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IMPACT ON THE INDIAN LABOUR MARKET DURING AND AFTER THE COVID-19 PANDEMIC

Amit Kundu[1] and Sayantani Santra[2]

[1]Professor, Department of Economics, Jadavpur University, West Bengal, India
E-mail: akundu29@gmail.com, amit.kundu@jadavpuruniversity.in
[2]UGC Junior Research Fellow, Department of Economics, Jadavpur University, West Bengal, India, sayantanisantra49@gmail.com
Corresponding Author E-mail: akundu29@gmail.com, amit.kundu@jadavpuruniversity.in

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Abstract: The paper aims to investigate the impact of the COVID-19 pandemic on the unemployment rates of different types of labour, including skilled and unskilled workers, as well as male and female workers, in both the rural and urban sectors of the Indian labour market. A significant percentage of Indian workers are informal. Applying the Difference-in-Difference method, it was observed that initially, due to the effect of the lockdown and the first wave of COVID-19, the unemployment rate increased among informal workers, skilled workers and overall rural and urban male workers. It is also proven that only the educated labour force was affected by a higher unemployment rate, even after the pandemic. However, no effect on the unemployment rate was observed among rural and urban female workers. This paper has also shown that in the first phase of the COVID-19 pandemic, in most states, greater unemployment occurred due to the dominance of the voluntarily unemployed labour force. However, after the pandemic, this number has decreased in most states. This paper proves that the creation of more man-days through MGNREGP can reduce the possibility of involuntary unemployment in rural India in the post-lockdown period.

Keywords: COVID-19 pandemic, Indian Labour Market, Skilled Labour, Unskilled Labour, Impact Evaluation, Voluntary Unemployment, Involuntary Unemployment.

JEL Classifications: J11, J21, J64, J71, R10, C23

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INTRODUCTION

The COVID-19 outbreak had spread across the world, and India was no exception. In recent times, a major economic disturbance in India occurred when we observed 68 days of complete lockdown from March 25, 2020, during the first phase of the COVID-19 pandemic. During the lockdown period, many small and medium-scale industries had to stop their production process, leading to a sharp rise in unemployment and loss of income among the major sections of the Indian population. However, at that time, lockdown and physical distancing were the only cost-effective ways available to prevent the spread of COVID-19.

According to *the Economic Survey* (2020-21), the MSME sector of India employs more than 11 crores of people and contributes roughly 30% to the GDP, and most of the workers in this sector are informal labourers. If we look at the Indian labour market, it is highly dominated by an informal workforce. According to the Periodic Labour Force Survey (2018-19), i.e., before the pandemic, 87.5% of the total workforce were informal workers[1] and only 12.5% were formal workers. Again, among the total informal labour force, 88.5% were male informal workers and 11.5% were female informal workers. Even before the pandemic, the CMIE report showed that the unemployment rate in June 2019 climbed to 7.91% but it was at 5.8% in June 2018 due to the effects of the demonetisation of high-value Indian currencies by the end of 2016 and the subsequent launch of Goods and Services Tax (GST) in early 2017. The COVID-19 pandemic worsened the situation deeply.

India introduced a complete nationwide lockdown on March 24, 2020, initially for three weeks, but that was extended, destroying almost all major economic activities in the Indian economy. Only essential economic activities such as the sale of grocery items, vegetables and medicine were allowed. According to the India-Situation-Report, July 2020, 467882 cases were active during the first phase of the COVID-19 pandemic. As per the National Income Estimates (May 2021), India's GDP dropped by 7.3% for the financial year 2020-21, the worst yearly contraction in the country's history. Small peddlers, daily wage earners and migrant workers who were mainly working in the informal sectors had lost their jobs (Vyas, 2020). By the end of 2020, India had shown a steady decline in daily active COVID cases except for Maharashtra, Kerala, Karnataka and West Bengal and the recovery rate also improved to 90%.

Apart from agriculture, the construction sector recruited more than 12% of the new working population. Agriculture remained the main income-generating sector during the pandemic. The demand for jobs through MGNREGS had increased, and till December 2020, 294.5 crore person days had been created under the scheme – a jump of 49.4% as compared to the previous year.

The Second wave of the COVID-19 outbreak was observed in May 2021, when the daily case count was more than 4 lakhs. But in most of the Indian states, it was a partial lockdown. India was divided into a 'red zone' and a 'green zone'. The lockdown was strictly maintained in the 'red' zone, but some economic activities had started in the 'green zone'. The vaccination programme had already been initiated. A good number of people also got a second dose of the vaccine. In the last week of August 2021, the situation was comparatively better, with just over 25 thousand daily confirmed cases. In 2022, the daily confirmed cases were much lower, and India's economic recovery from COVID-19 has been progressing well.

The basic objective of the paper is to investigate the impact of the COVID-19 pandemic on the unemployment rate in the Indian economy.[2]. It is a state-level analysis where each state is considered as a unit. The unemployment rate of a particular state in a particular time period is calculated as the number of persons who are not employed but willing to work and actively looking for a job in that time period as a percentage of the total labour force[3] of that state during that time period. Here we considered the impact of the pandemic on the unemployment rate of the overall informal workers (unskilled workers), highly educated formal workers, and overall rural and urban male and female workers separately. It was also investigated whether the dominance of voluntary or involuntary unemployment rate is responsible for the overall unemployment rate among the Indian labour force in all 27 states. Moreover, the paper shows the possible factors that may influence the probability of being involuntarily unemployed among different workers during the pandemic and the post-pandemic period, with the help of the Probit Model.

SURVEY OF LITERATURE AND RESEARCH OBJECTIVES

The impact of the COVID-19 pandemic on the Indian economy has been captured by many researchers in their studies. Chopra and Bijoy (2021) analysed the trends and patterns of unemployment in India during the pre-pandemic period from 1971 to 2019. They have witnessed joblessness growth in the economy and unemployment among illiterates was at its lowest during the pre-pandemic period. Joblessness was high among males in India, and finding a job was more challenging for urban females as compared to rural females.

The paper by Ali and Kamraju (2020), which provides a base for our research, has tried to reveal the effects of the COVID-19 pandemic on unemployment in India. Ray and Subramanian (2020) had talked about the philosophy of lockdown provoked by the COVID-19 pandemic in India and suggested several welfare measures to compensate for its negative impact on human lives. Srivastava (2020) had shown that while both urban and rural informal workers were harshly affected by the lockdown, migrant labourers were the worst sufferers.

