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Where Do They Come From, Where Do They Go? Labour Market Transitions in India

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WHERE DO THEY COME FROM, WHERE DO THEY GO? LABOUR MARKET TRANSITIONS IN URBAN INDIA

ABSTRACT: Using two rounds of the Periodic Labour Force Survey (PLFS) covering the periods 2017-18 and 2018-19, we construct a panel of urban Indian individuals aged 15 to 65, and analyse the dynamics of their participation – or non-participation – in the labour force. We construct transition probabilities to study the movement of individuals through three distinct statuses - employment, unemployment and non-participation – at the aggregate level and for different demographic groups. We find evidence of considerable movements from the labour force to non-participation; there exists a significant discouraged worker effect as well as a pronounced movement from employment outside the labour force, specifically for women. A majority of those unemployed in the beginning of the year remain so at the end of the year, indicating the presence of long-term unemployment. The reduction in unemployment rates from 2017-18 to 2018-19 hides significant weaknesses in Indian urban labour markets. This study represents an original contribution to the field of Indian labour economics, given the paucity of large-scale studies of the dynamics of Indian labour.

Keywords: Labour Market Transitions, Employment, Unemployment, India, PLFS

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1. INTRODUCTION

The release of the Periodic Labour Force Survey (PLFS) in 2017-18 revealed a disquieting truth about the Indian economy; the unemployment rate had jumped to 6.1% from 2.2% in 2011-12, the highest unemployment rate ever recorded in independent India since employment statistics began to be recorded. This finding was a source of sustained academic and political debate, coming so close to a national election.

The design of the PLFS lent itself to sustained debate. The construction of the sample differed from earlier rounds of the NSSO; highlighting this, certain writers contested the narrative of rising unemployment on the grounds that the results of the PLFS were not comparable with earlier NSSO surveys (Bhalla, 2019), while others held that the population figures derived from the PLFS were comparable with earlier surveys (Ramakumar, 2019).

Regardless of the controversy, the construction of the PLFS heralded a methodological innovation that allows the Indian researcher to conduct a deeper study of dynamic questions with respect to Indian labour markets. Simply put, the PLFS follows a sample of individuals over four successive quarters, allowing the researcher to build up a panel that tracks individuals over the course of a year. These panels have only been constructed for urban markets however, and thus fail to capture the dynamics of rural labour markets. Nonetheless, in allowing the researcher to, for the first time, study the transitions of individuals between different employment statuses in the Indian labour market, the PLFS represents an important step forward in developing a deeper understanding of the dynamics of labour in urban India.

Earlier rounds of the NSSO – up until the 68th – surveyed an individual at a single point in time, and hence remained unsuited to the task of studying deeper questions with regard to dynamism and transitions in labour markets. Breman's (2012) work on "footloose labour" studied the circulation of labourers amongst the informal sectors of the economy through fieldwork and an anthropological look at the lives of migrant labour; large-scale statistical studies remained missing. The study of labour market transitions has an extensive history for the developed economies, and allows not only for a deeper understanding of labour dynamics and the characterization of unemployment (Clark and Summers, 1979; Elsby, Hobijn and

Sahin, 2013, Elsby, Smith and Wadsworth, 2011, for example) but also allows for the construction and evaluation of important policy proposals[2].

This paper constructs a panel of urban individuals aged 15 to 65 to characterize, measure and estimate various aspects of flows of individuals between three states of the labour market, that of being employed, unemployed or out of the labour force altogether. We calculate transition probabilities that measure the probability of an individual transitioning from one state to the other, and hence estimate the relative importance of dynamic flows of labour. Moreover, we compare flows between 2017-18 and 2018-19 to see how labour markets have changed. We further estimate logistic regressions to examine the impact of demographic characteristics on the possibility of transition; using these logistic regressions, we construct conditional transition matrices across gender and education, and compare it with aggregate matrices. We then disaggregate transition probabilities across age and gender to examine whether transition probabilities change for different age groups for both men and women.

Our most important finding, beyond the calculation of transition probabilities, is the presence of a significant discouraged worker effect operating across both years, though its effect reduces in 2018-19 as compared to 2017-18. The flows from *unemployment* to *out of the labour force* are almost as significant as the flows from *unemployment* into *employment.* Movements out of the labour force are much higher for women relative to men, from both unemployment as well as employment, across the age distribution. Moreover, we find a worrying tendency towards long-term unemployment, with a majority of those unemployed in the beginning of the year find themselves unemployed three quarters later. The unemployment rate might have reduced from 2017-18 to 2018-19, but the reduction in the headline rate conceals significant weaknesses in the Indian urban labour market.

Section 2 introduces the theory behind the study of labour market transitions, while section 3 describes the dataset used. Section 4 and 5 examine both aggregate and conditional transition matrices respectively, while Section 6 examines transition probabilities along the age distribution. Section 7 concludes.

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[2] For example, Atkinson and Micklewright (1991) and Bradbury (2014) use labour market transitions to study the effects of unemployment compensation and insurance, Scopetta (2019) looks at the importance of policy to ease transitions in the context of automation and the digital economy, Bergin, Kelly and McGuinness (2015) look at the need for youth education and programs such as the Youth Guarantee in the context of youth unemployment in Ireland, while Fabrizi and Mussida (2009) examine the impact of labour market regulations in Italy in the nineties on the transition possibilities for the young and for women. This is by far not a comprehensive list, but is only chosen to show the breadth of questions addressed.

2. THE STUDY OF LABOUR MARKET TRANSITIONS

Assume that an individual may exist in any one of three states in the labour market: either employed (E), unemployed - i.e. seeking and/or available for work- (U), or being out of the labour force entirely (O) – also termed non-participation. An individual might transition from one of these states - in an initial period t - to any other of the three possible states in the subsequent period t+1. Therefore, between any two periods, there are a total of nine possible transitions occurring.

The transition probability may be calculated as follows: Assume an individual is in state $A_t$at time t and transitions to state B_{t+1}in the subsequent period. The transition probability p(AB) is measured by dividing the number of people who have made the transition between periods t and (t+1) by the total number of people in state A_t. It indicates the percentage of individuals who have made the transition from state A to state B between the two periods. With 9 such transitions possible, 9 transition probabilities can be calculated (Theeuwes, 1986).

$$p(AB) = \frac{A_t B_{t+1}}{A_t} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Transition matrices - which present the 9 possible transition probabilities - are estimated for 2017-18 and 2018-19, covering the transitions made between the first quarter of the year and the last quarter of that year, for all individuals aged 15 to 65. Their employment status is determined according to their Current Weekly Status (CWS), which determines their status based on their activities over the seven days prior to the date on which the survey was conducted. Individuals classified as unemployed correspond to status 81 and 82 of the CWS, while those classified as being out of the labour force correspond to statuses 91 and above[3]). Individuals classified as being employed correspond to statuses 11 to 72, covering the self-employed, casual workers and regular wage workers. We make no disaggregation – with regard to the present study - with regard to what kind of employment the individual is in and do not make a differentiation on formal, informal or precarious forms of work[4].

[3] As per the National Sample Survey, individuals having an activity status code from 11-72 are considered part of the workforce. This includes self-employed (11,12,21,61,62), regular wage (31,71 and 72) and casual wage (41, 42, 51) workers. Status code 81 corresponds to those who were looking for work but were unable to get work. 82 includes those who were available for work but could not get work.

[4] As mentioned below, Raj et.al (2020) and Kesar (2020) look at transitions into and out of informality in the Indian sector, while Bosch and Maloney (2010) examine such transitions in the Latin American context. Martinez-Granado (2002) finds that deteriorating economic conditions can push individuals into self-

There has been work done on the question of labour market transitions in the Indian context utilizing two rounds of the Indian Human Development Survey, carried out in 2004-05 and 2011-12. Kesar (2020) studied informality in the context of the Indian economy, examining transitions between informal and formal sources of work for households; Raj et al (2020) looked at the ability of individuals to transition from informal to formal jobs. Both studies found a limited ability to transition to more formal forms of work. Neog and Sahoo (2020) use the IHDS and the methodology of labour market transitions to examine patterns and correlates of intergenerational occupational mobility. Sarkar et al (2017) examined the question of women's transitions, examining the factors driving women to withdraw from labour markets. They find a greater probability of withdrawing from the labour force as household incomes increase; this represents a valuable addition to the already burgeoning literature on women's labour force withdrawals. While Sarkar el al's study is specifically on women, Kesar, Raj et al and Neog and Sahoo look at the circulation between different forms of work, and do not consider unemployment as a separate category.

