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DISCUSSION PAPER SERIES

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ABSTRACT

Employment Guaranteed? Social Protection during a Pandemic*

The Covid-19 pandemic has highlighted the potential of social protection programs in mitigating labor market shocks. We examine the role of one of the world's largest employment guarantee schemes, India's MG-NREGA, in cushioning job losses in one of the worst affected economies due to the pandemic. Our findings indicate that regions with greater historical state capacity to provide public workdays under the scheme generated relatively higher employment during the pandemic. Consequently, an increase in state capacity by one MG-NREGA workday per rural inhabitant in a district reduced job losses in rural areas in April-August 2020 by 7% overall and by 74% for rural women, over baseline employment rate. These cushioning effects strengthened as the mobility restrictions eased and were larger for women who were less mobile and less skilled. Our results suggest that employment guarantee programs can protect livelihoods, but for certain demographic groups relatively more than others depending on the nature and skill level of work offered.

JEL Classification: J68, H31

Keywords: employment, COVID-19, public employment guarantee, MG-NREGA, women

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1. Introduction

The Covid-19 pandemic is an unprecedented health and economic shock to the world economy. Most major economies 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) - 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 population 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 addition, the benefits of employment guarantee schemes may differ by worker characteristics, depending on the nature of work offered and skills required.

We measure the impact of the pandemic induced shutdown in one of the worst affected economies due to the crisis - India. We first assess the dynamic effects on individuals' employment status during the period April-August 2020 - Phase 1 of stringent mobility restrictions (April-May), with gradual easing in Phase 2 (June-July) and full relaxation in Phase 3 (August). We then examine the role of the nation-wide Mahatma Gandhi National Rural Employment Guarantee Act (MG-NREGA), the world's largest employment guarantee program initiated in 2006 and bolstered following the pandemic, in cushioning job losses overall and as the stringency of the restrictions eased during April-August 2020. To address the endogeneity of workdays generated under the program during the pandemic, we use historical data on employment generation under MG-NREGA in a district over five years, from 2014-18, to measure the capacity of the state to provide social protection during this crisis.

Using nation-wide, individual level panel data with over a million observations and employing

[1] An ILO report discusses the various schemes implemented in the Asia-Pacific region during this pandemic. 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 duration 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.

an approach akin to a difference-in-differences (DID) estimation strategy that compares changes in employment status pre (2019) and post (2020) pandemic, during January-March (control months) and April-August (treated months), we find that individual level employment fell precipitously during the lockdown phase of April-May 2020 relative to January-March 2020, compared to the change over the same period in 2019. Employment showed a V-shaped recovery post the lockdown (April-May) with easing of mobility restrictions (June-July) but tapered off and continued to remain below the pre-pandemic level as the economy reopened (August).

The DID estimates indicate that historical program capacity stemmed employment loss in rural areas and women therein, during this period. We find that an increase in state capacity to provide MG-NREGA by one day per rural inhabitant (approximately moving a district from 50^{th} to 95^{th} percentile of the MG-NREGA historical state capacity distribution) in a month reduced job losses in rural areas during April-August by 3.1 percentage points (pp) overall or 7% over the baseline employment rate. Rural women's employment increased relatively, by 8.6 pp or 74%, suggesting that not only were employment losses for women stemmed, women who were previously not in the labor force may have entered the labor market during the crisis in high state capacity districts. On the other hand, the effect on rural men's employment while positive, was small and insignificant. Overall, high historical state capacity to provide MG-NREGA cushioned job losses more in rural areas in Phase 3 (August 2020) - by 4.8 pp or by 10.8%, and 13.1 pp or almost 100% for rural women. These findings are robust to individual level heterogeneity, district and occupation specific trends.

To the best of our knowledge, this is the first paper to evaluate the effectiveness of a pre-existing public employment guarantee on nation-wide employment during the Covid-19 pandemic.[3] Our findings are validated by smaller, bespoke studies conducted during the pandemic. Using survey data from urban India Dhingra & Machin (2020) find that workers with a job guarantee before the crisis were 5 pp more likely to remain employed. A choice experiment with the same sample suggests low-wage workers were willing to work at 25% lower wage if their job can be guaranteed while women were significantly more likely to prefer a guaranteed job than men. While previous

[3]Studies suggest buffering (but perhaps small) effects of unemployment insurance during Covid-19 crisis on employment and income in the context of the U.S. (Altonji *et al.* (2020), East & Simon (2020), Moffitt & Ziliak (2020), Farrell *et al.* (2020)) but assessment of labor market impacts of social safety nets are largely absent for developing countries.

research has highlighted the role of MG-NREGA on women's workforce participation due to its mandated reservation of jobs for women, equal pay and access to work close to home (Afridi *et al.*, 2016), our results are also consistent with the role of women's jobs as insurance (Sabarwal *et al.*, 2011) and the counter cyclicality of women's labor force participation in developing countries (e.g. during the debt crises in Latin America in the 1990s (Skoufias & Parker, 2006)). Indeed, we find that MG-NREGA disproportionately benefited married women, women belonging to households with young children and less educated women during the crisis - markers of lower mobility and skills - and irrespective of their pre-crisis employment status.

Our findings have important policy implications. First, we show that employment guarantees can play a role in shielding job losses and aiding recovery from a negative economic shock. Second, the results highlight the relevance of the design of the employment guarantees in contributing towards their effectiveness. While rural areas and women - the less skilled and less mobile - benefited disproportionately from the low-wage, unskilled employment under MG-NREGA, such social protection eluded urban areas. Thus, the nature of work and required skills can determine relative benefits by demographic groups. Finally, our research contributes to the emerging literature on the relevance of state capacity in the development process (Muralidharan *et al.*, 2016) by indicating 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 job guarantee program. 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 shutdown to deal with the COVID-19 pandemic, on 24 March 2020 until April 14, which was later extended to May 30 (Phase 1). 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 (Phase 2). From August 1, Phase 3 of 'unlockdown' with removal of night curfew saw further relaxations of restrictions on economic activity and mobility.[4]

As a consequence of the shutdown, 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 4.2% growth in the GDP in 2019-20.[5]

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 shutdown 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 ordered activities related to the MG-NREGA to resume. It also increased allocation to the program's budget by Rs 40,000 crore. Consequently the program generated 2.02 billion person days of work until September 2020, compared with 1.88 billion for the entire fiscal year of 2019-20. Figure 1a shows the district level monthly average person days of work (from the MG-NREGA Public Data portal) per rural inhabitant (from Census 2011) generated under the scheme in 2020 and 2019.[6] The gender allocation of

[4] See: The Indian Express.

[5] See: The Indian Express.

[6] https://nregarep2.nic.in/netnrega/dynamic2/DynamicReport_new4.aspx. Figure 1a shows that the average work days generated were similar in 2019 and 2020 for January-March but there was a sudden plunge in April 2020 (due to the shutdown) 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, the peak agriculture season, but remained slightly higher in 2020 than in 2019 even during August.

work days under MG-NREGA, however, did not change from the pre-crisis period.[7]

Research indicates that MG-NREGA implementation has been uneven across districts of India (Shah & Mohanty, 2010; Dreze & Oldiges, 2009), 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 shutdown and when the restrictions eased. We plot the average number of work days generated in 2020 across districts which have historically (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 Figure 1b.[8] 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 0.53 to 1.12 work days per rural inhabitant) in work days generation between March to June 2020 compared to historically low performing districts (from 0.09 to 0.31 work days per rural inhabitant).[9] These findings are also in line with Narayanan *et al.* (2020) who show that the increased work generation post lockdown was largely correlated with past work day generation in a district.

