Indian Urban Workers’ Labour Market Transitions

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Abstract
This paper studies gross labour market flows and determinants of labour market transitions for urban Indian workers using a panel dataset constructed from Indian Periodic Labour Force Survey (PLFS) data for the period 2017–18 to 2019–20. Longitudinal studies based on the PLFS have been hampered by data problems that prevent a straightforward merging of the 2017–18 and 2018–19 data releases. In this paper, we propose and validate a matching procedure based on individual and household characteristics that can successfully link almost all records across these 2 years. We use the constructed dataset to document a number of stylised facts about gross worker flows and to estimate the effects of different individual characteristics and work histories on probabilities of job gain and loss.

Keywords   Labour markets · Gross flows · PLFS · India · Employment · Gender

JEL Classification J21 · J60 · J16 · C81

1 Introduction

The movement of workers from job to job and from employment to non-employment and back, and the simultaneous creation and destruction of jobs by firms, are the mechanisms through which labour markets reallocate resources in response to secular changes and shocks. How well they do this—in terms of efficiently matching workers to jobs with the least amount of resources lost in waiting and search—is an important determinant of individual welfare and aggregate productivity.

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For this reason, the study of labour market transitions and gross worker and job flows has been an important part of empirical labour economics for long. Some of the key contributions in this literature are: Abowd and Zellner (1985), Blanchard et al. (1990), Davis and Haltiwanger (1992), Davis et al. (1998), Shimer (2005), Hall (2005), Fujita and Ramey (2009), Shimer (2012), Elsby et al. (2013), Hall and Kudlyak (2019), and Ahn and Hamilton (2021). A recent review of evidence is provided by Davis et al. (2006). This empirical literature developed together with theoretical work on search and matching models of the labour market, surveyed for example in Rogerson and Shimer (2011).

The picture of the labour market that emerges from these studies is one of a constant churning in which firms create and destroy jobs in response to growth or shrinkage in their activity, and workers move from job to joblessness and other jobs either because their old job has been destroyed, or because of individual-level shocks, or in hopes of better opportunities. The changes observed in aggregate employment rates are just the small net surface result of this incessant process of reallocations at the microeconomic level. The wealth of empirical evidence on these flows that has been available for developed economies informs current research on the business cycle behaviour of the labour market and the normative and welfare impacts of different labour market institutions and policies.

Unfortunately, for long it was not possible to study these processes for the Indian economy because of the unavailability of any sources of panel data on workers. However, in just the last couple of years, such data has finally become available in the form of the official Periodic Labour Force Survey (PLFS) conducted by the National Sample Survey Office (NSSO) as well as the private Consumer Pyramids Household Survey (CPHS) of the Centre for Monitoring Indian Economy (CMIE).

The present study is part of the emerging literature that uses these sources to study labour market transitions in India. We use data from all three available annual microdata releases of the PLFS, viz., from 2017–18, 2018–19 and 2019–20, to look at gross worker flows for urban India. The paper is restricted to urban workers since the PLFS has a panel structure only for urban workers.

The paper is organised as follows. In Section 2, we review the existing literature on gross flows and labour market transitions both in developed countries and in developing countries including India. Section 3 describes the PLFS survey design and the method used by us to construct a combined panel dataset from the three annual data releases. This is a non-trivial task because of an undocumented change in sampling unit identifiers that makes it impossible to use the provided household and individual identifiers to merge the data from the 2017–18 and 2018–19 files. This is perhaps the reason why PLFS data has not been used much for longitudinal studies so far. We overcome this difficulty by developing a matching procedure based on individual and household characteristics that can match records between these two files with a high degree of accuracy. This procedure is described in Section 3.3.

In Section 4, we use this constructed dataset to compute gross flow rates across different labour market states and record a set of stylised facts that emerge. These facts mostly match what is observed in the case of other countries, but with some specificities as well, the most important being a large difference between the patterns
for men and women, and the existence of large flows between salaried employment, casual employment, and self-employment.

Section 5 documents large differences in gross flow rates between different industries, different forms of employment, and different states (provinces). It finds that while most of the differences between states can be explained by differences in the composition of economic activity, there still exists for some states an unexplained state-specific effect.

Finally, Section 6 looks at the determinants of job gains and losses at the individual level. The results once again show a vast difference between men and women in the probabilities of job gains and losses, and in the impact of marriage and childbearing on these probabilities. The results also show differences in labour market outcomes by age and level of education, and a significant impact of employment histories on transition probabilities.

2 Related Work

As we mentioned in the introduction, in countries where panel data for workers and firms have been available for a long period, there is extensive literature on gross employment flows. For the US economy the foundational works are Davis and Haltiwanger (1992) and Blanchard et al. (1990). Davis and Haltiwanger (1992) used employment data from firms and recorded how large gross flows of workers underlay the small net flows and how job creation and job destruction worked asymmetrically over the business cycle. Blanchard et al. (1990) is closer to our study in using data from household surveys, in their case the US Current Population Survey for the period 1968–1986. They, too, measured large gross flows. Their paper also pointed out a methodological challenge that subsequent studies, including ours continue to face. While gross flows are large compared to net flows, they are small compared to the size of the population since most persons continue in the same employment status from one quarter to the next. This means that gross flow measurements are much more sensitive to survey errors and noise compared to cross-sectional measurements of the occupancy of labour market states. While Blanchard et al. (1990) attempted to adjust for these problems drawing on the work of Abowd and Zellner (1985), ultimately the only solution is more precise surveys designed from the ground up to measure gross flows.

Some of the more recent work on the US economy, such as Fujita and Ramey (2009) and Shimer (2012), have continued to use gross flow data with an emphasis on studying the working of the labour market over the business cycle in order to evaluate the dominant search-and-matching models of unemployment (Rogerson & Shimer 2011). Another important emerging strand, found in Hall and Kudlyak (2019), is the study of heterogeneity in labour market trajectories across workers. They estimate a model that classifies workers into five distinct types based on these trajectories and find major differences between them in terms of their probabilities of losing and finding jobs. They show that most of the observed unemployment comes only from two of these types. While our paper looks only at aggregate flows,
the study of heterogeneity is a promising avenue of research for a country like India with its vast disparities and structural heterogeneities.