The methodology we follow differs from the literature in certain respects. For one, we estimate transitions between the first and fourth quarters of two years; this differs from much of the literature that utilizes the Current Population Survey (CPS) in the US, which estimates short-term transitions, either month-to-month or quarter-to-quarter. A person who has been identified as transitioning from unemployment to employment across the first and fourth quarter might make a number of different transitions within the year. As Gomes (2015) shows, the estimation of transition probabilities differs according to the period chosen. In spite of these difficulties, we justify our selection of calculating year-long transitions to give an overall characterization of some of the important aspects of dynamics in the Indian urban labour market, aspects which can form the foundation for further work going forward. We benchmark our results to those derived from similar long-term studies for a set of developed economies – the Nordic countries as estimated by Ward-Warmedinger and Macchiarelli (2014) – and a developing economy such as South Africa, as estimated by Essers (2016).

Secondly, our conditional transition matrices are the probabilities of transitions conditional on certain demographic characteristics. This differs from work that attempts an estimation of transition probabilities conditional on the labour market status in a previous month (Gomes, 2012, Krueger, Cramer and Cho, 2014, Kudlyak and Lange, 2018, Hall and Kudlyak, 2020).

employment. There exists, moreover, a vast literature on the nature of transitions between stable and unstable forms of employment; these aspects are not covered here.

We present matrices for both overall transitions, as well as disaggregated matrices according to gender and education status for both years. These are highly aggregative matrices, and do not fully allow us to understand the impact of demographic characteristics on the possibility of transitions. We then estimate conditional transition matrices, which are predicted probabilities of transitions estimated from logistic regressions of demographic characteristics on recorded transitions[5]. The logistic regressions take the following form:

$$\log[\mathrm{Tr}(AB)] = \beta_0 + \sum_{i=1}^{n} \beta_i . X_i + u_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

where log[Tr(AB)] is the log of the odds of transitioning from state A to B. The individual is coded 1 if she makes the transition, and 0 otherwise. The demographic characteristics chosen are age, gender, caste - with the Others category as the base, and ST, SC and OBC as the relevant categories - and education - workers without schooling form the base, and the relevant categories are workers with some schooling and those with graduate degrees and higher.

We draw the variables for our logistic regressions from a large literature that foregrounds the importance of certain demographic variables in explaining labour market transitions. Taking cues from a significant literature on youth unemployment and the impact of age on labour market transitions in the European context (Russell and O'Connell, 2001, Kelly et al, 2014, Sanderson, 2019, Kirchner Sala et al, 2015), we include age in our regressions to test whether younger workers face a greater possibility of enduring unemployment as compared to older workers. Nilsson (2018) looks at a voluminous literature on employment and unemployment transitions in developing economies, outlining the impact of education on labour market transitions; we thus test for three different educational achievements and its influence on worker flows. We include variables outlining caste of individuals to test whether social discrimination influences possibilities of transition, given the results of Couch and Fairlie (2010) and Couch et al (2018) that look at the impact of race on transition in the labour market.

A total of 9 logistic regressions are run, one for each relevant transition. The sample consists only of those individuals who are in state A in the initial time period (first quarter of the year). Odds ratios of each logistic regression for each year are presented. Predicted probabilities for gender and education are then calculated, and the relevant conditional transition matrices are presented, along with confidence intervals of each estimate. Moreover, we present graphical estimations of transition probabilities disaggregated by age and gender.

[5] In essence, these are the marginal effects for each transition for each covariate, evaluated at sample values.

3. DATA AND CONSTRUCTION OF THE PANEL

In the rotational panel scheme for the PLFS, every selected urban household is visited four times during the course of the survey. The first visit is conducted with the first visit questionnaire and the other three interviews are carried out with the revisit questionnaire. The rotational sample is for two years i.e. the sampling frame remains unchanged during this two year period.

To explain the urban rotational panel, let us assume that 100 households need to be surveyed in the first year of the two-year period. In the first quarter (July-September), 25% of the selected sample (25 households) will be surveyed. Let us call this set A. In the second quarter (October-December) another 25 households are visited for the first time. We call this set B. However, alongside them, the set which was interviewed in the earlier quarter, A is visited once more**.** Therefore, we have in the second quarter, (A + B) households being visited. In the third quarter (January-March), we have a new set, C, of 25 households being visited for the first time. Alongside them, set A is re-visited for a second time while set B is revisited for the first time. In the fourth quarter of the year (April-June), the remaining 25 households (D) are visited for the first time while A are visited for the fourth time, B for the third time and C have their first re visit. Thus, for a given year (July to June), set A is surveyed four times. In the fifth quarter (July-September of year 2, i.e. the first quarter of 2018-19), set A is entirely replaced by a new set called E and this process continues for the next three quarters – the second, third and fourth quarters of 2018-19 are labelled as Q5, Q6 and Q8. B, C and D sets are revisited in the second year. At the end of eight quarters, the sampling frame is updated.

Table 1: Revisits in the urban rotational panel, PLFS

Quarters	*1st Visit*	*2nd Visit (1st revisit)*	*3rd Visit (2nd revisit)*	*4th Visit (3rd revisit)*
First Quarter	A	.	.	.
Second Quarter	B	A	.	.
Third Quarter	C	B	A	.
Fourth Quarter	D	C	B	A
Fifth Quarter	E	D	C	B

Ideally, from the above, the PLFS dataset should allow us to create not only a panel of set of individuals interviewed for the first time in quarter 1 of 2017-18 (analogous to set A in the example given above) but also those individuals who are interviewed for the first time in quarters 2,3, and 4. Similarly for 2018-19, the panels should be created not only for those interviewed for the first time in the fifth quarter (1st quarter of the new set) but also those interviewed for the first time in quarters 6, 7 and 8. However, we found that the labeling schema of the first stage units (FSUs) provided for the 2017-18 dataset is completely different from that provided in the dataset for 2018-19. FSU ids help us to identify individuals and households across the different periods and without matching FSU numbers there is no way to match those individuals surveyed in 2017-18 with those surveyed in 2018-19. As such, it does not seem possible to construct any panel that covers any period overlapping the two years. We are left with constructing just two panels consisting of the set of individuals surveyed for the first time in quarters 1 and 5 respectively, given that their FSUs by extension their unique ids remain unchanged during the course of the year.

To construct our panel, we first merged the individual and household files of the first visit and revisit datasets to arrive at a consolidated first visit and a consolidated revisit file. We then removed the rural cases from the first visit file to create an all-urban sample. From the first visit file, we only took those cases interviewed in quarter 1 i.e. Q1V1[6]. From the revisit files, we filtered for Q2V2, Q3V3 and Q4V4[7] –i.e. the current weekly responses of the Q1V1 group for each subsequent revisit. The same exercise was carried out for the 2018-19 dataset. We merged these four different datasets and removed any individual whose unique id was not recorded for all four quarters. From the same we removed those not in the working population (15-65 years) to arrive at two panels, henceforth called the 2017-18 and 2018-19 panels. Both the panels consist of around 32000 individuals with women forming close to half of our respondents. Table 2 provides the detailed panel description.

[6] Q5V1 in case of the 2018-19 dataset.