3. Data

We use the Consumer Pyramids Household Survey (CPHS) data from the Centre for Monitoring Indian Economy (CMIE) - a nation-wide, household level panel data where each household is interviewed once every quarter in a year. The CPHS captures employment details and other socio-demographics of individual respondents in the household.[10] The sample of households surveyed on average in each of the three quarters of 2019 was 139,220 which fell due to attrition in 2020. Our analysis is, therefore, restricted to a balanced panel of 335,038 individuals residing in 113,812

[7] We divide the cumulative work days generated by gender (unfortunately, this information is not available at monthly frequency, unlike the total work days generated) by the number of months for which we have data to arrive at the average monthly workdays by gender. Between April-December 2020 (post shutdown), the proportion of monthly workdays received by women was 48.45%, whereas during April 2019 to March 2020 (pre-pandemic) it was 48.75%.

[8] We exclude 2019 from the calculation of historical MG-NREGA intensity.

[9] Figure A.1 in the Appendix shows the historical work days generated per rural inhabitant by district. As expected, the states of Rajasthan, Andhra Pradesh (including the regions of present day Telangana) generated more workdays historically and have been recognized as the best performing states since the inception of the program (Sukhtankar, 2016; Imbert & Papp, 2015).

[10] Other modules of the CPHS capture household incomes, assets and monthly expenditure. See Data Appendix for details.

households, who were surveyed in both 2019 and 2020. Later we check the robustness of our results to household attrition.

Our main outcome of interest is the employment status of an individual. We use employment data for the working age population, i.e. individuals aged 15-59 (measured in the quarter Dec 2019-Mar 2020, preceding the shutdown). Table 1, Panel A, includes the employment statistics for the sample in our analyses.[11] Employment rates are higher, on average, in rural areas than urban areas and among men than women. There was a distinct fall in proportion employed during April 2020, immediately after the lockdown which largely recovered by July 2020 but remained below the levels in the corresponding months of 2019 (Figure A.2 in the Appendix).[12]

4. Estimation Strategy

Using CPHS data for Jan-Aug 2019 and Jan-Aug 2020, we first examine the overall change in employment due to the crisis:

$$y_{icdmt} = \alpha_0 + \alpha_1((Apr - Aug)_m \times Post_t) + D_i + Post_t + M_m + D_{dt} + \epsilon_{icdmt} \quad (1)$$

where y_{icdmt} 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. $(Apr - Aug)_m$ is an indicator variable that takes a value one for the months of April-August and zero otherwise. $Post_t$ is an indicator variables that 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 coefficient (α_1) gives the effect on employment post the shutdown on March 24, 2020.[13] We also account for individual level heterogeneity (D_i), year fixed effects ($Post_t$), seasonality through month fixed effects (M_m) and district specific year fixed effects (D_{dt}) to allay any concern that the results are driven by district specific trends. We examine the overall employment impacts and the dynamic impacts (to estimate recovery) by sub-periods as

[11] Individuals' demographic characteristics including location (rural/urban) are measured at the time of the first survey (pre-pandemic). In our analyses, we include data for individuals surveyed both in 2019 and 2020.

[12] Panel A of Appendix Table A.1 shows the employment statistics overall and by region and gender, type of employment (Panel B), and unemployment (voluntary vs involuntary in Panel B) during the pre-lockdown period of Jan-Mar 2020 (period used as baseline in our analyses).

[13] To elaborate, α_1 is the difference between the first difference (i.e. change in employment between Apr-Aug 2020 and Jan-Mar 2020) and the second difference (i.e. change in employment between Apr-May 2019 - Jan-Mar 2019).

the stringency of the movement restrictions eased: Apr-May (stringent lockdown), June-July (some easing of restrictions) and Aug (further easing). Standard errors are clustered at the district-month-year level.

Next, we examine the effect of MG-NREGA on employment. To address the concern that contemporaneous workdays generated under MG-NREGA in 2020 are endogenous to the crisis, we exploit the earlier finding that the increase in provision of work days under the MG-NREGA during May-August 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).[14] Thus, we estimate the impact of historical state capacity to provide MG-NREGA work on employment post the shutdown in India using the below specification:

$$\begin{aligned} y_{icdmt} = \beta_0 + \beta_1((Apr-Aug)_m \times Post_t \times NREGA_{dm}) + \\ \delta_1((Apr-Aug)_m \times NREGA_{dm}) + \delta_2((Apr-Aug)_m \times Post_t) + \\ \delta_3(NREGA_{dm} \times Post_t) + D_i + Post_t + M_m + D_{dt} + D_{cmt} + \epsilon_{icdmt} \end{aligned} \quad (2)$$

where $NREGA_{dm}$ is the number of days in district d in month m generated under MG-NREGA during years 2014-2018, divided by the rural population (as per Census 2011) in the district. The above specification is again akin to a difference-in-differences strategy, with heterogeneous impacts across districts due to differences in historical state capacity to generate MG-NREGA workdays.[15] The coefficient β_1 gives the effect of an increase in past capacity to generate employment under MG-NREGA by one day per rural inhabitant, on employment, post the shutdown. Thus, a positive value of β_1 would indicate that districts with higher prior state capacity to generate employment under MG-NREGA suffered smaller employment losses post the shutdown.

The advantage of this specification is that it allows us to control for seasonal changes in employment, an important consideration in rural areas dependent on agriculture. Additionally, we control for occupation specific time fixed effects (D_{cmt}), which address the concern that districts with

[14] The correlation between MG-NREGA workdays days in 2020 and historical MG-NREGA is high (0.68) suggesting that historical generation of work days under MG-NREGA is likely to reflect the administrative capacity to respond to a labor market crisis.

[15] To elaborate, β_1 is the difference between the first difference (i.e. change in employment between Apr-Aug 2020 and Jan-Mar 2020 as historical state capacity increases by one person day per rural inhabitant) and the second difference (i.e. change in employment between Apr-Aug 2019 - Jan-Mar 2019 as historical state capacity increases by one person day per rural inhabitant).

higher historical MG-NREGA work days are characterised by different occupational/employment structure and hence suffered differential job losses relative to other districts.[16]

We estimate the above specification - overall and by region, i.e. rural and urban areas separately as the scheme is applicable only in the rural areas and consequently is expected to have a larger impact there. We further examine the heterogeneity in the effect of MG-NREGA by gender, given the program's mandate for reserving 1/3rd of jobs for women and existing evidence which suggests that women prefer job guarantees more than men.

5. Results

5.1. Employment trends

We find that overall employment was 5 pp or 12% ($p < 0.01$) lower in Apr-Aug 2020 than in the pre-lockdown months of Jan-Mar 2020, relative to the same difference in 2019 (Panel (a) of Figure A.3 in Appendix plots the coefficient α_1 in Equation 1, for the sample of all individuals aged 15-59).[17] Panel (a) of Figure 2 shows that employment was hit the hardest, by almost 10.9 pp or 26% ($p < 0.01$), during the months of Apr-May 2020. It was lower by 2.1 pp ($p < 0.01$) during June-July 2020, and by Aug 2020 it was almost back to its pre-lockdown levels.[18]

We show the heterogeneity in the employment effects by region and gender in Panel (b) and (c) of Figure 2, respectively. Sub-figures 2b(i) and 2c(i) plot the group wise effects on employment by region and gender, respectively. Sub-figures 2b(ii) and 2c(ii) plot the difference in these effects across the two groups within region and gender, respectively (difference in coefficients α_1 across the two demographic groups). We find that the fall in employment was similar in both rural and urban regions during Apr-Aug 2020, from the baseline months of Jan-Mar 2020, relative to 2019 and across all three phases.

There was a fall in the probability of employment for both men and women during Apr-Aug

[16]We include 15 occupational categories for the employed or those looking for work, viz. Industrial Workers, Wage Laborer, Self-employed, Farmer, Home-based worker, and two categories for those not employed and not looking for work: Home Maker and Others (Retired/Students).

