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Labour market dynamics and worker flows in India: Impact of Covid-19

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Abstract
The Covid-19 pandemic has had a significant impact on the labour market in India, resulting in unprecedented economic downturns and job losses. To understand the specifics of the labour force, it is necessary to assess the changes across different groups over time. This paper examines the distinct effects of the pandemic on various groups of working-age individuals in India, using data from the Consumer Pyramids Household Survey (CPHS) conducted by the Center for Monitoring the Indian Economy (CMIE) from November 2016 to January 2022, covering 16 waves. The study analyses labour flows and transition matrices to demonstrate how Covid-19 related restrictions affected different categories of individuals in the labour force, such as those who were employed, out of the labour force, or with data not available. The dataset also allows for the exploration of various types of heterogeneity, such as the impact of education levels on employment. The authors found that the impact of the pandemic on employment was more significant for those with primary or secondary education than for those with graduate or post-graduate education. The study also reveals a substantial increase in the category of "Data Not Available" during the lockdown period, reflecting the migration from urban to rural areas that occurred during that time. The paper also applies event analysis using a difference-in-differences approach to estimate the likelihood of getting a full-time job during the shocks experienced in the economy. The logistic regression model predicts the logit of the outcome variable from the predictor variables, and the relationship between the outcome variable and the predictor variables is nonlinear. The study period is from November 2016 to January 2020, and the data is quarterly. Overall, this research provides valuable insights into the impact of the Covid-19 crisis on the Indian labour market and adds to the existing literature on this topic. The study identifies gaps in the existing literature and aims to fill them by examining the impact of the pandemic on different employment categories and conducting event analysis to estimate the likelihood of getting a full-time job during the shocks experienced in the economy.

Keywords: Employment, labour dynamics, Covid – 19, reverse migration

Introduction

Monitoring the changes in the labour market is crucial for comprehending both the economic status and welfare implications resulting from those changes. The unemployment rate indicator is one of the most observed indicators in the economy. However, it is inadequate to solely examine the total number of unemployed due to the various differences within the labour market. To gain insight into the specifics of the labour force, such as income class, gender, educational attainments, skill levels, etc., it is necessary to assess the changes across these groups over time. Tracking labour flows at regular intervals is crucial, especially in the current Covid-19 crisis that has significantly impacted the economy and labour market. This is even more important in India, given its large population, demographic structure, heterogeneity, and development stage.

This paper examines the distinct effects of the Covid-19 pandemic on various groups of working-age individuals. The pandemic led to unprecedented economic downturns and job losses worldwide, including in India, where the GDP fell by more than 20% in the first quarter of 2021. The Indian government implemented strict lockdown measures to prevent the spread of the virus, which significantly impacted the job market, resulting in massive employment losses. While several papers have commented on the pandemic's impact on employment, none have generated labour flows or calculated transition probabilities, which this paper does. By analysing labour flows and transition matrices, the paper demonstrates how the Covid-19 related restrictions affected different categories of individuals in the labour force, such as those who were employed, out of the labour force, or with data not available. The dataset also allows for the exploration of various types of heterogeneity, such as the impact of education levels on employment. The authors found that the impact of the pandemic on employment was more significant for those with primary or secondary education than for those with graduate or post-graduate education. The study also reveals a substantial increase in the category of "Data Not Available" during the lockdown period, reflecting the migration from urban to rural areas that occurred during that time. Overall, this research provides valuable insights into the impact of the Covid-19 crisis on the Indian labour market, adding to the existing literature on this topic.

To expand our investigation, we also examine gender-based heterogeneity. As anticipated, there is a notable disparity in employment levels between men and women. We discover that, across all education categories and time periods, men are more likely to have full-time employment compared to women. While both men and women experienced the effects of Covid-19 regardless of their educational attainment, the impact varied among different education groups.

Literature Review

The Covid-19 pandemic has caused significant global labour market changes, including job losses and income declines. It is crucial to monitor and assess the trends of the labour market regularly. The paper by Partha Chatterjee and Aakash Dev (2023) uses a panel to build labour flow charts and transition matrices for India from January 2019 to December 2021 using the Consumer Pyramids Household Survey (CPHS) dataset from the Centre for Monitoring Indian Economy (CMIE). In addition to examining transitions between full-time and part-time employment, the research also examines transitions between employment, unemployment, and leaving the labour force. The paper considers labour market diversity and the varying effects of the pandemic on different echelons of education and gender. The article discovered that while all groups have been harmed, the degree of impact varies across groups based on the labour flow charts and transition probabilities. The amount of recovery is similarly varied and is based on educational attainment. The study by Rosa Abraham *et al* (2021) uses panel data from India to compare how the shock affected male and female worker outcomes in the labour market between Dec-Jan'19 to September 2020 and found that while highly educated female workers were more susceptible to losing their jobs, education protected male workers from losing their jobs. The paper by Rosa Abraham, Amit Bosale (2021) found that women were far more likely than men to lose their jobs and were also less likely to find new ones. Moreover, lower castes experienced job loss more severely than middle and upper castes did, as did daily wage workers than regular wage workers. Younger workers were more susceptible to losing their jobs than older workers. Younger people were less likely to get a job in August after losing it in April. A substantially higher frequency of transitions from wage employment to self-employment was discovered for people employed in December 2019 and August 2020 when the changes in work arrangements were studied compared to the seasonally corresponding time the previous year (Dec 2018 to Aug 2019).