[7]Q6V2, Q7V3 and Q8V4 respectively in case of the 2018-19 dataset

Table 2 Panel Statistics

	2017-18	2018-19
N	31846	31817
Sex (Female %)	49.9	49.6
Social Group (%)		
Scheduled tribe	8.5	8.3
Scheduled caste	14.2	13.5
OBC	37.3	39.0
Others	40.0	39.2
Religion		
Hindu	71.7	73.5
Islam	17.1	15.9
Christianity	7.5	6.7
Others	3.8	3.9
Average age (in years)	35.7	36.0
Educational profile (%)		
Not literate	12.3	11.2
Literate up to primary	12.3	12.3
Middle	21.4	20.6
Up to higher secondary	33.2	33.4
Graduation and above	20.8	22.6
Household type (%)		
Self employed	38.5	38.0
Regular wage	41.9	44.1
Casual labour	12.1	10.4
Others	7.5	7.5

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

4. TRANSITION MATRICES 2017-18 TO 2018-19

Table 3 presents the transition matrices for all individuals aged 15 to 65 in the Indian urban labour market, for 2017-18 and 2018-19. Q1 to Q4 outlines the transitions between the first and last quarters of 2017-18, while Q5 to Q8 outlines the period between the first and last quarter of 2018-19. Each cell represents the transition probability - as outlined in equation 1 – from employment (E), unemployment (U) or non-participation (O) in the initial quarter to any one of these three possible states in the final quarter of that year. Each row sums up to 100, as it takes account of all individuals who were in that particular state in the first quarter.

Table 3: Transition matrix: 2017-18 to 2018-19

	Q4		
Q1	*E*	*U*	*O*
E	91.7	3.1	5.2
U	22.2	58.1	19.7
O	3.2	2.1	94.7

	Q8		
Q5	*E*	*U*	*O*
E	93.0	2.2	4.8
U	24.3	58.2	17.5
O	2.9	1.4	95.8

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

Table 4: Transition Probabilities, Nordic Countries and South Africa

	Nordic Countries (2004-08)		
	E	*U*	*O*
E	91.3	2.6	6.2
U	39.7	43.7	18.3
O	16.0	5.0	79.1

	South Africa (2008-11)		
	E	*U*	*O*
E	71.6	9.9	18.5
U	31.0	28.5	40.5
O	22.1	21.1	56.8

Note: Data from the Nordic countries is from Ward-Warmedinger and Macchiarelli (2014), while that of South Africa is from Essers (2016)

We benchmark these results to that of the Nordic Countries – the Netherlands, Finland, Denmark and Sweden - and South Africa, as shown in Table 4. The figures for Sweden show the *average* yearly transition probabilities over the period 2004-2008 for individuals aged 16 to 64, while the figures for South Africa outline transitions for individuals aged 20 to 55 between the period 2008 and 2010/11[8]. Though direct comparisons cannot be drawn easily owing to the significant differences in these economies, we include these comparisons to contextualise the experience of the Indian economy.

On comparing Tables 3 and 4, we see that the Indian economy is far less dynamic than the other economies chosen; the movement from non-participation into the labour market as well from unemployment into employment are much higher for both South Africa and the Nordic countries. Movements from unemployment to non-participation is on par with that of the Nordic countries, though far lesser than that of South Africa. The share of the unemployed who remain in unemployment is much higher than either example, because outflows – either to unemployment or to non-participation – are lesser in comparison.

Table 3 indicates that Indian urban labour markets did see some improvements in 2018-19 as compared to 2017-18, with regard to employment. The flow of those employed in the first quarter into unemployment by the fourth quarter reduced from 3.1% to 2.2% over the years, while flows from employment out of the labour force reduced from 5.2% to 4.8%. More workers remained in employment in 2018-19 as compared to 2017-18.

The study of transitions from unemployment reveals important findings. For one, in both years, 58% of those unemployed in the first quarter are unemployed in the fourth quarter as well, indicating a serious problem of long-term unemployment. Of the remaining individuals who do transition out of unemployment, only 22.2% in 2017-18 - and 24.3% in 2018-19 - manage to move from unemployment into employment, while the remaining move out of the labour force altogether. In 2017-18, nearly 19.7% of those unemployed in the beginning of the year drop out of job search by the end of that year, a figure that reduces to roughly 18% in 2018-19. This speaks of a significant discouraged worker effect, where individuals, frustrated by long periods of unsuccessful job search, decide to cease searching for employment altogether. This effect has, no doubt, reduced in 2018-19, but still remains substantial.

Movements into the labour force are extremely low. Around 95% of these individuals outside the labour force remain so by the end of the year; the flows from non-participation into either employment or unemployment are extremely low. This speaks of another important characteristic of the Indian labour market; much of the flows between the labour force and

[8] Essers (2016) disaggregates the transition matrix for the unemployed in South Africa into “searching” and “discouraged”, the former defined as those who actively sought employment for a period of four weeks prior to the survey, while the latter are those that were willing to work but did not actively engage in search. We have aggregated these figures into the overall category of the “Unemployed” for ease of comparison.

those outside it flow from the former to the latter, rather than the other way around[9]. This can be seen in the relatively larger transition probabilities of flows from employment and unemployment to non-participation, relative to flows in the opposite direction[10].

Tables 5 to 9 present transition matrices disaggregated by gender and education, which reveal significant differences in worker flows that cannot be discerned in the aggregate matrix. Women experience higher flows out of the labour force as compared to men. More than 30% of unemployed women and around 16% to 18% of employed women leave the labour force by the end of the year; the comparative figures for men are 10%-13% for unemployment and around 2% for the employed. Men too, experience a significant discouraged worker effect, yet it pales in comparison to that of women; in both years, almost a third of unemployed women drop out of the labour force completely. Though long-term unemployment is larger for men, men do experience higher rates of flows from unemployment to employment. This paints a distressing picture for women; not only do they face a lower possibility of moving from unemployment to employment, a significant portion of them move out of the labour force entirely, regardless of whether they are employed or unemployed.

Table A1 (Appendix) outlines transition probabilities for men and women for the Nordic countries and South Africa, and may be used to compare with the results shown here. Indian men show significantly higher rates of being stuck in unemployment, primarily because movement from unemployment to employment is lower. The discouraged worker effect for Indian women is much larger than that of the Nordic countries, but lesser than that of South Africa. The movement from unemployment to employment for Indian women in both years is much lesser than both the Nordic countries and South Africa.

With regard to changes in worker flows over these years, the case of unemployment reveals interesting outcomes. For males, the flows from unemployment to employment have increased,

[9] The share of those employed in the first quarter of 2017-18 was 43%, the share of the unemployed was 5% and the share of those outside the labour force was 52%. Corresponding shares for 2018-19 were again 43%, 5% and 52% respectively.

[10] Care must be taken in the interpretation of these statistics. Relative to the total number of the employed, a larger proportion of those entering employment come from outside the labour force than from unemployment. In 2017-18, 60% of those who flowed into employment came from outside the labour force, with only 40% coming from the unemployed; these figures fell to 56% and 44% in 2018-19 respectively. Yet if one were to estimate these flows relative to their initial status, flows into employment from unemployment assume a much larger significance than those from outside the labour force. This difficulty in ranking the importance of flows arises, perhaps, because of low labour force participation rates and large proportion of the population outside the labour force in the Indian economy.

indicating better employment prospects. Moreover, the flows from unemployment out of the labour force have reduced, indicating a reduction of the discouraged worker effect. And yet the share of those stuck in long-term unemployment has increased, albeit marginally. This does not necessarily imply a paradoxical outcome; it may be the case that on seeing an improvement in employment outcomes, a larger proportion of the unemployed are convinced about staying on and searching for future employment.

