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ARTICLE

Creation and Destruction of Jobs in Urban Labour Market: Role of Gender, Caste and Religion in India

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Abstract
This study analyses labour market transitions from job to jobless or jobless to job by using Periodic Labour Force Survey (PLFS) of India in urban labour market by applying first-order Markov process in constructing transition matrices and panel logit regression model using personal level information from the PLFS in India for 2019–20. While education is assumed to be the most important factor influencing the process of transitions in the labour market, the circumstance variables like gender, caste and religion are expected to have significant effects on it in a country like India. The empirical results show a significant difference in labour market transitions between men and women. The movement of workers between job status was very low and the major part of the transition occurred in the form of job losses for each type of workers both among men and women and also among all working age group and young age group.

Keywords Unemployment · Labour mobility · Panel logit specifications

1 Introduction

Firms create jobs in expanding their activities and destroy jobs in dwindling production activities or adopting new sophisticated technology to continue their production activities. In response to such kind of activities by firms workers either get jobs or move away from job to joblessness. Sometimes, workers move from one job to other jobs in hope of better opportunities. Transitions in the labour market may occur in different form: workers who have jobs in a particular industry or occupation may move to another industry or occupation. Periodic Labour Force Survey (PLFS) data with a panel structure allow measurements of these kind of flows of the labour force. This study analyses labour market transitions from job to jobless or jobless to job by using PLFS of India in urban labour market.

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Estimates of labour market transitions are informative of labour market dynamics and provide insight into current and future changes in the distribution of workers across the economy. Labour market transition is useful to analyse employment challenges the workers have to face in a market based neoliberal economy by locating the major drivers for job transformation and ultimately by forecasting the transitions into unemployment and the transitions out of unemployment (Barnichon & Nekarda 2012; Barnichon & Garda 2016). International Labour Conference (ILC) (2019) calls for *effective measures to support people through the transitions they will face throughout their working lives*. The present study demonstrates how labour force surveys can be used to measure labour market transitions in urban India. Although a notable part of women are out of the labour force, this study is restricted to analyse the pattern of transitions within the labour force and tries to locate the relative role of the major determining factors in explaining transition to job losses and transition to job gains only.

In this study, we apply Markov process in constructing transition matrices and panel logit regression model to estimate the roles of castes and religion on transitions in losing jobs and getting jobs separately for men and women by using personal level information from the PLFS in India for 2019–20. We have constructed 4 quarterly panel for urban areas for 2019–20 which is described in Section 3. In Section 4, we have computed transitional probability of flow of the working age people as well as young age people Section 5 looks at determinants of labour market transition in urban India by using logit link function. Section 6 provides summary findings and conclusions. The empirical results show a significant difference in labour market transitions between men and women.

2 Related Literature

A large number of studies are available in the literature on the dynamics of labour market transitions, but majority of them focussed on developed countries. A little work is available for developing countries primarily because of the lack of appropriate panel data. The early works on this issue were conducted by Hall (1972) and Feldstein (1973) highlighting the role of transitions in understanding unemployment. The cyclical fluctuations in unemployment were analysed by Darby et al. (1985), Hall (2005), Shimer (2012) and many other scholars, but the underlying factors behind the fluctuations are different in different studies. A study by Elsby et al. (2015) focussed on transitions from one job to other by allowing the presence of unemployment for understanding fluctuations in unemployment rate. Nakamura et al. (2020) argue that recessions lead to a composition effect that shifts the pool of unemployed workers towards higher skilled individuals.

In the context of developing countries, labour market transitions are looked into mainly by focussing on transitions between informal and formal employment because of the dominance of the informal sector (ILO 2018, Tanzel & Ozdemir 2019, Gutierrez et al. 2019). A very limited research on labour market transitions in Indian labour markets is available in the literature, perhaps because of lack of appropriate household level panel data. However, by using Indian Human Development

Survey (IHDS) data for 2005 and 2012, Sarkar et al. (2019) examined labour market transitions of Indian women and observed that women have higher rate of transition from employment to unemployment and lower rate of transition to entry into employment compared to men. Later on, Deshpande and Singh (2021) looked into women's labour market transitions by using Consumer Pyramids Households Survey (CPHS) data from 2016 to 2019. Our study is closely related to the work of Menon and Nath (2021), and Bhattacharya (2021) who used PLFS data to estimate urban labour market transitions and gross flows of workers. This study is based on PLFS 2019–20, the latest wave of the survey. We have constructed 4 panels for 4 quarters in 2019–20 to calculate transitional probability on quarterly basis by segregating the labour market into self-employment, regular wage employment, casual wage employment, and unemployment in urban India.