The study employs two models. In the first regression, the paper calculates how social, demographic, and economic characteristics affect the likelihood of losing one's job, specifically for those who were employed in December 2019 (pre-lockdown) and lost their jobs in April 2020 (during the lockdown) or in August 2020 (post-lockdown). The likelihood of finding employment after losing it during the lockdown between April 2020 (during the lockdown) and August 2020 (after the lockdown) is then estimated using these factors. The research uses a binomial logistic regression with state-fixed effects for this estimation.

The paper by Abraham, R., A. Basole and S. Kesar (2020) [1] examines the impact of the Covid-19 pandemic on employment trajectories in India, focusing on the role of social identities using panel data from a large-scale survey conducted in India to analyse the changes in employment outcomes for individuals across various social identities, such as caste, religion, gender, and education. It highlights the importance of understanding how the pandemic affects different segments of society, particularly those historically marginalised due to social identities, to design effective policies to mitigate the crisis's adverse effects. The paper argues that studying the pandemic's impact on employment outcomes through a social identity lens can reveal important insights into the nature of inequality and discrimination in the Indian labour market.

The research explores how the pandemic has exacerbated pre-existing inequalities and created new ones, with vulnerable groups such as informal sector workers and migrant labourers bearing the brunt of the crisis's economic fallout. The authors use descriptive statistics and econometric models to examine the changes in employment outcomes across various social identities before and during the pandemic and conduct subgroup analysis to identify how different social identities interact to shape employment trajectories during the pandemic. The paper finds evidence of significant employment losses during the pandemic, particularly among informal sector workers and women.

Using information from the Periodic Labour Force Survey, the study by R. Kapoor (2020) [15] examines how the COVID-19 outbreak and the following quarantine have affected India's labour market (2018-19). The study demonstrates how India's labour market is susceptible because a disproportionately high percentage of the workforce participates in informal employment. Only 24% of workers are employed in salaried positions with regular pay, providing a constant income stream. The study also shows how the pandemic has widened the gap between less-educated workers who typically work in industries with high vulnerability, like manufacturing, construction, and agriculture, and the small percentage of more educated workers who hold regular formal jobs more conducive to remote work

Shania Bhalotia, Swati Dhingra, and Fjolla Kondirolli (2020) conducted a survey to know the impact of COVID-19 on urban workers. According to the survey, the impact of the pandemic on urban workers has been worse than the overall economic downturn. A majority of workers did not receive pay or assistance during this period, and the top 25% of income earners now make up 80% of total income, up from 64%. The greatest income losses have been experienced by lower-income informal workers.

The paper by Rajendra P. Mamgain (2021) [17] also investigates the impact of the COVID-19 pandemic-induced lockdown on the Indian labour market. Using data from the consumer pyramids household survey (CPHS) conducted by the Centre for Monitoring Indian Economy (CMIE), this article examines the extent and nature of job losses and the extraordinary growth in unemployment across gender, social group, and vocations between April–June 2020. Certain sections of society, including small traders, self-employed, migrant workers, daily wage labourers, youth, and women, who work predominantly in the informal sector of the Indian economy, are adversely affected the most. During COVID-19, the agriculture sector behaved as a sponge by absorbing the surplus labour leaving the economy for various well-known causes. The recovery rate on the labour market has been significantly slower for salaried positions, young employment, and employment in rural areas and among those with primary education. While a relatively small fraction of households reported increased incomes, the economic repercussions of these employment-related disruptions were considerably more severe. Even if the restoration to normalcy may take some time, there have been overall recessionary trends in employment in India well before the COVID-19 issue.

The paper by RB Bhagat *et al* (2020) [6] presents a clear and concise introduction to migration and COVID-19 in India. The study effectively highlights the challenges faced by migrants during the pandemic and the importance of developing strategies to mitigate the economic and social impact of COVID-19 on this population. Migrants have been badly hit by the wave of lockdowns. There is a need for policy measures to combat the rising tide of poverty, unemployment, and xenophobia brought on by the pandemic.