Table 5: Transition Matrix, Males: 2017-18 to 2018-19

	Q4		
Q1	*E*	*U*	*O*
E	94.6	3.3	2.1
U	27.6	59.1	13.3
O	5.6	4.4	90

	Q8		
Q5	*E*	*U*	*O*
E	95.7	2.3	2.0
U	29.1	60.2	10.7
O	4.7	2.7	92.6

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

Table 6: Transition Matrix, Females: 2017-18 to 2018-19

	Q4		
Q1	*E*	*U*	*O*
E	79.5	2.5	18.1
U	8.4	55.6	36.0
O	2.6	1.4	96.1

	Q8		
Q5	*E*	*U*	*O*
E	82.3	1.5	16.2
U	13	53.5	33.5
O	2.3	0.9	96.7

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

Table 7: Transition Matrix, No Schooling: 2017-18 to 2018-19

	Q4		
Q1	*E*	*U*	*O*
E	85.7	3.7	10.7
U	33.3	25	41.7
O	4.2	0.9	95

	Q8		
Q5	*E*	*U*	*O*
E	87.9	3.0	9.1
U	48.8	32.6	18.6
O	3.8	0.7	95.6

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

Table 8: Transition Matrix, Schooling: 2017-18 to 2018-19

	Q4		
Q1	*E*	*U*	*O*
E	91.9	3.3	4.8
U	28.9	52.6	18.5
O	2.9	1.7	95.4

	Q8		
Q5	*E*	*U*	*O*
E	92.9	2.3	4.8
U	30.7	51.4	18.0
O	2.6	1.0	96.3

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

Table 9: Transition Matrix, Graduates: 2017-18 to 2018-19

	Q4		
Q1	*E*	*U*	*O*
E	93.8	2.4	3.8
U	13.2	67.6	19.2
O	3.9	4.9	91.2

	Q8		
Q5	*E*	*U*	*O*
E	95	1.6	3.4
U	14.9	68.2	16.9
O	3.5	3.3	93.2

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

Changes in these flows are much more significant in the case of women. The share of employed women who remain in employment rises from 79.5% to 82.3%, while the flows from unemployment into employment rise from 8.4% to 13%. Both long-term unemployment and the discouraged worker effect can be seen to have reduced; however, the fact 33% of urban unemployed women leave the labour force in 2018-19 is a cause of serious concern.

As Tables 7 to 9 indicate, as the level of education rises, for any given year, the share of those retaining employment rises, the flows from employment to non-participation decreases, and the tendency towards long-term unemployment rises. Stark differences in worker flows are seen in the case of unemployment. Workers with no schooling see greater flows from unemployment to employment and non-participation. Graduates, however, experience much greater rates of long-term unemployment. Nearly 67.6% of unemployed graduates in 2017-18 and 68.2% in 2018-19 are unemployed in the first and fourth quarter of the year. The rise in long-term unemployment, however, coincides with a rise in flows for graduate workers from unemployment to employment, and a reduction in flows from unemployment out of the labour force; as with the case of males, the rise in long-term unemployment could indicate a relative increase in job-seekers' expectations of the future.

The biggest change in worker flows, however, is seen in the case of workers with no schooling. The rate of inflow from unemployment to employment rises from 33.3% in 2017-18 to almost 49% in 2018-19, while the discouraged worker effect falls significantly; the flow from unemployment to non-participation reduces from 41.7% to 18.6%. The discouraged worker effects fall less for graduate workers, with a marginal reduction for those with schooling.

The tables presented above are highly aggregative; one cannot say whether the reduction in the discouraged worker effect in case of women is primarily due to gender, or due to the interaction of some other effect. Moreover, the analysis does suffer, in some cases, from the problem of a low sample size[11]. These aggregate matrices, therefore, may not provide a comprehensive picture of the dynamics of the urban labour market.

5. CONDITIONAL TRANSITION MATRICES

To account for the problems outlined above, conditional transition matrices were constructed. Logistic regressions - as outlined in equation 2 - were run for each form of worker flows seen in the labour market; the odds ratios are presented in the appendix (Table A2). From these odds ratios, conditional transition matrices were constructed, by estimating marginal effects. The estimated transition probabilities are presented as percentages, along with their confidence intervals, in Tables 10 to 14.

The conditional transitional matrices indicate that the initial insights drawn from the aggregate matrices hold good, even when one controls for other variables. The share of men experiencing long-term unemployment in 2018-19 has increased relative to the previous year, but, as mentioned above, this might indicate improved economic conditions, as it coincides with reduced flows from unemployment to non-participation, and hence a reduced discouraged worker effect. There does exist clear evidence of an improvement in economic conditions for women, with a larger share of the employed being retained in employment in 2018-19 as compared to a year before, a greater flow from unemployment to employment, and a reduction in the discouraged worker effect. However, the discouraged worker effect remains a significant

[11] This problem is acute in the case of unemployment for workers with no schooling - they number only around 60 in total in 2017-18, and around 86 in 2018-19.

force determining the flows of urban unemployed women; the conditional flows from unemployment out of the labour force for women were measured at 37.19% in 2017-18 and 35.24% in 2018-19.

Table 10: Conditional Transition Matrix: Males 2017-18 to 2018-19

	Q4		
Q1	*E*	*U*	*O*
E	94.61 (0.9419, 0.9503)	3.25 (0.0292, 0.0358)	2.13 (0.0186, 0.0240)
U	26.4 (0.2396, 0.2884)	60.44 (0.5769, 0.6318)	13.09 (0.1112, 0.1505)
O	6.02 (0.0519, 0.0685)	3.71 (0.0310, 0.0432)	90.08 (0.8906, 0.9109)

	Q8		
Q5	*E*	*U*	*O*
E	95.68 (0.9530, 0.9606)	2.36 (0.0208, 0.0264)	1.96 (0.0170, 0.0222)
U	27.5 (0.2507, 0.2994)	62.05 (0.5934, 0.6476)	10.37 (0.0855, 0.1219)
O	5.05 (0.0431, 0.0579)	2.33 (0.0185, 0.0280)	92.5 (0.9164, 0.9338)

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

Table 11: Conditional Transition Matrix: Females 2017-18 to 2018-19

	Q4		
Q1	*E*	*U*	*O*
E	79.44 (0.7785, 0.8103)	2.5 (0.0190, 0.0311)	18.29 (0.1675, 0.1984)
U	9.73 (0.0678, 0.1268)	52.27 (0.4763, 0.5690)	37.19 (0.3255, 0.4182)
O	2.49 (0.022, 0.0275)	1.47 (0.0125 , 0.0169)	96.06 (0.9572, 0.9640)

	Q8		
Q5	*E*	*U*	*O*
E	82.18 (0.8070, 0.8365)	1.47 (0.0102, 0.0191)	16.63 (0.1517, 0.1808)
U	15.69 (0.1224, 0.1913)	49.02 (0.4465, 0.5340)	35.24 (0.3073, 0.3975)
O	2.3 (0.0204, 0.0256)	0.98 (0.008, 0.0116)	96.73 (0.9642, 0.9705)

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

Table 12: Conditional Transition Matrix: No Schooling 2017-18 to 2018-19

	Q4		
Q1	*E*	*U*	*O*
E	88.72 (0.8724, 0.9021)	4.67 (0.0345, 0.0589)	6.37 (0.0539, 0.0735)
U	23.07 (0.1345, 0.3269)	33.38 (0.2045, 0.4631)	43.24 (0.3116, 0.5531)
O	4.36 (0.0345, 0.0528)	1.59 (0.0087, 0.0231)	93.7 (0.9255, 0.9485)

	Q8		
Q5	*E*	*U*	*O*
E	90.72 (0.8928, 0.9215)	4.02 (0.0280, 0.0524)	5.55 (0.0455, 0.0655)
U	33.85 (0.2409, 0.4361)	44.13 (0.3292, 0.5535)	18.96 (0.1047, 0.2746)
O	3.83 (0.0295, 0.0472)	1.27 (0.0061, 0.0192)	94.76 (0.9368, 0.9584)

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

Table 11: Conditional Transition Matrix: Schooling 2017-18 to 2018-19

	Q4		
Q1	*E*	*U*	*O*
E	91.23 (0.9063, 0.9183)	3.17 (0.0281, 0.0353)	5.62 (0.0512, 0.0611)
U	26.55 (0.2374, 0.2937)	51.99 (0.4856, 0.5543)	20.84 (0.1801, 0.2367)
O	2.86 (0.0255, 0.0317)	1.57 (0.0135, 0.0179)	95.57 (0.9520, 0.9594)