Despande (2020) had examined that in India, the gender gap between men and women in average hours spent on domestic work decreased in the first month of the lockdown and even in the post-lockdown period due to a shift in the male distribution of hours. On the other hand, the paper by Chauhan (2021) showed that the pandemic, with its consequent lockdowns, has exacerbated existing gender inequalities and increased women's burden of unpaid work even more.

Goswami, Mandal and Nath (2021) with the help of panel regression analysis showed that states experiencing the higher spread of the virus and larger employment dependence on the secondary and tertiary sectors had suffered significantly larger economic losses whereas, the states with a better containment strategy, healthcare capabilities and relatively larger employment share in the primary sector had experienced smaller losses. Bussolo et al. (2021), using the CPHS household panel dataset, had shown that within the same industry and district, informal wage workers were significantly more vulnerable to the loss of employment than formal workers during the early phase of COVID-19 (April 2020). However, their employment and income differentials narrowed after April 2020. Victor et al. (2021) investigated the inflation-unemployment dynamics during the recession and COVID-19 times in India and the UK. The study revealed that recession had given way to stagflation in India, but in the UK, it had led to a more severe recession in the short run. Vishwakarma (2022) investigated joblessness among the young generation at the time of COVID-19 and after the pandemic in India.

In this background, the following research questions were addressed:

1. The study investigated the impact of the COVID-19 pandemic on the unemployment rate among different types of labour (e.g., informal, formal, etc.) in India using the difference-in-difference method.
2. During the pandemic, a large section of the labour force withdrew from the job market, i.e., they became voluntarily unemployed. The research examined whether, in a particular state and among a particular type of labour, voluntarily unemployed individuals outnumbered involuntarily unemployed individuals. It also investigated whether this pattern of unemployment (i.e., voluntary unemployment dominating involuntary unemployment) changed over time across different states and labour categories.
3. The study also sought to determine whether the outbreak of COVID-19 was the sole factor responsible for the dominance of involuntary unemployment observed in various states during and after the pandemic.

METHODOLOGY

Sources of Data:

The entire investigation was conducted using CMIE data on employment and unemployment published during different periods. The employment/ unemployment status of each eligible household member was recorded as of the date of the survey. Each state was considered a unit of analysis. Sources of data for other necessary variables used in this investigation have been cited in the appropriate sections of this text. To analyse the impact of the pandemic and the economic lockdown on the Indian labour market, four time periods were considered, each covering different phases of the pandemic: the pre-pandemic period (CMIE wave: Sept–Dec 2019), the first wave of COVID-19 (CMIE wave: May–Aug 2020), the second wave (CMIE wave: May–Aug 2021), and the post-pandemic period (CMIE wave: May–Aug 2022).

The unemployment rate of informal and formal labourers in different states in different phases of the COVID-19 pandemic and after the Pandemic

During the lockdown period, an estimated 14 crore people lost their jobs while a major section of workers working in different private enterprises had to face either job loss or salary cuts (CMIE 2020). Here, based on CMIE data, initially, the unemployment rate of the labour force whose educational qualification[4] was less than the 12th standard was considered. It can be explained as the unemployment rate of the informal labour force. Even according to the report of Periodic Labour Force Survey 2017-18, the education level of near about 90% of informal workers (home-based workers, domestic workers, waste pickers, informal construction workers and informal transport workers) was below the higher secondary level. Centre for Monitoring Indian Economy in its January 2019 report mentioned that nearly 11 million people lost jobs in 2018 after the demonetisation and implementation of GST. Hence, before the outbreak of COVID-19, the unemployment situation in India was not impressive. It was observed from the CMIE data that in 2019, some of the states such as Gujarat, Himachal Pradesh, Jammu & Kashmir, Tripura and Uttar Pradesh witnessed high unemployment rates of informal labourers, which was even higher in comparison to the pandemic period. During the first and second phases of the pandemic, the unemployment rate of the informal labour force was very low in Meghalaya (1.64% and 0.6%), Assam (3.05% and 1.71%) and Gujarat (3.86% and 1.33%). But high unemployment rates were observed in Haryana (30.61% and 28.08%), Delhi (25.79% and 20.08%), etc. When the pandemic was over, the unemployment rate became very low in Chhattisgarh (0.45%), Andhra Pradesh and Puducherry and was very high in Haryana (25.54%), Rajasthan and Assam. Haryana's unemployment was the highest in the country during the pandemic. It was mainly due to the first COVID-19 lockdown and increased migration of workers to Haryana from states like Uttar Pradesh, Bihar, etc.

Next, we shall discuss the impact of the pandemic on the labour market of the educated labour force that has at least a graduation degree. According to Galore and Zeira (1991), this type of labour force can be considered as skilled workers as they have invested in human capital and are willing to work in the formal sector. From the CMIE data, it was observed that the unemployment rate of the educated labour force increased during the first wave of COVID-19 in all the states except Jammu & Kashmir, Odisha and Telangana. Himachal Pradesh (53.25%) had shown the highest unemployment rate, and the lowest unemployment rate was observed in Karnataka (7.18%) during the first wave of COVID-19. During the second wave of the pandemic, Rajasthan (55.75%)

had the highest unemployment rate, and the lowest unemployment rate was observed in Assam (2.34%). When the pandemic was over, a low unemployment rate was observed in states such as Chhattisgarh, Gujarat, Madhya Pradesh, and Meghalaya, but the states with high unemployment rates were Rajasthan, Jammu & Kashmir, Himachal Pradesh, Jharkhand, Bihar and Haryana. As per the CMIE report (January-April 2022), some states such as Rajasthan, Bihar and Andhra Pradesh had not been able to provide jobs for more than one-third of their graduates.

Analysis of the unemployment rates in the rural and urban sectors in terms of gender in different states of India during the pandemic and just after the pandemic

According to Rosa, Bhosle and Keshar (2021), during the pandemic, women were seven times more likely to lose work during the lockdown period. It was also shown that women were eleven times more likely not to return to work subsequently compared to men. Walters (2020) and Acharya (2007) mentioned that women were marginally less likely than men to be in regular employment, and COVID-19 had increased the vulnerability of women workers in most of the states of India. Hence, it is required to investigate how the pandemic affected the unemployment rate of the gender-specific labour force (both highly educated and less educated), both in the rural and urban areas of India.