3 Data

The PLFS for 2019–20 is used in this study. It is a quarterly survey started in 2017–18 by replacing the earlier quinquennial employment and unemployment surveys conducted by the National Sample Survey Organisation (NSSO). The PLFS uses stratified, multi-staged random sampling with rotational panel in urban areas. The first-stage units (FSUs) are urban frame survey blocks and the ultimate sampling units are households. In PLFS, the urban stratum is formed on the basis of population size within each NSSO region. Stratum 1 in urban area consists of all towns with population less than 50,000. All towns with population 50,000 or more but less than 3 lakhs form stratum 2, all towns with population 3 lakhs or more but less than 15 lakhs are considered as stratum 3, and each city within the NSSO region with population 15 lakhs or more is treated as a separate stratum. No sub-stratification is done in urban areas. In PLFS, stratification at the second stage (3 in rural and 4 in urban areas) is made on the basis of education level of the members of the household, and 75 per cent of the sample units in the selected block were chosen among the households with at least one member having secondary level education or above.

PLFS is the first official household survey in India with a rotational panel structure in urban areas with a new panel starting every quarter and being visited for four successive quarters. Rotational panel facilitates to use the information contained in earlier occasions for capturing the dynamic behaviour of labour force characteristics over time. The rotational samples are overlapping. The PLFS in India uses *four-in-then-out* rotation design where the household units in a given panel in urban areas are interviewed for four consecutive quarters, and are then dropped from the sample permanently. In this survey each household selected in the sample appears 4 times in 4 consecutive quarters. The household is interviewed first by using the first visit schedule and next three times by using the revisit schedule. The survey schedule is designed for 2 years cycle and the cycle is divided into 8 quarters. Thus, the sampling frame for 2019–20 is different from it used for 2017–18 and 2018–19.

Total annual allocation of FSUs are divided into four equal parts. The first set of sample households (S_{11}) taken from one fourth of the annual allocation of urban

FSUs is considered for visit 1 schedule in the first quarter of the cycle. In the second quarter, the second panel of households (S_{12}) from another one fourth urban FSUs is considered for visit 1 schedule and S_{11} is taken again for the revisit schedule. In the third quarter, visit 1 schedule is used for a new set of households S_{13} taken from another one fourth urban FSUs, and revisit schedule is used for S_{11} and S_{12}. In the fourth quarter, a new panel of households (S_{14}) from the rest one fourth urban FSUs is surveyed by using visit 1 schedule, and households of S_{11}, S_{12} and S_{13} are surveyed with revisit schedule. Therefore, the households in S_{11} are surveyed four times in four consecutive quarters in the first year of the 2 years cycle.

In the fifth quarter (first quarter in the second year), a new sample of households (S_{15}) from one fourth of the annual allocation of urban FSUs for the second year is interviewed with visit 1 schedule, and households from S_{12}, S_{13} and S_{14} are surveyed with revisit schedule. This will continue without any modification of the survey schedules till eight quarter, i.e. for 2 years. In the first quarter of the second 2 years cycle a new sample households (S_{21}) is surveyed by using updated version of visit 1 schedule, and the panels S_{16}, S_{17} and S_{18} are surveyed by using the first cycle's frame of the revisit schedule. In this way, the periodic survey will continue with rotational panel.

PLFS provides quarterly estimates of key labour market indicators in the urban economy on the basis of the Current Weekly Status (CWS) approach. It captures both the supply of and demand for labour. Persons who are employed, unemployed and economically inactive are considered as potential labour supply. Labour demand is created by employers by offering pay against the services provided by the employees. For measuring the dynamic behaviour of labour force in the short interval of a quarter, the approach of CWS is considered appropriate and has been incorporated in the design of the schedule for collection and generation of employment and unemployment indicators.

Attrition and misclassification error are the major problems in using rotational panel survey to find out flows of persons from one state to another state of employment. Job transitions cannot be observed for those who are not matched on consecutive survey waves because of temporary sample drop-outs, incorrect survey responses, or incorrect identifiers. This gives the problem of attrition which creates probability of occurrence of a person in particular state non-random. Misclassification error appears because of respondents' misreport about their status of employment. If a person, for example, was unemployed in one survey wave is incorrectly classified as employed in the next survey wave, even though the person has actually not changed employment status, overestimates the measure of transition probabilities. By using PLFS data, transitions can be calculated between Q1 and Q2, between Q2 and Q3, and between Q3 and Q4 for every year; they cannot be calculated correctly between Q4 of one year and Q1 of the next year if the problem of attrition appears in the data.