	Q8		
Q5	*E*	*U*	*O*
E	92.34 (0.9177, 0.9291)	2.21 (0.0191, 0.0252)	5.44 (0.0495, 0.0593)
U	28.35 (0.2530, 0.3141)	50.45 (0.4690, 0.54)	20.92 (0.1798, 0.2385)
O	2.6 (0.023, 0.0289)	0.93 (0.0076, 0.0109)	96.49 (0.9615, 0.9682)

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

Table 14: Conditional Transition Matrix: Graduates 2017-18 to 2018-19

	Q4		
Q1	*E*	*U*	*O*
E	94.19 (0.9344, 0.9493)	2.42 (0.0191, 0.0292)	3.6 (0.0301, 0.0419)
U	15.84 (0.1299, 0.1870)	67.35 (0.6387, 0.7084)	16.64 (0.1401, 0.1927)
O	3.85 (0.0308, 0.0461)	5.14 (0.0424, 0.0605)	91.21 (0.9008, 0.9223)

	Q8		
Q5	*E*	*U*	*O*
E	95.25 (0.9460, 0.9590)	1.62 (0.0122, 0.0202)	3.27 (0.0273, 0.0382)
U	18.2 (0.1534, 0.2107)	67.21 (0.6387, 0.7055)	14.51 (0.1209, 0.1693)
O	3.54 (0.0281, 0.0427)	3.95 (0.0309, 0.0481)	92.82 (0.9178, 0.9386)

Source: PLFS panel for 2017-18 and 2018-19 as constructed by the authors

With regard to education, similar patterns are seen as in the case of the aggregate matrices; the share of those in employment who retain employment rises with education levels, as does the share of those in long-term unemployment. In both years, the conditional matrices estimate the share of long-term unemployment amongst graduates at 67%. For those with schooling and graduates, 2018-19 does seem to bring with it a slight improvement in economic conditions, as witnessed in an increased flow from unemployment to employment; while 16% of unemployed graduates move into employment in 2017-18, this figure rises to 18.2% by 2018-18. While the flow from unemployment out of the labour force reduces for graduates, it remains roughly constant for those with schooling.

In the case of those workers with no schooling, interpretation of the estimates for worker flows from unemployment becomes difficult. The point estimates spell out the same story as the aggregate matrix, that of a significant increase in the flows from unemployment to employment, a larger share of those who remain unemployed, and a significant reduction of flows from unemployment to non-participation in 2018-19 as compared to 2017-18. However, confidence intervals for these estimates do not allow for as easy an interpretation.

The overall narrative behind the dynamics of India's urban labour markets becomes clearer on consideration of these tables. Firstly, there does exist evidence of an improvement in economic conditions in 2018-19 as compared to 2017-18, following the significant negative shocks experienced during demonetization and GST (Vyas, 2018). Secondly, there exists a significant discouraged worker effect operating in the economy, with women experiencing it in much higher proportion as compared to men. The movement of women from the ranks of the employed out of the labour force is also a serious cause for concern.

6. TRANSITIONS BY AGE AND GENDER

Much of the literature with respect to transitions testifies to the existence of significant differences in outcomes when disaggregated by age (as mentioned above). For one, younger workers face higher rates of unemployment, in both developed and developing economies. In many developing economies, younger workers face significant hardships in being able to transition into employment on completion of their education.

In order to account for the differences in outcomes across different ages, we calculate predicted probabilities of transitions at 5-year intervals from ages 15 to 65 across males and females for both years. The graphs indicate significant commonalities and differences in labour market experiences when disaggregated by age, across both years and both genders[12].

Let us examine certain regularities in the experiences of gender in labour markets, experiences that are common across both years. Across both years, and at any given age, we notice that males have a higher conditional probability of staying in employment as compared to women, if they were initially in employment in the first quarter (Figure 1). Moreover, these probabilities rise along with age; in essence, this implies the majority of those who retained employment over the year were older male workers.

A different situation is seen with regard to flows from employment to unemployment (Figure 2). A larger proportion of these flows comprise of men as compared to women, and of younger workers as compared to older workers. When it comes to moving from employment out of the labour force, women display a much higher probability as compared to men (Figure 3). A significant proportion of older employed women seem to be exiting the labour market at ages far below retirement age.

[12] In certain categories, low absolute numbers in the sample make interpretation difficult; the use of confidence intervals throw better light on the accuracy of the estimates. The graphs presented in this section do not make use of confidence intervals, as a graphical interpretation of trends across years becomes difficult when confidence intervals are graphed onto the figure. The appendix – Figures A1 and A2 - carries graphical representations of transition probabilities across ages along with the relevant confidence intervals.