[17]Our estimate lines up with others'. See https://unemploymentinindia.cmie.com/kommon/bin/sr.php?kall=wtabnav&tab=4080&nvdt=20200526081826533&nvpc=091000000000&nvtype=COMMENTS

[18]We also examine the effect on employment by type of work in Appendix Table A.2. We find that during Apr-Aug 2020, the proportion of casual workers fell by 3.27 pp (22%), followed by salaried (by 1.05 pp or 15%) and lastly the self-employed (by 0.51 pp or 3%).

relative to their pre-lockdown levels (Panel (c) of Figure A.3 in Appendix), after accounting for changes during 2019 over the same time period, but it was more pronounced for men (8.6 pp or 12% ($p < 0.01$)) than women (0.7 pp or 8% ($p < 0.01$)). This holds in all the three phases (Panel (c) of Figure 2). However, the magnitude of the gender difference falls with the easing of restrictions as male employment recovers.[19]

5.2. Overall effect of MG-NREGA

The first row of Table 2 reports the estimates of the effect of historical MG-NREGA state capacity during the entire period Apr-Aug (β_1 in Equation 2). The subsequent rows report the coefficients for the most stringent lockdown period of Apr-May (Row 2), and the gradual easing in June-July (Row 3) and Aug (Row 4), respectively. Columns (1) and (2) show the effects for the rural areas while (3) and (4) show these for the urban areas. We find that an additional historical person day under MG-NREGA per rural inhabitant increased the probability of employment relative to the pre-lockdown months by 3.1 pp (or 7%) in Apr-Aug in the rural areas, relative to 2019. Given that the overall loss in rural employment post the shutdown was 5 pp (Table A.2, Panel B, Column (1)), these estimates suggest that employment losses in areas with higher MG-NREGA state capacity were substantially lower. The results in column (2) show that there was a positive but insignificant effect of past state capacity to generate MG-NREGA during the most stringent shutdown period of Apr-May (2.9 pp). But with the gradual easing of restrictions, an increase in historical workdays under MG-NREGA by one day per rural person in a district increased the probability of employment in rural areas significantly by 3 and 4.8 pp during June-July and Aug 2020, respectively, from Jan-Mar 2020 and relative to 2019. Since on average districts at the 50^{th} and 95^{th} percentile generated 0.16 and 1.26 person days of MG-NREGA work per month per rural inhabitant during 2014-18, respectively, the marginal effects indicate cushioning of employment loss when a district shifts from mid to upper end of historical MG-NREGA state capacity distribution.

We conclude, therefore, that although the impact of state capacity to generate MG-NREGA works was muted during the shutdown, it played a significant role in cushioning job losses in rural areas thereafter. The smaller effect of MG-NREGA state capacity during Apr-May 2020 could

[19] Note, however, that if we restrict the sample to only those individuals who were employed before the lockdown, the fall in employment is proportionally larger for women than men - in line with Deshpande (2020).

be a result of a fall in actual MG-NREGA workdays generated during late Mar-Apr (strictest shutdown period) in districts that were historically generating greater employment under MG-NREGA (Figure 1a). The increase in actual workdays generation was mostly during June-July while in August the increase was around 20% from the baseline.

A caveat to the above findings is that our measure of historical MG-NREGA workdays generation capacity per rural inhabitant (as per Census 2011) in a district does not take into account the changes in population levels across rural-urban areas following the shutdown due to the massive exodus of workers from urban areas towards their rural homes during Apr-July 2020, and who began returning to the cities in Aug 2020.[20] Although reliable data on migrant workers' movements during this period is absent, it is instructive to discuss how our estimates may be affected by these movements. If the pre-pandemic out-migration rates across both high and low historical state capacity regions were similar, then the swelling of population is likely to be similar across all areas, and hence is subsumed in the fixed effects. However, if out-migration rates were higher (lower) in districts with historically high MG-NREGA state capacity, then our estimates are likely to be lower (upper) bounds of the true impact during April-July because the rural population would have increased relatively more (less) in these districts undermining any increase in the availability of MG-NREGA jobs. Using migration data from National Sample Survey (2007), we find that the correlation between pre-crisis district level out-migration rates and historical MG-NREGA annual state capacity is 0.18. The correlation is low, but given the direction, suggests that a larger number of migrants moved back to regions with higher historical MG-NREGA state capacity. Hence, these estimates are a likely lower bound on the true effects of prior state capacity on employment during April-July and an upper bound for August when rural migrants began to return to the cities.[21] Hence, the dynamic impact of MG-NREGA may not be entirely attributable to the ability of the state to respond to the crisis but may also reflect the relative movement of population during this period. Nevertheless, the overall impact for Apr-Aug 2020 balances out the two opposing directions of any systematic bias.

[20] Several newspaper reports documented the movement of workers from urban to rural India during Apr-May 2020. See: Scroll, The Economic Times.

[21] The reverse movement of workers from rural to urban areas from Aug 2020 is well documented: See Business Today.

5.2.1. Effect of MG-NREGA by gender

We restrict our attention to rural India here, since a positive effect of historical capacity to generate work under MG-NREGA is observed above on rural employment only. Columns (5) and (6) of Table 2 report the effects on rural women while columns (7) and (8) report the effects on rural men. The overall estimates for Apr-Aug show that the marginal effect of an increase in average historical workdays under MG-NREGA by one day per rural inhabitant increased the probability of employment for women by 8.6 pp (or by 74% over baseline employment rate).

The overall fall in women's employment in rural areas was 1 pp (Table A.2, Panel D, Column (1)), hence these effects suggest that women who were previously not employed may have entered the work force in historically high MG-NREGA state capacity areas. While these results are in line with existing literature on counter cyclicality of women's labor force participation, they also highlight the fact that availability of suitable employment opportunities can play a role in effectuating it. Examining the effects by sub-periods, Column (6) of Table 2 shows that MG-NREGA had a significantly positive effect on women's employment in all the three phases, which strengthened over time (over 7.6 pp in Apr-July and 13.1 pp in Aug). On the other hand, the effect on rural men remains insignificant in all the three phases (Columns (7)-(8)).[22]

The above results indicate that the effect of historical state capacity in generating women's employment increased as the lockdown restrictions eased. In addition to the lower generation of MG-NREGA works during Apr-May, this could also be due to women benefiting from lower demand for work as predominantly male migrants moved back to their urban workplace in August. We provide evidence for the latter channel and other possible mechanisms in the next section.

5.2.2. Why did women benefit more?

Reservation for women in MG-NREGA jobs and possibly higher allocation of MG-NREGA work days to women during the crisis are not sufficient to explain our results (women workers made up for approx. 48.5% of work days, before and after the pandemic, see Sub-section 2.2.2). Existing

[22] We also examine the effect of NREGA on the intensive margin of employment i.e., on the number of hours worked in a day. However, since data on hours worked is available only from September 2019 we are unable to correct for seasonality in employment using a DID approach. Instead, utilizing data for Jan 2020 - Aug 2020 and computing the single difference or change in average hours of work post the lockdown for rural women as the historical MG-NREGA generation capacity increased by one person per rural inhabitant, we again find a significantly positive effect of MG-NREGA on rural women and an insignificant effect on rural men (Table A.3 in Appendix).

literature indicates that women prefer jobs near home due to mobility restrictions, safety concerns and the need to balance care work with market work (Fletcher *et al.*, 2019) as well as a guaranteed job (Dhingra & Machin, 2020). Since MG-NREGA guarantees work within the village precincts it meets many, if not all, of the preferred job characteristics of women.[23]

