. The Act also mandates reservation of 1/3rd of jobs in each MG-NREGA project for women.

Post the national lockdown on March 24, 2020, the provision of employment under the program also came to a halt. On April 15, 2020, however, the Government of India issued an order allowing activities related to the MG-NREGA to resume. It also increased the allocation to the program's budget by Rs 40,000 crore. Consequently the program generated 2.02 billion person days of work

[6] The daily updated data since 20th March 2020 covers approximately 3% of India's population since it is available only for those users who consent to share their location history.

[7] https://economictimes.indiatimes.com/news/economy/indicators/india-q2-gdp-live-news-november-27/liveblog/79439880.cmsy-September 2020)

until September 2020, compared with 1.88 billion for the entire fiscal year of 2019-20. We plot the district level monthly average person days of work per rural person generated under the scheme in years 2020 and 2019 in Figure 1a from the MG-NREGA Public Data Portal, which is then divided by the rural population of the district as per the latest Census in 2011.[8] The average work days generated were similar across years 2019 and 2020 for the months of January-March but there was a sudden plunge in the days generated under the scheme in April 2020 (due to the lockdown) relative to 2019 level. Thereafter, the average work days generated in May-June 2020 saw a sharp spike, which again fell in July-August 2020, as the agricultural season (*kharif*) started. However, in comparison to 2019, the average work days generated under the program were still higher in 2020 than in 2019 during the months of September-October.

Research indicates that MG-NREGA implementation has been uneven across districts of India (Dreze & Oldiges, n.d.; Shah & Mohanty, 2010), and program fund utilization is typically better in states with higher capacity but lower need. We check whether past capacity to generate work under MG-NREGA affected the supply of work days under MG-NREGA during the lockdown and when the restrictions eased. We plot the average number of work days generated in 2020 across districts which have historically (in the five years of 2014-18) generated above median MG-NREGA work days per rural inhabitant and those that have generated below-median work days under the program in the past in Figure 1b.[9] The plot shows that districts with historically higher state capacity to generate work days under MG-NREGA not only generated more work days in 2020 but also witnessed a sharper absolute rise (from 0.5 to 1.3 work days per rural inhabitant) in work days generation between March 2020 to June 2020 compared to low performance districts (from 0.1 to 0.35 work days per rural inhabitant).

2.3. PM-GKRA

To help reduce the hardship of migrant workers who lost their main source of livelihood during the pandemic, the Prime Minister's Gram Kalyan Rozgar Abhiyan (PM-GKRA) Scheme was announced in May 2020 with a twin objective of providing employment to the skilled and as a strategy to develop rural infrastructure. This scheme was launched to ensure that migrant workers get work

[8] https://nregarep2.nic.in/netnrega/dynamic2/DynamicReport_new4.aspx.
[9] We exclude 2019 from the calculation of historical MG-NREGA intensity.

close to their homes (in their own villages or villages close by) thereby restricting movement and provides them with financial stability. The program was to be implemented in mission mode for 125 days from June 20, 2020 with focused implementation of 25 categories of work/activities with an outlay of Rs. 50,000 crores, covering 116 districts in 6 states (Districts listed in Annexure I, Implementation Guideline, GoI).[10] The projects include construction of roads, housing for poor, child care centers and Community Complexes, among others. It is important to note that almost all projects selected under PM-GKRA were already ongoing and funded under various departments. Of the 25 work types of PM-GKRA, 11 overlap with MGNREGA (Implementation Guideline, GoI). However, the daily wage under MGNREGA was Rs. 182, while it was Rs 202 under PM-GKRA.[11]

3. Data

We use the Consumer Pyramids Household Survey (CPHS) data from the Centre for Monitoring Indian Economy (CMIE) - household level panel data where every household is interviewed once every quarter in a year. The CPHS surveys all states of India and capture employment related details of respondents and other socio-demographics.[12] Compared to Periodic Labor Force survey conducted by the Ministry of Statistics and Program Implementation in 2017-18 where the sample size was 102,113 households, the sample of households surveyed in CPHS in year 2019 on an average across the three quarters was 139,220.[13]

We use individual level employment data from January 2019-August 2020. The demographic characteristics like gender and location (rural/urban) of individuals are determined at the time of

[10] Bihar (32 districts), Uttar Pradesh (31), Madhya Pradesh (24), Rajasthan (22), Jharkhand (3) and Odisha (4). Figure B.1 shows the districts covered under the scheme. However, it appears that upcoming state elections influenced the districts targetted by the program (Afridi, Dhillon and Roy Choudhury, 2020: https://indianexpress.com/article/opinion/columns/migrant-workers-crisis-coronavirus-employment-mgnrega-6705781/)

[11] Around 242 million work days were generated under the PM-GKRA program till August 31 across the 116 districts, which on an average comes to 0.81 work days per person across these districts. Although the PM-GKRA program was intended to generate employment in 25 categories of work, the actual person days generated as of August 31st were clustered on few activities (http://gkra.nic.in/). Among these, four categories of work constitute about 75% of the total works generated —42% are in rural housing, 14% in water conservation and harvesting works, 10% in laying of fiber optic cable and 8% in plantations.

[12] Other modules of the survey also capture household and member incomes, household assets and monthly expenditure.

[13] The demographic profile of households surveyed in CPHS and PLFS are very similar. For instance, 84% households follow the Hindu religion, 10% are Muslims and the remaining composed by other religions in CPHS. The caste composition of the sample is as follows: 21% Scheduled Classes (SC), 6% Scheduled Tribes (ST) and 39% Other Backward Classes (OBC). The remaining 34% is constituted by other caste categories. These figures are very similar to those reported in PLFS-2017-18.

first survey. The age of an individual is measured in the quarter preceding the pandemic. The number of households surveyed on average in a quarter in 2020 falls to 88,886 due to attrition, i.e. a fall of over 36% when the survey was switched from in-person to telephone mode when the pandemic hit. Even though the sample size is large enough compared to other surveys like PLFS which are considered nationally representative, our analyses shows that the attrition was not random. Households with certain characteristics were more likely to exit than others. Therefore, in our current analyses we keep the same sample of households that could be reached in 2020 throughout the specifications so that estimates are not affected by changing composition of the sample. We also check the robustness of our main results to household attrition.

For each individual aged 15 and above, the survey captures the employment status as on the date of the survey. If an individual is engaged in any economic activity either on the day of the survey or on the day preceding the survey or generally regularly engaged in an economic activity she/he is considered employed (even if unable to work in the past few days due to illness or other contingencies). Among the individuals who report themselves to be not employed, the survey further records their alternative status - unemployed, willing and looking for a job; unemployed, willing but not looking for a job; and unemployed, not willing to work and not looking for a job.

In our analyses we use employment data for the working age population in India i.e. individuals aged 15-59 (in the quarter December 2019-January 2020). Figure A.2 shows the proportion of individuals aged 15-59 employed by month during 2020 and 2019. There was a distinct fall in proportion employed during April 2020, immediately after the lockdown which had largely recovered by July 2020 but remained below the levels in the corresponding months of 2019. The survey further records the details of employment, including the nature of occupation (19 categories), industry of occupation (38 categories), type of employment (full time/part time) and employment arrangement (casual labor, salaried (permanent/temporary), self-employed).

Table 1, Panel A, includes the summary statistics for employment for the sample in our analyses. The figures show that employment rates are higher, on average, in rural areas than urban areas, among men than women, and among older persons than the youth.[14] Additionally, in Panel A of

[14] We compare the employment rates (proportion of people employed) in the CPHS and the Periodic Labor Force Survey (PLFS) for the months July 2017-June 18. We find that for the age group 15-59, the overall employment rate from the CPHS data was 72% for men and was 10% for women. The corresponding figures from PLFS using weekly (daily) status were 71% (61%) for men and 20% (14%) for women. Therefore, the employment rates for men are comparable mostly while those for women are almost half for women in the CPHS using weekly status but

Table A.1 the summary statistics for overall employment by region and gender, type of employment (conditional on being employed in Panel B) and unemployment (voluntary vs involuntary in Panel C) during the pre-lockdown period of January-March 2020 (period used as baseline in our analyses) are shown, suggesting similar overall patterns of employment across demographic groups. Panel B shows that the structure of the work force in India was largely dominated by informal employment during the pre-lockdown period.[15] Panel C indicates that those who were voluntarily not working or looking for work dominated the unemployed category.[16] Figure A.3 exhibits the trends in employment for the sample in our analyses for each demographic group. We discuss these trends with the estimation results later.

In addition to the CPHS, we utilize data on person days generated in each month from the MG-NREGA and GKRA Public Data Portals.[17]

4. Estimation Strategy

We use CMIE's Consumer Pyramids Household Survey (CPHS) data for the periods January-August 2019 and January-August 2020 to measure employment for those aged 15-59 years. We first estimate the impact of the lockdown in India due to the pandemic on employment using the below specification:

$$y_{idmt} = \beta_0 + \sum_{j=1}^{3} \beta^j (M_m^j \times Post_t) + D_i + Post_t + M_m + D_{dt} + \epsilon_{idmt} \tag{1}$$

where y_{idmy} is a dummy that takes value one if individual i in district d in month m in year t was employed and zero otherwise. We categorize the months in 2020 into three phases post the lockdown on March 24, 2020, to evaluate the effects on employment as the stringency on mobility restrictions eased. The aggregated months are denoted by $j \in (1, 2, 3)$. Here, M_m^1 is a dummy variable that equals one for April-May (stringent lockdown) and zero otherwise. Similarly, M_m^2

three fourths using the daily status definition in PLFS. We compare the PLFS employment rates for rural women (14.5%) and urban women (13.7%) with those in CPHS (12% for rural women and 9% urban women) and see that the difference seems to be higher for urban women. One reason for the difference for women's employment rates could be the framing of the questions across the two surveys. However, the broad patterns across regions for women are similar - lower for urban women than rural women.

[15] The proportion of self employed is the highest at 46%, followed by casual employment at 36% and lastly salaried employment at 16%.

[16] Around 6% of total working age population was involuntary unemployed in India during the baseline time period.

[17] See: GKRA portal

refers to months June-July (some easing of restrictions) and M_m^3 refers to August (further easing). These aggregate month indicators are interacted with an indicator variable, $Post_t$ which takes a value of one for the year 2020 and zero otherwise.

The above specification is akin to a difference-in-differences strategy where the coefficients (β^j) give the effect on employment in each time period post the lockdown.[18] Here β_1, β_2 and β_3 give the effect on employment during April-May, June-July and August in the year 2020, relative to January-March 2020 (first difference), respectively, controlling for seasonality in employment in 2019 for the same months (second difference). The advantage of this specification is that it allows one to control for seasonal changes in employment, which can play an important role in rural areas dependent on agriculture sector. We also account for individual level heterogeneity (D_i), year fixed effects ($Post_t$) and seasonality through month fixed effects (M_m). We allow for district specific year fixed effects to allay any concern that the results are driven by district specific trends in employment. Standard errors are clustered at the district-month-year level.