Initially, the rural area was considered. Based on state-level CMIE data of different periods, it was observed that during the first wave of COVID-19, a sharp enhancement of the unemployment rate among the rural male labour force was observed in most of the states, and it was observed to be maximum in Haryana (26.8%), followed by Jharkhand, Bihar and Delhi. On the opposite side, the lowest unemployment rate of the rural male labour force was observed in Meghalaya (1.7%), followed by Odisha and Gujarat. In the post-pandemic situation, the unemployment rate of the rural male labour force is still the highest in Haryana (22.6%) and the lowest in Chhattisgarh (0.8%).

But a mixed picture was observed in terms of the unemployment rate of the rural female labour force. During the first wave of the pandemic, very low unemployment among rural women was observed in Gujarat (2.5%), Andhra Pradesh, Assam, Meghalaya, Puducherry and Karnataka. It may have happened because a larger section of the women's labour force was not willing to join the labour market. Jammu & Kashmir witnessed the highest unemployment rate of rural females among 27 major states of India in different phases of the pandemic. Lack of infrastructure like girls' schools, higher education institutions and an efficient transportation system, many violence cases, decades-long militancy, etc., contributed to women's unemployment in Jammu & Kashmir. Apart from Jammu & Kashmir, the unemployment rate of rural women was very high in Haryana, Bihar, Jharkhand, Rajasthan, etc., during the lockdown period. If we compare the pre-pandemic and post-pandemic states, it is observed that the unemployment situation of the rural male labour force is more or less the same. Rather, during the post-pandemic period, the rural female unemployment rate has decreased in some states like Chhattisgarh (1.4%), Maharashtra (1.5%), Odisha (7.5%), Karnataka (13.3%), etc. But high unemployment rates of rural women were observed in Jammu and Kashmir (87.9%), Haryana (74.4%), Bihar (65.8%) and Rajasthan (62.9%) during the post-pandemic period.

In April 2020, the International Labour Organisation estimated that near about 40 crores of informal workers in India might move into acute poverty due to the pandemic. The unemployment rate in urban areas was about 20.8% during April-June 2020, which was 8.9% in the same quarter in the previous year. The pre-COVID-19 situation identified that the female unemployment rate had generally been higher than the male unemployment rate in India (7.3% vs. 9.8% during the October-December quarter of 2019). Due to the outbreak of COVID-19, this gap seems to have widened. During the October-December quarter of 2020, the unemployment rate for females was 13.1%, as compared to 9.5% for males (Source: *Quarterly Periodic Labour Force Survey Reports, Ministry of Statistics and Program Implementation; PRS*).

Next, we look at how the unemployment rate among males and females in urban India has changed over time during the pandemic and after the pandemic. For the urban male workers, the unemployment rate was lowest in Odisha (2%) in the first phase of the pandemic and Gujarat (1.9%) in the second phase of the pandemic. On the contrary, the maximum unemployment rate in the first phase of the pandemic was observed in Jharkhand (31%) and in the second phase, it was observed in Haryana (30.5%). But in the post-pandemic stage, the lowest unemployment rate among male workers was observed in Chhattisgarh (0.6%) and the highest unemployment rate was observed in Rajasthan (23.4%).

For urban female workers, during the pandemic, the lowest unemployment rate of the urban female labour force was observed in Odisha (4.1%) during the first phase and in Gujarat (3.3%) during the second phase. But the urban female unemployment rate was the highest in Haryana (81.9%) during the first phase of the pandemic and in Rajasthan (92.1%) during the second phase of the pandemic. After the pandemic, the unemployment rate was the lowest in Chhattisgarh (0.9%) and the highest in Rajasthan (90.1%).

Impact of the COVID-19 Pandemic on the Indian Labour Market

To investigate whether the COVID-19 outbreak had any impact on the unemployment rate in India, a difference-in-difference estimation procedure was employed. The difference-in-difference estimator is used to estimate the effect of a specific intervention by comparing the changes in outcome over time between the population affected by the intervention and a population not affected by the intervention. The standard Difference-in-Difference model can be expressed as:

$$\text{Unemploymentrate}_{jit} = \beta_0 + \beta_1 \text{ (Time)} + \beta_2 \text{ (Intervention)} + \beta_3 \text{ (Time X Intervention)} + \varepsilon_{jit}$$

Here, the outcome variable is the unemployment rate of the j^{th} type of worker of the i^{th} state in the t^{th} period, and the intervention is the pandemic due to the outbreak of COVID-19.

If we want to investigate any change in the unemployment rate in India due to the outbreak of COVID-19 over time, two periods of panel data are required. After considering each state as a unit, we considered the state-wise unemployment rate as an outcome variable just before the pre-COVID period (which is considered the base-line period) in comparison to the same during the time period after the outburst of first wave of COVID-19, during the time of second wave and the time period in which the pandemic had almost gone and normal economic activities in all parts of India had again started. So, in this investigation, three end-line periods were considered, i.e., 2020, 2021 and 2022, respectively. Here, based on the literature on impact evaluation applying the Difference-in-Difference method, it is required to be mentioned that there is no comparison group in this context, and all the considered states became treatment groups as COVID-19 had affected all the states of India. In these designs, we usually compare one group's outcomes before and after treatment instead of comparing outcomes between different groups.

As all the state people were affected by COVID during the endline period, then in Eq.1, the 'Time' and 'Intervention' terms become redundant because the 'Time *X* intervention' term will always take the value 1 for all the states. In this background, the modified difference-in-difference equation can be written as

$$\text{Unemploymentrat}_{jit} = \beta_0 + \beta_3 \,(\text{Time} \times \text{Intervention}) + \varepsilon_{jit}$$

Now, if the value of the parameter estimates, $\widehat{\beta_3}$ in Eq.1A (presented in Table 1) becomes statistically significant and positive, then only one can claim

Table 1: Results of the Difference-in-Difference estimate among different types of workers

Type of worker	*Baseline: September 2019 and Endline: August 2020 (Impact of the first Wave of COVID-19, including the lockdown period)*		*Baseline: September 2019 and Endline: August 2021 (Impact of the second Wave of COVID-19, including the partial lockdown period)*		*Baseline: September 2019 and Endline: August 2022 (when the spread of COVID-19 has reduced)*	
	$\widehat{\beta_3}$	*Impact*	$\widehat{\beta_3}$	*Impact*	$\widehat{\beta_3}$	*Impact*
Informal worker (whose educational qualification is less than 12th standard)	3.02* (1.281)	Positive	-0.523 (1.932)	Zero	-1.670 (1.837)	Zero
Formal worker (whose educational qualification is at least a Graduation)	8.413*** (2.707)	Positive	6.510** (3.024)	Positive	3.282* (2.892)	Positive
Rural Male worker	5.267*** (1.470)	Positive	1.918 (1.467)	Zero	1.037 (1.417)	Zero
Rural Female worker	-0.211 (6.024)	Zero	-3.429 (6.364)	Zero	-5.5 (6.683)	Zero
Urban Male worker	4.892** (1.909)	Positive	1.255 (1.822)	Zero	-0.437 (1.724)	Zero
Urban Female worker	-2.992 (5.922)	Zero	-5.503 (6.45)	Zero	-7.796 (6.592)	Zero
***=> Significant at 1% level, **=> Significant at 5% level, *=> Significant at 10% level The standard errors are given in the parentheses.						