In order to assess how these supply side factors may have influenced the impact of the program, we examine the heterogeneous effects of historical MG-NREGA state capacity by marital status (likely indicator of limited mobility), whether individuals' household has primary school going children (indicator of limited mobility and need to balance care work with market work), lower education and poverty (may have greater preference for guaranteed jobs). Thus in Table 3 we analyse the impact of MG-NREGA on employment of rural women by the following individual characteristics: (1) *Ever married* (dummy variable that takes a value one for women who were ever married, else zero), (2) *Education* (dummy variable that takes value one for women with education below primary level, else zero) and (3) *Employment* (dummy equals one for women who were employed in the preceding quarter before the lockdown, else zero) to check whether women already in the labor force or new entrants to the labor market took up MG-NREGA work during the pandemic; household characteristics: (4) *Young children* (dummy variable that equals one for households with a child up to 12 years of age, else zero) and (5) *Poor* (takes value one for households in the bottom two deciles of a constructed assets index, else zero); and lastly, we examine whether the cushioning of women's employment varied by the proportion of migrant population of a district, i.e. (6) *Low migrant* - dummy equals one for individuals residing in rural districts without seasonal out-migrant workers, and zero if the district has a positive number of rural out-migrants in the year 2007, the latest year for which such information is available.[24]

The first row of Table 3 reports the heterogeneous effects of MG-NREGA by these characteristics on rural women's employment. The second row reports the impact for the base category ($Z = 0$). The row 'Estimate ($Z = 1$)' in the bottom panel reports the sum of the first two rows in the table i.e., the impact for the main category ($Z = 1$). We find that rural women in all these categories ($Z = 0$ as well as $Z = 1$) gained employment in areas with historically high MG-NREGA state

[23]Since we account for both time invariant and time varying district level heterogeneity in the labor market in our analysis, any difference in employment opportunities (by gender) between high and low capacity districts cannot explain our results.

[24]For details on construction of the asset index and calculation of number of seasonal migrant workers in a district, refer to Appendix B.

capacity but there were significant differences across these categories by marital status, education, children and poverty levels. Column (1) shows that ever married women's employment increased by 4.5 pp (33%) more than women who were never married and employment of women with primary school going children increased by 3.9 pp more (33%) than those in households with no child in that age group (Column (4)). These results support the hypothesis that limited mobility and the need to balance child care duties could have led to women accessing a public guarantee program like MG-NREGA more than men.

Similarly, results in Row (1) of Columns (2) and (5) in Table 3 indicate that employment of women who were less educated or in households classified as poor increased relatively more due to MG-NREGA by 4.7 pp and 4.9 pp, respectively. However, we do not find any significant difference in employment increase due to MG-NREGA state capacity by previous employment status of women (Column (3), Table 3), suggesting that employment of women who were previously employed as well as those who were not increased post shutdown in regions with historically high MG-NREGA state capacity. We also find that rural women in districts having low migrant worker population witnessed a larger increase in employment during Apr-Aug due to MG-NREGA state capacity by 11.8 pp (Column (6)). As discussed earlier, this finding can be attributed to lower demand for limited MG-NREGA jobs in low migrant areas, as primarily male migrant workers returned to rural regions post the shutdown.[25]

On the other hand, while employment of less educated men and those in poorer households was cushioned more due to MG-NREGA (Appendix Table A.4, Columns (2) and (5)), there were no differential employment effects along the dimensions of marriage or children in the household for rural men (Columns (1), (3) and (4)). Although employment of rural men residing in districts with low migrant worker population was also cushioned more due to MG-NREGA state capacity (Column (6)), the magnitude of impact was smaller for men (8 pp for men vs 11.8 pp for women). These results suggest that mobility and child care concerns were additional factors due to which women may have benefited more from MG-NREGA during the crisis.

[25] We obtain similar results when we analyse contemporaneous work provided under MG-NREGA on changes in employment status of rural women post lockdown and the heterogeneity in these effects. We also examined these heterogeneous impacts on the intensive margin of employment i.e., on the number of hours worked in a day. We continue to find a differentially higher significant effect of MG-NREGA on ever married, less educated women and in districts with low migrant workers. The coefficient on children and poor remains positive but is imprecise (Columns (4)-(9), Table A.3 in Appendix).

5.3. Robustness Checks

Attrition: We carry out inverse-probability weighted estimation to check the robustness of our results to attrition (see Appendix B for methodology), reported in Table A.5 in Appendix, Columns (1)-(3). The previous conclusions continue to hold - there is a decline in employment post the national lockdown by 5 pp (Column (1)) and historical capacity to generate MG-NREGA works cushions losses for rural women (Column (2)) but not for rural men (Column (3)).

Placebo: We undertake a falsification exercise using data from Jan-Aug 2018 and Jan-Aug 2019 and defining $Post_t$ as the year 2019 in Table A.5 in Appendix. Since there was no pandemic induced shutdown during 2019, we should not see any systematic employment trends for this period. As expected, we find no significant difference between the probability of employment in Apr-Aug 2019, in comparison to Jan-Mar 2019 (Column (4)), relative to that of 2018. The effect of historical state capacity to generate MG-NREGA workdays on rural employment is also not significant in Columns (5) and (6) for either rural women or men.

District Seasonality: Our results are also robust to controlling for district-month fixed effects to account for seasonality in employment at a geographically disaggregated level. These are omitted for brevity.

6. Conclusion

In this paper we analyse the extent to which an employment guarantee program was able to stem employment loss in India during the Covid-19 crisis. Using individual level panel data and accounting for seasonal trends in employment, individual and regional heterogeneity, our findings suggest that districts with higher pre-pandemic capacity to generate public works employment under MG-NREGA were able to cushion job losses significantly in rural areas and more so for rural women. We find no spillover effects on urban employment, highlighting the need for complementary policies in urban areas.[26] Furthermore, rural women who were less likely to be mobile and/or had child care responsibilities gained more from the program, suggesting that the nature of guaranteed

[26] 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.

jobs can be a critical determinant of which demographic groups benefit from such social protection.

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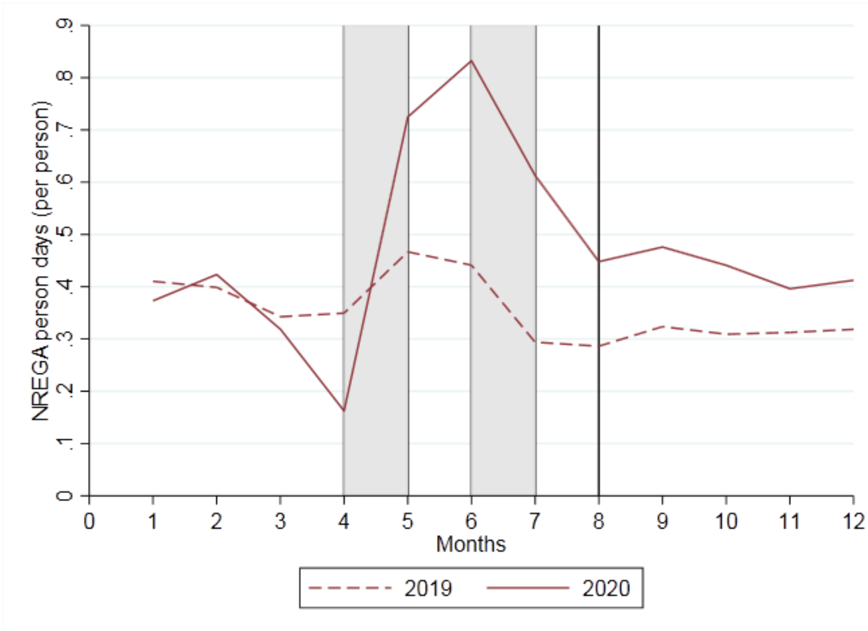
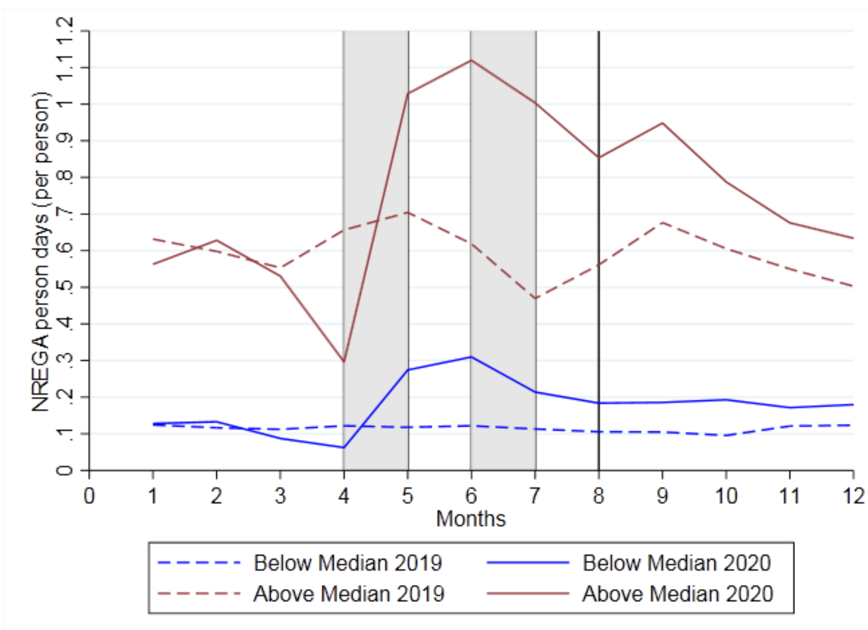
Figure 1: MG-NREGA person days per rural inhabitant