The paper by Maurizio Bussolo, Ananya Kotia and Siddharth Sharma (2021) presents their analysis of the impact of the pandemic on employment, wages, and working hours using data from the Periodic Labour Force Survey (PLFS) and the Consumer Pyramids Household Survey (CPHS). They find that the pandemic has significantly impacted employment in the formal and informal sectors, with the largest job losses occurring in the informal sector. The paper also finds that the pandemic has led to wage cuts and reduced working hours for many workers. The authors explore the heterogeneity of the impact of the pandemic on different demographic groups and regions. The paper finds that women and younger workers have been disproportionately affected by job losses and wage cuts. The paper also finds significant regional differences, with some states experiencing more severe labour market impacts than others. Finally, the authors discuss the policy implications of their findings. They argue that the Indian government needs to provide more targeted relief measures for workers in the informal sector, who have been hit hardest by the pandemic.

The research by Marianne Bertrand *et al* (2020) explained the changes in unemployment, employment, income, and consumption that occurred during and after the lockdown period. The conclusions from the paper are, employment to population ratio has not yet returned to its pre-lockdown levels, Per-capita income levels remained depressed in June, Very few occupations have been spared from the negative income shock, Changes in per-capita household income during and post-lockdown are similar across the income distribution, except for the top of that distribution, There is a lot of variation across Indian states in the extent of the economic downturn and Per-capita spending on basic food items remains sharply depressed through August.

Jack Blundell and Stephen Machin (2020) worked on the effect of the COVID-19 crisis on self-employed workers, focusing on their interaction with government support. The findings of the LSE-CEP Survey of UK Self-employment in May 2020 reveal that the Covid-19 crisis has significantly impacted the self-employed, with around 75% reporting a decrease in work during April 2020. The greatest reductions in self-employment hours and income have been experienced by older, lower-income individuals without employees. Although there are no gender differences in the aggregate, self-employed women who can work from home are more adversely affected than men who can work from home. Additionally, one-third of self-employed workers have felt their health is at risk while working during the pandemic, particularly those employed in app-based jobs. The survey also indicates that higher-income self-employed individuals are more likely to apply for the Coronavirus Self-employment Income Support Scheme. Over 40% of those who have not applied are unsure if they are eligible. The self-employed generally expect their work to return to normal by September 2020, but a fifth of them think it will take until 2021, and 1 in 20 believe their work will never return to normal. The self-employed highly value income support, with solo self-employed individuals valuing it twice as much as the self-employed with employees. On average, the self-employed are willing to give up 10% of their regular income to secure similar support for future shocks.

The paper by Coibion, Gorodnichenko, and Weber's (2020) [12] provides an early assessment of the impact of the COVID-19 pandemic on the labour market in the United States. The authors use data from weekly surveys conducted by the Census Bureau to provide a snapshot of the labour market during the early stages of the pandemic, focusing on changes in employment, hours worked, and earnings. Using data from the Census Bureau's weekly surveys, the authors show that employment declined sharply in March and April of 2020, with particularly large declines in the leisure and hospitality sector. The authors also show that hours worked declined significantly during this period, with many workers experiencing reduced hours or temporary furloughs. They examine the impact of the pandemic on earnings, showing that the decline in employment and hours worked was accompanied by a sharp decline in earnings for many workers. The authors note that the decline in earnings was particularly severe for workers in low-wage occupations, who were more likely to be employed in the hardest-hit sectors of the economy. The authors conclude by highlighting the importance of policy responses addressing the pandemic's immediate economic impacts, such as providing support for workers who have lost their jobs or experienced reduced hours. They also note that longer-term policy responses may be needed to address the structural changes resulting from the pandemic, such as the acceleration of automation and the shift to remote work. The lack of data on the condition of migrant workers in India adversely affects their welfare. Most workers are excluded from welfare schemes due to a lack of data and recognition. (S. Irudaya *et al* (2020) [14]. The paper effectively highlights the challenges faced by migrant workers in India during the pandemic, including restrictions on mobility and access to basic necessities, as well as the gender and mental health dimensions of the crisis. The paper provides a valuable contribution to the literature on the impact of the COVID-19 pandemic on migration and provides useful insightor policymakers and researchers working in this area. The migration of the labour force in India has been significantly impacted by the COVID-19 pandemic. Millions of migrant workers are now unemployed due to the lockout and following fear of the economic downturn, particularly those who work in unorganised industries without contracts or whose contracts are about to expire. (A. Khanna, 2020) [16]. With many migrant workers returning to their villages as others wait for the lockdown to be lifted, this has caused a serious migratory crisis. In addition to disrupting agricultural output, transportation networks, and supply chains, the pandemic also poses a problem for food security and the management of malnutrition, particularly in children. National migration policies are required so that migrants leaving or returning to places where there are health issues can be helped and protected. In order to lessen food insecurity and the pressure on migrants to return to their countries of origin, it is also necessary to create resilient food systems.