that the unemployment rate among a particular type of worker in India has increased in the end-line period in comparison to the baseline period. But if the estimated value is statistically insignificant, for a particular type of worker, it will be concluded that COVID-19 ultimately could not create any overall impact on the unemployment rate among that particular type of worker in the Indian labour market during the experimental periods.

RESULTS AND DISCUSSIONS

Table 1 shows that during the pandemic and after the pandemic, the most affected workers who lost their jobs were educated, skilled workers whose educational qualifications were beyond higher secondary (plus 12 levels). Among the informal workers, initially, a good percentage had lost their jobs during the time of the first wave of COVID-19. But during the second wave and after the pandemic, the unemployment rate in India had gone back to the pre-COVID-19 period. Therefore, we observe a 'zero' impact on the unemployment rate of those types of workers after the pandemic. The unemployment rate in India among overall rural male and urban male workers has increased after the pandemic, mainly due to the lockdown period. But it again decreased during the time of the second wave of COVID-19, and after the pandemic was almost over. So, the table shows a 'zero' impact. The pandemic failed to create an overall impact on the unemployment rate among female workers in both rural and urban areas.

The dominant cause of greater unemployment (combining involuntary and voluntary unemployment) among different types of workers in the Indian labour market during the pandemic and after the pandemic

From the previous section, it is already evident that the unemployment rate of labourers was mostly affected due to the outbreak of COVID-19. Now it is required to investigate the cause of unemployment among different types of workers, i.e., whether the involuntary labour force dominates over the voluntary labour force or not. Voluntary unemployment is attributed to the individual's decision, but involuntary unemployment happens due to a lack of labour demand in the employment market. Sometimes an individual is voluntarily unemployed because (s)he has rejected the low-paid job. But involuntary unemployment incorporates the firing of workers because of an economic crisis, industrial decline or pandemic. Frictional unemployment can also be incorporated as voluntary unemployment because this unemployment problem occurs from the inevitable time delays in finding new entries with 'justified' remuneration. It can also be called 'search unemployment'.

It was observed that a good percentage of people who had lost their jobs with the onset of the lockdown had not taken up new jobs due to the uncertainty and the fear of the COVID-19 infection. The Government of India announced the Pradhan Mantri Garib Kalyan Yojana, by providing 5 kg of rice or wheat and 1 kg of pulses to eligible people free of cost, in addition to the regular entitlement on the quota of food grains. The scheme was initially meant to be implemented from April 2020 to April 2021, and during the second wave, it was extended up to November 2021. This food security programme may also be one of the reasons behind the existence of a voluntarily unemployed labour force in any particular state during the pandemic, because this could also have kept the household dependent on informal work at the reserved level. During the first phase of the outbreak of COVID-19, employment opportunities in all types of private enterprises declined. Sometimes they offered low wages to the workers. Due to these reasons, some people in the labour force rejected employment opportunities because they did not receive the desired wage or salary. Sometimes, (s)he could not find the job which (s)he wished for and was voluntarily unemployed. During the time of the second wave, due to vaccination coverage, it was expected that the fear of COVID would go down, more working people would join the job market, and the intensity of voluntary unemployed people would decline.

To investigate this, we considered the following model:

1. F_{it} => Unemployed individuals of the i^{th} state in the t^{th} time period who are willing to work and active job seekers.
2. G_{it} =>The unemployed labour force of the i^{th} state in the t^{th} time period who are willing to work but inactive job seekers.
3. H_{it} => The greater labour force of the i^{th} state in the t^{th} time period, where
4. $H_{it} = C_{it} + G_{it}$ where C_{it} denotes the total labour force of the i^{th} state in the t^{th} period who are willing to join the job market. It can be called the total supply of the willing labour force of a state in that particular period. Here H_{it}, F_{it}, G_{it} and C_{it} all are measured in thousands.

Hence, the greater unemployment rate (after considering all types of job seeker labour force) of the i^{th} state in the t^{th} time period can be expressed as

$$GUER_{it} = \frac{F_{it} + G_{it}}{H_{it}} = \frac{F_{it}}{H_{it}} + \frac{G_{it}}{H_{it}} = A_{it} + B_{it} \tag{2}$$

(Here, A_{it} indicates the greater involuntary unemployment rate of the i^{th} state in the t^{th} time period, and B_{it} indicates the voluntary unemployment rate of the i^{th} state in the t^{th} time period.

Now, $A = \frac{F}{H}$.

Then, taking the log on both sides, we get: $\ln A = \ln F - \ln H$ Eq. 3

Lastly, after differentiating both sides of Eq. 3 with respect to time, we get Eq.4:

$$\frac{1}{A}\frac{dA}{dt} = \frac{1}{F}\frac{dF}{dt} - \frac{1}{H}\frac{dH}{dt} \text{ i.e., } \frac{\dot{A}}{A} = \frac{\dot{F}}{F} - \frac{\dot{H}}{H} \tag{4}$$

Similarly, we have $\frac{\dot{B}}{B} = \frac{\dot{G}}{G} - \frac{\dot{H}}{H}$ Eq. 5

Therefore, using Eq. 4 and Eq. 5, we get $\frac{\dot{A}}{A} - \frac{\dot{B}}{B} = \frac{\dot{F}}{F} = \frac{\dot{G}}{G}$ Eq. 6

Now if $\frac{\dot{F}}{F} = \frac{\dot{G}}{G}$ then only $\frac{\dot{A}}{A} = \frac{\dot{B}}{B}$ happens in a particular state in the t^{th} period over the $(t-1)^{th}$ period which indicates that in a particular state within a certain time period, the rate of change of greater involuntarily unemployed workforce dominates over the rate of change of greater voluntarily unemployed workforce (i.e., a greater proportion of the workforce is involuntarily unemployed than voluntarily unemployed among a certain type of workforce).