For countries other than the US, Burda and Wyplosz (1994) in their study covering France, Germany, Spain, and United Kingdom (UK) showed that contrary to the perception of stagnation in European labour markets, there were large gross flows in opposite directions underlying the relatively static unemployment rates. Elsby et al. (2013) estimate flow rates between employment states for OECD countries by using unemployment data categorized by unemployment duration and find that variations in the unemployment rate is driven by fluctuations in both inflows into and outflows from unemployment in all countries though the relative contribution of these two gross flows varies from country to country.

Research on gross labour market flows in developing countries is relatively sparse due to data availability issues. Among the few studies that are available Gallego and Tessada (2012) use job creation and destruction data from Brazil, Chile, Colombia, and Mexico for 1978–2001 to show that sudden stops in capital flows have asymmetric effects, with the increase in job destruction being much stronger than the decrease in job creation. Moreover, they find that job creation and destruction effects are unevenly spread across industrial sectors. Yassine (2015) looks at gross flows over a decade in the Egyptian labour market, drawing a picture of stagnation even at the gross flows level with very rare transition in employment states, though there is an increase in mobility (and volatility) in later years.

For India too we only have limited studies of gross labour market flows since high-frequency panel datasets have only now started to become available. However, there are a number of pioneering studies which have looked at these questions.

Mitra and Tsujita (2016) study labour mobility in slums of Delhi through a panel dataset constructed from two rounds of primary surveys conducted in 2007–08 and 2012, respectively. While the emphasis of their paper is on income mobility, they do document relatively large gross flows of workers across sectors of employment. For the sector with the largest number of workers—manufacturing—only 80% of the workers employed in that sector in 2007–08 were still employed in it 5 years later in 2012. The corresponding figures for the next two biggest sectors—sales and trade and services—were 79% and 85%, respectively (Mitra & Tsujita 2016, Table 3). As the authors note, these numbers only provide a lower bound on the gross flows as they do not capture job-to-job movements within a sector.

Sarkar et al. (2019) use Indian Human Development Survey (IHDS) panel data from 2005 and 2012 to look at labour market transitions of Indian women in the context of the debate around the low and decreasing Labour Force Participation Rate (LFPR) of Indian women. They find that women have higher exit probabilities from and lower entry probability into employment compared to men. They also study different determinants of entry and exit. The key limitation of their paper, imposed by their data source, is the long gap of 7 years between the two observations. As a result, they face serious attrition problems with 20% of women in the 2005 sample not being present in the 2012 sample. Also, their data source prevents them from observing labour market movements at higher frequencies, which we find to be significant.
Deshpande and Singh (2021) use CPHS data from 2016–2019 to look at women’s labour market transitions, once again in the context of the women’s LFPR debate. The panel design of the CPHS allows them to track individuals over the entire study period and one of their key findings, corroborated by the present study, is that the low cross-sectional labour participation rate of women does not truly capture the work histories of women. They find large gross movements of women into and out of work at a quarterly frequency. Though the average cross-sectional LFPR of women was only 14.6% in their data, the percentage of women who were observed to be employed at least once in the entire study period was much higher at 44.0%.

The papers closest to the present one are those of Menon and Nath (2022) and Mitra et al. (2022). Menon and Nath (2022) look at urban labour market transitions and gross flows using PLFS data. However, they only work with the 2017–18 and 2018–19 data releases, and do not address the coding change between these two data releases. They are, therefore, forced to split worker histories at the boundary of these 2 years. From each year, they consider only one panel—that which started in the first quarter in that year—and only look at transitions at an annual frequency. They also look at only three broad labour market states—employment, unemployment, and non-participation. In contrast, our recoding algorithm allows us to merge data from 2017–18 and 2018–19 files, which we further combine with the 2019–20 files to create one combined dataset that includes all the PLFS data released so far. As a result, we work with much larger sample sizes. We look at all the panels and calculate transition rates at a quarterly frequency with a finer set of labour market states which distinguishes between salaried work, casual work, and self-employment. As a result, we are able to pick out gross flows at a higher granularity that brings out more clearly the dynamic nature of the urban Indian labour market.

Mitra et al. (2022) use PLFS data from 2017–18 to study labour market volatility. In the part of their work that comes closest to ours, they look at the number of times a given worker changes their type of employment and find statistically significant effects for caste, education, household size, gender, and age. In contrast to our study, their study is limited to a single year. They look at the total number of changes in employment type over the period of study without separating these changes into flows between particular pairs of employment states as we do in this paper.

3 Data

3.1 Survey Design

The PLFS is a quarterly survey on employment issues conducted by the NSSO of the Government of India. Started in 2017–18, it replaces the earlier quinquennial employment–unemployment surveys of the NSSO. Annual reports and microdata for the survey are published in a July–June cycle. So far, data has been released for the years 2017–18, 2018–19, and 2019–20. The design of the survey is documented in NSSO (2016).

The PLFS covers both rural and urban areas. In urban areas it has a rotational panel design, with a new panel starting every quarter and being visited for four
successive quarters. This is the first official household survey in India with a panel structure and the primary aim of this paper is to use this structure to study transition processes in the labour market that cannot be captured by purely cross-sectional data. Since rural households are visited only once, this paper is restricted to urban households.

The PLFS is a stratified, multi-stage survey. We describe the sample design only for the urban areas. The first-stage units (FSUs) are urban blocks from the Urban Frame Survey of the NSSO. This sampling frame changes every 2 years, so in the period of our study one sampling frame is used for 2017–18 and 2018–19, and another for 2019–20.

Table 1 gives the number of households in each panel visited in each quarter. The staggered pattern of the table demonstrates the rotating nature of the panels. The Table starts with 2017-Q3 since the PLFS follows a July–June cycle. Following the official PLFS documentation, the panels are identified as $P_{ij}$, where $i$ refers to the sampling frame used and $j$ to the serial number of the panel.

The broad outline of the survey design is as follows. A first stage of stratification is carried out by dividing towns and cities on the basis of population. From these strata, blocks, which are the first-stage units, are selected using probability proportional to size with replacement. Larger blocks are divided into sub-blocks and only two sub-blocks are selected from these blocks for further sampling.