We then look at the heterogeneity in the overall effects on employment by individual's sector of residence (rural/urban, recorded when the individual was first surveyed in the CPHS and hence before the lockdown due to the pandemic), gender and age (recorded in the quarter preceding the pandemic), using the below specification:

$$y_{icdmt} = \beta_0 + \sum_{j=1}^{3} \beta_1^j (M_m^j \times Post_t) + \sum_{j=1}^{3} \beta_2^j (M_m^j \times X_{ic}) + \beta_3^j (Post_t \times X_{ic}) + \sum_{j=1}^{3} \delta^j (M_m^j \times Post_t \times X_{ic}) + D_{ic} + Post_t + M_m + D_{dt} + D_{ct} + \epsilon_{icdmt} \quad (2)$$

where y_{icdmy} is a dummy that takes value one if individual i in occupation c in district d in month m in year t was employed and zero otherwise. X_{ic} is a dummy variable that varies along the heterogeneity indicator. In our analysis, $X \in (Rural, Woman, Youth)$ where $Rural$ takes a value one if a person lives in rural areas and zero otherwise, $Woman$ takes a value one for women in the sample and zero otherwise and $Youth$ takes a value one for people aged 15-29 and zero otherwise. The coefficients δ_1, δ_2 and δ_3 give the differential effects on groups varying along the dimension

[18] For instance, β^1 is the difference between the first difference (i.e. change in employment between April-May 2020 and January-March 2020) and the second difference (i.e. change in employment between April-May 2019 - January-March 2019). β^2 and β^3 can be interpreted in a similar manner.

X, for the time period of April-May, June-July and August in year 2020, respectively. Here, we additionally control for occupation specific time fixed effects in employment post the lockdown to look at within occupation changes across heterogeneous groups. For instance, there could be a differential occupational structure for men and women before the lockdown and hence a differential fall in employment across gender due to differential recovery across sectors as the restrictions eased. We measure occupation category of an individual as in the previous quarter before the lockdown (i.e. December 2019-March 2020).[19]

Next, we look at the effect of social safety nets on changes in employment post the lockdown. To deal with the concern that contemporaneous work days under MG-NREGA are endogenous, we exploit the earlier finding that the increase in provision of work days under the MG-NREGA during May-July 2020 was higher in districts which on an average in the past have shown greater state capacity in providing employment under the scheme (Figure 1b). The historical generation of work days under MG-NREGA is then likely to reflect the capacity of the administration to respond to the crisis due to the pandemic. To estimate the effect of MG-NREGA state capacity on employment - both overall and as the mobility restrictions eased - we interact the number of days in district d in month m generated under MG-NREGA ($NREGA_{dm}$) during years 2014-2018, divided by the rural population (as per Census 2011) in the district, with $M_m^j \times Post_t$. The estimates here can be interpreted as the effect of past capacity to generate employment under MG-NREGA on employment post the lockdown. Areas that had generated greater MG-NREGA work days can have the required administrative machinery to quickly put in place action plans for permissible works. Indeed, we find that the correlation between MG-NREGA days in 2020 and historical MG-NREGA is high (0.68).

We look at the differential effect of historical MG-NREGA state capacity by month post the lockdown because it is possible that the marginal effect of MG-NREGA state capacity on employment changed at the extensive margin as the extent of job losses changed. For instance, it is possible that during usual times capacity to generate MG-NREGA workdays played a role in increasing days

[19]Occupational categories for employed: Industrial Workers, Wage Labourer, Support Staff, Organised Farmer, White-Collar Professional Employees and Other Employees, Self Employed Entrepreneur, Agricultural Labourer, White Collar Clerical Employees, Businessman, Small Farmer, Non-Industrial Technical Employee, Small Trader/Hawker/ Businessman without Fixed Premises, Qualified Self Employed Professionals, Home-based Worker, Manager and Legislator/Social Worker/ Activists. For those who were not employed: Home Maker and Others (Retired/Students).

of work on the intensive margin only but when there were massive job losses it additionally affected employment at the extensive margin as well. We examine the effects of MG-NREGA state capacity in rural and urban areas separately as the scheme is applcicable only in the rural areas and consequently is expected to have a larger impact in rural areas. We further examine the heterogeneity in the effect of MG-NREGA by gender and age. One concern with this specification may be that districts with higher historical MG-NREGA work days are characterised by different occupational structure. This might result in differential job losses in these areas relative to others. This could lead to a differential decline in overall employment rates across regions performing differently on MG-NREGA work generation capacity. Hence, we control for the underlying initial occupational structure.

The PM-GKRA program was aimed at providing employment to the returnee rural migrants. It specifically targeted districts with 25,000 or more returnee migrants. For the PM-GKRA estimation, therefore, we restrict the sample to states where at least one district was classified under this scheme and match the districts on outward historical migration rates which are calculated from NSS (2007-08) data.[20] To analyse the effect of PM-GKRA on employment we estimate the specification as in equation 1 but now interact $GKRA_d$ which equals one if district d was declared eligible to receive funds under the PM-GKRA scheme and zero otherwise, with $M_m^j \times Post_t$. The coefficient on this interaction gives the additional effect on employment in the districts classified as PM-GKRA on employment as the lockdown restrictions eased. We plot the coefficients for June-July and August since the scheme started in June 2020. We estimate these separately for rural and urban areas and then look at heterogeneity by gender and age. Additionally, we also control for occupation specific time fixed effects for each time period post the lockdown in all estimations.

5. Results

We first report the impact of each phase of the lockdown on overall employment. We then disaggregate impacts by region, gender and age to assess effects by demographic groups. Finally, we estimate the effect of social protection in alleviating the fall in employment.

[20] This nationally representative household survey asks whether a household member had spent one to six months away for work within the past year. Thereby capturing short-term migration movements. We take a weighted sum of the number of migrants from each district and divide it by population of the district (Census, 2011) to calculate the migration rates.

5.1. Employment

The point estimates of Equation 1 (i.e. β^j) are plotted in Figure 2 for each time period post the lockdown. The estimates show that employment was 11 percentage point lower ($p < 0.01$) in April-May 2020 than that in the pre-lockdown months of January-March 2020, relative to the same difference in 2019. During June-July 2020, the employment rate was lower by 2 percentage point ($p < 0.01$) and by August 2020 it was almost back to the pre-lockdown levels.

We now look at the heterogeneity in these effects by region, gender and age category. In the first set of heterogeneity results, we do not control for occupation specific time fixed effects post the lockdown. Figure 3 plots the absolute effects on employment for each group in a category and also the difference in these effects across groups within a category. For instance, since the heterogeneity is along rural indicator variable, the effect on employment in urban areas is given by β_1^j (in Equation 2) where each time period is denoted by j. The effect on employment in rural areas is given by $\beta_1^j + \delta^j$. These effects are plotted in Sub-figure 3a(i). The plots show that employment fell in both urban and rural areas during April-May 2020 and recovered by August 2020. The difference in the coefficients across rural and urban areas (effect on employment in rural areas - effect on employment in urban areas) i.e. δ^j in Equation 2, is then plotted in Sub-figure 3a(ii) for each time period. The fall in employment during April-May 2020, from the baseline months of Jan-March 2020, relative to 2019, was somewhat proportionally smaller for rural areas than urban areas by 1.1 percentage point but imprecise (positive difference between the coefficients rural-urban in Sub-figure 3a(ii)). However, by June-August the difference in employment change from the baseline months of Jan-March, relative to 2019, across rural and urban areas was precisely zero.[21]

Similarly, Sub-figure 3b(i) plots the coefficients by gender and Sub-figure 3b(ii) shows the difference in the coefficients between women and men for each phase. There was a fall in the probability of employment for both men and women during April-May relative to their pre-lockdown levels, after accounting for changes during 2019 over the same time period, but it was much more pronounced for men (18 percentage point ($p < 0.01$)) than women (2 percentage point ($p < 0.01$)).[22]

[21] We also examine the effect on employment by type of work. The results are shown in Table A.2. We find that during the phase of lockdown during April-May 2020, proportion of casual workers fell sharply (by 8 percentage point ($p < 0.01$) or almost 50%), followed by proportion of self employed (by 1.9 percentage point ($p < 0.01$) or 10%) and lastly for salaried (by 1.1 percentage point ($p < 0.01$) or 16%).

[22] This effect is on the overall employment rate. However, if one conditions on an individual being employed before the lockdown, the fall in employment is larger for women than men (Deshpande (2020)). The results on conditional

The employment rate for men continues to be lower in June-July 2020 and August 2020 compared to the pre-lockdown levels by 4 and 2 percentage point ($p < 0.01$) respectively while for women it is back to the pre-lockdown levels, compared to the change over baseline months for the same time period in 2019.

Sub-figures 3c(i) and 3c(ii) show the effect by age and can be interpreted in a similar manner. We find a significantly larger fall in employment post the lockdown on older workers in the age category of 30 and above (12.5 percentage point ($p < 0.01$)) than the younger workers aged 15-29 years (7 percentage point ($p < 0.01$)) relative to their pre-lockdown levels, after accounting for changes during 2019 over the same time period). However, the trend reverses during June-August, wherein the employment loss was proportionally higher for younger workers than for older workers from the pre-lockdown levels, relative to 2019 by almost 3 percentage ($p < 0.01$) point. Therefore, the lockdown had gender-differentiated and age-differentiated impacts (Chiplunkar *et al.* (2020)).

Next, we check whether initial differences in the occupational structure influence the findings above by accounting for occupation specific trends for each lockdown phase. Figure 4 plots the difference in coefficients across the three demographic categories. We find that the fall in employment was significantly higher in urban areas than rural areas (by 3 percentage point ($p < 0.01$)), even within the same occupation category (Figure 4a) during the stringent phase of the lockdown and that the difference dissipated over time. This is similar to our previous finding but the difference during April-May across regions are starker now. However, the difference across women and men overturns now. Figure 4a shows a higher fall in employment among women than men, within the same occupation. This is driven by the fact that women who were working in the pre-lockdown period saw a higher decline in employment but women who were not working entered the work force post the lockdown, at a differential rate than in 2019 for the same time period.[23] The overall results in Figure 3b(ii) show the average of the two effects while Figure 4b shows the average of within occupation changes for men and women. The results for younger workers also become more pronounced after controlling for differential impacts of the lockdown and its easing on occupations.

employment have bee omitted for brevity since we are interested in overall employment effects. The conditional and the unconditional results by gender taken together show that women who were not working entered into the labor force while those already working witnessed a fall in their employment. This kept the overall fall in employment for women smaller than for men.

[23] These results are in line with those reported by Deshpande (2020) on the gendered effects of COVID-19 lockdown in India. An increase in participation in workforce by women due to negative income shocks in developing countries has also been noted in earlier studies (Bhalotra & Umaña-Aponte, 2010).

We now find that within the same occupation category, the loss in employment was proportionally larger among the youth than for older workers (by 13 percentage point ($p < 0.01$) during April-May 2020 and 21 percentage point ($p < 0.01$) in August 2020), from the baseline months of January-March 2020, relative to 2019 (Sub-figure 4c).[24]

5.2. Social safety nets

Next, we look at the role played by employment social safety nets in cushioning the effect of the lockdown and the labor market recovery.