But if the opposite situation happens, i.e. if $\frac{\dot{F}}{F} = \frac{\dot{G}}{G}$ then $\frac{\dot{A}}{A} = \frac{\dot{B}}{B}$ which indicates that between the t^{th} period and $(t-1)^{th}$ period, a greater unemployment problem of a particular labour force in any particular state arises due to the dominance of voluntarily unemployed persons over involuntarily unemployed persons.

The dominance of the voluntary unemployment rate over the greater involuntary unemployment rate may also happen if employment generation happens in a particular state in the concerned time period, and a major section of the involuntarily unemployed labourers in the previous period have become employed or migrated to other areas. This will reduce the value of $\frac{\dot{A}}{A}$. Some voluntarily unemployed persons of the previous period may also have joined the labour market after the intensity of the pandemic subsides. But if the involuntarily unemployed labourer is proportionately less than the voluntarily unemployed labourer of the t^{th} period, then also the dominance of voluntary unemployment is observed in certain states during the post-pandemic period.[5].

With the help of the aforementioned model, we have derived the dominant cause of greater unemployment rate based on CMIE data during the COVID-19 pandemic and after the pandemic among different types of labour force in 27 states of India (i.e., the dominant cause of unemployment between 2019 and 2020, 2020 and 2021 and between 2021 and 2022) and this can be presented with the help of Table 2:

Table 2: The number of states (out of 27 states) in which we witnessed the dominance of voluntary unemployment over involuntary unemployment of different types of workers during the pandemic and the post-pandemic period

Types of Workers[6]	*First wave of the COVID-19 pandemic (2019-2020)*	*Second Wave of COVID-19 Pandemic (2020-2021)*	*Post-pandemic Period (2021-2022)*
Overall Formal Workers	13	9	9
Overall Informal Workers	15	8	7
Overall Rural Workers	15	10	9
Overall Urban Workers	16	10	10

Source: Calculated and Compiled by Authors

Discussions from Table 2

It is evident from Table 2 that during the first phase of the pandemic majority of overall formal and informal workers and overall urban and rural workers were voluntarily unemployed in most of the states. However, this tendency decreased during the second phase and further dropped when the pandemic's intensity was minimal. It is observed that among 27 states of India, just after the outbreak of COVID-19, the majority of the formal workers in 13 states had voluntarily decided not to participate in the job market. But during the second wave, the number of such states decreased to 9 states, and after the pandemic, it remained at 9 states. There is no such state that has shown the dominance of voluntary unemployment among formal workers in all three considered time periods. On the other hand, it is evident that among the informal workers, one can observe the dominance of voluntary unemployment in 15 out of 27 states, but it dropped to 8 states during the time of the second wave of the pandemic. In the post-pandemic stage, it had dropped to 7 Indian states only. Again, 15 states (out of 27) had shown the dominance of voluntary unemployment among rural labourers over involuntary unemployment during the first wave of COVID-19. During the second wave of the pandemic and the post-pandemic period, the number of states that showed the same tendency was 10 and 9, respectively. However, one can observe that 16 states have shown the dominance of voluntary unemployment among urban workers over involuntary unemployment during the outbreak of the first wave of COVID-19. But this tendency among urban workers dropped to 10 states during the second wave of COVID-19 and remained at 10 when the pandemic's intensity was minimal. Uttar Pradesh is the only state that has experienced the dominance of voluntary unemployment among overall urban workers throughout the different phases of the pandemic.

Possible factors that may influence the possibility of being involuntarily unemployed among different types of workers across 27 states of India during the pandemic and the post-pandemic period

Involuntary unemployment refers to the situation where people are willing to work at the existing wage rate but are not getting a job. It happens due to a lack of labour demand in the employment market due to the economic crisis, industrial decline or pandemic. A large fraction of India's firms are small, informal and operate in the unorganised sector. These MSMEs are uniformly spread across rural and urban areas of India and are equally represented in the manufacturing, trade and services sectors. According to Walter (2021), the lockdown to prevent the spread of COVID-19 disrupted the operations of these MSMEs. This may be the reason for the sudden hike in the involuntary unemployment rate among informal workers during the pandemic period. The impact of the pandemic appears to have been on workers who had less formal education, and even those who were highly educated.

We come to know that in most of the states, all types of labourers preferred to remain voluntarily unemployed during the outbreak of the pandemic, but this tendency had gradually declined with the decline in the number of active COVID cases over time. When the pandemic's intensity had been declining, the dominance of involuntarily unemployed persons had been increasing among all types of labourers in most of the states. Against this backdrop, we wanted to identify the possible factors that may have influenced the dominant cause of greater unemployment rate (or what were the factors which could have influenced the probability of being involuntarily unemployed among different types of labourers) in different states among different workers (say Rural Workers and Urban Workers; Formal and Informal Workers) during the pandemic and after the pandemic[7]. Here, the dominant cause of the greater unemployment rate was treated as a 'binary response' and took the value of either 1 or 0. It was considered as '1' when we observed that the rate of change of the involuntarily unemployed workforce between the t^{th} and $(t-1)^{th}$ period dominated over the rate of change of the voluntarily unemployed workforce between the t^{th} and $(t-1)^{th}$ period among a particular type of worker in a particular state. If the opposite situation happened, it would be considered as '0'. Therefore, to investigate those factors, we considered the following Probit Model. Here we took 27 states of India, considering each state as a cross-section unit (i=27). We carried out the analysis by estimating the Probit Model separately for the periods (2019-20), (2020-21) and (2021-22) for the concerned workers. For the year 2019, we used the CMIE data of the wave, September-December 2019. We had considered the CMIE's wave, May-August 2020 for the year 2020, May-August 2021 for the year 2021 and May-August 2022 for the year 2022, respectively.

The following equation shows the Probit Model.

$$\mathrm{DGUnemprate}_{ijt} = \alpha_0 + \alpha_1 \mathrm{Noofactivecase}_{it} + \alpha_2 \log \mathrm{PSDP}_{it} + \alpha_3 \left(\frac{G}{B}\right) ijt + \alpha_4 \mathrm{MGNREGADAY}_{it} + \varepsilon_{ijt} \tag{7}$$

where $\mathrm{DGUnemprate}_{ijt}$ implies the dominant cause of the greater unemployment rate of the j^{th} type of worker of the i^{th} state in the t^{th} period and ε implies the random error term.