Households in blocks are stratified on the basis of the general education level of their members. From these second-stage strata, households are selected for panels on the basis of simple random sampling without replacement.
3.2 Initial Validation

We merge the data files for all the 3 years and run the following validation checks to ensure that distinct households or persons are not merged together due to data errors in the source data.

1. The religion and social group of the household should not have changed.
2. The size of the household should not have changed by more than 3.
3. A person’s gender and relation to the head of the household should not have changed.
4. A person’s age should not have changed by more than 4 years.\(^1\)

While some of these variables can in fact genuinely change for households and persons, the frequency of such changes is rare enough that most reported changes are likely to be due to data errors. We, therefore, remove all the records of households which fail any of these tests, removing the records of the entire household in case any of its members fails any of the person-level tests. 634 households are removed from the sample as a result.

3.3 Constructing the Panel Dataset

In the microdata files, each household is supposed to be uniquely identified by the combination of panel number, FSU number, sub-block number, second stage stratum number, and sample household number. Each person within a household has a person number which remains the same across visits. In principle, this should lead to a simple linking of households and individuals across different years’ microdata files. However, a number of problems emerge in actually carrying out this process using the files provided by the NSSO. These data issues have also been documented by Menon and Nath (2022) and Abdul-Razak and Sahoo (2021).

First, the panel identifier is not provided in the released data. We work around this by inferring panel numbers by combining the known panel schedule with the visit number and the year and quarter of the visit in the dataset.

Second, in the 2017–18 revisit file for persons, the quarter numbers are recorded as 3, 4 or 5 instead of the expected 2, 3 and 4. Tabulating the visit numbers against the quarter numbers shows no third visits in the reported quarter 3 and no fourth visits in the reported quarter 4. Thus, the most plausible explanation is that quarter 2 has been incorrectly coded as quarter 3 and so on. We correct the records with this assumption.

The third, and gravest, difficulty is that an entirely different sets of FSU numbers are used in the 2017–18 and the 2018–19 data releases even though both years are supposed to use the same sampling frame. This change is not explained in the PLFS

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\(^1\) Given that each person is followed over four quarters, age in years should not change by more than 1. However, examination of the reported age distribution shows significant bunching around multiples of 2 and 5 which suggests imprecise reporting of age. Since the purpose of this step is only to prevent incorrect linking, we keep a wider acceptance range for reported age.
documentation. Because of this change, it is not possible to directly link data across these 2 years.

We develop a matching procedure to overcome this problem. We consider the development of this procedure to be a major contribution of this paper since in the absence of such a procedure it would be impossible to link together panels that began in 2017–18 and were continued into 2018–19. For these panels, we would lose the opportunity to track households over the entire four-quarter span of observation.

Our procedure is based on the hypothesis, eventually confirmed, that the change in the FSU number is a simple renumbering and not a reorganization of the FSU, and that within the renumbered FSUs the sub-block serial number, second-stage stratum number, and sample household numbers still point to the same household.

Our matching procedure is applied district-by-district. For each district, we consider all possible (FSU number in 2017–18, FSU number in 2018–19) pairs as renumbering candidates. To each of these pairs of FSU numbers, we assign a score. The score is computed as follows.

Given a candidate pair (OLD, NEW) of FSU numbers, we try to match each household in FSU number OLD in the 2017–18 data with the household in FSU number NEW in the 2018–19 data that has the same sub-block, second-stage stratum, and household number. The two households are taken to be matched if they have the same panel number, religion and social group, and if each of their corresponding members have the same sex, relation to the head of the household and general education level. The total number of households which successfully match on these criteria becomes the score of that FSU number pair.

For the FSU number pair which corresponds to the actual renumbering all households would match, other than households whose characteristics or membership changes. For other FSU number, pairs matches would happen only by accident. Therefore, our scoring rule can be expected to give the highest score to the correct renumbering if a renumbering has actually happened.

We chose to exclude households of size one or two to avoid spurious matches, since a small number of household members makes it much more likely that the individual-level matching criteria will be satisfied by accident. The variables on which we match, specially the general education level, could presumably change over time, but the proportion of genuinely matching households with such changes is likely to be very small at a quarterly frequency. To minimize the possibility of genuine changes causing failed matches, we consider for each household only the last visit in 2017–18 and the first visit in 2018–19.

Once each (FSU number in 2017–18, FSU number in 2018–19) pair has been scored, for each FSU number in 2017–18 we pick the FSU number in 2018–19 with the highest score. In case a 2018–19 FSU number is selected as the best match for more than one 2017–18 FSU number, we drop all the pairs involved.

At the end of this process, we are able to find best matches for 4272 out of the 4320 FSUs from 2017–18 that were to be revisited in 2018–19.

To check on the quality of this mapping, we use it to rewrite all the FSU numbers in the 2017–18 data with our inferred renumbering and rerun the validation tests from Section 3.2. Only 62 out of 34,452 households that were to be matched fail these validation tests. This confirms our hypothesis that FSUs were renumbered.
and not reorganized, and demonstrates the procedure’s success in inferring that renumbering.

Note that it is appropriate to validate the procedure by comparing variables like religion or relation to head which were used in the scoring function for FSU renumbering candidate pairs. This is because the validation is run on the entire set of households and not just on the set of matching households which were used for the scoring. Had we been mistaken in our assumption that the FSUs had only been renumbered and not reorganized or had we not correctly inferred the renumbering, the set of matching households would be very small during the scoring stage and subsequently linking all the other households using the FSU renumbering inferred would have led to a large number of households failing the validation tests.

As a further check on this procedure, we run it on the 2018–19 and 2019–20 datasets in which no change in FSU numbers actually occurred. Our procedure correctly matches each FSU number in 2018–19 to itself in 2019–20, further confirming its validity.

Subsequent to the circulation of the working paper version of this paper, Enevoldsen (2022) showed that the FSU number mapping found by the above process can be obtained by the following digit substitutions in the FSU numbers: $0 \rightarrow 6$, $6 \rightarrow 8$, $8 \rightarrow 9$, $9 \rightarrow 3$, $3 \rightarrow 0$ and $1 \rightarrow 4$, $4 \rightarrow 7$, $7 \rightarrow 2$, $2 \rightarrow 5$, $5 \rightarrow 1$. This has also been verified by us. The simplicity of the transformation further strengthens our confidence in the procedure.