5.2.1. MG-NREGA

We first assess the generation of employment under MG-NREGA during 2020 and its correlation with employment changes using the estimation strategy discussed above. The results in this specification are potentially lower bounds on true effects since there can be differential trends in employment in areas which generated contemporaneously higher work days under the program. While we control for occupation specific time fixed effects, given the contemporaneous nature of the work generation, endogeneity cannot be ruled out. Figure A.4 plots the regression coefficients from a specification that interacts monthly work days generated under MG-NREGA per rural person in a district with each of the three phases. Sub-figures A.4a and A.4b plot the effects for rural and urban areas, respectively, for each period. The estimates show that an increase in work days under MG-NREGA by one day per rural person in a district increased the probability of employment in rural areas significantly by 4 and 3 percentage point ($p < 0.01$) during April-May 2020 and June-July 2020 respectively, in comparison to the effect of MG-NREGA during January-March 2020, relative to its effects in 2019. This effect peters out by August 2020 and we see no additional effect of MG-NREGA on the extensive margin of employment in August 2020 relative to its effect during the period January-March 2020, controlling for its effects in 2019. We also see no positive effect

[24] We also examine heterogeneous effects for those having more than school education and others. Here we find that the relative fall in employment from the baseline months of January-March 2020 was higher for the less educated during April-May 2020 by 2.4 percentage point ($p < 0.01$), relative to the same change in 2019 but during June-August 2020, the more educated suffered a higher fall in employment by almost 1.5 percentage point ($p < 0.01$). Thus, as the lockdown eased, those with more than school education suffered a greater loss in employment. These differences are largely determined by differential pre pandemic occupational structure across education groups. Within the same occupation group category, the less educated suffered a higher fall in employment by 5.8 percentage point ($p < 0.01$) during April-May 2020 and then by 2.8 percentage point ($p < 0.01$) during June-August 2020.

of MG-NREGA on employment probability in urban areas. This dynamic effect of MG-NREGA on rural employment could be due to this measure of MG-NREGA being endogenous and partly determined by changes in demand across regions post the lockdown.[25]

To address the endogeneity of work demanded under MG-NREGA to the economic crisis, we restrict ourselves to past performance of the program. Given the differential investment by district administrations in capacity to generate workdays under MG-NREGA, we expect that districts with greater pre-existing capacity to generate employment under the scheme would have managed to increase work days provision more than the other districts. This was confirmed in our earlier discussion based on Figure 1b, which plots current MG-NREGA work days generation given district level historical capacity. The districts with greater state capacity did respond faster to the crises as they had the required administrative ability to utilise program funds better. Therefore, we examine whether the pre-lockdown state capacity to provide workdays under MG-NREGA across districts played a role in off-setting job losses due to the pandemic induced lockdown. In all the specifications we control for occupation specific time fixed effects post the lockdown to ensure that our findings are not driven by differential occupational structures between areas which have historically shown higher state capacity for MG-NREGA work generation and other areas. Also, we look at the differential effects over time since large job losses can lead social safety nets to have differential effects on employment at the extensive margin. This scheme was targeted at rural areas and therefore we expect it to have larger effects in rural than urban areas.[26]

Figure 5 plots the estimates of the interaction of historical generation of work days with each time period post the lockdown. Sub-figure 5a shows that an additional historical person day under MG-NREGA per rural person leads to an increased probability of employment relative to the pre-lockdown months by 3 percentage point ($p < 0.1$) in June-July and 8 percentage point ($p < 0.05$) in August in the rural areas, relative to the same difference in 2019. While the coefficients for all the three periods are positive, they are imprecisely estimated for April-May. In contrast to the rural areas, the marginal effect of historical state capacity on employment in urban regions changes sign from negative (April-June) to positive (August) in Sub-figure 5b but is insignificant during

[25] If anything the effect of MG-NREGA is in the negative direction in urban areas (somewhat significant for August) perhaps reflecting the fact that greater workdays were likely to be generated in areas which had suffered larger employment losses as time progressed.

[26] Some positive effects could also be observed in urban areas due to general equilibrium effects coming from increased local demand in rural areas from government employment schemes.

June-August. We conclude, therefore, that the impact of state capacity to generate MG-NREGA works was muted in early months post the lockdown, and at best played a role in cushioning job losses in rural areas.

Next, we analyse the heterogeneous effects of historical MG-NREGA generation capacity on changes in employment post the lockdown. Given the positive effect of historical capacity to generate work under MG-NREGA on rural employment, we examine the heterogeneity in the effect of historical MG-NREGA work generation on employment by gender and age in rural areas only. The estimates for the effect of historical MG-NREGA on employment for men and women in each phase are plotted in Sub-figure 6a(i) and the differences between the effects on women and men are plotted in sub-figure 6a(ii). The estimates show that the marginal effect of increase in average historical work days under MG-NREGA by one day per rural person led to a slightly higher increase in probability of employment for women than men during April-June 2020 by 3 percentage points (imprecise) but during August 2020 it led to a significant 13 percentage point ($p < 0.01$) differential increase in women's employment. The estimates for the effect of historical MG-NREGA on employment for youth and older individuals for each phase and the differences between these effects by age (sub-figures 6b(i) and 6b(ii)) again show that initially there were no differential effects by age. However, in August 2020, older individuals gained more in employment than youth (by 7 percentage point ($p < 0.05$)) in areas where historically state capacity for MG-NREGA work days generation was greater by one work day per rural person.[27]

In addition to the above, we also examine the heterogeneous effect of the scheme by education and find that less educated individuals suffered a smaller loss in employment as the historical capacity to generate works under MG-NREGA increased by one day per person, by approximately 2.8 percentage point (imprecise) in June-July and 12 percentage point ($p < 0.05$) in August 2020. Taken together, these results point to the fact that higher existing state capacity to generate work days under the employment guarantee scheme of MG-NREGA, led to smaller losses in employment

[27] We also examine the heterogenous effects on employment for contemporaneous workdays generated under MG-NREGA and find that the results are broadly in line with the results using historical work days generated under MG-NREGA as shown in Figure A.5. An increase in work days under MG-NREGA by one person per rural person is associated with a slightly higher increase in probability of employment for women than men during all the three periods by 7 percentage points (significant at 1% for June-August) and the trajectory is upwards (almost 13 percentage points ($p < 0.01$)) during August 2020 (Sub-figure A.5a(ii)). The heterogeneity estimates by age also show that initially the positive effects of MG-NREGA on employment for youth and older individuals were similar but over time, and significantly so in August (by 5 percentage point ($p < 0.1$)), older individuals see a higher increase in probability of employment due to MG-NREGA than the youth (Sub-figure A.5b(ii)).

but the impact only kicked in during June-July and was the highest in magnitude in August. The smaller effect in April-May could be a result of a larger fall in actual NREGA work days generated during late March-April (when the lockdown was imposed) in districts that were historically generating greater employment under NREGA. However, the increase in actual work days generation was mostly during June-July while in August the increase was around 20% from the baseline. Notably, our measure of historical workdays generation capacity per person (with population measured in Census 2011) in a district does not take into account the changing population levels across rural-urban areas post the lockdown. There was a massive exodus of workers who suffered unemployment in urban areas post the lockdown towards their rural homes during April-May 2020.[28] Therefore, our measure does not capture the swelling of population in rural areas along side an increased provision of MG-NREGA works. We expect the impact of the past state capacity to be muted, if increased provision of work days under the guarantee scheme was insufficient to meet the needs of the people, given that more individuals were now looking for work in the same local rural labor market. The reverse movement of workers from rural towards urban areas was documented from August 2020 onwards.[29] Hence, the largest marginal effects of past state capacity to generate MG-NREGA works on employment (at the extensive margin) in rural labor markets were observed in August, when possibly the competition for these jobs had reduced as labor returned to urban areas. Also, with the return of young men back to their previous workplaces, the employment benefits from the social safety nets accrued more for women and older individuals, as the restrictions eased.

5.2.2. GKRA

We report the results for the PM-GKRA program from June onwards since the scheme was announced in May and became effective in June 2020. Again, in all the specifications we control for occupation specific time fixed effects. The overall effects on employment for rural and urban areas are shown in Figure B.2a and Figure B.2b, respectively. We can see that the additional effect on employment change from the baseline months of January-March 2020, relative to the same time period in 2019, in rural areas if a district is classified under the PM-GKRA scheme is precisely zero

[28] Many articles documented the movement of workers from urban to rural India during April-May 2020. See: Scroll, The Economic Times.

[29] See: Business Today.

while that in urban areas is significantly positive (by 1 percentage point ($p < 0.1$) in June-July and 7 percentage point ($p < 0.05$) in August) and increasing over time. The estimates for the heterogeneity in the impacts of PM-GKRA in urban areas by gender and age are then plotted in Figure B.3a(ii) and B.3b(ii), respectively. We do find any heterogeneous effects of PM-GKRA on employment change from baseline months, relative to 2019, by gender or age in June-July but in August both women (by 7 percentage points ($p < 0.01$)) and older workers (by 4 percentage point ($p < 0.05$)) gain relatively more in terms of employment in PM-GKRA districts.

5.3. Robustness Check for Attrition

We carry out inverse-probability weighted estimation to check the robustness of our results to attrition. We estimate the selection probabilities i.e. the probability of being present in 2020 for an individual surveyed in 2019 using the location (rural/urban), Principal Components Analysis (PCA) of assets owned and observed household characteristics.[30] Our results do not change and are therefore not driven by a systematic attrition of the sample. This analysis has been omitted for brevity.

6. Conclusion

In this paper we analyse the labor market impacts of pandemic induced economic shock and the extent to which employment guarantees were able to stem them over three phases of mobility restrictions in India. Using individual level panel data and accounting for seasonal trends in employment, individual and regional heterogeneity, our findings suggest that states with higher pre-pandemic capacity to generate work were able to cushion job losses and more so for women and older workers in rural areas under MG-NREGA as the restrictions eased. The skilled workforce in urban areas may have benefitted from PM-GKRA program. Our results indicate that the nature of employment

[30] PCA of ownership of residence, refrigerators, air conditioners, coolers, washing machines, televisions, computers, cars, two-wheelers, inverters, tractors and cattle; household characteristics include: age group (based on the distribution of members of a household by their age), income group (based on the annual income of the household i.e. the the income of all its members from all sources during a 12 month period), occupation group (based on the composition of the members of the household by the nature of their occupation as specified in the Master Cue of CPHS indicators), education group (based on composition of the maximum education level of household members who are 25 years of age or more), gender group (based on the distribution of members of a household by their gender), water access group (based on the number of hours that a household receives water during a day), power access group (based on the number of hours that a household receives continuous electricity) and family size group (based on the number of members in a household).

guarantees may need to vary by the characteristics of the workforce - minimum wages and types of work. Our findings are also in line with (Narayanan *et al.*, 2020) who show that the increased work generation was largely correlated with past work days generation in the district. Hence existing state capacity is critical in shaping the effectiveness of state response to economic shocks.