Hence, the variables that may be responsible for the dominance of the involuntary unemployment rate over the greater voluntary unemployment rate are explained below:

(i) Number of Active Covid Cases of i^{th} state in t^{th} period ($Noofactivecase_{it}$): Due to the pandemic, it was difficult to follow proper physical distancing between two workers during the time of production process. This problem became more acute in informal sectors where employers failed to provide safety to their workers. As a result, such sectors were bound to shut down their production process during the lockdown period, and they were at stake even after the lockdown.

Therefore, it is expected that as the number of active cases goes up, the probability of being involuntarily unemployed among all types of labourers would also increase. To carry out the analysis for all types of workers, we considered the data on the number of active cases in July 2020, July 2021 and July 2022 (as of July 2020, the number of tests for COVID-19 had increased) for periods 2019-20, 2020-21 and 2021-22. (Source: *indiastat.com*)

(ii) Per Capita State Net Domestic Product of i^{th} state in t^{th} period ($PSDP_{it}$): It is defined as the net value of all the final goods and services produced within a state's geographic borders at a particular point in time. Generally, when PSDP increases, it leads to an enhancement of the economic activities of the concerned state, which in turn generates employment opportunities in the state economy. As a result, demand for labour increases in the economy. Therefore, it is expected that PSDP can be a determining factor in reducing the involuntary unemployment rate among different types of workers. Here, we took its logarithm value. In this case, we had used the data on PSDP of financial years, 2019-20, 2020-21 and 2021-22, respectively. (Source of Data: *Indian Economy Report of RBI in different considered periods*)

(iii) The total number of voluntarily unemployed persons (G) of the j^{th} type of worker as a proportion of the total population of persons > 15 years of the i^{th} state in the t^{th} period $(G/B)_{ijt}$): The variable (G/B) shows how many of the j^{th} type of workers of the i^{th} state do not want to participate voluntarily in the labour market in the t^{th} time period. It represents the supply side of labour. If the number of voluntarily unemployed individuals increases, the supply of the willing labour force will fall, but if the reverse happens, then the size of the labour force will increase. If (G/B) increases, the probability of being involuntarily unemployed may decrease in the economy. For our analysis, we had considered the data on (G/B) for the CMIE waves, May-August 2020, May-August 2021 and May-August 2022 for periods 2019-20, 2020-21 and 2021-22, respectively. (Source: *CMIE data*)

(iv) Number of person-days generated under the MGNREGA scheme in the ith state at the tth time period ($MGNREGA_{it}$): The demand for jobs through MGNREGS had increased by 49.4% during the pandemic. Such a guaranteed public employment programme in rural areas had made it possible to offer work to more people there during the pandemic. If the number of person-days of work generated under the MGNREGA scheme increases, then there is a possibility that the rate of change of the involuntary unemployment rate will go down in rural areas of the concerned states. In this case, we had used the data on the number of person-days generated under MGNREGA for financial years 2019-20, 2020-21 and 2021-22. (Source: *Ministry of Rural Development, GOI*)

RESULTS AND DISCUSSIONS

The results of the Probit Model Estimation (by using Eq. 7 for different workers) are presented in the following Table 3.

Table 3: The Results of the Probit Model Estimation for overall Rural Workers (no segregation based on gender and educational qualification)

Dependent Variable: DGUnemprate						
2019-2020		*2020-2021*		*2021-2022*		
Explanatory Variables	*Value of the coefficient*	*Marginal coefficient*	*Value of the coefficient*	*Marginal coefficient*	*Value of the coefficient*	*Marginal coefficient*
No of active cases	-0.000049 (0.000071)	$-3.82e^{-10}$	0.000031 (0.000031)	0.00001	0.000262* (0.00016)	0.00006**
Log PSDP	-2.278 (3.246)	-0.000018	1.678 (1.395)	0.5535	2.8550** (1.379)	0.6978*
G/B	-450.48 (360.11)	-0.0035	-13.942 (19.74)	-4.599	9.503 (13.623)	2.323
MGNREGADAY	-0.00121 (0.00243)	$-9.44e^{-09}$	0.00042 (0.00021)	0.00014	-0.00078** (0.00034)	-0.00019**
LR χ^2 (4)	26.71***		8.82*		15.02***	
Pseudo R^2	0.7201		0.2477		0.4369	
The standard errors are given in parentheses. ***=> significant at 1% level, **=> significant at 5% level, *=> significant at 10% level						

Source: Author's Calculation (using STATA)

Results and Discussions of Table 3

(i) During both the first and second waves of the pandemic, some rural labourers withdrew from the labour force and became voluntarily unemployed due to fear of COVID-19 infection in most of the states. The rural areas were not much affected by the number of active cases during the initial stages of COVID-19 because of the lack of enough testing. For this reason, the number of active COVID-19 cases had no significant impact on the dominance of involuntarily unemployed workers among rural workers during the first and second waves of the pandemic. After the pandemic, most states witnessed the dominance of involuntary unemployment over voluntary unemployment among rural workers. The introduction of free vaccination against COVID-19 and the decline in support from the Public Distribution System had encouraged rural workers to join the labour market after the pandemic. This may be the reason for the sudden hike in the involuntary unemployment rate. It is evident from Table 3 that the variable, *Noofactivecase,* had a positive and significant impact on the dependent variable during the post-pandemic period only. It implies that as the number of active cases goes up, the probability of being involuntarily unemployed among rural workers would also increase.

(ii) The coefficient of log PSDP is positive and statistically significant for rural workers during the period (2021-22). It may happen because when SDP increases, economic activity will also increase in the economy. Therefore, the demand for labour will increase during that period. As demand for labour increases, voluntarily unemployed persons in the previous period (who had withdrawn themselves from the labour market due to fear of COVID infection) would want to join the job market. As a result, the supply of both skilled and unskilled rural labourers will also increase. If the supply of labour force exceeds the demand for labour force, we have a situation of excess supply of labour force, which results in a sudden hike in the rate of change of the involuntary unemployment rate among rural workers.

(iii) It is evident from the aforementioned table that during the post-pandemic period (2021-22), the coefficient of MGNREGADAY is negative and statistically significant, which establishes the fact that as the number of person-days generated under MGNREGA goes up, the probability of being involuntarily unemployed among the rural workers will decline. This employment programme had provided work for needy rural people (who had wanted to join the labour market when the pandemic's intensity was minimal) closer to home, at decent working conditions.

Next, we shall discuss the results of the Probit model estimation for overall urban, overall informal and overall formal workers in Tables 4, 5 and 6, respectively.