4 Transitional Matrix

We have constructed transitional matrix displaying the probability of move from status i in quarter $t-1$ (shown in Tables 1 to 3 rows) to status j in quarter t (shown in Tables 1 to 3 columns) as a percentage of total labour force of status i in quarter $t-1$ by using Markov Chains model. Let X_{t} be the random variable which describes the employment status of a person in the labour market at time t. We assume X_t being discrete taking 4 distinct values for self-employment, regular wage employment, casual wage employment and unemployment. We assume that the data generating process of X_t follows first order discrete Markov process:

$$P\left(X_t = i | X_{t-1}, X_{t-2}, \ldots, X_1\right) = P\left(X_t = i | X_{t-1}\right)$$

where $i=1,\ldots,4$ denotes the of employment in the domain of X_t.

This Markov process implies that once $Xt-1$ is known, the process has no memory of the past. All further past values of the process, indeed, are not relevant for the determination of future conditional probabilities.

The probabilities of moving from state i to state j between time $t-1$ and t are expressed as

$$p_{ij(t)} = P\left(X_t = j | X_{t-1} = i\right)$$

Here $p_{ij(t)}$ are the transition probabilities between i, $j=1,\ldots,4$ different states. We organise the overall set of transition probabilities between labour market states in the form of a 4×4 transition matrix:

$M_{(t)} = \left[p_{ij(t)}\right]$, which is a stochastic matrix with $\sum_{j=1}^{4} p_{ij(t)} = 1 \forall$i, j, t. Therefore, the probabilities in the row must sum to 1.

We have constructed M matrix for men and women by taking working age group as well as young age group (Tables 1, 3). The entry in the i-th row and j-th column is the percentage of labour force in status i who move/ go to status j in the next quarter. Employment status is segregated into 4 mutually exclusive categories, namely self-employed, regular paid worker, casual wage worker and unemployed. Regular salaried workers are mostly associated with the formal sector and self-employed and casual workers are associated more with the informal sector.[1] Transitional probability shown in cell (i, j) is the weighted average over 4 consecutive quarters by using sampling weight and is expressed as a percentage to total labour force in status i. The diagonal cells in the matrix show the percentage of workers who do not change their status of employment in the next quarter and off diagonal cells represent the flow from employment status shown in rows to employment status shown in columns.

Tables 1 and 2 present the transitional matrices for all working age and young age labour force, respectively. First three rows for men and women show transitional probabilities of outflow from the labour market while the last row provides inflow of

[1] Although regular paid workers are in better conditions as compared to casual workers, a notable share of regular paid workers in India labour market are absorbed without enjoying social security benefits in the informal sector or even in the formal sector. For example, sanitary workers may be regular paid but informally employed by the Municipal Corporation.

Table 1 Transitional probability (in per cent) of job shift among working age (15–65 years) labour force: 2019–20

	Self-employed	Regular paid job	Casual employment	Unemployed	Transition rate
Male					
Self-employed	80.8	1.0	0.5	17.7	19.2
Regular paid job	0.6	81.4	0.4	17.7	18.7
Casual employment	1.8	1.3	73.8	23.0	26.2
Unemployed	13.2	13.4	5.6	67.8	32.2
Female					
Self-employed	87.5	0.9	0.3	11.3	12.5
Regular paid job	0.5	80.0	0.2	19.3	20.0
Casual employment	2.1	2.3	76.4	19.2	23.6
Unemployed	4.2	13.0	3.1	79.7	20.3

Source: Author's calculation using PLFS 2019–20 unit level data for urban areas

Table 2 Transitional probability (in per cent) of job shift among young age (15–29 years) labour force: 2019–20

	Self-employed	Regular paid job	Casual employment	Unemployed	Changing state
Male					
Self-employed	80.0	1.5	0.6	17.8	20.0
Regular paid job	0.5	80.4	0.3	18.8	20.0
Casual employment	1.7	1.3	72.1	24.9	27.9
Unemployed	6.1	10.0	4.3	79.5	20.5
Female					
Self-employed	85.9	1.1	0.3	12.8	14.1
Regular paid job	0.4	77.8	0.02	21.8	22.2
Casual employment	2.6	1.7	67.0	28.7	33.0
Unemployed	1.4	7.4	1.0	90.3	9.7