Figure 1: Employment to Employment

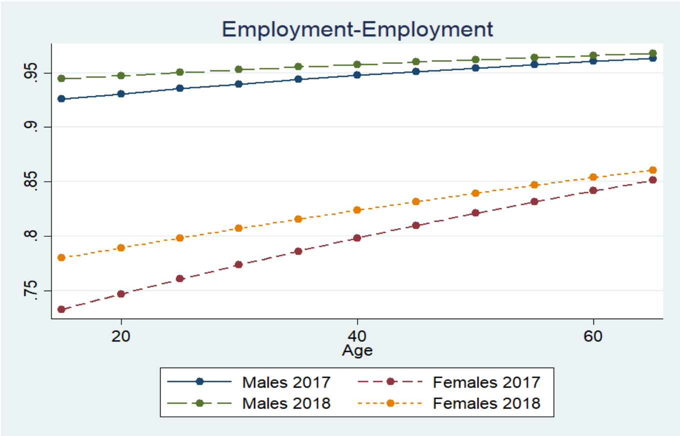


Figure 2: Employment to Unemployment

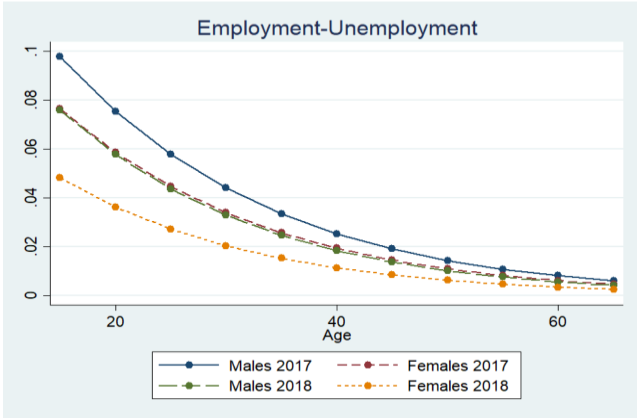


Figure 3: Employment to Out of the Labour Force

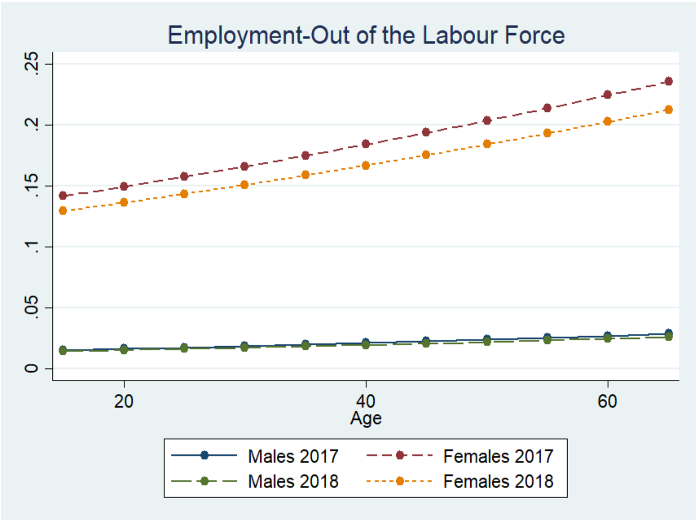


Figure 4: Unemployment to Employment

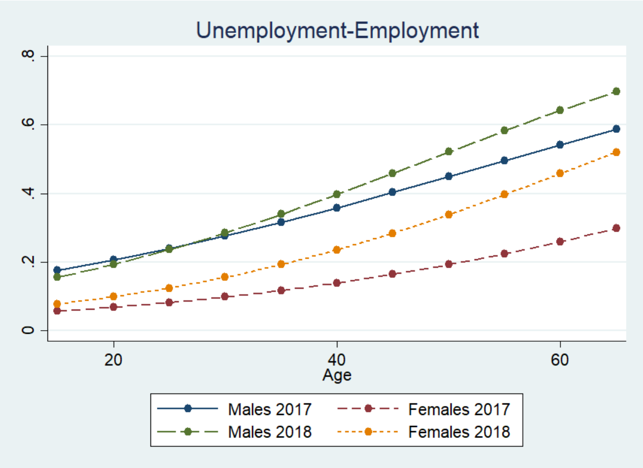


Figure 5: Unemployment to Unemployment

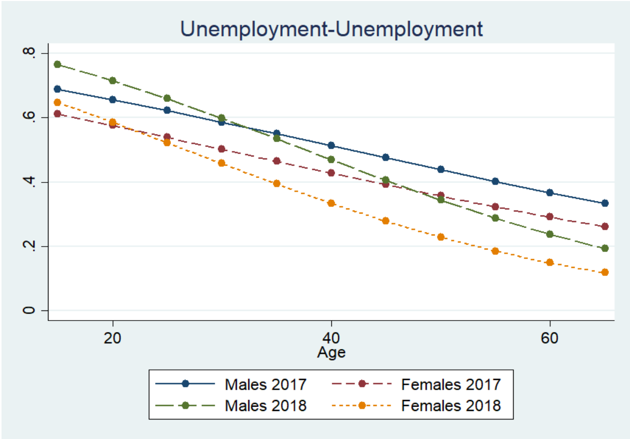


Figure 6: Unemployment to Out of the Labour Force

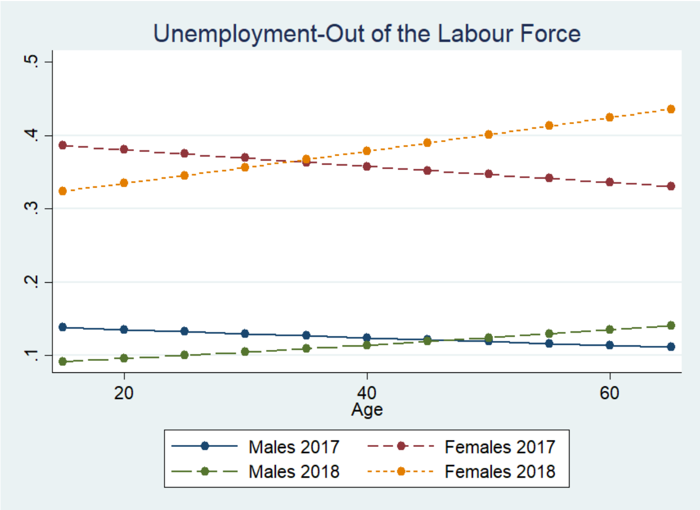


Figure 7: Out of the Labour Force to Employment

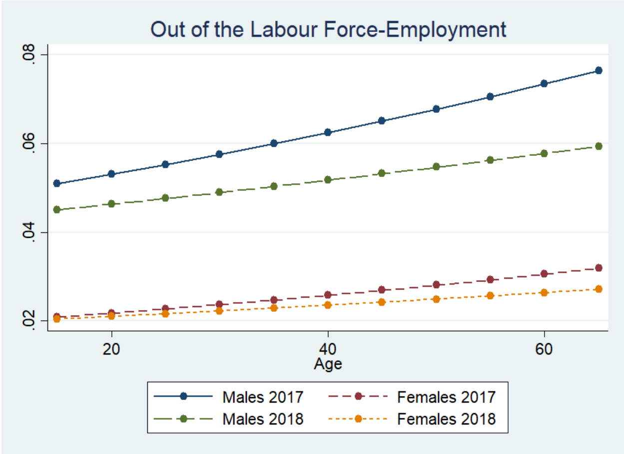


Figure 8: Out of the Labour Force to Unemployment

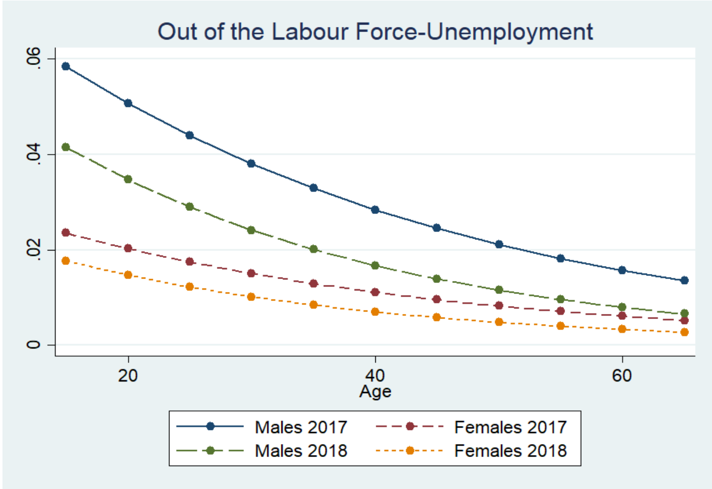
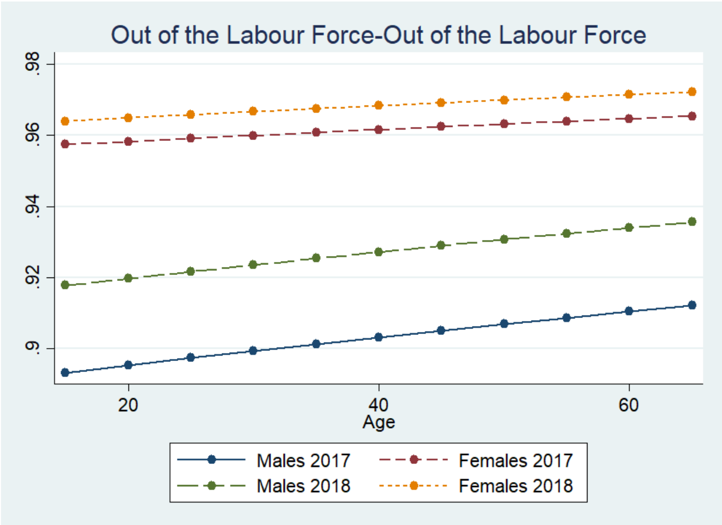


Figure 9: Out of the Labour Force to Out of the Labour Force



Similar patterns are seen for all other movements. Men have higher transition probabilities for flows into employment – from both unemployment (Figure 4) and from non-participation (Figure 7) – than women, and these probabilities increase with age. Men have higher transition probabilities for flows into unemployment – from both unemployment (Figure 5) and from non-participation (Figure 8) – than women, and these probabilities *decrease* with age. Women have higher flows into non-participation (Figures 6 and 9), probabilities that increase with age (except for movements from unemployment to non-participation in 2017).

These empirical estimates allow us to draw certain stylized facts about the behaviour of individuals in Indian urban labour markets. The movement into employment is largely dominated by older men, while the flows into unemployment is dominated by younger males. Women make up much of the flows out of the labour force, and it is largely older women who seem to be moving out[13].

Next, we turn to an examination of the changes in flows in 2018-19 relative to 2017-18. With regard to the flows from employment alone, across all three types of flows (Figures 1, 2 and 3), the changes do indicate an improvement in economic conditions. The probabilities of retention of employment have increased, whereas the flows out of employment have reduced for all ages. Flows into employment and unemployment from those outside the labour force have reduced for all ages for both men and women (Figures 7 and 8), while the proportion of those outside the labour force for all four quarters has increased (Figure 9). One possible interpretation of such an outcome is that, given the relative improvement in economic conditions in 2018-19, individuals who would not have otherwise sought work – such as students or those engaged in domestic activities – saw a reduced need to enter the labour force.