The rest of this paper uses the dataset with the 2017–18 FSU numbers replaced by the inferred 2018–19 renumbering. Households belonging the few FSUs which could not be matched as taken as attrited at the end of 2017–18.

### 3.4 Age Group and Study Period

All our analyses are restricted to individuals in the working age group of 15–65 years.

We only use data from 2017-Q3 to 2019-Q4 in order to exclude the impact of the COVID pandemic.

### 3.5 Employment Status

The PLFS collects information regarding employment status for three different reference periods—the usual principal/subsidiary status with a reference period of 365 days prior to the visit (collected only on the first visit), daily statuses for each day of the week prior to the visit, and a current weekly status derived from these daily statuses.

All our analyses are based on the current weekly status. The usual status is not collected on revisits and is therefore not useful in a longitudinal study.
The labour market states we use in the tabulations are obtained by combining PLFS’s two-digit status codes (NSSO 2016) into a smaller number of categories. The list of states and their description is given in Table 2.

### Table 2: Employment states. Source: Author’s calculations based on PLFS data

| State  | Description                                      | PLFS codes |
|--------|--------------------------------------------------|------------|
| slf-emp | Self-employed in household enterprise or helper in household enterprise | 11,12,21   |
| csl-emp | Casual wage labour                               | 41, 42, 51 |
| sal-emp | Regular salaried/wage employee                   | 31         |
| sck-emp | Had work but did not work due to sickness         | 61, 71     |
| nwrk   | Had work but did not work due to other reasons    | 62, 72     |
| unemp  | Unemployed (not engaged in work but available for work) | 81, 82 |
| nopart | Not in labour force (not available for work)      | 91, 92, 93, 94, 95, 97, 98, 99 |
| attrit | Attrited from the sample                         |            |

### Table 3: Percentage of households attrited in each visit after first. Source: Author’s calculations based on PLFS data

| Visit | % of households attrited |
|-------|--------------------------|
|       | Panel                    |
|       | P11  P12  P13  P14  P15  P16  P17  P18  P21 |
| 2     | 2.6  2.1  2.5  1.8  1.5  1.7  0.0  2.5  0.7 |
| 3     | 4.0  3.6  3.1  2.9  2.7  1.6  3.9  0.2  |
| 4     | 5.3  4.0  3.8  3.8  2.6  4.7  0.4  |

The labour market states we use in the tabulations are obtained by combining PLFS’s two-digit status codes (NSSO 2016) into a smaller number of categories. The list of states and their description is given in Table 2.

#### 3.6 Attrition

Table 3 gives the attrition rates. The attrition rates are comparable to other surveys of a similar nature. In fact, some of the attrition rates of less than 1% are quite unusual and surprising.

Still, attrition is a cause for concern since the attrition rate will turn out to be comparable in magnitude of the gross flows between labour market states measuring which is the focus of this paper. Attrition would not make a difference if the histories of those attrited were to be similar to those not attrited. But this is unlikely to be true, since at least one source of attrition is individuals moving from their previous address and the labour market trajectories of these movers are likely to be different from those who continue to stay at the same address.
There exists literature on adjusting for attrition in longitudinal surveys, and in the context of gross labour flows. Abowd and Zellner (1985) and Feng and Hu (2013) for example use such adjustments. But these adjustments require strong assumptions about the unobserved attrition process which we are not comfortable making. We, therefore, report attrition rates side-by-side with the estimated flow rates so that readers may judge for themselves the worst case bounds on the effects of attrition on the estimates on the lines of Manski (2009).

4 Gross Flows

4.1 Method

In this section, we use observations of the same individual over pairs of successive quarters to compute gross flow rates between the labour market states defined in Table 2.

For each gender and each period, we form matrices of gross flows where the entry in the \( i \)-th row and the \( j \)-th column in the quarter \( t \) matrix is the estimated number of individuals in labour market state \( i \) in quarter \( t \) who moved to labour market state \( j \) in quarter \( t + 1 \) as a percentage of the total population of that gender in that quarter. Sampling weights provided by the NSSO are used while calculating these percentages. We then average these matrices over all quarters \( t \) in our study period to produce Table 4. The numbers in parentheses in the Table are transition probabilities expressed as percentages, where the parenthesised entry in the \( i \)-th row and \( j \)-th column is number of persons in state \( i \) who go to state \( j \) in the next quarter, as a percentage of the total number of persons in state \( i \) in the initial quarter. These probabilities are also averaged over quarters.

Both the row totals and column totals in the Table are a measure of the percentage of population in each labour market state, the row totals being the measure of individuals in the state in quarter \( t \) and the column totals being a measure of individuals in quarter \( t + 1 \). The two totals do not exactly match for two reasons. First, if we number our quarters from 1 to \( N \) then the row totals are an average over quarters 1 to \( N - 1 \) while the column totals are an average over quarters 2 to \( N \). Second, the set of individuals included in the calculation between quarter \( t \) to \( t + 1 \) is not the same as the set of individuals included in the calculation between quarter \( t + 1 \) and \( t + 2 \) because of households entering and leaving the survey and because of attrition.

4.2 Stylised Facts

Table 4 presents us with a number of stylised facts.

1. *Changes of state are infrequent.* In the two tables, most of the flows are concentrated along the diagonal. On an average, in each quarter, only 6.32%
of women and 10.68% of men change their labour market state. This has a very important implication for measurement. Sources of measurement error or attrition bias which may be small with respect to the overall sample size may be