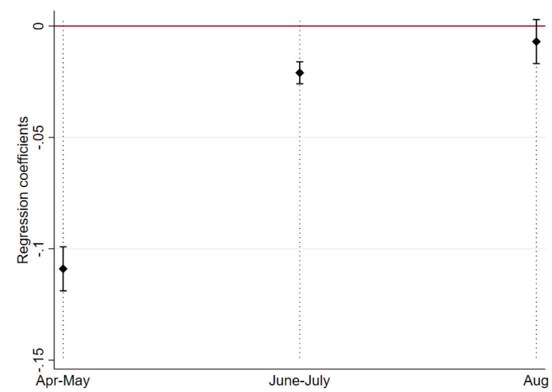
a: Current



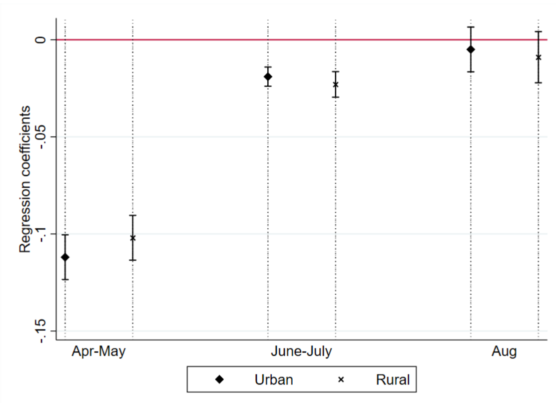
b: Historical (2014-18)

Source: NREGA Public Data Portal (2014-2020).
Note: The persondays generated were divided by the rural population of the district (Census 2011). The median in panel (b) is defined using the average historical MG-NREGA persondays generated in a district between 2014-18.

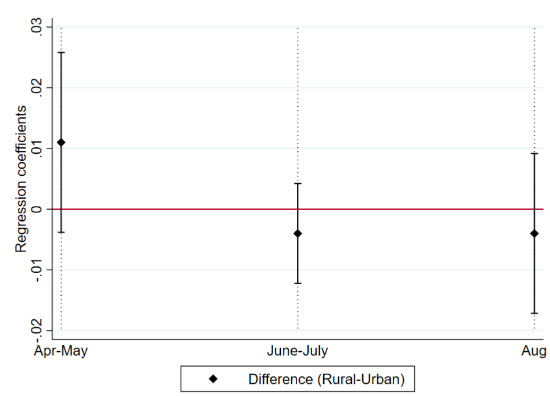
Figure 2: Impact of Shutdown on Employment



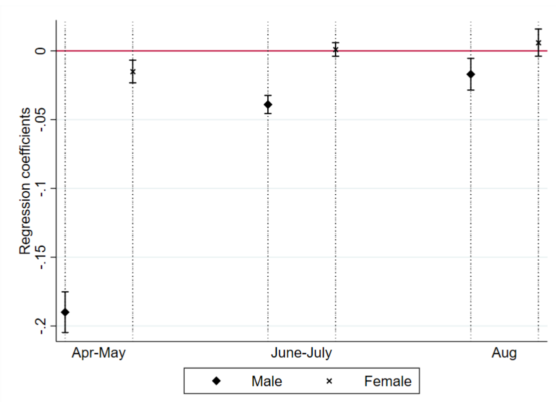
a: Overall



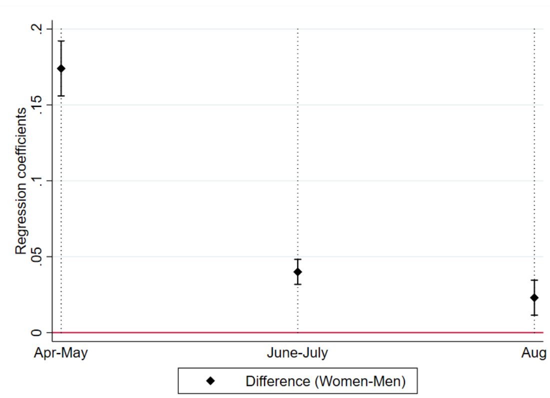
b(i): Region



b(ii): Difference (Region)



c(i): Gender



c(ii): Difference (Gender)

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

Table 1: Summary Statistics

Variable	Number of units	Obs	Mean	S.D.	Definition
Panel A: Employment (Individual-Month-Year level)					
Overall	335,038	1,040,918	0.41	0.49	Proportion employed
Region					
Rural	114,509	350,907	0.43	0.49	Proportion employed in rural areas
Urban	220,529	690,011	0.40	0.49	Proportion employed in urban areas
Gender					
Men	179,167	557,788	0.65	0.48	Proportion of men employed
Women	155,871	483,130	0.08	0.28	Proportion of women employed
Panel B: MG-NREGA (District-Month level)					
NREGA 2020	580	4,630	0.49	0.75	Persondays per rural person in 2020
NREGA 2019	580	4,630	0.37	0.62	Persondays per rural person in 2019
Historical NREGA	580	4,630	0.41	0.99	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 (Jan-Aug 2019 and for Jan-Aug 2020). The data for work days (Jan-Aug) generated under MG-NREGA (2014-2020) are taken from NREGA Public Data Portal and normalized by district rural population (Census 2011).