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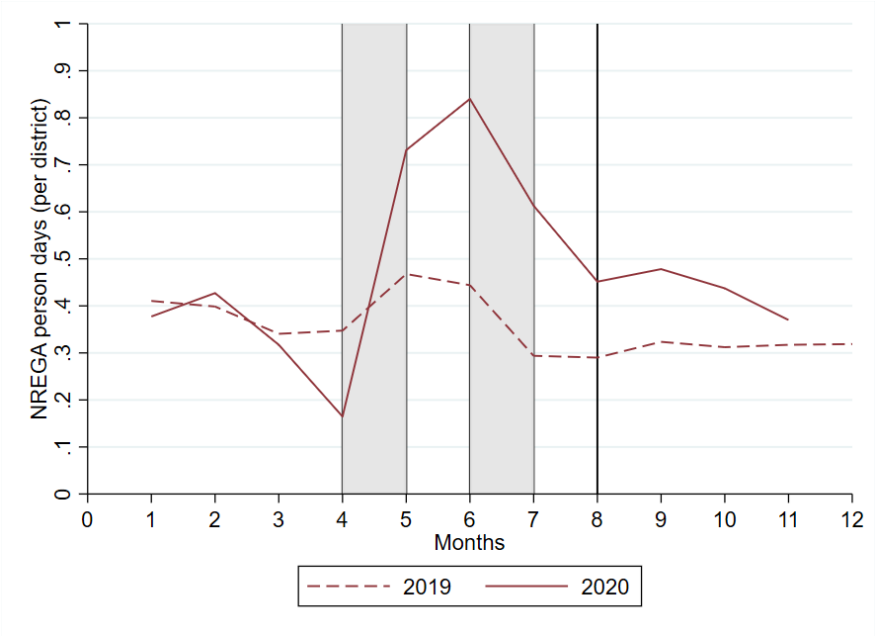
Table 1: Summary Statistics

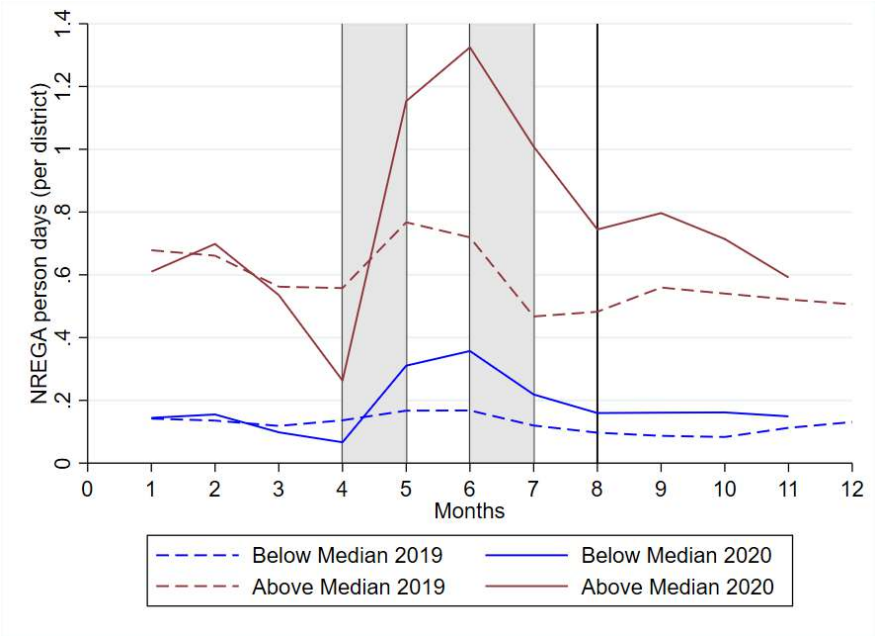
Panel A: Proportion Employed (Individual level)				
Variable	Obs	Mean	S.D.	Definition
Overall	1141735	0.41	0.49	Proportion employed
Region				
Rural	451724	0.43	0.49	Proportion employed in rural areas
Urban	690011	0.40	0.49	Proportion employed in urban areas
Gender				
Men	658605	0.65	0.48	Proportion of men employed
Women	483130	0.08	0.28	Proportion of women employed
Age category				
Youth	414271	0.25	0.43	Proportion employed in ages 15-30
Older	727464	0.50	0.50	Proportion employed in ages 31-59
Panel B: MG-NREGA (District-Month level)				
NREGA 2020	4830	0.49	0.75	Persondays per rural person in 2020
NREGA 2019	4830	0.37	0.62	Persondays per rural person in 2019
Historical NREGA	4830	0.31	0.44	Persondays per rural person in 2014-18

Source: The data for employment is from the Consumer Pyramids Household Survey for the relevant period in the sample (January-August 2019 and for January-August 2020). The data for work days generated under MGNREGA (years 2014-2020) are taken from the portal (NREGA) and Census (2011) and normalized by district rural population according to Census 2011.

Figure 1: MG-NREGA person days per rural inhabitant



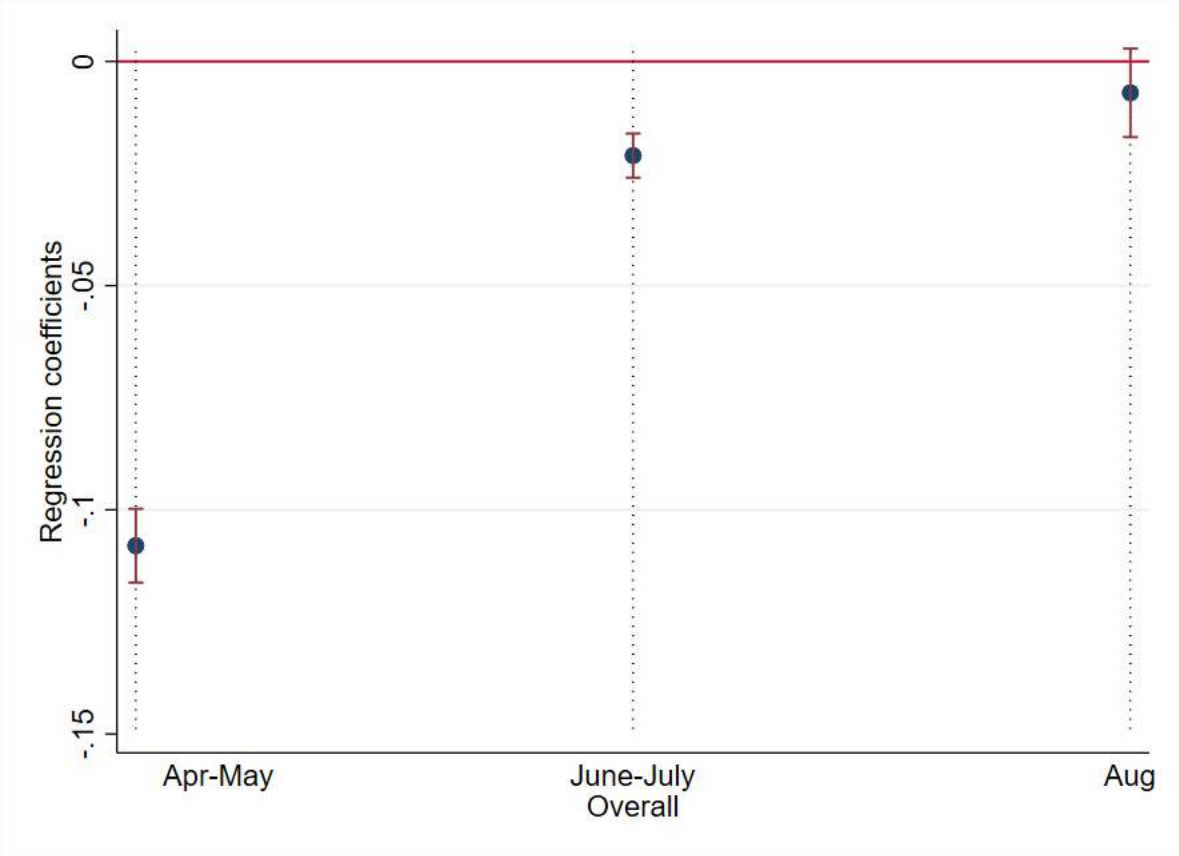
a: Current



b: Historical (2014-18)

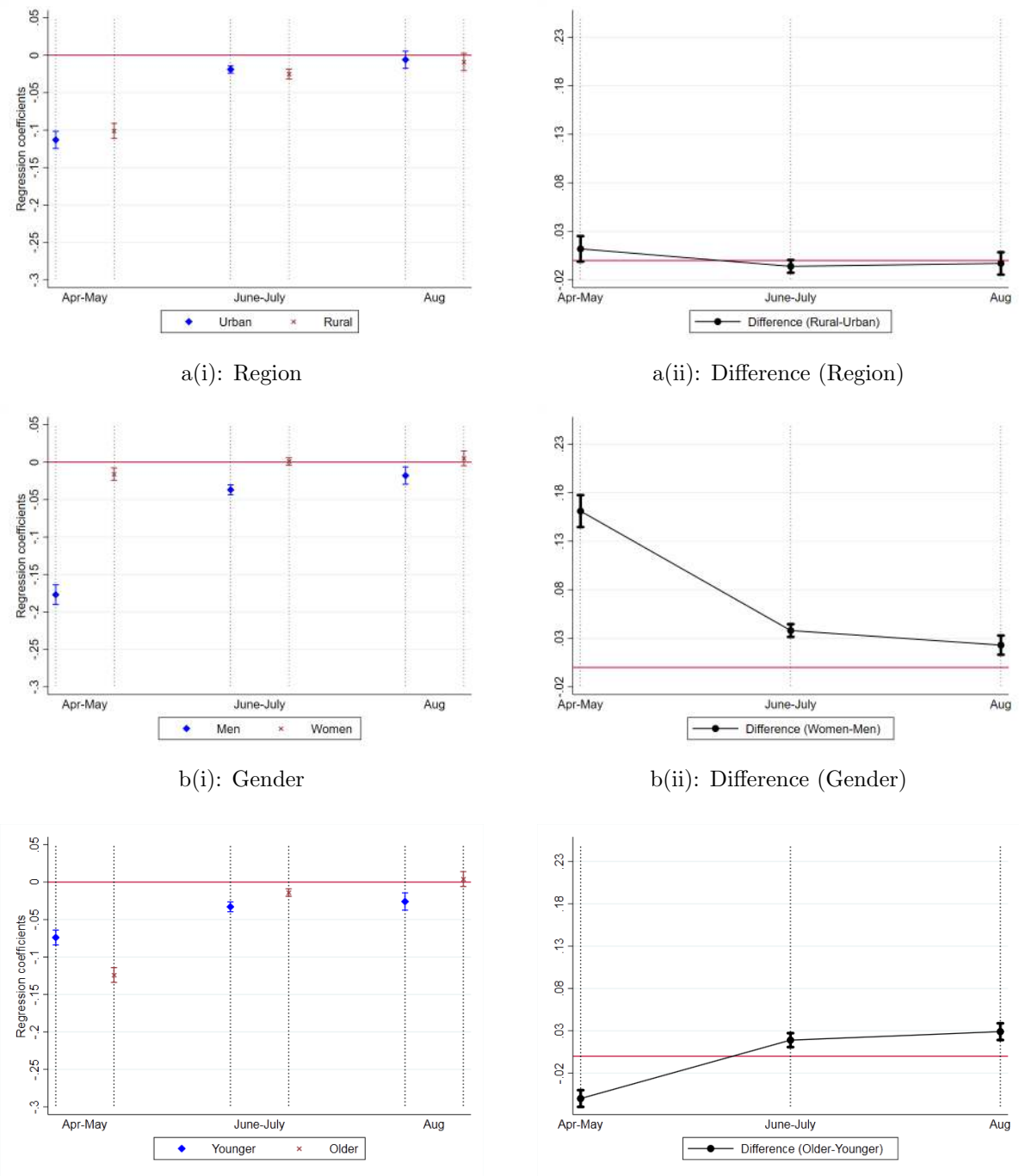
Source: MG-NREGA data (2014-2020) from MGNREGA Public Portal data.
Note: The persondays generated were divided by the rural population of the district (Census 2011). The median slicing has been done using the average historical MG-NREGA persondays generated by a district between 2014-18.