| Emp. status [t] | percentage |
|----------------|------------|
| Emp. status [t+1] | slf-emp | csl-emp | sal-emp | unemp | nopart | sck-emp | nwkr | attrit | ALL |
| **Female** | | | | | | | | | |
| slf-emp | 4.66 | 0.04 | 0.09 | 0.05 | 0.79 | 0.02 | 0.09 | 0.09 | 5.82 |
| | (79.97) | (0.66) | (1.52) | (0.92) | (13.53) | (0.29) | (1.58) | (1.52) | (100.00) |
| csl-emp | 0.06 | 1.20 | 0.09 | 0.08 | 0.31 | 0.00 | 0.00 | 0.03 | 1.78 |
| | (3.44) | (67.27) | (5.11) | (4.25) | (17.66) | (0.07) | (0.28) | (1.91) | (100.00) |
| sal-emp | 0.08 | 0.05 | 8.75 | 0.10 | 0.58 | 0.02 | 0.17 | 0.31 | 10.06 |
| | (0.77) | (0.52) | (86.98) | (1.02) | (5.72) | (0.17) | (1.74) | (3.09) | (100.00) |
| unemp | 0.04 | 0.08 | 0.10 | 1.57 | 0.56 | 0.00 | 0.00 | 0.10 | 2.46 |
| | (1.78) | (3.31) | (4.10) | (63.60) | (22.92) | (0.01) | (0.12) | (4.16) | (100.00) |
| nopart | 0.76 | 0.26 | 0.56 | 0.50 | 75.56 | 0.01 | 0.00 | 0.03 | 1.76 |
| | (0.96) | (0.32) | (0.71) | (0.63) | (95.12) | (0.01) | (0.04) | (2.22) | (100.00) |
| sck-emp | 0.01 | 0.00 | 0.02 | 0.00 | 0.01 | 0.01 | 0.00 | 0.00 | 0.06 |
| | (23.93) | (0.00) | (38.05) | (1.82) | (17.68) | (11.50) | (4.99) | (2.03) | (100.00) |
| nwkr | 0.10 | 0.00 | 0.16 | 0.00 | 0.05 | 0.00 | 0.05 | 0.01 | 0.39 |
| | (25.87) | (1.19) | (42.27) | (1.29) | (11.76) | (0.76) | (13.71) | (3.15) | (100.00) |
| ALL | 5.71 | 1.63 | 9.78 | 2.31 | 77.85 | 0.05 | 0.36 | 2.31 | 100.00 |
| | (5.71) | (1.63) | (9.78) | (2.31) | (77.85) | (0.05) | (0.36) | (2.31) | (100.00) |
| **Male** | | | | | | | | | |
| slf-emp | 24.13 | 0.32 | 0.58 | 0.36 | 0.35 | 0.07 | 0.32 | 0.60 | 26.73 |
| | (90.27) | (1.22) | (2.16) | (1.34) | (1.31) | (0.25) | (1.21) | (2.23) | (100.00) |
| csl-emp | 0.35 | 7.90 | 0.35 | 0.48 | 0.23 | 0.01 | 0.04 | 0.28 | 9.62 |
| | (3.63) | (82.06) | (3.60) | (4.98) | (2.39) | (0.06) | (0.38) | (2.90) | (100.00) |
| sal-emp | 0.56 | 0.29 | 30.07 | 0.51 | 0.35 | 0.05 | 0.28 | 1.05 | 33.16 |
| | (1.69) | (0.87) | (90.69) | (1.52) | (1.04) | (0.14) | (0.86) | (3.18) | (100.00) |
| unemp | 0.37 | 0.54 | 0.49 | 4.44 | 0.59 | 0.00 | 0.03 | 0.34 | 6.80 |
| | (5.50) | (7.93) | (7.22) | (65.29) | (8.70) | (0.04) | (0.37) | (4.96) | (100.00) |
| nopart | 0.32 | 0.21 | 0.30 | 0.55 | 20.49 | 0.00 | 0.01 | 0.63 | 22.52 |
| | (1.44) | (0.93) | (1.33) | (2.45) | (90.97) | (0.02) | (0.06) | (2.82) | (100.00) |
| sck-emp | 0.09 | 0.01 | 0.05 | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 | 0.20 |
| | (42.38) | (4.68) | (27.04) | (3.01) | (5.94) | (10.76) | (3.25) | (2.94) | (100.00) |
| nwkr | 0.41 | 0.05 | 0.29 | 0.04 | 0.02 | 0.01 | 0.11 | 0.03 | 0.96 |
| | (42.18) | (5.01) | (30.61) | (4.40) | (2.47) | (5.92) | (11.16) | (3.59) | (100.00) |
| ALL | 26.23 | 9.31 | 32.14 | 6.38 | 22.04 | 0.15 | 0.80 | 2.94 | 100.00 |
| | (26.23) | (9.31) | (32.14) | (6.38) | (22.04) | (0.15) | (0.80) | (2.94) | (100.00) |
large enough to swamp the small number of observations of state transitions. Therefore, a much higher level of accuracy of observation is required for surveys meant to study transitions compared to surveys meant to study cross-sectional features. It is, therefore, worrying that the PLFS does not include mechanisms like reinterviews of a subset of respondents a short while after the original interview to quantify measurement errors.

2. **Gross flows are much larger than net flows.** Even though gross flows are small relative to the size of the population, they are much larger than net flows. This indeed is the basic fact motivating the study of gross labour market flows, reconfirmed in our case. For example, on an average in every quarter 0.10% of women moved from salaried employment to unemployment while at the same time 0.10% of women moved back from unemployment to salaried employment. Thus, on the net there is no flow from salaried employment to unemployment, though every quarter there is a significant number of women moving between these two employment states. These changes at the individual level which have obvious welfare implications would be completely missed by a study of net flows.

3. **Labour market conditions are very different for men and women.** The low occupancy in employment states for women reconfirms the low LFPR for women in India on which there is already an extensive literature. But the tables bring out the fact that this substantial difference in stocks is accompanied also by a substantial difference in flows in the sense that women experience much large inflows and outflows into employment. For example, the transition probability for women in salaried employment to move into unemployment or nonparticipation is $1.02 + 5.72 = 6.74\%$, whereas for men the corresponding transition probability is $1.52 + 1.04 = 2.56\%$. These high proportionate rates of outflows for women are matched by equally high rates of inflows. Similar comparisons hold for casual work and self-employment. Thus, while women participate less in employment at any given moment of time, there is a much greater flux of women moving into and out of employment. This matches the results of Sarkar et al. (2019) and Deshpande and Singh (2021) who also find that Indian women move into and out of employment at a significantly higher rate than Indian men.