Table 2: Impact of MG-NREGA on Employment

	Rural		Urban		Rural Female		Rural Male	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Apr-Aug×NREGA	0.031**		-0.013		0.086***		0.010	
	(0.012)		(0.013)		(0.020)		(0.015)	
Apr-May×NREGA		0.029		-0.012		0.076***		0.011
		(0.021)		(0.018)		(0.029)		(0.025)
June-July×NREGA		0.030**		0.002		0.076***		0.013
		(0.013)		(0.013)		(0.021)		(0.015)
Aug×NREGA		0.048**		0.015		0.131***		0.031
		(0.024)		(0.027)		(0.040)		(0.031)
Observations	346,836	346,836	683,210	683,210	159,842	159,839	186,993	186,993
R-squared	0.891	0.893	0.892	0.895	0.799	0.802	0.850	0.853
Mean Y	0.446		0.407		0.116		0.73	
Fixed Effects								
Individual	✓	✓	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Dist × Year	✓	✓	✓	✓	✓	✓	✓	✓
Occ × Month-Year	✓	✓	✓	✓	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2019-2020), NREGA Public Data Portal (2014-18) and Census (2011).
Note: The classification of region and gender is as of quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census, 2011) is the measure of historical MG-NREGA. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. Mean (Y) refers to the mean of the dependent variable in the months before the national lockdown i.e., Jan-Mar 2020. Standard errors clustered at district-month-year level reported in parantheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3: Heterogenous Impact of MG-NREGA on Employment of Rural Women

	Individual			Household		District
Characteristic (Z)	Ever Married	Less Educated	Previously Employed	Young Children	Poor	Low Migrant
	(1)	(2)	(3)	(4)	(5)	(6)
Apr-Aug × NREGA × Z	0.045**	0.047*	0.086	0.039**	0.049*	0.118***
	(0.022)	(0.026)	(0.068)	(0.016)	(0.029)	(0.048)
Apr-Aug × NREGA	0.049**	0.073***	0.071***	0.073***	0.071***	0.049**
	(0.019)	(0.018)	(0.019)	(0.021)	(0.021)	(0.018)
Apr-Aug × Z	0.019*	0.015*	-0.964***	-0.025***	0.009	-0.029
	(0.011)	(0.008)	(0.142)	(0.005)	(0.009)	(0.014)
NREGA × Z	-0.042***	-0.041**	-0.168***	-0.015	-0.017	-0.156***
	(0.016)	(0.016)	(0.040)	(0.010)	(0.019)	(0.051)
Observations	159,842	159,842	159,842	159,842	159,842	154,269
R-squared	0.799	0.799	0.801	0.799	0.799	0.800
Estimate (Z=1)	0.094***	0.12***	0.157***	0.111***	0.121***	0.166***
Mean Y (Z=1)	0.138	0.165	1	0.122	0.155	0.095
Mean Y (Z=0)	0.038	0.101	0	0.112	0.105	0.142
Fixed Effects						
Individual	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
District × Year	✓	✓	✓	✓	✓	✓
Occ × Month-Year	✓	✓	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2019-2020), NREGA Public Data Portal (2014-18), Census (2011) and Employment and Unemployment Survey, NSS (2007).

Note: The classification of all characteristics is per the quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. Ever married indicates individuals who were ever married. Less Educated is indicator for below primary education. Previously Employed is indicator for those employed. Young Children indicates households with children aged upto 12 years of age and Poor indicates households falling in the bottom two deciles of the distribution of PCA of assets owned by a household. Low migrant is indicator for districts that have no out-migrants (NSS, 2007). The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census 2011) is the measure of historical MG-NREGA. Mean (Y) refers to the mean of the dependent variable in the months before the national lockdown i.e., Jan-Mar 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. There are fewer observations in Column (6) because migration data for some districts are missing in NSS 2007. Standard errors clustered at district-month-year level reported in parantheses (*** p<0.01, ** p<0.05, * p<0.1).

APPENDIX - FOR ONLINE PUBLICATION

A. Additional Tables and Figures

Table A.1: Summary Statistics (before national shutdown)

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
Gender (Rural)				
Men	49951	0.73	0.44	Proportion of men employed
Women	42883	0.12	0.32	Proportion of women employed
Gender (Urban)				
Men	94276	0.70	0.46	Proportion of men employed
Women	82740	0.07	0.26	Proportion of women employed
Panel B: Employment type				
Casual	269850	0.15	0.36	Daily/monthly wage labour
Salaried	269850	0.07	0.25	Permanent salaried work
Selfemp	269850	0.20	0.40	Self-employed
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 both the panels, we use the pre-pandemic months of 2020 i.e. January-March. The sample includes all individuals aged 15-59.

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

	Employed (1)	Casual (2)	Salaried (3)	Selfemp (4)	Unemp (5)	Not in LF (6)
			Panel A: Overall			
Apr-Aug×Post	-0.050***	-0.033***	-0.010***	-0.005**	0.034***	0.016***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	1,030,046	1,030,046	1,030,046	1,030,046	1,030,046	1,030,046
R-squared	0.884	0.715	0.771	0.767	0.590	0.877
Mean (Y)	0.42	0.15	0.068	0.195	0.057	0.523
			Panel B: Rural			
Apr-Aug×Post	-0.049***	-0.038***	-0.011***	0.004	0.032***	0.017***
	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)
Observations	346,836	346,836	346,836	346,836	346,836	346,836
R-squared	0.884	0.725	0.761	0.797	0.590	0.881
Mean (Y)	0.446	0.166	0.033	0.236	0.049	0.505
			Panel C: Urban			
Apr-Aug×Post	-0.049***	-0.029***	-0.010***	-0.009***	0.033***	0.015***
	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.004)
Observations	683,210	683,210	683,210	683,210	683,210	683,210
R-squared	0.885	0.710	0.771	0.747	0.591	0.875
Mean (Y)	0.407	0.141	0.087	0.173	0.061	0.533
			Panel D: Rural Female			
Apr-Aug×Post	-0.010*	-0.008**	-0.003***	0.001	0.013***	-0.003
	(0.005)	(0.004)	(0.001)	(0.003)	(0.004)	(0.006)
Observations	159,843	159,843	159,843	159,843	159,843	159,843
R-squared	0.769	0.710	0.775	0.724	0.634	0.752
Mean (Y)	0.116	0.057	0.009	0.05	0.033	0.851
			Panel E: Rural Male			
Apr-Aug×Post	-0.083***	-0.064***	-0.018***	0.006	0.049***	0.034***
	(0.006)	(0.007)	(0.003)	(0.006)	(0.006)	(0.004)
Observations	186,993	186,993	186,993	186,993	186,993	186,993
R-squared	0.841	0.708	0.756	0.762	0.576	0.832
Mean (Y)	0.73	0.26	0.054	0.396	0.062	0.208
Fixed Effets						
Individual	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
District × Year	✓	✓	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2019-2020).
Note: In all panels, the sample includes individuals aged 15-59 who are classified into one of the employment categories as per their employment status in the pre-pandemic quarter i.e. Dec, 2019-Mar, 2020. The panel B and C have the rural and urban samples, respectively. Panel D and E have the female and male sample from rural regions, respectively. The Mean (Y) are calculated from the pre-pandemic months of 2020 i.e. Jan-Mar. Standard errors clustered at district-month-year level reported in parantheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table A.3: Impact of MG-NREGA on Hours Worked

	Rural			Rural Women Hetero (Z)					
				Individual			Household		District
	Overall	Female	Male	Ever Married	Less Educated	Previously Employed	Young Children	Poor	Low Migrant
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Apr-Aug × NREGA	0.158	0.441***	0.028						
	(0.143)	(0.131)	(0.246)						
Apr-Aug × NREGA × Z				0.272*	0.427**	0.584	0.251	0.340	0.563***
				(0.156)	(0.217)	(0.467)	(0.173)	(0.234)	(0.294)
Observations	90,672	41,558	49,114	41,558	41,558	41,558	41,558	41,558	39,896
R-squared	0.856	0.820	0.792	0.820	0.820	0.823	0.820	0.820	0.818
Mean Y	3.443	0.798	5.714						
Mean Y (Z=1)				1.045	1.137	6.888	0.853	1.083	0.657
Mean Y (Z=0)				0.292	0.696	0	0.776	0.721	0.976
Fixed Effects									
Individual	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occ × Month-Year	✓	✓	✓	✓	✓	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2020), NREGA Public Data Portal (2014-18), Census (2011) and Employment and Unemployment Survey, NSS (2007).
Note: The classification of all characteristics is per the quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. Ever married indicates individuals who were ever married. Less Educated is indicator for below primary education. Previously Employed is indicator for those employed. Young Children indicates households with children aged upto 12 years of age and Poor indicates households falling in the bottom two deciles of the distribution of PCA of assets owned by a household. Low migrant is indicator for districts that have no out-migrants (NSS, 2007). The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census 2011) is the measure of historical MG-NREGA. Mean (Y) refers to the mean of the dependent variable in the months before the national lockdown i.e. Jan-Mar 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. There are fewer observations in Column (9) because migration data for some districts were missing. Standard errors clustered at district-month-year level reported in parantheses (*** p<0.01, ** p<0.05, * p<0.1).