Figure 2: Impact of Lockdown Phases on Overall Employment



Source: Consumer Pyramids Household Survey Dataa (2019-2020).
Note: We have individual, month and year fixed effects in addition to controls for district specific time trends. Standard errors clustered at district-month-year level. 90% confidence bands are plotted around the regression coefficients.

Figure 3: Impact of Lockdown Phases on Employment by Region, Gender and Age



a(i): Region

a(ii): Difference (Region)

b(i): Gender

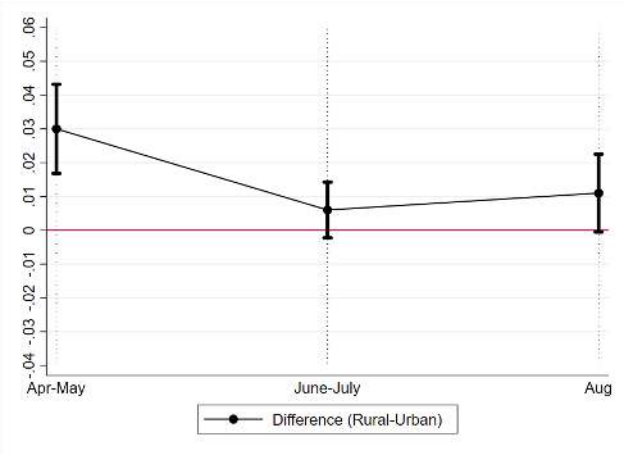
b(ii): Difference (Gender)

c(i): Age

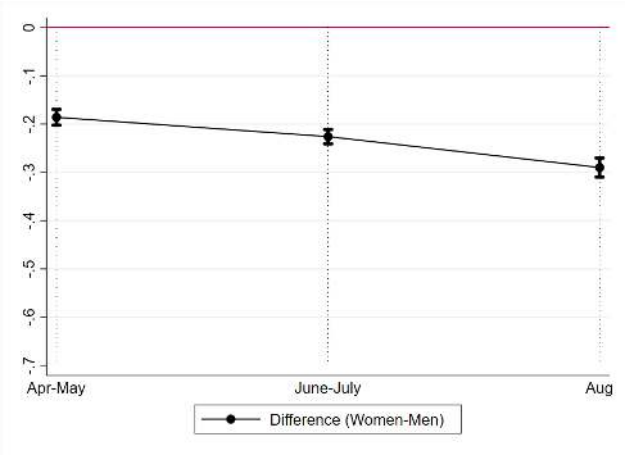
c(ii): Difference (Age)

Source: Consumer Pyramids Household Survey (2019-2020).
Note: The classification of region, gender and age is as of the quarter preceding the pandemic i.e. December, 2019-March, 2020. Standard errors clustered at district-month-year level. 90% confidence bands are plotted around the regression coefficients.

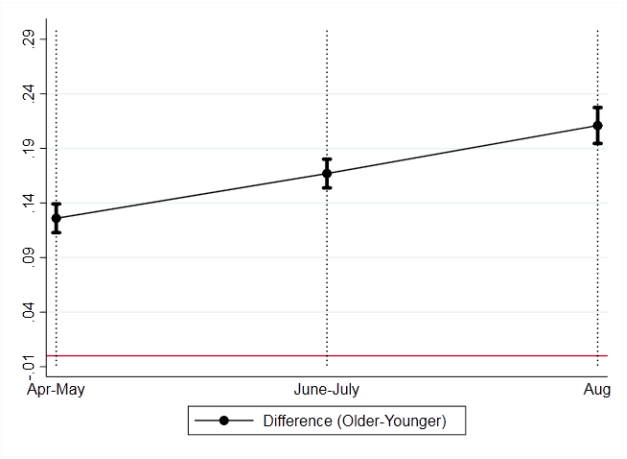
Figure 4: Impact of Lockdown Phases on Employment by Region, Gender and Age (Conditional)



a: Region



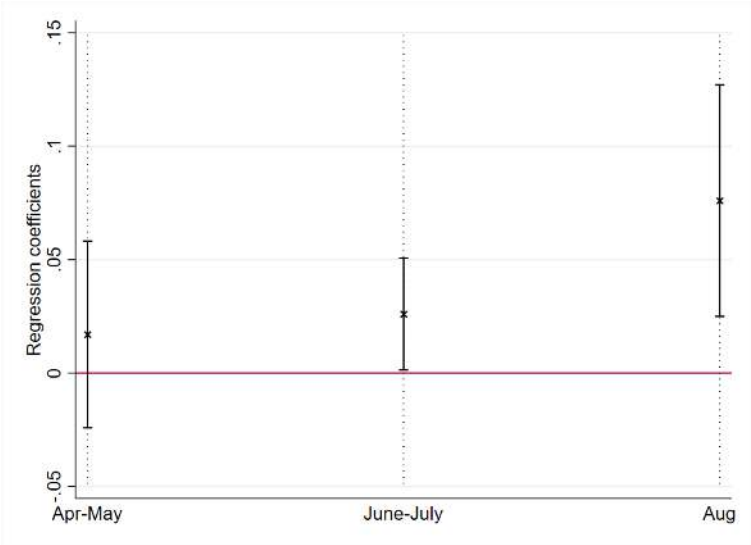
b: Gender



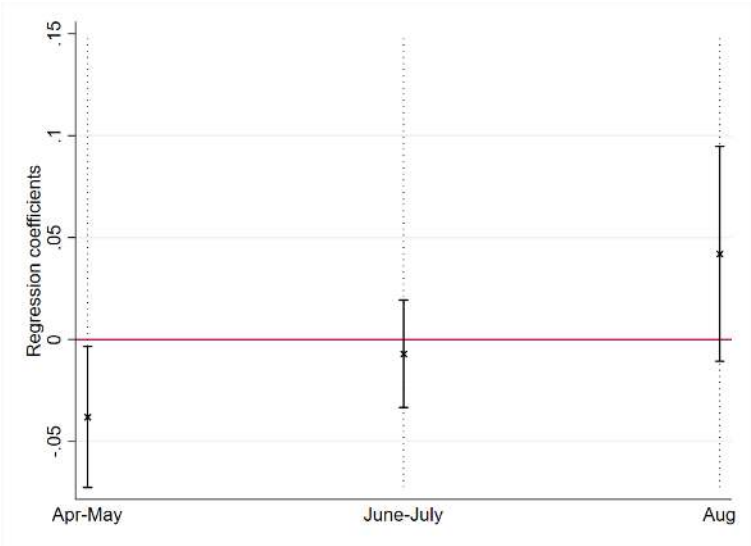
c: Age

Source: Consumer Pyramids Household Survey (2019-2020).
Note: The classification of region, gender and age is as of the quarter preceding the pandemic i.e. December, 2019-March, 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. Standard errors clustered at district-month-year level. 90% confidence bands are plotted around the regression coefficients.

Figure 5: Impact of MG-NREGA by Lockdown Phases on Employment (Conditional)



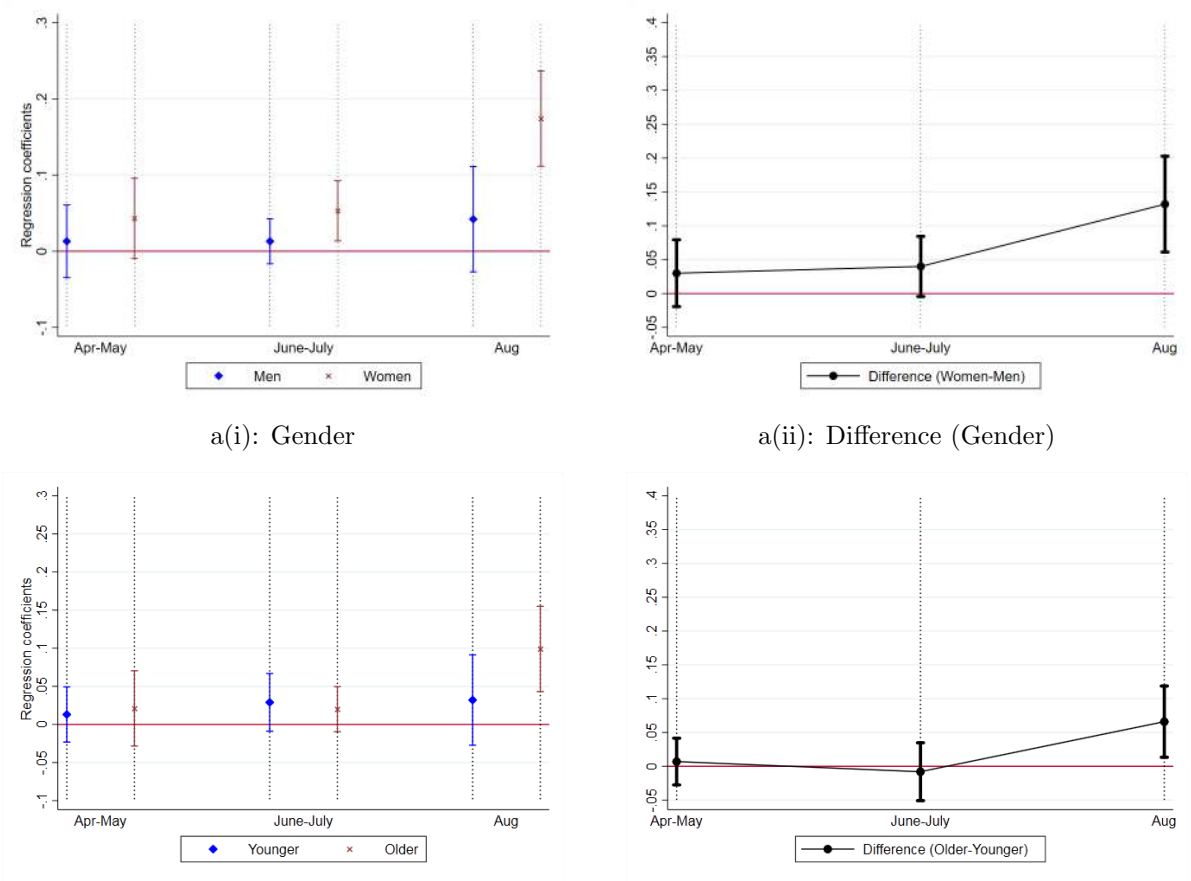
a: Rural



b: Urban

Source: Consumer Pyramids Household Survey (2019-2020) and MGNREGA Public Data Portal (2014-18).
Note: The classification of region is as of the quarter preceding the pandemic i.e. December, 2019-March, 2020. The monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) is the measure of historical MG-NREGA. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. Standard errors clustered at district-month-year level. 90% confidence bands are plotted around the regression coefficients.