The paper by Partha Chatterjee *et al* (2020) proposed in this paper how to determine the necessary steps and establish a clear strategy for dealing with the virus and the economy. This includes deciding which geographical areas, industries, and firms should be allowed to function first and when. The paper attempts to address these questions and propose a strategy that enables the economy to operate while maintaining adequate social distancing measures. The paper

suggests a three-step approach to identify districts and industries where economic activities can resume gradually with necessary precautions. In the first step, districts are identified based on their current infection rates, and higher and lower cutoffs are determined by the OLS Regression. High-risk areas above the higher cutoff are completely shut down, while medium-risk and low-risk districts are identified based on their infection rates. In the second step, industries are categorized based on the percentage of the workforce that can work from home. Industries with a high WFH score can operate in all districts, while those with lower scores can operate in intermediate-risk districts with minimal on-site employees. In the third step, industries are ranked according to their centrality, and more central industries can resume partial production in medium-risk to low-risk districts, even if their WFH score is low. The decision to open more sectors simultaneously or to adopt a graded response depends on the infection rate of the district.
There is large-scale unemployment across the country, worsened by the major contraction in the GDP of the country. There is a need for government policies that generate employment as well as create demand. Government policies like MNREGA and Skill India can help ease the burden if implemented judiciously. (Ashwini Deshpande, 2020). The paper by Sohini Sengupta (2020) critically analyzes the impact of the COVID-19 pandemic on migrant informal workers in India. The paper aims to investigate how poverty, informality, and inequality are worsened by the pandemic and to evaluate existing social policies that aim to protect this vulnerable group
Post Covid 19, the labour sector faces large-scale unemployment and insecurity. Welfare measures by the government have failed to tackle this rising trend due to many issues. Also, the accountability of employers needs to improve for the workers' voices to be heard. There has been an erosion in social progress made in the country in the past two decades due to the pandemic and its induced lockdowns. The workplace needs to provide greater social security and working conditions for migrant workers to return to the cities after the lockdown was eased. Rural social protection schemes should be applied in towns and cities as well. Farmers require increased trust in the state. The Public Distribution system needs to be more portable.
Due to the pandemic, small businesses and SMEs were impacted as well. The paper by Alfaro *et al* (2020) [4] examines the impact of the COVID-19 pandemic on informal and small businesses in emerging market economies (EMEs). The authors argue that these businesses are particularly vulnerable to the economic shocks caused by the pandemic due to their limited access to formal credit markets, weak institutional support, and lack of financial reserves. The authors showcase that while advanced economies have implemented aggressive fiscal and monetary policy measures to mitigate the impact of the pandemic, EMEs face unique challenges due to their limited policy space, higher debt burdens, and weaker institutional frameworks. The authors then turn their attention to the informal sector in EMEs, which they argue plays a critical role in these economies, providing livelihoods for a large proportion of the population and contributing to economic growth. However, informal firms are often excluded from formal credit markets and lack legal protections, making them particularly vulnerable to economic shocks. They discuss the impact of the pandemic on small businesses in EMEs, which they argue face similar challenges to informal firms due to their limited access to formal credit markets and weak institutional support, and provide evidence from surveys conducted in several EMEs, which show that small businesses have experienced significant revenue and employment declines since the pandemic's onset. The authors highlight the importance of policy responses that recognize informal and small businesses' unique challenges in EMEs. They argue that these businesses play a critical role in these economies and that policy responses should be tailored to support their needs.
The literature gap suggested no studies which first tried to investigate the magnitude of the impact of Covid – 19 across different employment categories across India, secondly which did not apply event analysis to estimate the likelihood of getting a full-time job during the shocks experienced in the economy and thirdly which tried to capture transitions of labour dynamics from 2016-2021 wherein India experienced major crisis – COVID-19.
Therefore, the objective of this paper is to assess the magnitude of the impact of Covid – 19 across different employment categories. Second, to compare the impact of Covid – 19 on Self-Employed v/s Unemployed and finally conducting event analysis for estimation of the likelihood of getting a full-time job during the shocks experienced in the economy

Data and Methodology

The Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy, is our primary data set (CMIE). The CPHS is administered three times each year to a panel of approximately 170,000 Indian families. The same homes are interviewed a second time during the period of May to September, and a third time during the period of October to December. Due to the COVID lockdown in India after the third week of March, the face-to-face interview format was changed to a telephone interview, allowing CMIE to continue data collection. The survey collects data on the demographic characteristics of household members, as well as their sources of income, consumption expenditures, and acquired assets. In addition, it collects data on the employment status of every member of the household, as well as the industry of employment, occupational status, and other job-related information for the working members of the household. The time period of our study is November 2016 to January 2022 covering 16 waves.