The reductions in the magnitudes of flows from non-participation into the labour force were much higher for men than for women. This larger relative reduction in male flows is a puzzle, given what we know of the tendency for women to exit the labour force when economic conditions improve (Sarkar et al, op cit). What our empirical estimates establish is that while women have a larger tendency to remain – as well as transition – out of the labour force as compared to men, men seem to have experienced a larger *change* in the tendency to transition *into* the labour force as compared to women.

[13] These assertions are to be tempered a bit when one takes into account confidence intervals of these estimates, which are shown in the appendix.

The flows from unemployment present a more mixed trend, with its effects differing across ages. Consider the flows from unemployment to employment (Figure 4). Women in 2018-19 see a larger probability of such flows as compared to 20117-18 across all ages, though the gap increases as age increases; older women saw a much greater probability of moving from unemployment into employment as compared to younger women. For men, however, the probability of these flows *decreased* for young men – aged 15 to 25 – in 2018-19 as compared to the previous year, before rising for older workers. While older unemployed males were better off in 2018-19, younger unemployed males seemed to suffer worse prospects of securing employment.

A similar situation is seen with regard to those stuck in unemployment over four quarters (Figure 5). Younger unemployed individuals – both males and females – faced a greater probability of staying unemployed in 2018-18 as compared to those in 2017-18. The age groups which faced a higher probability of unemployment were older for men than for women: while men aged 15 to 35 faced higher probabilities of being stuck in long-term unemployment, the age groups for women were around 15 to 25. These predicted probabilities reduced for both older men and women.

With regard to flows from unemployment out of the labour force – a measure of the discouraged worker effect – both younger men and women see a reduction in this effect operating, while older individuals see an increase in this effect in 2018-19 relative to the previous year (Figure 6). The age range over which the discouraged worker effect changes is different for men and women; unemployed women aged 15 to 35 see a reduction in the discouraged worker effect, while for men, the reduction is seen in ages 15 to 45. It is worrying, however, to see such a significant increase in the discouraged worker effect for unemployed women above the age of 35 in 2018-19 as compared to 2017-18.

The rise in long-term unemployment and fall in the discouraged worker effect for certain age groups may be linked. Given relative improvement in the labour market – as evidenced by increased transitions into – and larger retentions of – employment – a greater proportion of workers would be inclined to stay and search for work for longer before dropping out of the labour market. And yet it is difficult to understand why these two changes are seen only for younger workers. Even though older women seem to experience reduced flows of remaining in long-term unemployment (Figure 5), increased flows from unemployment to employment (Figure 4), and reduced flows from employment out of the labour force (Figure 3), they experience a larger discouraged worker effect in 2018-19, though larger confidence intervals indicate greater uncertainty about the strength of this effect for older workers (see Appendix). Further research is required to establish the strength of these differences across ages for this effect.

7. CONCLUSION

The study of labour market transitions provides a powerful tool to analyse dynamics in the Indian urban labour market, a tool unavailable till now. This exploratory study studies transitions amongst workers aged 15 to 65 in urban India in order to establish certain narratives regarding labour flows, analyse changes in 2018-19 relative to 2017-18, as well as point out avenues for further research.

The study of these transitions establishes the existence of significant movements out of the labour force, movements that are much more prominent than flows the other way around. The fact that more women lie out of the labour force is a feature that has been extensively studied in a vast literature. Yet previous studies are unable to precisely delineate the forms of this non-participation; do they occur as part of a discouraged worker effect, or with women never entering the labour force at all? Our estimates show that while there does exist a significantly high female discouraged worker effect – more than a third of unemployed women leave the labour force after three quarters of continuous unemployment, significantly higher than men – a worryingly high proportion of employed women – roughly 16% to 18% - leave the labour force as well.

Our study tracks changes in worker flows across both years, disaggregated by age and gender. We establish evidence of improving labour market conditions in 2018-19 as compared to 2017-18, with greater flows occurring into unemployment, and a relative reduction in the discouraged worker effect. We also find evidence of longer stays in unemployment for younger men and women, perhaps motivated by the increased expectations of finding employment in a (relatively) improved labour market. However, though the discouraged worker effect has reduced, we find an increased tendency to move out of the labour force for older unemployed women in 2018-19.

This work provides a framework to understand the study of aggregate transitions in the urban labour market of India, to highlight certain important aspects of worker flows, and to point out avenues for further research. An important aspect of research is to understand what are the questions to be asked; our study represents a modest step forward in that direction.

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APPENDIX

Table A1: Transition Probabilities by Gender: Nordic Countries and South Africa

Men

	Nordic Countries (2004-08)		
	E	*U*	*O*
E	92.9	2.6	4.6
U	40.2	46.2	15.6
O	15.3	4.8	80.1

	South Africa (2008-11)		
	E	*U*	*O*
E	77.5	10.0	12.5
U	39.8	25.5	34.8
O	29.2	20.8	50.0

Women

	Nordic Countries (2004-08)		
	E	*U*	*O*
E	89.4	2.7	8.1
U	39.5	41.1	21.0
O	16.6	5.1	78.3

	South Africa (2008-11)		
	E	*U*	*O*
E	65.4	9.9	24.7
U	27.3	29.5	43.2
O	19.2	21.3	59.5

Source: Same as Table 2

Table A2: Consolidated Odds Ratios

	Employment-Employment		Employment-Unemployment		Employment-OLF	
	2017-18	**2018-19**	**2017-18**	**2018-19**	**2017-18**	**2018-19**
Age	1.015019**	1.011319**	0.944246**	0.9424714**	1.012684	1.012109**
Female	0.2163329**	0.205177**	0.7609718	0.6135969**	10.45183	10.10917**
Caste						
ST	2.029755**	1.699724**	0.4852831**	0.5292895*	0.5127618	0.6113762**
SC	0.8197047*	0.8127323*	1.398259*	1.549958**	1.090903	1.04348
OBC	0.8380394*	0.8301679*	1.205049	1.184044	1.169593	1.183065
Education						
Schooling	1.345719**	1.249432*	0.6632516**	0.5349543**	0.8620257	0.977369
Graduates	2.143794**	2.128006**	0.5003887**	0.3887056**	0.5205679	0.5524277**
Constant	7.384459**	11.26046**	0.3590253**	0.336196**	0.0161488	0.0137621**
Number of obs	13777	13780	13777	13780	13777	13780

	Unemployment-Employment		Unemployment-Unemployment		Unemployment-OLF	
	2017-18	**2018-19**	**2017-18**	**2018-19**	**2017-18**	**2018-19**
Age	1.0406**	1.054491**	0.9691019**	0.9467682**	0.9950403	1.009749
Female	0.2768291**	0.4490698**	0.6973467**	0.549988**	4.048969**	4.800224**
Caste						
ST	0.3030775**	0.3918631**	2.181731**	1.905018**	0.789361	0.7674087
SC	0.9469128	1.533671*	1.008288	0.8724531	1.038632	0.6985046
OBC	1.074286	1.394668*	1.084497	0.8606309	0.7976157	0.8367563
Education						
Schooling	1.228256	0.7503961	2.230206*	1.316215	0.3102632**	1.146101
Graduates	0.6038249	0.3967479**	4.361553**	2.818872**	0.2300732**	0.7025349
Constant	0.1399027**	0.1206814	1.121819	4.362335**	0.6478312	0.1091239**
Number of obs	1562	1550	1562	1550	1562	1550

	OLF-Employment		OLF-Unemployment		OLF-OLF	
	2017-18	**2018-19**	**2017-18**	**2018-19**	**2017-18**	**2018-19**
Age	1.008712**	1.005851*	0.9698664**	0.962745**	1.004364*	1.005364*
Female	0.3966259**	0.4408729**	0.3828293**	0.4105839**	2.703841**	2.417905**
Caste						
ST	0.9977941	0.6292396*	1.445064	1.138684	0.8535723	1.262804
SC	1.294813	1.7196**	1.396425*	2.279203**	0.7379551**	0.5147408**
OBC	1.113401	1.176511	1.273798	1.110686	0.8430758*	0.8522167
Education						