Table A.4: Heterogenous Impact of MG-NREGA on Employment of Rural Men

	Individual			Household		District
Characteristic (Z)	Ever Married (1)	Less Educated (2)	Previously Employed (3)	Young Children (4)	Poor (5)	Low Migrant (6)
Apr-Aug $\times$ NREGA $\times$ Z	-0.018	0.053***	0.003	0.016	0.075***	0.080***
	(0.025)	(0.020)	(0.026)	(0.017)	(0.024)	(0.031)
Apr-Aug $\times$ NREGA	0.026	0.001	0.006	0.009	-0.007	-0.018
	(0.021)	(0.015)	(0.021)	(0.016)	(0.017)	(0.020)
Apr-Aug $\times$ Z	0.318***	0.030***	-1.105***	0.068***	0.009	-0.021
	(0.016)	(0.011)	(0.051)	(0.007)	(0.011)	(0.014)
NREGA $\times$ Z	0.002	-0.005	-0.065***	-0.006	-0.002	-0.128***
	(0.014)	(0.011)	(0.016)	(0.009)	(0.014)	(0.035)
Observations	186,993	186,993	186,993	186,993	186,993	180,375
R-squared	0.855	0.850	0.852	0.850	0.850	0.849
Estimate (Z=1)	0.008	0.054***	0.009	0.025	0.068***	0.062***
Mean Y (Z=1)	0.964	0.909	1	0.88	0.755	0.728
Mean Y (Z=0)	0.381	0.709	0	0.666	0.724	0.732
Fixed Effects						
Individual	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
District $\times$ Year	✓	✓	✓	✓	✓	✓
Occ $\times$ Month-Year	✓	✓	✓	✓	✓	✓

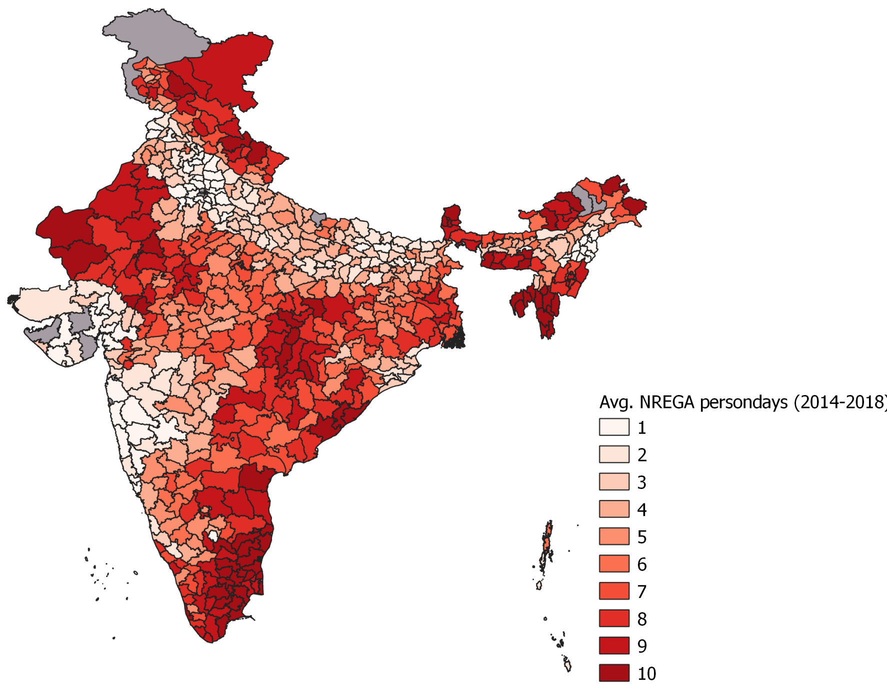
Source: Consumer Pyramids Household Survey (2019-2020), NREGA Public Data Portal (2014-18), Census (2011) and Employment and Unemployment Survey, NSS (2007).
Note: The classification of all characteristics is per the quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. Ever married indicates individuals who were ever married. Less Educated is indicator for below primary education. Previously Employed is indicator for those employed. Young Children indicates households with children aged upto 12 years of age and Poor indicates households falling in the bottom two deciles of the distribution of PCA of assets owned by a household. Low migrant is indicator for districts that have no out-migrants (NSS, 2007). The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census 2011) is the measure of historical MG-NREGA. Mean (Y) refers to the mean of the dependent variable in the months before the national lockdown i.e. Jan-Mar 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. There are fewer observations in Column (6) because migration data for some districts were missing. Standard errors clustered at district-month-year level reported in parantheses (*** p<0.01, ** p<0.05, * p<0.1).

Table A.5: Robustness Checks: Attrition and Placebo

	Attrition			Placebo		
		Rural			Rural	
	Overall	Female	Male	Overall	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Apr-Aug	-0.050***			-0.001		
	(0.003)			(0.002)		
Apr-Aug × NREGA		0.089***	0.008		0.017	0.011
		(0.020)	(0.016)		(0.014)	(0.008)
Observations	1,025,526	158,788	185,843	1,141,207	180,884	204,749
R-squared	0.883	0.800	0.849	0.903	0.779	0.879
Fixed Effects						
Individual	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
District × Year	✓	✓	✓	✓	✓	✓
Occ × Month-Year		✓	✓		✓	✓

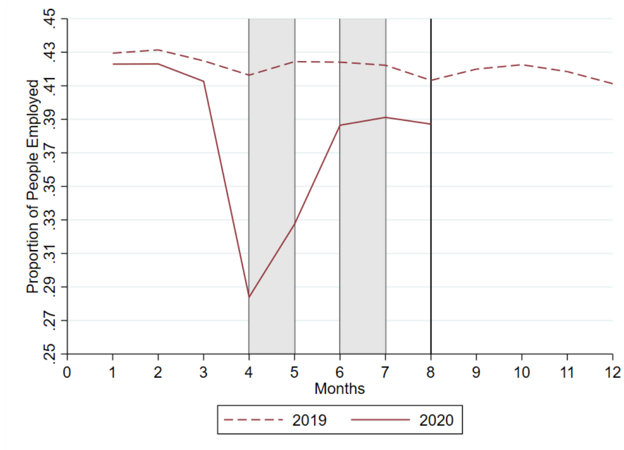
Source: Consumer Pyramids Household Survey (2019-2020), NREGA Public Data Portal (2014-18) and Census (2011).
Note: For attrition, the selection probabilities estimated using the location, PCA of assets owned and observed household characteristics. The classification of region and gender is as of quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census 2011) is the measure of historical MG-NREGA. Estimates in Column (2)-(3) and (5)-(6) conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. Standard errors clustered at district-month-year level reported in parantheses (**** p<0.01, ** p<0.05, * p<0.1*).