Table 1: Data variables and their values

Columns	Values
HH_ID	Primary Key
MEM_ID	Primary Key
MONTH_SLOT	Used to set time
GENDER	0 if male, 1 if female
RELIGION	0 if Hindu, 1 for rest

EDUCATION	0 for lesser than primary
AGE_YRS	0 if less than 35
EMPLOYMENT_STATUS	1 if employed
Type of Employment	1 if Full Time
TIME_SPENT_ON_WORK_FOR_EMPLOYER	time values as given
TIME_SPENT_ON_WORK_AS_UNPAID_TRAINEE	time values as given
TIME_SPENT_ON_WORK_AS_UNPAID_VOLUNTEER	time values as given
TIME_SPENT_ON_TRAVEL	time values as given
TIME_SPENT_ON_LEARNING	time values as given
TIME_SPENT_ON_RELIGIOUS_ACTIVITIES	time values as given
TIME_SPENT_ON_OUTDOOR_SPORTS	time values as given
TIME_SPENT_ON_HANGING_OUT_OR_WITH_FRIENDS	time values as given
TIME_SPENT_ON_INDOOR_ENTERTAINMENT	time values as given
TIME_SPENT_ON_OTHER_ACTIVITIES_FOR_SELF	time values as given
During Covid	1 between Mar 2020 and Jun 2021
Post Covid	1 after Jun 2021
Pre-Covid	1 before Mar 2020.

Methodology

1. Logit Regression

Logistic regression is a statistical technique that is used to model relationships between a categorical outcome variable and one or more categorical or continuous predictor variables. The central mathematical concept that underlies logistic regression is the logit, which is the natural logarithm of an odds ratio.

The odds ratio is derived from two odds, and the natural logarithm of the odds ratio is a logit. In logistic regression, the logit of the outcome variable is predicted from one or more predictor variables. The logistic model predicts the logit of the outcome variable from the predictor variables, and the relationship between the outcome variable and the predictor variables is nonlinear. (Peng *et. al*, 2002) [18] Our study used multinomial logistic regression because the dependent variable, job status, is separated into three categories: full-time, part-time, and unemployment. Our study period is Nov'16 to January'20 and data is quarterly.

The Logistic Regression equation is given below

$$(Y) = ln\ ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \sum \beta_i X_i$$

$$\pi = Probability\ (Y = outcome\ of\ interest \mid X)$$

Where,

Y = Employment Type (Full Time employed, Part Time employed, Unemployed)

X_i = Gender, Religion, Education, Age, Marital Status, status of employment (Un-employed or Regular employment), time use.

2. Event Study Methodology using Difference in Difference approach

An event study design is a phased adoption design in which units may or may not be treated at all. It also employs a difference-in-differences design in which units are either treated for the first time at time or are never treated. (Liyang Sun, 2020) We use a Dichotomous dependent variable over multiple periods across different employment types.

$$Employed_{it} = \alpha\ EmploymentType_i + \sum_t \beta_t\ WAVE_t + \sum_{t,c} \gamma_{t,c} EmploymentType_i \times WAVE_t + \sum_{t,j} \lambda_{jt}\left(X_j \times WAVE_t\right) + \varepsilon_{it}$$

Where, the dependent variable Employed is binary, 1 if employed, 0 if unemployed. The EmploymentType variable represents the type of employment the worker holds, part-time, full-time or self-employed. The $WAVE_t$ variable is the dummy variable that separates the panel based on time. The X_j variable is the time-fixed variable such as gender, education type, religion. The approach of event study analyses the heterogeneous influence of COVID on various employment kinds for each time period. Hence, not only are we able to assess the differential impact of the lockdowns, but we can also determine whether the recovery in subsequent months varies by worker type.

Results and Discussions

Logit Regression Methodology

Logit regression is a type of statistical model used to analyze binary outcome data, where the response variable takes on one of two possible values (e.g., yes/no, success/failure). There are three main types of logit regression models: common effect model, fixed effect model, and random effect model.

Common Effect Model: In this model, the relationship between the binary response variable and the predictor variables is assumed to be the same for all individuals in the sample. This means that the coefficients of the predictor variables are assumed to be constant across all individuals. This model is appropriate when there are no significant differences between individuals in terms of how the predictor variables affect the response variable.

Fixed Effect Model: In this model, the relationship between the binary response variable and the predictor variables is assumed to vary across individuals. This means that the coefficients of the predictor variables are allowed to differ across individuals. This model is appropriate when there are significant differences between individuals in terms of how the predictor variables affect the response variable, and when there are enough observations for each individual to estimate the coefficients accurately.