Figure 6: Impact of MG-NREGA by Lockdown Phases on Employment by Gender and Age (Rural, Conditional)



a(i): Gender

a(ii): Difference (Gender)

b(i): Age

b(ii): Difference (Age)

Source: Consumer Pyramids Household Survey (2019-2020) and MGNREGA Public Data Portal (2014-18).
Note: The classification of region, gender and age is as of quarter preceding the pandemic i.e. December, 2019-March, 2020. The monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) is the measure of historical MG-NREGA. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. Standard errors clustered at district-month-year level. 90% confidence bands are plotted around the regression coefficients.

A. Additional Tables and Figures

Table A.1: Summary Statistics (Pre-lockdown)

Variable	Obs	Mean	S.D.	Definition
Panel A: Employment				
Overall	269850	0.42	0.49	Proportion employed
Region				
Rural	92834	0.45	0.50	Proportion employed in rural areas
Urban	177016	0.41	0.49	Proportion employed in urban areas
Gender				
Men	144227	0.71	0.45	Proportion of men employed
Women	125623	0.09	0.28	Proportion of women employed
Age category				
Youth	101438	0.24	0.43	Proportion employed in ages 15-30
Older	168412	0.53	0.50	Proportion employed in ages 31-59
Gender (Rural)				
Men	49951	0.73	0.44	Proportion of men employed
Women	42883	0.12	0.32	Proportion of women employed
Age category (Rural)				
Youth	35723	0.27	0.44	Proportion employed in ages 15-30
Older	57111	0.56	0.50	Proportion employed in ages 31-59
Gender (Urban)				
Men	94276	0.70	0.46	Proportion of men employed
Women	82740	0.07	0.26	Proportion of women employed
Age category (Urban)				
Youth	65715	0.23	0.42	Proportion employed in ages 15-30
Older	111301	0.51	0.50	Proportion employed in ages 31-59
Panel B: Employment type				
Casual	113403	0.36	0.48	Daily/monthly wage labour
Salaried	113403	0.16	0.37	Permanent salaried work
Selfemp	113403	0.46	0.50	Self-employed
Panel C: Unemployment				
Unemp (Involuntary)	269850	0.06	0.23	Willing to work but not finding work
Unemp (Voluntary)	269850	0.52	0.50	Not willing to work

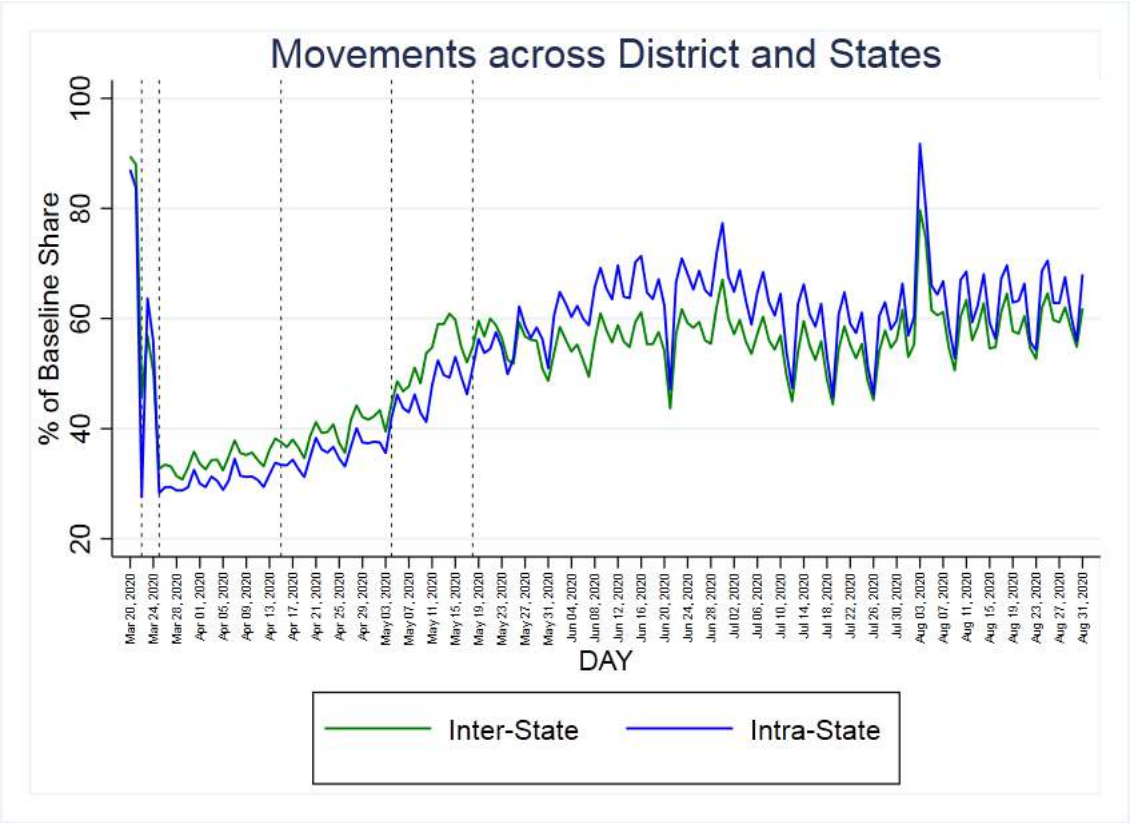
Source: Consumer Pyramids Household Survey (2019-2020).
Note: In all the three panels, we use the pre-pandemic months of 2020 i.e. January-March. The sample includes all individuals aged 15-59 in Panel A and Panel C. In Panel B, the sample includes individuals aged 15-59 who were employed in during January-March 2020.

Table A.2: Impact of Lockdown Phases by Type of Employment

VARIABLES	Casual	Salaried	Selfemp	Unemp	Not in LF
April-May × Post	-0.0756***	-0.0111***	-0.0194***	0.103***	0.0051
	(0.005)	(0.0026)	(0.0037)	(0.0053)	(0.0044)
June-July × Post	-0.0110***	-0.0098***	0.00077	-0.0002	0.0214***
	(0.0031)	(0.002)	(0.0027)	(0.0032)	(0.0037)
August × Post	-0.0087	-0.0126***	0.0160***	-0.0265***	0.0336***
	(0.0054)	(0.0036)	(0.0048)	(0.0065)	(0.0052)
Observations	1,128,941	1,128,941	1,128,941	1,128,941	1,128,941
R-squared	0.714	0.768	0.766	0.593	0.876
Pre crisis mean	0.15	0.07	0.20	0.06	0.52

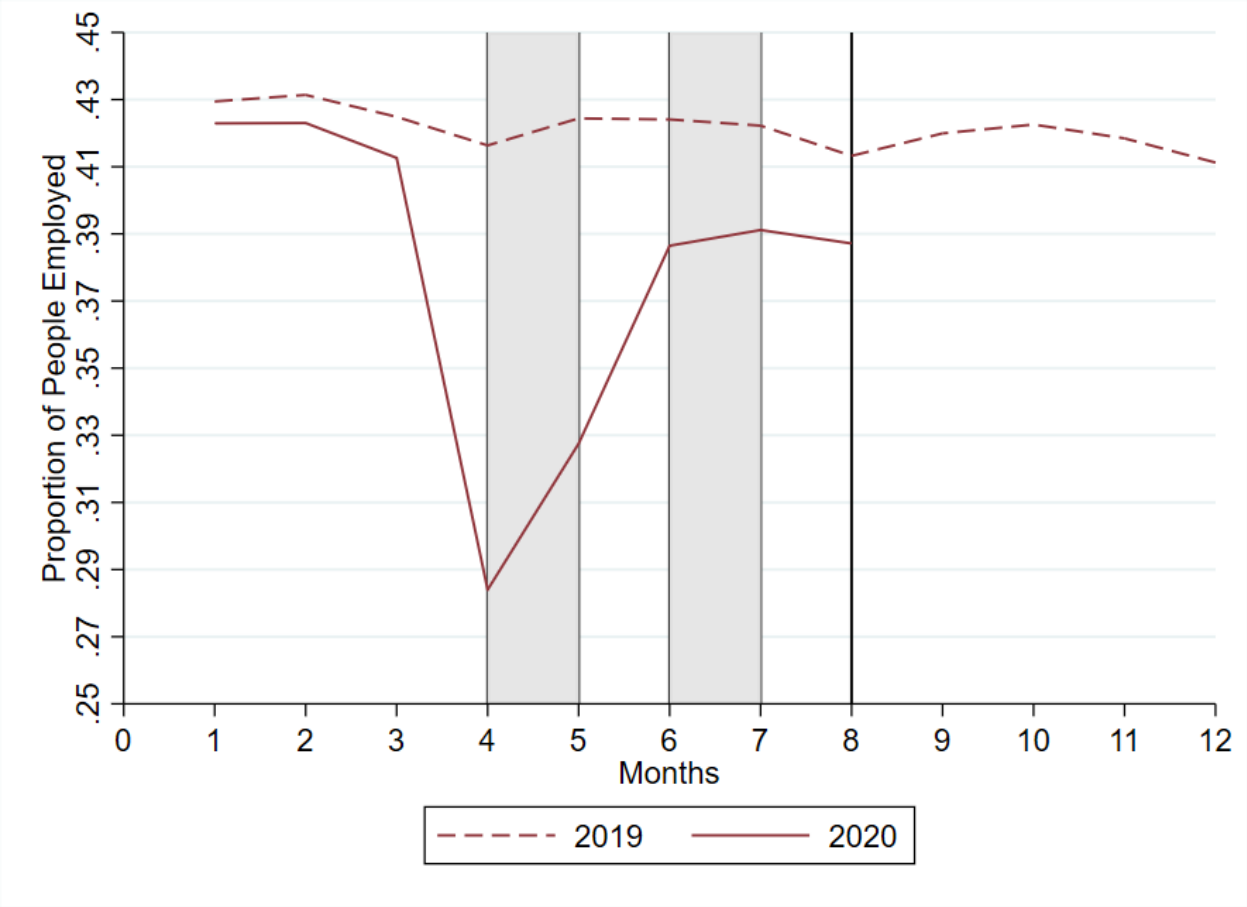
Source: Consumer Pyramids Household Survey (2019-2020).
Note: The sample includes all individuals aged 15-59 in Panel A. In Panel B, the sample includes individuals aged 15-59 who are classified into one of the employment categories in the pre-pandemic quarter i.e. December, 2019-March, 2020. The pre-crisis mean are calculated from the pre-pandemic months of 2020 i.e. January-March.