Figure A.1: Average MG-NREGA persondays (2014-18) per rural inhabitant

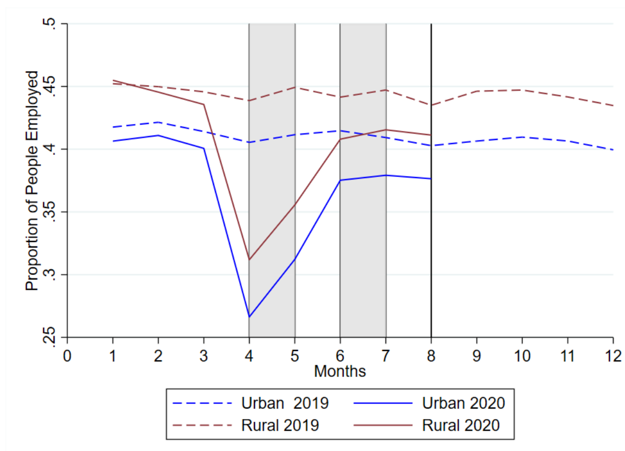


Source: NREGA Public Data Portal (2014-2020).
Note: The districts with missing data for MG-NREGA are colored grey.

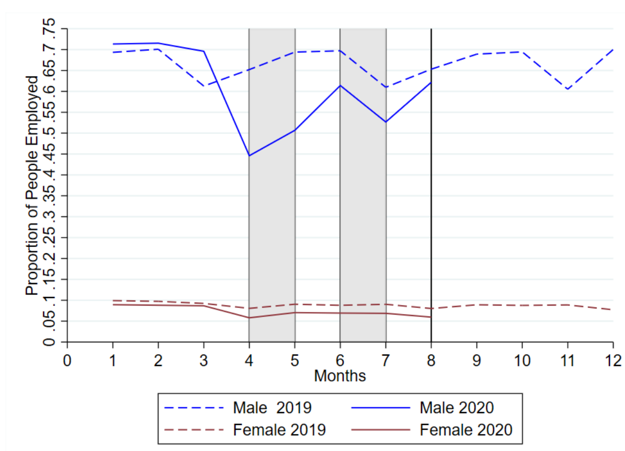
Figure A.2: Employment by Year, Region and Gender



a: Year



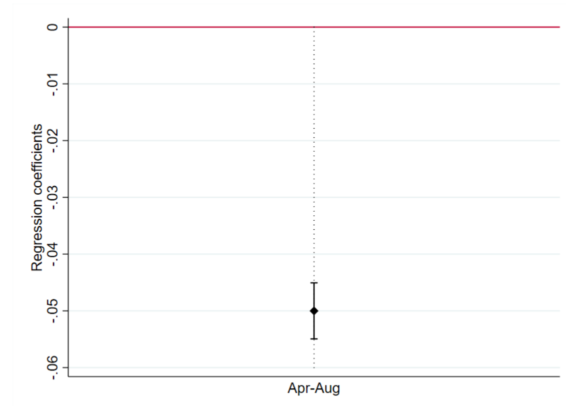
b: Region



c: Gender

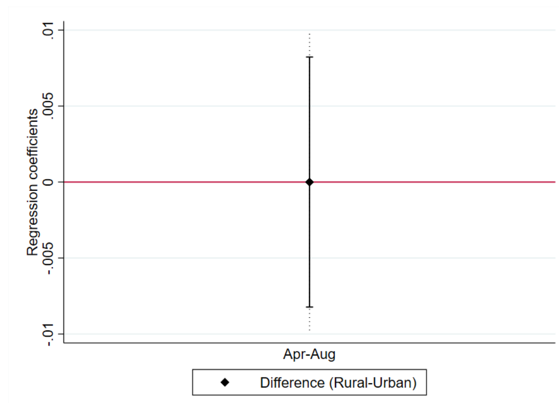
Source: Consumer Pyramids Household Survey (2019-2020).
Note: The classification of region and gender is taken from the quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020.

Figure A.3: Impact of Shutdown on Overall Employment

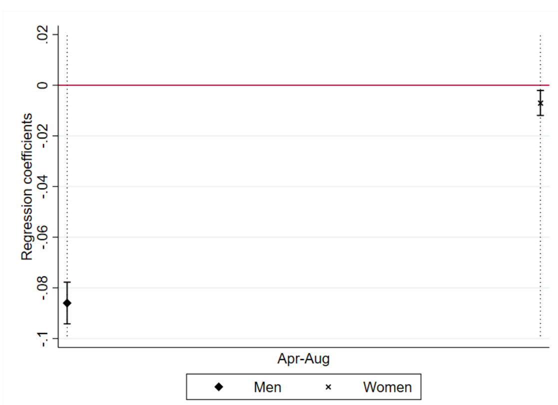


a: Overall

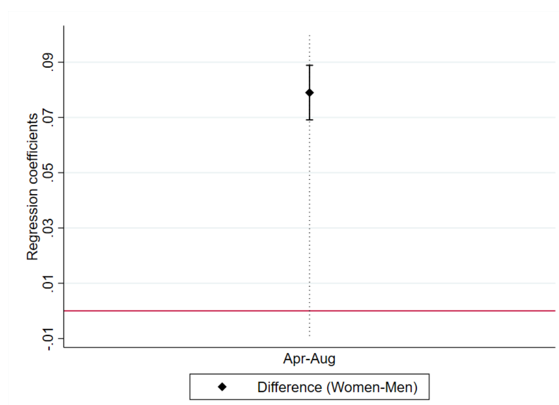
b(i): Region



b(ii): Difference (Region)



c(i): Gender



c(ii): Difference (Gender)

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

B. Data Appendix

B.1. CPHS vs. PLFS

The CPHS sample is comparable to the Periodic Labor Force Survey (PLFS) conducted by the Ministry of Statistics and Program Implementation in 2017-18 whose sample size was 102,113 households. In the CPHS 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.

We compare the employment rates (proportion of people employed) in the CPHS and the Periodic Labor Force Survey (PLFS) for the months of July 2017-June 2018. We find that for the age group 15-59, the overall employment rate from the CPHS data was 65% for men and was 8% 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 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.

B.2. Employment

For each individual aged 15 and above, the CPHS 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. The CPHS also 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).

B.3. Asset Index

We construct binary indicators of ownership of assets in the quarter preceding the crisis i.e. December 2019-March 2020, that equals one for households that own it and zero otherwise. These include - ownership of refrigerator, air conditioner, cooler, washing machine, television, computer, car, two-wheeler, inverter, tractor and cattle. We then use the Principal Components Analysis (PCA) to generate the asset index (the first principal component) over these indicators. We generate deciles of the asset index separately for rural and urban regions. The households falling in the bottom two deciles of this distribution, for their respective region, are classified as poor households.

B.4. Migration

We use the NSS Employment and Unemployment Survey 64^{th} Round (2007-08) to construct a measure of district level, rural seasonal out-migrants. NSS records data on the members of the household that were away from home in search of work for up to six months. We take a weighted sum of the number of household members residing in rural areas that migrated for work from a district. This provides us migration data for 470 Districts of the total of 502 Districts for which CPHS data (2019-20) is available. For the remaining districts, out-migration data could not be mapped to the CPHS districts and is thus missing. We use this measure of rural seasonal out-migrants to construct an indicator for low migration districts. 'Low migrant' district takes value one when the reported number of out-migrants are nil and zero otherwise. 64% of the districts in our analysis are low migrant districts.

B.5. Inverse-probability weights

We estimate the selection probabilities i.e. the probability of being present in 2020 for a household surveyed in 2019 using the pre-pandemic location (rural/urban) of the household, the constructed asset index and other observed household characteristics. Household characteristics include - ownership of mobile phone by any member of the household, 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 income of all its members from all sources during 12 months), occupation group (based on the composition of the members of the household by the nature of their occupation), education group (based on the 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). These predicted probabilities are then used to generate the inverse-probability weights for attrition correction.