4. **Unemployment and non-participation overlap.** For women, flows into all three categories of employment is higher from non-participation than from unemployment. This could be explained by the very high percentage of women in the non-participation state. However, even for men the flow from non-participation to employment is substantial. For example, 0.30% of the male population moved from non-participation to salaried employment which is not negligible compared to the 0.49% of the male population that moved from unemployment to salaried employment. These direct movements from non-participation to employment could have two sources. One, it would include workers who complete their job searches between two observations and hence are never observed in the searching state. But, equally important is the possibility of response or measurement errors. Because of the stigma associated with unemployment some of the unemployed may respond that they are not looking for work. Or the responses of some of the non-employed may be incorrectly coded. In any case, our results show that it would be inappropriate to focus excessively on the unemployment rate as a
4. A measure of the functioning of the labour market. Among those recorded as non-participating, there are many who do wish to participate.

5. **Job-to-job flows are significant.** There are significant gross flows between the three employment states of salaried employment, casual employment, and self-employment. So, for example, compared to 0.49% of the male population flowing from unemployment to salaried work each quarter, 0.35% flow from casual work and 0.58% flow from self-employment each quarter. Thus, these categories of work do not exist in ironclad compartments and employment-to-employment flows are as important as non-employment-to-employment flows. In fact, we know from the studies in countries where matched employer-employee records are available that there exists substantial job-to-job flows. We cannot capture these flows in our data since we have no employer identifiers, but movement between the different kinds of employment gives us a glimpse of these flows. Also, to the extent that salaried work is associated more with the formal sector and self-employment and casual work are associated more with the informal sector, these flows show that there exists significant worker porosity between these sectors of the urban Indian economy.

6. **‘nwrk’ requires further disaggregation** The PLFS uses the employment status codes 62 and 72 for individuals who had work in household enterprises or had salaried employment, respectively, but did not work due to reasons other than sickness. We aggregate these two codes into our ‘nwrk’ state. There are significant flows to this state from employment states, specially from salaried employment. For example, for women the flow from salaried employment to ‘nwrk’ is 0.17% of women, while the corresponding flow from salaried employment to unemployment is lower at 0.1%. While part of these flows would be persons taking a break or vacation, it is quite possible that they also include persons temporarily laid off or not being able to work due to disruptions in production. To unpack this further, we look at individuals who transition from either salaried employment or self-employment to the state ‘nwrk’ and compare their earnings before and after the transition. Figure 1 presents the empirical cumulative distribution function of the ratio of earnings after to earnings before entering the ‘nwrk’ state. There is a large jump in both cases at 1, showing that for a large fraction—around 50% for salaried employment and 25% for self-employed—there is no change in earnings on moving to this state, so the transition is likely to be a voluntary break from work.

![Fig. 1 Earnings before and during ‘nwrk’](image-url)
around 25% in both cases there is actually a reported increase in income.² And for around 25% in the case of salaried employees and around 50% in the case of the self-employed there is a decrease in income which might indicate some sort of involuntary inactivity. A look at the PLFS data for the post-COVID period shows a substantial increase in flows into ‘nwrk’ and in the proportion of individuals earning nothing after entering this state. Given these indications of heterogeneity it would be useful if future versions of PLFS were to unpack this category further.

5 Diversity in Flow Rates by Industry and Region

To compare the labour market transition rates by industry and regions, we use the following definitions, following Davis and Haltiwanger (1992),

² The self-employment category includes unpaid family workers whose incomes are recorded as zero and whose income can only increase when they move to another state.
The definitions of entry rate and exit rates differ from the usual definition of growth rates only in using the average of the occupancy in time \( t \) and \( t + 1 \) in the denominator, instead of the occupancy only at time \( t \). The advantage of these alternative definition is that they produce numbers bounded between 0 and 2, making comparisons easier.

Figure 2 shows the average all-India entry and exit rates for two-digit NIC 2008 industry codes (CSO 2008). Figure 3 shows the average entry and exit rates from employment for the different states (provinces) of India. In both cases, data for men and women and for casual-, salaried- and self-employment are plotted separately.

\[
E_{i,t} = \text{set of workers in labour market state } i \text{ at time } t \\
\#S = \text{number of elements in the set } S \\
\text{Entry rate}_{i,t} = \frac{\#(E_{i,t} \cap E_{i,t+1})}{\left(\#E_{i,t} + \#E_{i,t+1}\right)/2} \\
\text{Exit rate}_{i,t} = \frac{\#(E_{i,t} \cap E_{i,t+1}^c)}{\left(\#E_{i,t} + \#E_{i,t+1}\right)/2} \\
\text{Gross flow}_{i,t} = \text{Entry rate}_{i,t} + \text{Exit rate}_{i,t}
\]

The definitions of entry rate and exit rates differ from the usual definition of growth rates only in using the average of the occupancy in time \( t \) and \( t + 1 \) in the denominator, instead of the occupancy only at time \( t \). The advantage of these alternative definition is that they produce numbers bounded between 0 and 2, making comparisons easier.

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The first observation from these figures is the high degree of clustering in most cases around the dashed 45-degree line. Industries and states with high entry rates also tend to have high exit rates. Thus, the variation of entry and exit rates across states and industries is not due to the net expansion or shrinkage of industries. Rather it is due to the intrinsic labour market conditions in each industry.

The second observation is that the variation between industries and states is quite large. Even if one looks at a narrowly defined group such as salaried male workers, entry and exit rates range from 0.1 to 0.25 across 2-digit industries and 0.01 to 0.1 for entry and exit from work in different states.

One difficulty in interpreting the two figures separately is that the industry-wise composition of employment differs from state to state. To the extent that labour market transition rates are influenced by both state-specific and industry-specific factors, looking at each separately is subject to confounding. An industry might show high turnover because it is primarily situated in a state with weak labour market protections. On the other hand, a state might show a high turnover because most of its workers are employed in industries where hiring and firing is cheap.