Random Effect Model: In this model, the relationship between the binary response variable and the predictor variables is assumed to vary across individuals, but the variation is assumed to be random. This means that the coefficients of the predictor variables are assumed to be drawn from a common distribution. This model is appropriate when there are significant differences between individuals in terms of how the predictor variables affect the response variable, but when there are not enough observations for each individual to estimate the coefficients accurately.

In summary, the common effect model assumes a constant relationship between the predictor variables and the response variable across all individuals, while the fixed effect model and random effect model allow for variation in this relationship across individuals. The choice of which model to use depends on the research question and the nature of the data.

To choose between Fixed and Random effect model, the Sargan's statistic is used after fitting the data for Random Effect model. If $p < 0.05$, it means that fixed effect model is a better fit.

The results in table 2 show the Random effect model.

Table 2: Random Effects model is fitted

Regression results					
EmplStat	**Coef.**	**St.Err.**	**t-value**	**p-value**	**Sig**
age_yrs	-0.003	0	-67.14	0	***
educationC	0.022	0	214.36	0	***
genderC	-0.084	0.006	-15.13	0	***
hanging_out_or_wit	-0.007	0	-18.82	0	***
other_activities_f	0.003	0	46.15	0	***
outdoor_sports	0.029	0.001	42.56	0	***
religionC	-0.005	0.001	-4.31	0	***
religious_activiti	-0.012	0.001	-15.57	0	***
time_spent_on_lear~g	0.019	0	83.2	0	***
time_spent_on_travel	0.008	0.001	11.62	0	***
work_as_unpaid_tra	0.003	0.002	1.56	0.119	
work_as_unpaid_vol	-0.043	0.002	-22.42	0	***
work_for_employer	0	0	22.35	0	***
work_for_hh_and_me	0	0	-0.4	0.691	
Ddurcov	0.032	0.001	40.34	0	***
Constant	0.515	0.003	164.66	0	***
Mean dependent var		0.487	SD dependent var		0.907
R-squared		0.01	Number of obs		9259659
F-test		5616.823	Prob > F		0
Akaike crit. (AIC)		18119867.1	Bayesian crit. (BIC)		18120091.76
**** p<.01, ** p<.05, * p<.1*					

The Sargan statistic comes out to be p = 0.0000, which implies that Fixed Effect model is more suitable.

The data is then fitted to the Fixed effects model and Table 03 tabulates the results.

Tabl 3: Fixed Effects Model

EmplStat	**Coef.**	**St.Err.**	**p-value**	**Sig**
age_yrs	-0.023	0.000	0.0000	***
typeC	5.293	0.060	0.0000	***
educationC	0.124	0.001	0.0000	***
genderC	-0.963	0.033	0.0000	***
hanging_out_or_wit	-0.073	0.003	0.0000	***
other_activities_f	0.019	0.000	0.0000	***
outdoor_sports	-0.011	0.005	0.0220	**
religionC	-0.029	0.008	0.0000	***
religious_activiti	-0.091	0.006	0.0000	***
time_spent_on_lear~g	-0.021	0.001	0.0000	***
time_spent_on_travel	1.091	0.005	0.0000	***
work_as_unpaid_tra	-0.188	0.014	0.0000	***
work_as_unpaid_vol	-0.748	0.014	0.0000	***
work_for_employer	0.017	0.000	0.0000	***
work_for_hh_and_me	-0.051	0.001	0.0000	***
Ddurcov	0.007	0.006	0.2670	

In the above table 03, we find that the coefficient corresponding to Age is -0.023. So, the chances of being employed decrease as Age increases. The coefficient corresponding to Education is 0.124. So, the probability of being employed increases as the level of Education increases.

The coefficient corresponding to Gender is -0.963. This implies the chances of females being employed is lower than males.

The coefficient of Time Spent Hanging Out or With Friends comes out to be -0.073, which implies that the odds of being employed decrease as time spent on these activities increases.

The coefficient of Time Spent on Other Activities for Self comes out to be 0.019, which means that the chances of being employed increase as time spent on these activities increases.

The coefficient of Time Spent on Outdoor Sports comes out to be -0.011, which implies that the odds of being employed decrease as time spent on outdoor sports increases.

The coefficient of Religion is -0.029. Therefore, the person from the minority is more probably employed than the person from the majority. The coefficient of Time Spent on Religious Activities comes out to be -0.091, which implies that the odds of being employed decrease as time spent on religious activities increases.

The coefficient of Time Spent on Learning comes out to be -0.021, which means that the chances of being employed decrease as time spent on learning increases.