Source: As for Table 1

the labour force who are not in employment. Transition rate was the highest among young women workers who were in casual wage employment. We observe flows between the three employment states of salaried employment, casual employment and self-employment. But, the movement of workers between job status was very low and the major part of the transition occurred in the form of job losses for each type of workers both among men and women, and also among all working age group and young age group. The rate of job loss was higher among workers who were in casual wage employment and it was much higher among young women workers of

Table 3 Transitional probability (in per cent) of job shift among working age labour force during COVID-19

	Self-employed	Regular paid job	Casual employment	Unemployed	Transition rate
Male					
Self-employed	59.0	0.4	0.3	40.3	41.0
Regular paid job	0.7	57.6	0.2	41.4	42.4
Casual employment	1.6	0.6	45.5	52.3	54.5
Unemployed	12.9	14.6	3.1	69.5	30.5
Female					
Self-employed	73.9	0.7	0.0	25.3	26.1
Regular paid job	0.9	55.7	0.1	43.3	44.3
Casual employment	0.6	0.6	52.0	46.8	48.1
Unemployed	4.4	12.3	1.6	81.7	18.3

Row indicates quarter 3 and column indicates quarter 4 of PLFS 2019–20

Source: As for Table 1

this category. Workers in regular paid job also moved to the state of joblessness and the rate of job loss among them was the highest for young age women.

Nearly 1 per cent of self-employed men worker shifted to regular paid job both among men and women in working age labour force, while the rate of transition of this type was little higher among the young people. Less than 1 per cent of workers in regular paid job shifted to self-employment or casual employment and the rate of transition of this type was even less among women and young workers. Movement of the labour force from unemployed to employment of any type occurred and at the highest rate among men who shifted to regular paid job and self-employment at a rate around 13 per cent in each. Higher rate of unemployment for women particularly young women reconfirms low labour force participation rate for women in India as supported by the existing literature. The pattern of inflow into the labour market for women is different from that among men. Unemployed women preferred regular paid jobs to self-employment or casual wage employment. Moreover, the transitional probability for women in regular paid jobs to unemployment was higher than men and the difference is much higher for unemployed youth.

Quarter 4 of the PLFS covers the period of the initial phase of COVID-19 pandemic (April–June 2000). Table 2 provides the transitional matrix covering only quarters 3 and 4 of PLFS 2019–20. Transition from job to no-job state increased substantially during the post-COVID period. Casual wage workers were the most sufferer who lost their jobs and the rate of job loss was more among men workers. Over 50 per cent of men workers who were in casual employment just before pandemic were in no work state earning nothing during the post COVID period. The rate of flow into no work state among women casual workers was little less. In regular paid job, more than 40 per cent workers became jobless and the rate of transition in this phase was more among women workers. The post-COVID period also shows a substantial increase in flows into no work state for those who were in self-employment before starting of the pandemic. Also, a proportion of persons who had no job before the pandemic period got jobs in the post-pandemic phase mainly as self-employed and regular paid worker and the rate of flow in this direction was more among men.

5 Transition to Job Loss and Gain

Binary response model with logit link is used to estimate the conditional probabilities of losing jobs and gaining jobs in a panel data random effect framework:

$$y_{it}^{*} = \beta_0 + \beta_1 \text{education}_{it} + \gamma_1 \exp_{it} + \gamma_2 \exp_{it}^2 + \sum_{j=1}^{3} \delta_j D_j^{H_{it}} + \sum_{k=1}^{3} \theta_k D_k^{C_{it}} + u_{it}$$

$$u_{it} = \mu_i + \varepsilon_{it}$$

Here $i = 1, 2, \ldots\ldots n$, $t = 1, 2, 3, 4$

μ_i are iid $N \sim \left(0, \sigma_\mu^2\right)$

ε_{it} are i.i.d. logistic distributed with mean zero and variance $\sigma_\varepsilon^2 = \frac{\pi^2}{3}$, independently of μ_i Random effect model may be better fitted in our dataset because we have micro panel with very large number of cross section unit over 4 time points (quarters) in 2019–20. The choice of random effect model is confirmed by Hausman test.