To try and decompose the industry and state effects, we estimate the following linear model which imposes an additive structure on these effects:

\[
\text{[Gross flow rate]} = \sum_{i,j,k} \beta_{ijk} D^I_i D^T_j D^G_k + \sum_{l,k} \gamma_{lk} D^S_l D^G_k + \text{[Period dummies]}
\]

Here we use the gross flow rate—the sum of entry and exit rates—as a dependent variable that captures the rate of labour turnover. On the right-hand side are a range of dummy variables

1. \(D^I_i\): industry dummies, where \(i\) ranges over 2-digit industry codes.
2. \(D^T_j\): employment type dummies, where \(j\) ranges over \{slf-emp, csl-emp, sal-emp\}.
3. \(D^G_k\): gender dummies, where \(k\) ranges over \{Male, Female\}.
4. \(D^S_l\): state dummies, where \(l\) ranges over the states of India

The regression is fit to observations of gross flow rates in each quarter for each state, industry, employment type, and gender combination. To avoid noisy data from combinations with very few sample observations, we only keep those combinations whose total sampling multiplier is greater than \(5 \times 10^7\) for women and \(10^8\) for men.

The regression is estimated without an intercept and therefore coefficients for all possible industry-employment type-gender combinations can be estimated. For the state-gender combinations, Maharashtra-Male is taken as the baseline.

Tables 5 and 6 give the statistically significant coefficients for industry, employment type, gender combinations and state, gender combinations, respectively.

Even after controlling for state effects, the results of Table 5 shows a wide variation in gross flow rates among industries and forms of employment, with coefficients ranging from 0.26 for male salaried workers in chemical manufacturing to 1.0 for...
female casual workers in the manufacture of textiles. Even within the same industry, workers with different forms of employment face different conditions. For example

| Industry                                      | NIC Code | Emp. Status | Coefficient Female | Coefficient Male |
|-----------------------------------------------|----------|-------------|--------------------|-----------------|
| Manufacture of chemical and chemical products | 20       | sal-emp    | 0.26               |                 |
| Food and beverage service activities         | 56       | sal-emp    | 0.27               |                 |
| Manufacture of food products                 | 10       | slf-emp    | 0.27               |                 |
| Wholesale trade, except of motor vehicles    | 46       | sal-emp    | 0.30               |                 |
| Land transport and transport via pipelines   | 49       | csl-emp    | 0.33               |                 |
| Other manufacturing                          | 32       | sal-emp    | 0.34               |                 |
| Land transport and transport via pipelines   | 49       | slf-emp    | 0.34               |                 |
| Wholesale trade, except of motor vehicles    | 46       | slf-emp    | 0.39               |                 |
| Computer programming etc                     | 62       | sal-emp    | 0.47               | 0.32            |
| Security and investigation agencies          | 80       | sal-emp    | 0.40               |                 |
| Public administration and defence            | 84       | sal-emp    | 0.50               | 0.30            |
| Education                                    | 85       | sal-emp    | 0.47               | 0.34            |
| Land transport and transport via pipelines   | 49       | sal-emp    | 0.41               |                 |
| Manufacture of wearing apparel               | 14       | sal-emp    | 0.55               | 0.29            |
| Manufacture of textiles                      | 13       | sal-emp    | 0.49               | 0.34            |
| Food and beverage service activities         | 56       | slf-emp    | 0.49               | 0.36            |
| Human health activities                      | 86       | sal-emp    | 0.43               |                 |
| Activities of households as employers of domestic personnel | 97 | sal-emp | 0.46 | 0.41 |
| Other personal service activities            | 96       | sal-emp    | 0.44               |                 |
| Retail trade, except of motor vehicles       | 47       | slf-emp    | 0.54               | 0.33            |
| Crop and animal production                   | 01       | slf-emp    | 0.52               | 0.35            |
| Manufacture of wearing apparel               | 14       | slf-emp    | 0.65               | 0.27            |
| Financial services, except insurance and pension | 64 | sal-emp | 0.63 | 0.30 |
| Manufacture of tobacco products              | 12       | slf-emp    | 0.63               | 0.30            |
| Retail trade, except of motor vehicles       | 47       | sal-emp    | 0.55               | 0.43            |
| Specialized construction activities          | 43       | csl-emp    | 0.50               |                 |
| Construction of buildings                    | 41       | slf-emp    | 0.51               |                 |
| Manufacture of textiles                      | 13       | slf-emp    | 0.57               | 0.44            |
| Crop and animal production                   | 01       | csl-emp    | 0.72               | 0.30            |
| Construction of buildings                    | 41       | csl-emp    | 0.60               | 0.49            |
| Other personal service activities            | 96       | slf-emp    | 0.86               | 0.33            |
| Education                                    | 85       | slf-emp    | 0.64               |                 |
| Manufacture of textiles                      | 13       | csl-emp    | 1.00               |                 |
| Manufacture of rubber and plastic products   | 22       | sal-emp    | 1.06               |                 |
in education, salaried women have a gross flow estimate of 0.47 while self-employed women have a gross flow estimate of 0.64.

When it comes to states, the most significant fact about Table 6 is the small number of entries. For most state-gender combinations the estimated coefficient is not statistically significant, confirming that most of the variation among states is driven by differences in industrial composition among states and not state-specific factors.

Unfortunately, there is no discernable pattern among the states whose coefficients are in fact statistically significant. We must conclude that these differences must be explained by idiosyncratic factors.

### 6 Determinants of Job Loss and Gain

The analysis in the previous sections looked at gross flows between consecutive pairs of quarters. However, our data actually tracks workers for up to four quarters. In this section, we use this additional information to look at how labour market states of workers are correlated over longer time spans. At the same time we extend our study of gender differences and see how other worker characteristics influence labour market transitions for men and women.

To keep the analysis tractable we collapse the labour market states into just two: employment and non-employment. We choose not to use the traditional three-way classification of employment, unemployment and non-participation in the light of our observation earlier on the possible conceptual and measurement overlap between unemployment and non-participation.

To track the transitions between these two states we define two dummy variables: Lost and Gained. Lost is 1 for observations in which the individual is employed in that quarter but is not employed in the next quarter, and 0 otherwise. Gained is 1 for observations in which the individual is not employed in that quarter but is employed in the next quarter. Thus, Gained and Lost measure movements into and out of employment. For the interpretation of the results to follow it must be remembered that both these variables have the value 0 both for those who are out of

| Table 6 Regression coefficients, state $\gamma_k$ (only coefficients significant at 5% level of significance, baseline Maharashtra-Male). Source: Author’s calculations based on PLFS data |
|----------------------------------|-----------------|-----------------|
| State                           | Female          | Male            |
| Telangana                       | −0.16           | −0.08           |
| Karnataka                       | −0.11           |                 |
| Gujrat                          | −0.09           | −0.05           |
| Maharashtra                     | −0.08           | −0.06           |
| Andhra Pradesh                  | −0.08           |                 |
| Tamil Nadu                      | −0.07           |                 |
| Madhya Pradesh                  | 0.04            |                 |
| Uttar Pradesh                   | 0.06            |                 |
| Haryana                         | 0.09            |                 |
| Kerala                          | 0.09            |                 |
employment and remain out of employment and for those who are in employment and remain in employment.