The coefficient of Time Spent on Travel comes out to be 1.091, which implies that the odds of being employed increase as time spent on travel increases.
The coefficient of Time Spent on Work as an Unpaid Trainee comes out to be -0.188, which means that the chances of being employed decrease as time spent on work as unpaid trainee increases.
The coefficient of Time Spent on Work as an Unpaid Volunteer comes out to be -0.748, which means that the chances of being employed decrease as time spent on work as unpaid volunteer increases.
The coefficient of Time Spent on Work for an Employer comes out to be 0.017, which implies that the odds of being employed increase as time spent on work for employer increases.
The coefficient of Time Spent on self-work and work for the household comes out to be -0.051, which means that the chances of being employed decrease as time spent on these increases.
The coefficient corresponding to COVID is 0.007, which is insignificant.
Since the dummy variable for Covid 19 came out to be insignificant, another analysis is carried out where Employment Status is 1 only if employed. The results are tabulated below in Figure 04.

Table 4: Conditional fixed-effects logistic regression

EmplStat (dependent variable)	Coef.	St. Err.	p-value	Sig
age_yrs	-0.05	0.001	0	***
typeC	5.293	0.06	0	***
educationC	0.063	0.001	0	***
genderC	-0.694	0.053	0	***
hanging_out_or_wit	-0.187	0.005	0	***
other_activities_f	-0.095	0.001	0	***
outdoor_sports	0.101	0.008	0	***
religionC	-0.075	0.013	0	***
religious_activiti	-0.009	0.01	0.371	
time_spent_on_lear~g	0.096	0.002	0	***
time_spent_on_travel	-0.053	0.01	0	***
work_as_unpaid_tra	0.155	0.014	0	***
work_as_unpaid_vol	-0.025	0.017	0.139	
work_for_employer	0.01	0	0	***
work_for_hh_and_me	0.019	0.002	0	***
Ddurcov	-0.469	0.015	0	***
Dprecov	-1.162	0.021	0	***
Mean dependent var	0.591	SD dependent var	1.025	
Pseudo r-squared	0.639	Number of obs	2554772	
Chi-square	1232533.134	Prob > chi2	0	
Akaike crit. (AIC)	695655.068	Bayesian crit. (BIC)	695871.877	
*** *p<.01, ** p<.05, * p<.1*				

Here, the variable for during covid is negative and significant, suggesting the decrease in probability of being employed. It is also interesting to note that the time spent on learning variables is now positively correlated and significant, implying that as time spent on learning increases, the chances of being employed increases.

Event Study Methodology

The below figure 01 shows the coefficient of Employment status.

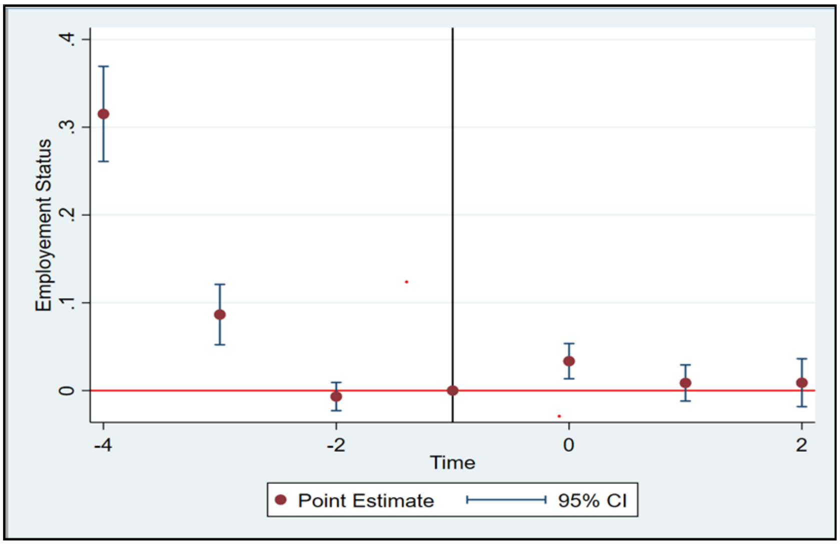

Fig 1: Event Study analysis

Post-Covid, the employment status has fallen which indicates that the probability of getting employed decreased drastically after the pandemic. Post-Covid, the value becomes little positive, indicating that after the lockdown lifted, the employment increased.

The table 05 shows the results of a linear regression model with the treatment variable "during covid" and other variables related to employment, demographics, religion, state, and time.