Figure A.1: Daily Movements in India



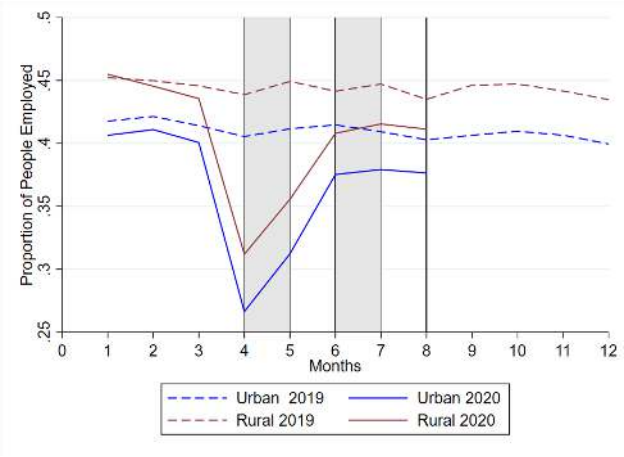
Source: Facebook Data for Good (2020).
*Note:*Daily movements at district level between 08:00-16:00 UTC. Inter-state movements are movements across districts located in different states. Intra-state movements include the movements within the district and across districts within the state.

Figure A.2: Employment by year

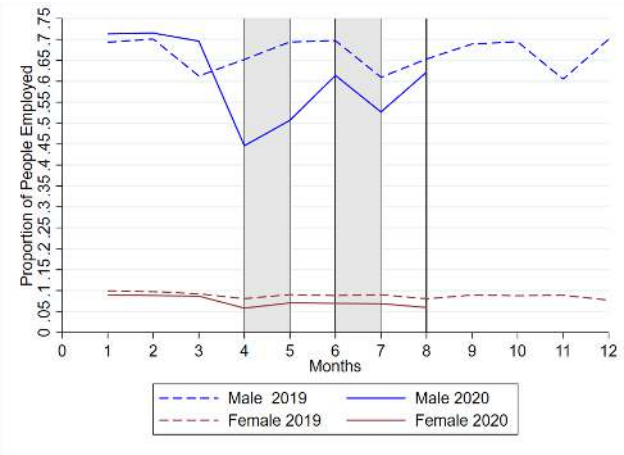


Source: Consumer Pyramids Household Survey (2019-2020).

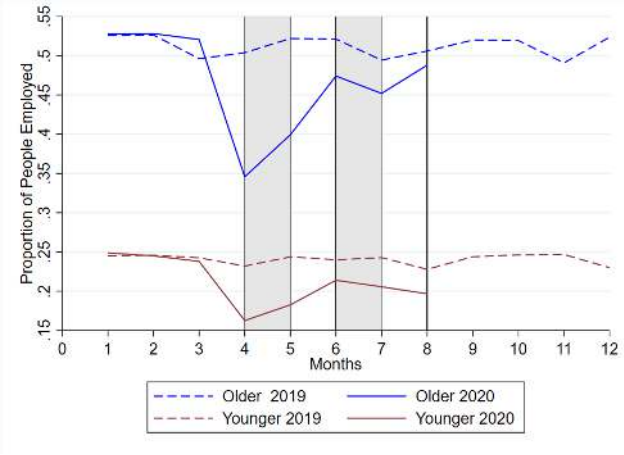
Figure A.3: Employment by Region, Gender and Age



a: Region



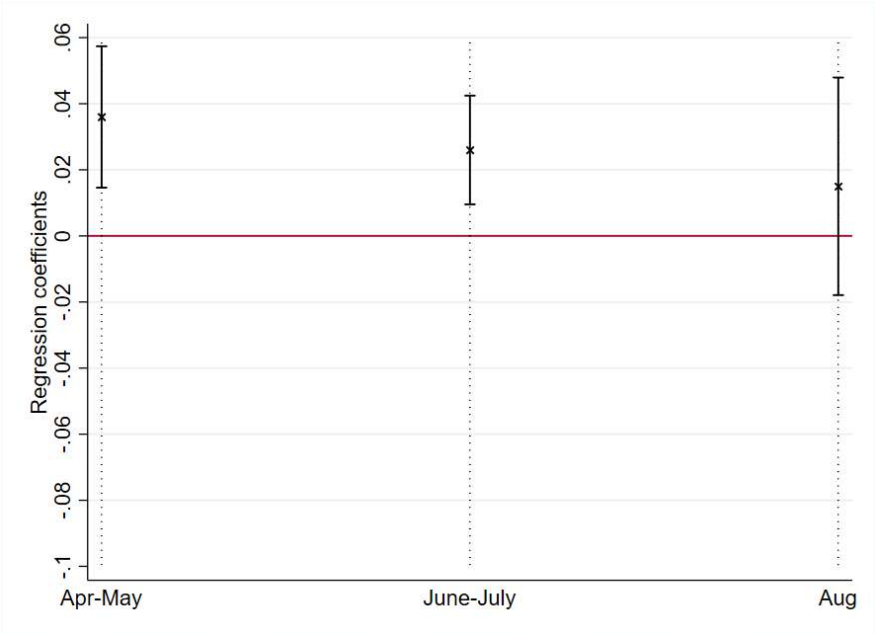
b: Gender



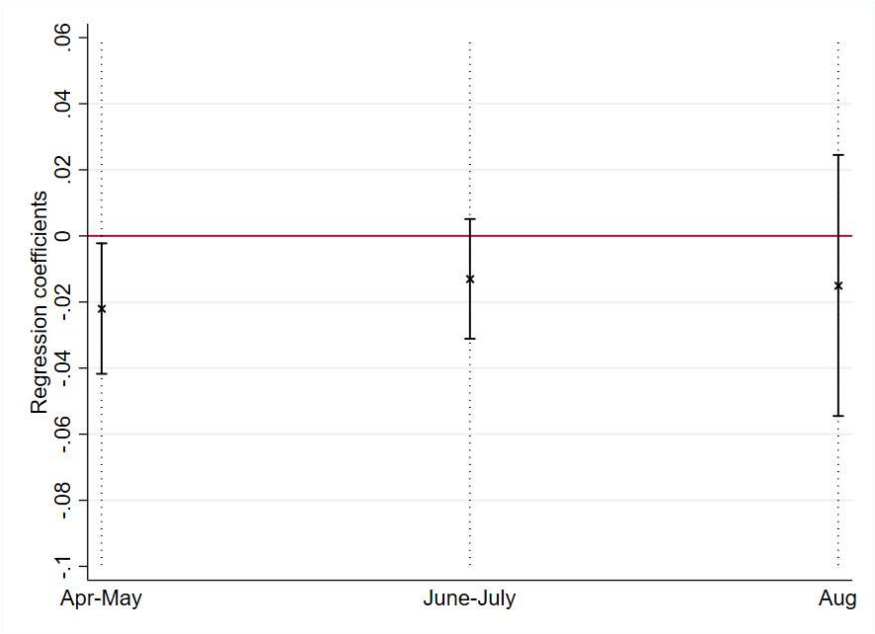
c: Age

Source: Consumer Pyramids Household Survey (2019-2020) and MGNREGA Public Data Portal (2019-20).
Note: The classification of region, gender and age is taken from the quarter preceding the pandemic i.e. December, 2019-March, 2020.

Figure A.4: Impact of MG-NREGA by Lockdown Phases on Employment (contemporaneous and conditional)



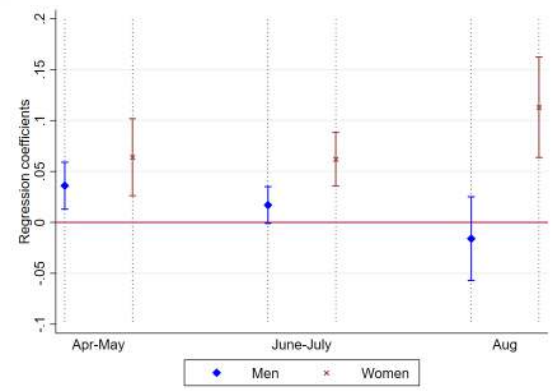
a: Rural



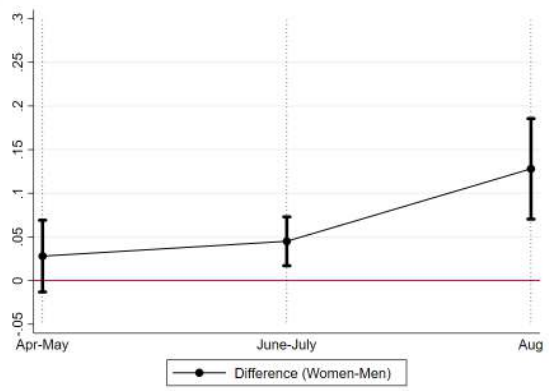
b: Urban

Source: Consumer Pyramids Household Survey (2019-2020) and MGNREGA Public Data Portal (2019-20).
Note: The classification of region is taken from the quarter preceding the pandemic i.e. December, 2019-March, 2020. The monthly persondays generated under MG-NREGA in 2019 and 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. Standard errors clustered at district-month-year level. 90% confidence bands are plotted around the regression coefficients.