Table 4: The Results of the Probit Model Estimation for Overall Urban Workers[8] (No segregation based on gender and educational qualification)

	Dependent Variable: DGUnemprate			
	2019-2020		*2020-2021*	
Explanatory Variables	*Value of the coefficient*	*Marginal coefficient*	*Value of the coefficient*	*Marginal coefficient*
No of active cases	$-8.29e^{-06}$ ($6.25e^{-06}$)	$-2.18e^{-06}$	$-2.90e^{-06}$ ($9.02\ e^{-06}$)	$-1.06\ e^{-06}$
Log PSDP	-1.121 (1.311)	-0.294	2.9770** (1.3668)	1.092**
G/B	-77.07** (32.38)	-20.273***	-11.213 (12.67)	-4.116
LR chi^2 (3)	17.97***		7.95**	
Pseudo R^2	0.4923		0.2233	
The standard errors are given in the parentheses. ***=> significant at 1% level, **=> significant at 5% level, *=> significant at 10% level				

Source: Calculated by authors (using STATA)

Table 5: The Results of the Probit Model Estimation for Overall Informal Workers[9] (No segregation based on gender and region)

	Dependent Variable: DGUnemprate			
	2019-2020		*2020-2021*	
Explanatory Variables	*Value of the coefficient*	*Marginal coefficient*	*Value of the coefficient*	*Marginal coefficient*
No of active cases	-0.000014 (0.000011)	$-4.16e^{-06}$	$-5.68e^{-06}$ ($9.79e^{-06}$)	$-1.72e^{-06}$
Log PSDP	-1.391 (1.414)	-0.401	3.8813** (1.659)	1.172**
G/B	-76.78** (33.007)	-22.148***	-6.704 (11.047)	-2.025
LR χ^2 (3)	19.37***		9.49**	
Pseudo R^2	0.5222		0.2891	
The standard errors are given in parentheses. ***=> significant at 1% level, **=> significant at 5% level, *=> significant at 10% level				

Source: Calculated by authors based on CMIE data (using STATA)

Table 6: The Results of the Probit Model Estimation for Overall Formal Workers[10] (No segregation based on gender and region)

	Dependent Variable: DGUnemprate	
	2019-2020	
Explanatory Variables	*Value of the coefficient*	*Marginal coefficient*
No of active cases	$4.60e^{-07}$ ($2.90e^{-06}$)	$1.77e^{-07}$
Log PSDP	0.0825 (1.146)	0.0318
G/B	-40.99*** (15.025)	-15.802***
LR χ^2 (3)	12.48***	
Pseudo R^2	0.3339	
The standard errors are given in the parentheses. ***=> significant at 1% level, **=> significant at 5% level, *=> significant at 10% level		

Source: Author's calculation based on CMIE data (using STATA)

Discussions of Table 4, Table 5 and Table 6

The coefficients of (G/B) are negative and statistically significant for overall urban, overall informal and overall formal workers during the first wave of COVID-19 only. The urban labour force consists of informal and formal labourers who reside in urban areas. As we all know, urban areas are densely populated in India. Therefore, in urban areas, especially in informal sectors, it was difficult to follow physical distancing at the time of work during the first wave of COVID-19. Hence, most of the male involuntarily unemployed and employed persons who belonged to the age group (>50 years) and some fraction of the female labour force of different age groups withdrew themselves (both formal and informal) from the labour force due to fear of COVID infection and family constraints. As a result, voluntarily unemployed persons (G) as a proportion of the total population (B), i.e. (G/B), would increase. Therefore, we can say that the possibility of the dominance of voluntary unemployment over involuntary unemployment will be higher due to a higher value of (G/B) in most of the states during the first wave of the pandemic. But this tendency had declined gradually over time, and after the pandemic, most of the states had shown the dominance of involuntary unemployment.[11]. When we move to the second wave (2020-21) of the pandemic, the coefficient of (G/B) becomes insignificant for urban and informal workers. It is because during the second wave of the pandemic, the economic activities had already started in non-contaminated zones, even free vaccination had been implemented by the Indian government, which reduced the fear of COVID-19 infection. The additional support from the Public Distribution System (PDS) from the government was also reduced at that time. Therefore, the intensity of voluntary unemployment has declined in the second wave because in India, near about 80% of the workforce is informal in nature, and a large percentage of it lies below the poverty line (Roy & Kundu, 2019). Therefore, the informal workforce had no other option but to join the labour market. However, this condition tends to create an impact on the dominant cause of the greater unemployment rate among urban workers. This is also happening for both formal and informal workers.

The coefficients of log PSDP are positive and statistically significant for overall urban and overall informal workers during the period 2020-21.

CONCLUSION

The Indian labour market is dominated by informal workers, and a major percentage of the informal workers are male workers. The COVID-19 pandemic had created an impact on the unemployment rate in India. The most affected labour force was the educated labourers who had at least a graduation degree. Even after the pandemic was over, the unemployment rate of such a labour force had still increased. Initially, during the first wave of COVID-19, the problem of unemployment increased among overall informal, rural male and urban male workers. But a 'zero' impact on the unemployment rate among those workers has been observed after the pandemic was over. Their unemployment rate position was back to more or less the pre-COVID state. No significant change had been observed in the female labour force's unemployment rate even during the time of the pandemic due to their low labour participation rate. Their unemployment rate was high enough in the pre-pandemic period. It is observed that in most of the states, all types of labourers preferred voluntary unemployment during the pandemic. But this tendency had gradually declined with the decline of the spread of infection over the years. The labour force wanted to join the job market, but due to a lack of employment opportunities in most of the states, those labourers had become involuntarily unemployed even after the pandemic. While investigating the factors that were responsible for the probability of being involuntarily unemployed among different types of workers, we found that an employment scheme like MGNREGA had reduced the dominance of involuntary unemployment among overall rural workers when the pandemic's intensity was minimal. The rise in the number of active COVID-19 cases and the rise in PSDP were also responsible for the hike in involuntary unemployment in rural areas after the pandemic. Besides that, when the number of voluntarily unemployed persons as a proportion of the total population increased during the first wave of COVID-19, the possibility of the dominance of involuntary unemployment decreased among overall urban, formal and informal workers during that period. On the other hand, the increase in PSDP has increased the probability of being involuntarily unemployed among overall urban and informal workers during the pandemic.