In our models, the outcome variables are dummy variables for losing jobs and gaining jobs and obtained by using the following rule:

$$y_{it}^{JL} = \begin{matrix} 1, & \text{If a person is unemployed in the next quarter, but employed in the present quarter} \\ 0 & \text{elsewhere.} \end{matrix}$$

$$y_{it}^{JG} = \begin{matrix} 1, & \text{If a person employed in the next quarter who is unemployed in the present quarter} \\ 0 & \text{elsewhere.} \end{matrix}$$

Thus, $y_{it}^{JL} = 1$ and $y_{it}^{JG} = 1$ represent transition from employment to unemployment and transition from unemployment to employment, and their value equals zero indicates no transition. As the main focus of this study is to analyse job gains or job losses, transitions between employment status are not considered in empirical model. Explanatory variables are year of schooling representing level of education, work experience and its square value, dummies capturing different types of households, and dummies covering different castes. By taking self-employed households as a reference group, 3 dummies for regular paid workers' households, casual workers' households and other households are used to find out the differential effects on job losses or gains among different types of employment. To estimate caste differentiation in the transitional process, 3 dummies for scheduled castes, other backward castes and upper castes are used by taking scheduled tribes as the reference group.

We have estimated conditional probabilities of losing jobs and gaining jobs separately for men and women.

We estimate the model by applying method of maximum likelihood in panel data framework to get the possible impact of the covariates on conditional probability of losing or gaining jobs during over 4 quarters 2019–20 separately for men and women workers:

$$P\left(y_{it}^{JL} \neq 0 | X_{it}\right) = P\left(X_{it}\beta + \mu_i\right)$$

The estimated marginal effects by using the full sample will be helpful to understand the relative role of the covariates used in Eq. (1) in explaining the transitions in the form of job losses and job gains during this period. To estimate the model, full sample data are used to get more robust result of panel data random effect model.

Table 4 gives the estimated coefficients of the explanatory factors shown in Eq. (1) in explaining conditional probabilities of losing and gaining jobs for male and female working age people who are in labour market. The figures in parentheses represent standard errors. As the level of education increases, the probability of job loss as well as job gain decreases for male workers. But, for female with higher level of education the probability of transitioning to job loss is more as compared to male workers. Although a considerable part of females are out of the labour force, this study is restricted to capture the transitioning among the working people only. Among male working age people, those in employment are less likely to lose their jobs and those out of employment are less likely to move into employment primarily because of the lack of jobs matching with their education level. Female workers are more vulnerable in terms of their job conditions. This result implies that although higher education level enhances job security for male workers, it fails to improve job security for female workers. Higher the age, higher is the probability of losing jobs both for male and female, but at a diminishing rate. The rate of response of probability of job loss for women is more than that for men. However, there is no significant relationship between the conditional probability of getting new jobs and age both for men and women.

Being a family member of regular salaried household the probability of job loss is less for men and is more for women as compared to the reference household type self-employed. The chance of getting new jobs among male working age members of this household type is also less. This is presumably because majority of the regular salaried households are well-off and well-endowed than self-employed households in India and members of such households seek good quality decent jobs. Also, as the marginal utility of entering into job market among female members of these households is less, they can refuse to continue if the job conditions are not good. Households characterised by casual employment are normally worse-off than self-employed households, and family members of these households are more eager to get jobs at any conditions. As the majority of workers, particularly women, of these households are more vulnerable, the probability of out of employment among

Table 4 Determinants of labour market transition: Logit estimates

	Model 1: Job loss for male	Model 2: Job loss for female	Model 3: Job gain for male	Model 4: Job gain for female
Year of schooling	– 0.01**	0.02***	– 0.003	0.02**
	(0.00)	(0.01)	(0.01)	(0.01)
Age	0.03***	0.03**	– 0.01	0.05
	(0.01)	(0.01)	(0.01)	(0.03)
Age^2	– 0.00***	– 0.00**	0.00	– 0.005
	(0.00)	(0.00)	(0.00)	(0.00)
Household type				
Regular wage	– 0.05	0.34***	– 0.12*	0.19
	(0.03)	(0.07)	(0.07)	(0.16)
Casual labour	0.07	0.17*	0.05	0.26
	(0.05)	(0.11)	(0.09)	(0.22)
Others	– 0.55***	– 0.34	– 0.04	– 0.15
	(0.11)	(0.23)	(0.19)	(0.47)
Castes				
Scheduled castes	0.36***	0.28*	0.90***	0.55
	(0.08)	(0.15)	(0.20)	(0.36)
Other backward casts	0.25***	0.36***	0.61***	0.35
	(0.08)	(0.14)	(0.19)	(0.34)
Upper castes	0.27***	0.38***	0.61***	0.37
	(0.08)	(0.14)	(0.19)	(0.35)
Religion				
Muslim	0.16**	– 0.17	0.35**	1.08**
	(0.08)	(0.17)	(0.15)	(0.45)
Hindu	– 0.04	– 0.11	– 0.21	0.56
	(0.07)	(0.14)	(0.14)	(0.42)
Christian	– 0.30***	– 0.29*	– 0.3	0.16
	(0.11)	(0.19)	(0.23)	(0.53)
Constant	– 2.78***	– 3.78***	– 4.08***	– 6.43***
	(0.17)	(0.36)	(0.35)	(0.86)
$ln\sigma_{\mu}^{2}$	– 14.13	– 22.3	– 10.5	– 11.3
σ_{μ}	0.00	0.00	0.005	0.003
ρ	0.00	0.00	0.00	0.00