Table 5: Linear regression model with the treatment variable "during covid"

EmplStat (dependent variable)	Coef.	Std.Err.	P>t
typeC	0.409	0.009	0
educationC	0.007	0.001	0
genderC			
F	-0.109	0.017	0
religionC			
Buddhist	-0.026	0.002	0
Christian	-0.006	0.004	0.096
Khasi	-0.013	0.003	0.001
Muslim	0.01	0.012	0.421
Not Applicable	0.03	0.016	0.082
Other Religion	-0.006	0.01	0.55
Parsi	-0.012	0.011	0.285
Religion not stated	-0.319	0.075	0
Sikh	-0.012	0.008	0.142
stateC			
Assam	0.049	0	0
Bihar	-0.017	0.001	0
Chandigarh	-0.05	0.004	0
Chhattisgarh	-0.006	0.001	0
Delhi	-0.004	0.002	0.102
Goa	0.38	0.003	0
Gujarat	0.029	0.001	0
Haryana	0.042	0.002	0
Himachal Pradesh	0.076	0.001	0
Jammu & Kashmir	0.164	0.006	0
Jharkhand	-0.009	0.001	0
Karnataka	0.061	0.001	0
Kerala	-0.008	0.002	0.001
Madhya Pradesh	-0.01	0.001	0
Maharashtra	0.031	0.001	0
Meghalaya	0.016	0.004	0
Odisha	0.015	0.001	0
Puducherry	-0.004	0.001	0
Punjab	-0.016	0.005	0.003
Rajasthan	0.084	0.001	0
Sikkim	-0.002	0.005	0.611
Tamil Nadu	0.03	0.002	0
Telangana	0.014	0.001	0
Tripura	0.008	0.003	0.005
Uttar Pradesh	0.012	0.002	0
Uttarakhand	-0.05	0.002	0
West Bengal	0.089	0.002	0
lead4	0.316	0.026	0
lead3	0.087	0.017	0
lead2	-0.006	0.008	0.421
lag0	0.034	0.01	0.002
lag1	0.009	0.01	0.392
lag2	0.009	0.014	0.493
_cons	0.122	0.015	0

Linear regression Number of obs = 9,259,659
F(15, 27) = . Prob > F = . R-squared = 0.3300 Root MSE = .5659

(Std. Err. adjusted for 28 clusters in stateC)

The model which includes table 05 and Figure 01, was estimated using 9,259,659 observations, and the standard errors were adjusted for clustering at the state level. The overall model fit is indicated by an R-squared value of 0.33, which means that the model explains 33% of the variation in the dependent variable. The coefficients for the "during covid" variable and other independent variables indicate their effect on the dependent variable, which is not mentioned in the output. The coefficient for "during covid" is 0.409 with a standard error of 0.009, and a p-value of 0, indicating that the variable is statistically significant and positively associated with the dependent variable. Among the demographic variables, being female has a negative association with the dependent variable (-0.109, p<0.001), while the religion variable shows mixed effects with significant coefficients for some religions and non-significant coefficients for others. For example, being Buddhist or Khasi is associated with a negative effect on the dependent variable (p<0.01), while being Muslim or Sikh is associated with non-significant coefficients. The state variable shows a mixed effect on the dependent variable with some states having a positive effect while others have a negative effect. The lead and lag variables represent time and show the effect of the dependent variable over time. In this model, the lead4 variable has a positive effect on the dependent variable (0.316, p<0.001), while the lag0 variable has a positive effect (0.034, p<0.01), and the lag2 variable has a non-significant effect.

Policy Implication

Age discrimination in employment should be discouraged: It is important to address the negative impact of age on employment prospects, as the regression analysis shows that older individuals have a lower chance of being employed. To promote fairness and equal opportunities in the workplace, policies should be put in place to encourage employers to evaluate candidates based on their skills and experience rather than their age. Education should be prioritized: The positive coefficient for education highlights the importance of education in employment. It is crucial to ensure that everyone has equal access to education, particularly for those from disadvantaged backgrounds, in order to improve their chances of employment. Gender-based employment discrimination should be addressed: The negative coefficient for gender indicates that gender-based employment discrimination is a concern, especially in male-dominated industries. To promote gender equality and fair employment practices, policies should be implemented to address and prevent discrimination in the workplace. Time management skills should be encouraged: The negative coefficients for spending excessive time on hanging out with friends, outdoor sports, religious activities, learning, and unpaid work as a trainee or volunteer can reduce employment prospects. It is essential to encourage individuals to develop good time management skills and prioritize their time between various activities to increase their chances of employment. Travel can be encouraged as a means to improve employment prospects: The positive coefficient for time spent on travel suggests that individuals who travel more have a higher probability of being employed. Policies that promote travel for job seekers, such as travel subsidies and job opportunity information in other areas, can improve employment prospects. Policies should be implemented to support unpaid work for employers: The positive coefficient for time spent working for an employer highlights the importance of unpaid work in gaining work experience and improving employment prospects. Policies should be put in place to support unpaid work, such as internships or apprenticeships, to help individuals gain valuable experience. The negative coefficient for time spent on self-work and work for the household suggests that individuals who spend more time on these activities are less likely to be employed. To promote fair and equal employment practices, policies should be put in place to support individuals who engage in these activities, such as providing support for caregivers and creating opportunities for individuals to balance work and household responsibilities.

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