Notes

1. Informal workers are here considered those workers who do not have any secure employment contract, worker's benefit or any type of social security benefit from the employer.
2. According to the general CMIE Report, a person is said to be employed when that person is engaged in any economic activity either on the day of the survey or the day preceding the survey or is regularly engaged in economic activity in at least one hour in the entire reference period.
3. Here the labour force that belongs to the age group of more than 15 years is considered.
4. According to CMIE data, in this context population estimates of Labour Force & Unemployment were calculated on the basis of Maximum Educational Qualification and not on the basis of age.
5. For example, we can cite the situation of Andhra Pradesh. In 2021, F (total involuntarily unemployed workforce) = 525, G (Voluntarily unemployed labour force) = 49, H (Greater Labour Force) = 15307 and E (Employed) = 14733. Here, F, G, H and E are all measured in thousands. In 2022, F = 124, E=14961, G=92 and H= 15177, respectively (all in thousands). In 2022, the involuntarily unemployed labour force had decreased, and the voluntarily unemployed labour force had increased. There is a slight fall in the greater labour force. Therefore, $\frac{\dot{F}}{F}$ = -0.7638 and $\frac{\dot{G}}{G}$ = 0.8776. So, $\frac{\dot{F}}{F} - \frac{\dot{G}}{G} = -1.6414 < 0$ which establishes the fact that

the rate of the change of voluntarily unemployed labour force is more than the rate of change of the involuntarily unemployed labour force. Again, $\frac{\dot{E}}{E}$ i.e., rate of change of the number of employed persons over the year becomes 0.0155 and that is more than $\frac{\dot{F}}{F}$, This indicates that during the post-pandemic period, the rate of change of employment generation in that particular state was more than the rate of change of involuntarily unemployed labour force. Again as $\frac{\dot{E}}{E} < \frac{\dot{G}}{G}$ we can say that the rate of change of voluntarily unemployed persons was more than the rate of change of employment generation in the post-pandemic phase. Therefore, during the post-pandemic period, the rate of change of voluntarily unemployed labour force in that particular state was more than the rate of change of involuntarily unemployed labour force. Here, no segregation of the formal workforce has been done on the basis of gender.

6. Here we have considered overall formal and informal workers which indicates that there is no segregation of workers based on gender and region. Similarly, overall rural and urban workers indicate that there is no segregation of workers based on gender and educational qualification.
7. The dominant cause of the greater unemployment rate among different types of workers is described in Table 2 of the previous section.
8. The Probit model for overall urban workers is statistically insignificant for the period, 2021-22.
9. The Probit model for overall informal workers is statistically insignificant for the period, 2021-22.
10. The Probit model for overall formal workers is statistically insignificant for the periods, 2020-21 and 2021-22.
11. See Table 2.

Referebces

Abraham, R., Basole, A., & Kesar, S. (2021). *Down or out: The gendered impact of the Covid-19 pandemic on India's labour market* (CSE Working Paper No. 40).

Acharya, S. (2008). Poverty alleviation and the industrial employment of women (The case of Nepal). *Journal of International Development, 20*(5), 670–685. https://doi.org/10.1002/jid.1457

Ali, M. A., & Kamraju, M. (2020). A study on the impact of the COVID-19 pandemic on unemployment in India. In *Reimaging the new normal—the transformational lens of COVID-19* (pp. 50–61). The Bhopal School of Social Sciences.

Annual Report (2019, 2020, & 2021). *Periodic Labour Force Survey 2017–18, 2018–19 & 2019–2020*. National Statistical Office (NSO), Ministry of Statistics and Programme Implementation (MOSPI).

Bussolo, M., Kotia, A., & Sharma, S. (2021). *Workers at risk: Panel data evidence on the COVID-19 labour market crisis in India* (Policy Research Working Paper No. 9584). World Bank Group. https://doi.org/10.1596/1813-9450-9584

Chakraborty, S. (2020, August 29). COVID-19 and women informal sector workers in India. *Economic & Political Weekly, 35*, 17–21.

Chauhan, P. (2020). Gendering COVID-19: Impact of the pandemic on women's burden of unpaid work in India. *Springer Nature, 38*, 395–419. https://doi.org/10.1007/s11199-020-01145-6

Chopra, C., & Bijoy, N. (2021). Dynamics of unemployment situation in India. *International Journal of Advanced Research in Commerce, Management & Social Science (IJARCMSS), 4*(2I), 185–195.

Deshpande, A. (2020). *The COVID-19 pandemic and lockdown: First order effects on gender gaps in employment and domestic time use in India* (GLO Discussion Paper No. 607). Global Labor Organization (GLO).

Galor, O., & Zeira, J. (1993). Income distribution and macroeconomics. *The Review of Economic Studies, 60*(1), 35–52. https://doi.org/10.2307/2297811

Goswami, B., Mandal, R., & Nath, H. K. (2021). COVID-19 pandemic and economic performances of the states in India. *Economic Analysis and Policy, 69*, 461–479. https://doi.org/10.1016/j.eap.2020.12.015

International Labour Office. (2020). *World employment and social outlook: Trends 2020*. ILO Flagship Report.

Shameem, S., & Rajeswari, M. (2022). Impact of COVID-19 pandemic on unemployment in India. *Journal of Economic Issues, 1*(1), 72–78.

Standing Committee on Labour. (2021). *Social security and welfare measures for inter-state migrant workers*. PRS Legislative Research, Lok Sabha Secretariat.

Victor, V., Karakunnel, J. J., Loganathan, S., & Meyer, D. F. (2021). From a recession to the COVID-19 pandemic: Inflation-unemployment comparison between the UK and India. *Economies, 9*(2), 73. https://doi.org/10.3390/economies9020073

Vishwakarma, R. (2022). Unemployment analysis during and after COVID-19. *YMER, 21*(7), 499–511.

Vyas, M. (2020). Impact of lockdown on labour in India. *The Indian Journal of Labour Economics, 63*(Suppl 1), S73–S77. https://doi.org/10.1007/s41027-020-00232-6

Walter, D. (2020). Implications of COVID-19 for labour and employment in India. *The Indian Journal of Labour Economics, 63*(Suppl 1), S47–S51. https://doi.org/10.1007/s41027-020-00230-8

Appendix

Summary Statistics

Name of the Variables	*2019-20*		*2020-21*		*2021-22*	
	Mean	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*
No. of Active Cases	73249.89	92634.25	19325.04	32325.84	3835.74	7177.35
PSDP	124308.3	69648.6	118091.2	66219.5	157548.9	142830.5
MGNREGADAY	957.75	947.33	1409.362	1418.701	1313.94	1272.24

(G/B) is different for different types of workers