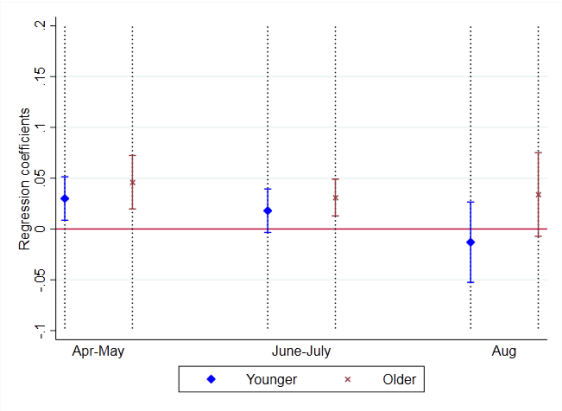
Figure A.5: Impact of MG-NREGA by Lockdown Phases on Employment by Gender and Age (Rural - contemporanous and conditional)



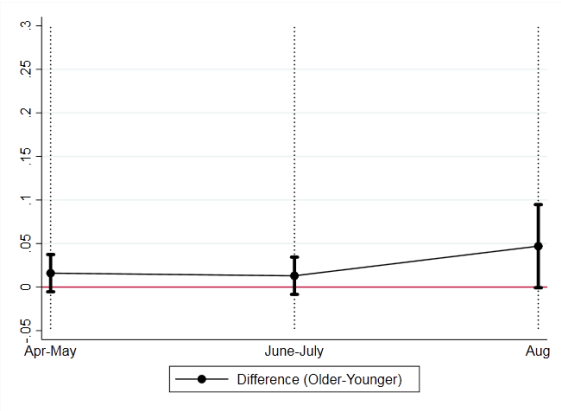
a(i): Gender



a(ii): Difference (Gender)



b(i): Age

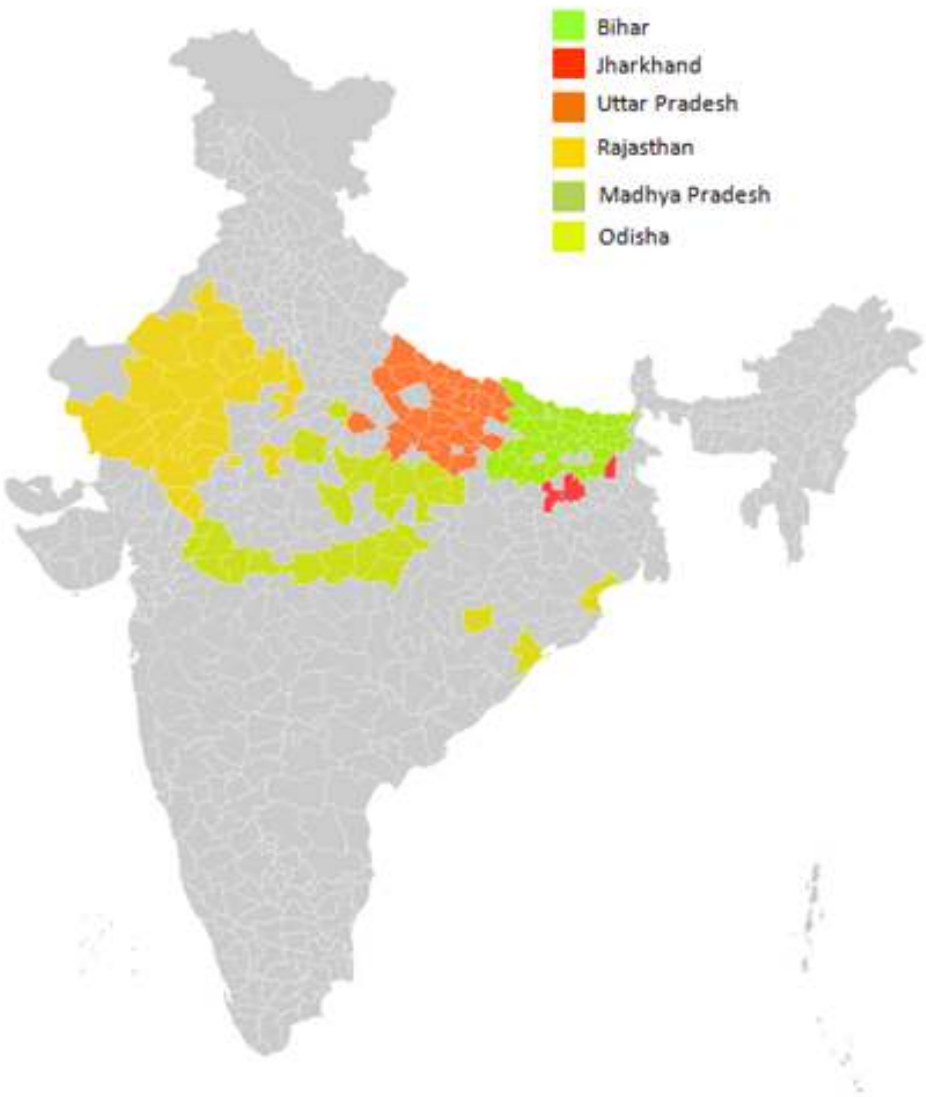


b(ii): Difference (Age)

Source: Consumer Pyramids Household Survey (2019-2020) and MGNREGA Public Data Portal (2019-20).
Note: The classification of region, gender and age is taken from the quarter preceding the pandemic i.e. December, 2019-March, 2020. The monthly persondays generated under MG-NREGA in 2019 and 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. Standard errors clustered at district-month-year level. 90% confidence bands are plotted around the regression coefficients.

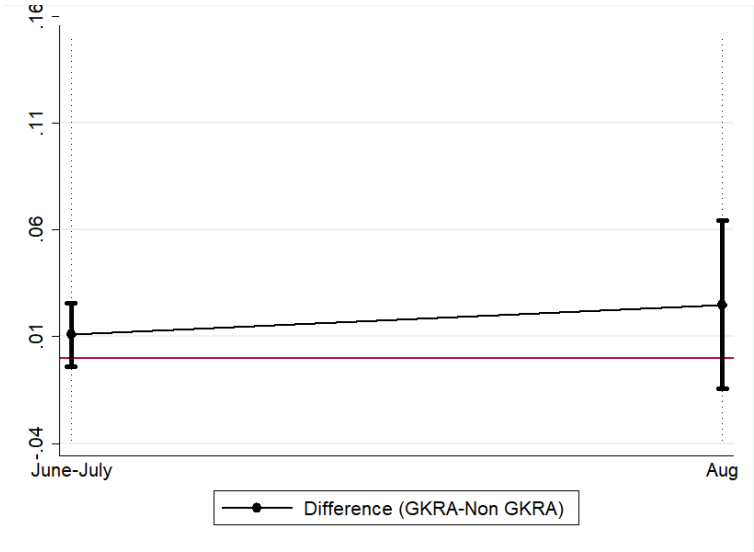
B. GKRA

Figure B.1: PM-GKRA districts

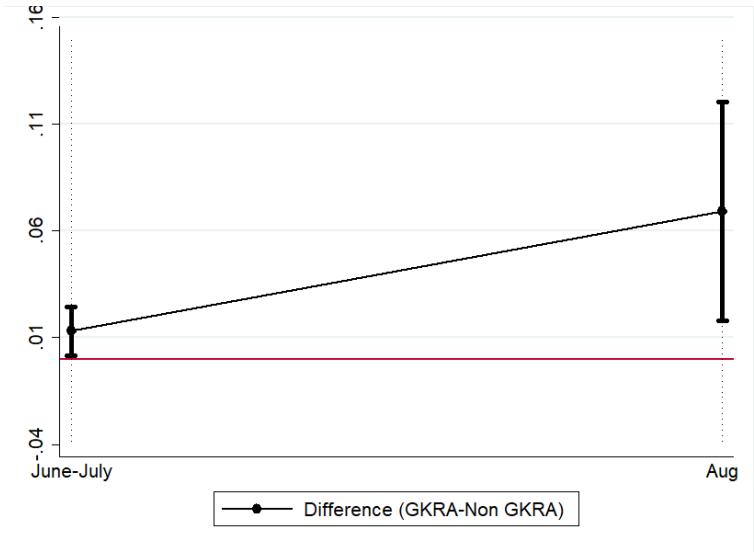


Source: PM-GKRA Public Data Portal (2020): http://gkra.nic.in/.

Figure B.2: Impact of PM-GKRA by Lockdown Phases on Employment (conditional)



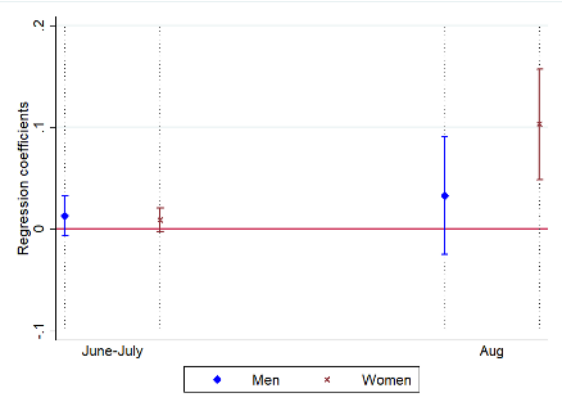
a: Rural



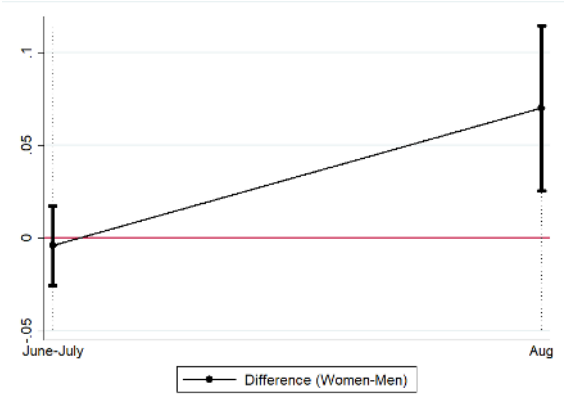
b: Urban

Source: Consumer Pyramids Household Survey (2019-2020) and PM-GKRA Public Data Portal (2020)(http://gkra.nic.in/).
Note: The classification of region is taken from the quarter preceding the pandemic i.e. December, 2019-March, 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. Standard errors clustered at district-month-year level. 90% confidence bands are plotted around the regression coefficients.

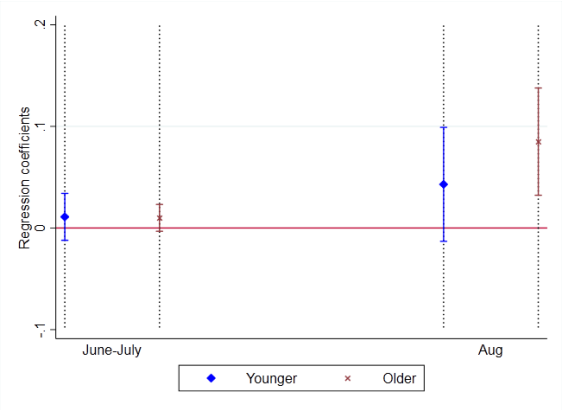
Figure B.3: Impact of PM-GKRA by Lockdown Phases on Employment by Gender and Age (Urban, conditional)



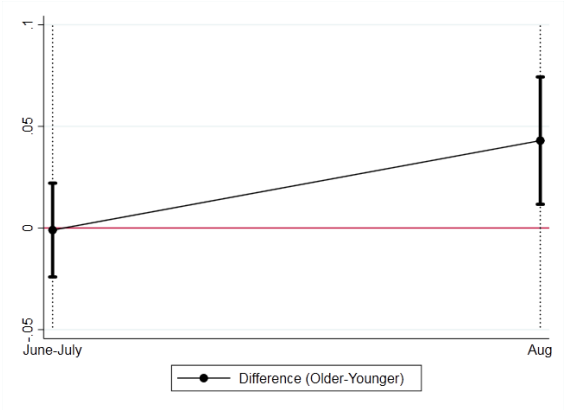
a(i): Gender



a(ii): Difference (Gender)



b(i): Age



b(ii): Difference (Age)

Source: Consumer Pyramids Household Survey (2019-2020) and PM-GKRA Public Data Portal (2020)(http://gkra.nic.in/).
Note: The classification of region, gender and age is taken from the quarter preceding the pandemic i.e. December, 2019-March, 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. Standard errors clustered at district-month-year level. 90% confidence bands are plotted around the regression coefficients.