As explanatory variables, we use the following worker characteristics:

1. **Very.Young**: Has the value 1 if the individual’s age is less than 21 and 0 otherwise.
2. **Young**: Has the value 1 if the individual’s age is between 21 and 30 and 0 otherwise.
3. **Graduate**: Has the value 1 if the individual’s general education level is graduation or higher and 0 otherwise.
4. **Has.Child**: Has the value 1 if the individual belongs to a family which has a child less than 5 years of age and 0 otherwise. We have to use this proxy for child-bearing since the data does not provide any information to link parents to children.
5. **Married**: Has the value 1 if the individual is currently married and 0 otherwise.

We also include as explanatory variables the following two summaries of the individual’s employment history:

1. **E.Ratio**: It is the net fraction of periods in which the individual has been observed to be employed. For worker $i$ in quarter $t$, let $E_i$ be the total number of quarters (not necessarily consecutive) up to and including $t$ in which we have observed them to be employed and $N_i$ be the total number of quarters (not necessarily consecutive) up to and including $t$ in which we have observed them not to be employed. Let $V_i$ be the visit number (between 1 and 4) for that individual in quarter $t$. Then we define:

$$E.\text{ratio}_i = \frac{E_i - N_i}{V_i}$$

2. **EN.Streak** For individual $i$ in quarter $t$, this is the number of consecutive periods up to and including $t$ for which they have been in the same state that they are in quarter $t$. So for an employed individual this is the number of consecutive periods we have observed them to be employed while for non-employed individuals this is the number of consecutive periods we have observed them not in employment. This is set up as a categorical variable.

Using these variables we estimate the following equations using logit.

$$\frac{\text{Lost/Gained}}{\text{Lost/Gained}} = 1 + \text{Very.Young} + \text{Young} + \text{Graduate}$$

$$+ \text{Has.Child} + \text{Married} + \text{E.Ratio} + \text{EN.Streak}$$

$$+ \text{[Period dummies]} + \text{[Visit no. dummies]}$$

The equation for **Lost** is run on the set of individuals in employment while the equation on **Gained** is run on the set of individuals not in of employment. For each individual, data from visits up to one less than the last recorded visit is used.
since the variables Lost and Gained are defined by looking one quarter ahead. Observations for all quarters and all workers are pooled together. Each model is estimated separately for men and women.

Table 7 gives the average marginal effects from the logit models. The numbers in parentheses are standard errors.

Being ‘very young’, i.e. being in the age group 15–20, increases the probability of job losses and decreases the probability of job gains. There are two potential explanations for this. One would be the precarity of the job market for young, inexperienced and less-educated workers. The other would be the fact that this is the age range for school and undergraduate education, and individuals in educational institutions in these age groups are more likely to continue education than join employment and those in employment are likely to leave employment to continue their education. Indeed, in our sample, 81.10% of the ‘very young’ who are not in employment report attending educational institutions. Of those leaving employment in this age group, 27.55% report attending an educational institution in the next quarter. Thus education does have a role to play. However, even if the equations for Lost are estimated after dropping observations with employment to education transitions, being ‘very young’ still has a positive, significant effect, showing that precarity plays a role too.

For the young, i.e. the age group 21–30, the probabilities for both job loss and job gain are higher than the baseline. In this age group the outcomes for men and women diverge significantly. The additional loss probability for women is now more
than three times that for men. The additional gain probability is positive and significant for men and very small and statistically insignificant for women. In this age group while men are more likely to enter employment, presumably after completing their education, women are losing employment.

Being a graduate reduces the probability of both job loss and job gain for both men and women. This is presumably because those with graduate and higher degrees have a more secure work life. Those in employment are less likely to lose jobs, and those out of employment are there by choice and not because of unwanted job loss, and hence are less likely to move into employment.

Having a child in the family does not have a statistically significant effect on the probability of job loss. The effect on job gain is significant and in opposite directions for men and women: negative (though small in magnitude) for women and positive for men.

The effect of marriage too is quite different for men and women. Being married reduces the probability of job loss and increases the probability of job gain for men. For women, it is the opposite: the probability of job loss goes up and that of job gain goes down.

Overall, the picture that emerges is that of a gender- and age-differentiated labour market with women and the young facing greater employment instability.

When it comes to work histories the EN.Streak variables are negative and significant in all regressions. To recall, these measure that number of consecutive prior quarter in which the individual has been in the same state as in the quarter of observation. Thus this variable has a different meaning in the Gained and Lost regressions. For the Gained equation, estimated on the sample of individuals not in employment, it is the number of consecutive prior quarters they have not been in employment. For the Lost equation, estimated for the sample of individuals in employment, it is the number of consecutive prior quarters they have been in employment. Thus the results show the existence of inertia in job market states. Prolonged periods of non-employment perpetuate non-employment and prolonged periods of employment perpetuate employment. The magnitude of the estimated effects is larger for streaks of length three compared with streaks of length two, showing that this inertia becomes stronger the longer the worker is in employment or non-employment.

Even after controlling for the streak variables, the variable E.Ratio remains statistically and economically significant: negative in job loss regressions and positive in job gain regressions. Thus it is not only consecutive spans of employment and non-employment which affect the probabilities of job gains and losses. Past occurrences of employment make getting back into employment more likely and getting out of employment less likely, even after controlling for the immediately prior history.
7 Conclusion

This study reveals a rich world of micro-level transitions in the urban Indian labour market with a great degree of diversity across genders, industries, and regions. It is hoped that as more data becomes available we will be able to better tease out the institutional factors underlying this diversity. Essential to that endeavour would be panel data on jobs from the firm side and the ability to match workers and employers. The introduction of PLFS gives us hope that Indian official data would expand to cover these aspects as well.

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