$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

Source: As for Table 1

them is more as compared to family members with similar characteristics of self-employed households.

To find out the differential effects on conditional probability of labour market transition to get job or to be jobless among different castes, scheduled tribe is taken as the reference social group. Significant difference is observed between different castes in the occurrence of labour market transitions in comparison with scheduled tribes people. The estimated coefficients of the dummies representing scheduled castes, other backward castes and upper castes are positive and significant at less than 1 per cent level, implying that the conditional probability of both job loss and job gain is higher among people of these social groups comparing with those in scheduled tribes households. These results do not necessarily imply that the working age people of scheduled tribes families are much better of than those in other castes. People of scheduled tribes families who are in employment are very less in number, but they enjoy more job securities than the workers from upper castes and even scheduled castes because of the reservation policy of the government of India. Perhaps, for this reason the probability of job loss among scheduled tribes workers is much less than other workers. Economic conditions of most of the scheduled tribes households is very miserable and more volatile than other people. These people are less endowed to get a job despite the affirmative policies of the government, and for this reason the non-tribal who are not in employment have more chance to move into employment.

Transitioning of job loss among Muslims was more and it was less among Christian working age labour force as compared to other religions in probabilistic sense. But, religious factor in labour market transition has no significant effect among Hindus.

The lower panel of Table 4 provides panel level variance components. σ_μ is the measure of cross section heterogeneity in the data, ρ is the proportion of the total variance contributed by the panel-level variance component When ρ is zero, the panel-level variance component has no importance, and the panel estimator is no different from the pooled estimator. A likelihood-ratio test of this is included at the bottom of the output. This test formally compares the pooled estimator (logit) with the panel estimator.

6 Conclusions

This study analyses the nature of labour market transitions through which workers move from job to jobless or one job to other jobs in urban India by using rotational panel data constructed from PLFS 2019–20. PLFS is the first official household survey in India with a rotational panel structure in urban areas with a new panel starting every quarter and being visited for four successive quarters. It provides quarterly estimates of key labour market indicators in the urban economy on the basis of the CWS approach. Our analysis is restricted for working age people with two age cohorts 15–29 years and 30–65 years in the urban sector. Labour market transition is measured by the movements into and out of employment. The explanatory factors include person and household specific characteristics. The binary response model is used to find out how productivity related factors like education and other factors which are beyond individual's control like gender, caste and religion influence labour market transitions in urban areas.

In this study, we explore transitions in urban labour market in India at the personal level separately for men and women by using rotational panel data from PLFS 2019–20. The study observes flows between the three employment states of salaried employment, casual employment and self-employment. But, the movement of workers between job status was very low and the major part of the transition occurred in the form of job losses for each type of workers both among men and women, and also among all working age group and young age group. The rate of job loss was higher among workers who were in casual wage employment and it was much higher among young women workers of this category. Workers in regular paid job also moved to the state of joblessness and the rate of job loss among them was the highest for young age women. Transition from job to no-job state increased substantially during the post-COVID period. Casual wage workers were the most sufferer who lost their jobs and the rate of job loss was more among men workers.

As the level of education increases, the probability of job loss as well as job gain decreases for male workers. But, for female with higher level of education the probability of transitioning is more. Female workers are more vulnerable in terms of their job conditions. Being a family member of regular salaried household, the probability of job loss is less for men and is more for women as compared to the reference household type self-employed. Households characterised by casual employment are normally worse-off than self-employed households, and family members of these households are more eager to get jobs at any conditions. Significant difference is observed between different castes in the occurrence of labour market transitions. Transitioning of job loss among Muslims was more and it was less among Christian working age labour force as compared to other religions in probabilistic sense.

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Declarations

Conflict of interest There is no conflict of interest in this article

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