Schooling	0.6434679**	0.6676133**	0.9848197	0.7267877	1.460206**	1.526773**
Graduates	0.8761226	0.9212278	3.424911**	3.283538**	0.6923626**	0.7109677*
Constant	0.0598954	0.0509453	0.0632289**	0.0560776**	7.358872**	9.726384**
Number of obs	16434	16400	16434	16400	16434	16400

Note: '' indicates significance at 5% l.o.s, '**' indicates significance at 1% l.o.s.*

Figures A1: Transitions 2017-18 with Confidence Intervals

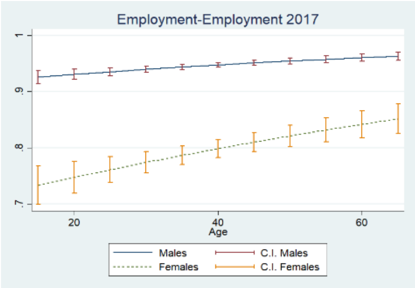

Figure a) Employment-Employment

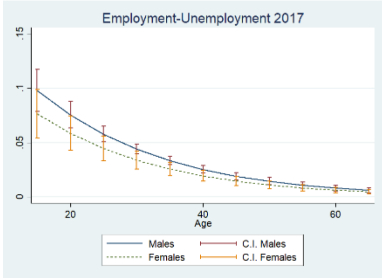

Figure b) Employment-Unemployment

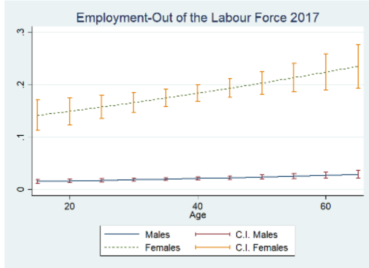

Figure c) Employment-Out of the Labour Force

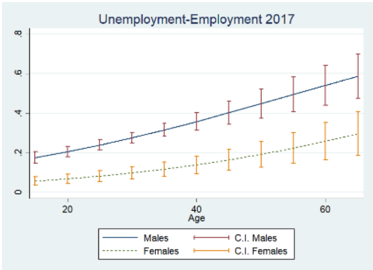

Figure d) Unemployment-Employment

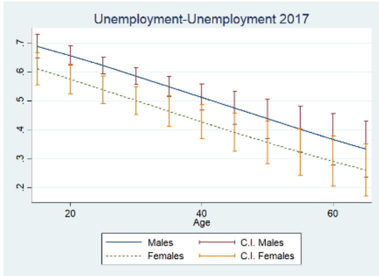

Figure e) Unemployment-Unemployment

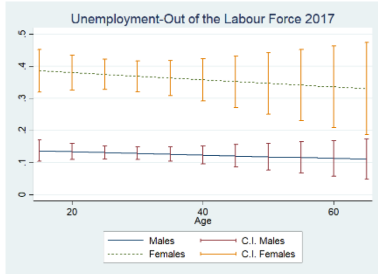

Figure f) Unemployment-Out of the Labor Force

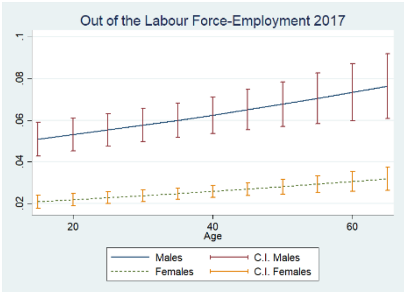

Figure g) Out of the Labour Force-Employment

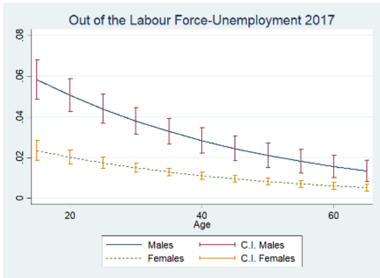

Figure h) Out of the Labour Force-Unemployment

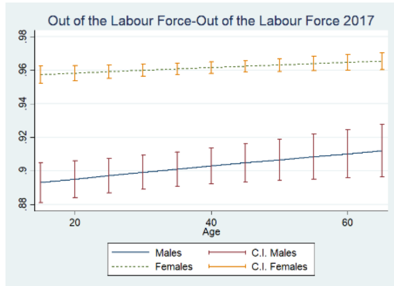

Figure i) Out of the Labour Force-Out of the Labour Force

Figures A2: Transitions 2018-19 with Confidence Intervals

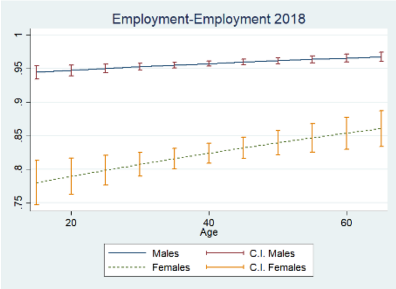

Figure a) Employment-Employment

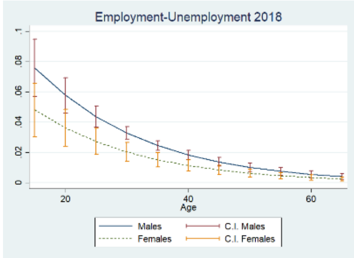

Figure b) Employment-Unemployment

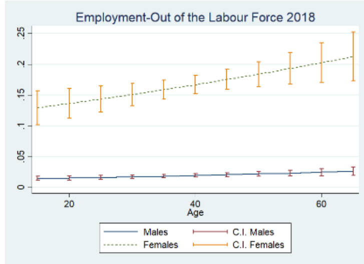

Figure c) Employment-Out of the Labour Force

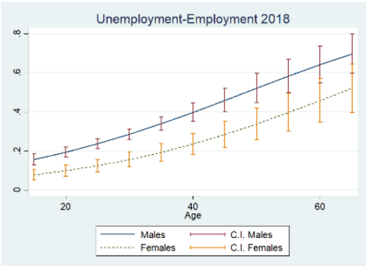

Figure d) Unemployment-Employment

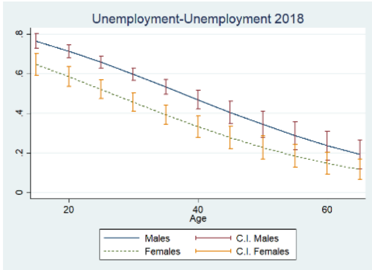

Figure e) Unemployment-Unemployment

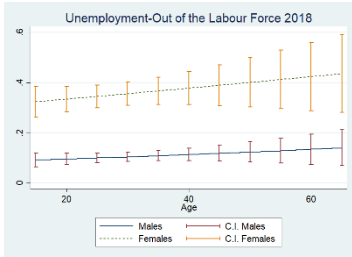

Figure f) Unemployment-Out of the Labour Force

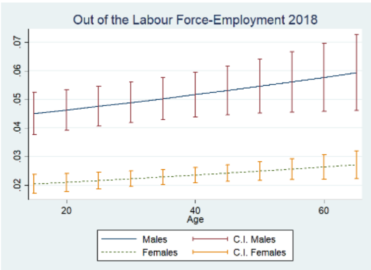

Figure g) Out of the Labour Force-Employment

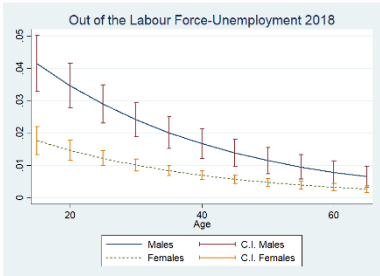

Figure h) Out of the Labour Force-Unemployment

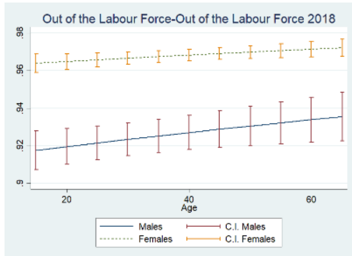

Figure i) Out of the Labour Force-Out of the Labour Force