Azim Premji University

CSE Working Paper

#50

Labour Market Flows and Gender Differentials in Urban Unemployment Over the Pandemic

Paaritosh Nath and Rahul Menon

May 2023

Centre for Sustainable Employment

cse@azimpremjiuniversity.edu.in

LABOUR MARKET FLOWS AND GENDER DIFFERENTIALS IN URBAN UNEMPLOYMENT OVER THE PANDEMIC[1]

Abstract: Utilising data from the Periodic Labour Force Survey, we estimate quarterly changes in urban labour market flows over the period 2018 to 2022 and the impact on unemployment rates for men and women. Our analysis provides non-intuitive explanations for established findings as well as pointing out important questions for further study. Both men and women's unemployment rates have reduced in 2022 compared to 2018, showing rapid reductions following the high levels reached during the lockdown. Women's unemployment rates have consistently been higher than men throughout this period. The gap between men and women's unemployment rates reduced during the lockdown, but have shown signs of increasing since 2021, even as unemployment rates have fallen. For women, flows from the labour force to non-participation play a larger role in explaining changes in unemployment rates as compared to men. Flows from the labour force to non-participation, however, have reduced since the pandemic, providing an explanation as to why labour force participation rates have increased, namely, women staying for longer in the labour force rather than more women entering it. Despite rising labour force participation rates, the gender gap in unemployment rates have risen, in contrast to developed economies.

Paaritosh Nath, Azim Premji University[2]

Rahul Menon, O.P. Jindal Global University[3]

[1] 1 The authors would like to thank the anonymous reviewer for their comments. The usual disclaimer applies.

[2] paaritosh.nath@apu.edu.in

[3] rahul.menon@jgu.edu.in

INTRODUCTION

The question of unemployment in India - long thought to be of relatively minor importance in a developing economy - has emerged as an important question following two events: the release of the Periodic Labour Force Survey (PLFS) for the year 2017-18 – which recorded a historically high unemployment rate of 6.1% - and the impact of the coronavirus pandemic. Making use of methodological innovations introduced by the PLFS, this paper examines labour market flows from July 2018 to September 2022 to examine the factors influencing changes in unemployment rates across genders. This allows for an examination of the impacts of the two waves of the pandemic on urban labour markets. While both periods saw a rise in unemployment rates followed by significant declines, the first wave was marked by much higher increases in unemployment – due to the nationwide lockdown – and a faster rate of reduction. While urban women suffer from higher unemployment rates than men – a structural feature that necessitates urgent attention form policy and academia alike – the first wave saw a narrowing of the gender unemployment gap, a narrowing not seen during the second wave.

This paper utilizes data from the PLFS to analyse factors driving changes in unemployment rates between men and women, and the gender differential in unemployment rates from 2018 to 2022. We analyse flows in the labour market between employment, unemployment and non-participation, presenting a dynamic analysis of unemployment and gender differences, an original contribution to a question that has not received much attention till date. The new design of the PLFS follows urban individuals once every quarter for four quarters, allowing for an examination of labour market flows (in contrast to earlier surveys undertaken by the National Sample Survey Office (NSSO)). This analysis can only be undertaken for the urban sector, and hence we cannot say anything about rural flows. By calculating rates of labour market transitions, we study the influence of job-finding and job-loss on the unemployment rate, and are able to separate out the relative contributions of direct flows – between employment and unemployment – and indirect flows – from within the labour force to activities outside the labour force and back into the labour force again – to changes in unemployment rates between genders.

Our analysis throws up important findings regarding urban unemployment and the labour market difficulties faced by women, while providing explanations for some significant outcomes. For one, employment generation rates are extremely low, particularly for women. The only times job creation rates rose were in the quarters immediately after the first and second waves, helping reduce unemployment rates caused by the dislocations of the two pandemic waves. These surges were short-lived, and employment generation rates always fell back to their previous low levels soon after.

Our analysis shows that indirect flows play a much greater role in influencing women's unemployment rates as compared to men. The flows from employment and unemployment to non-participation are higher for women than men, though there has been a significant reduction in these flows over time. The reduction in both these flows also explains the rise in labour force participation rates, brought about by individuals staying in the labour force for longer, rather than being caused by increased rates of entry. However, despite rising labour force participation rates for women and falling unemployment rates for both genders, the gender gap in unemployment rates have worsened since 2021, owing to faster reductions in men's unemployment rates when compared to women. While it is still too early to say whether these are permanent or temporary changes, this study aims to highlight its importance and possible implications for future changes in unemployment.

In this analysis, we make no distinction between "decent" or precarious jobs. We simply look at movements into and out of the overall category of employment. Secondly, while aware of the significant difficulties in conceptually measuring the "unemployed" during such times of massive upheavals such as a pandemic, our analysis uses the categorisation of the 'unemployed' as provided in the official PLFS documentation[4]. Furthermore, this period covers a relatively short period – July 2018 to September 2022 – and hence these findings should not be taken as definitive outlines of long-term trends of the economy or of labour flows. Our main intention is simply to categorise and evaluate different forms of labour market flows and its differential impact on unemployment for men and women, bringing into focus some important aspects of unemployment that require urgent attention and study.

[4] Based on a survey of 8530 individuals between May-July 2020, Bhalotia et al (2020) report that while 15.5% of the sample report being unemployed in the week before the interview, a figure which rises to 21.7% if those receiving 0 income were included. Mishra and Das (2022) classify those workers who received zero income while being employed as unemployed. Abraham (2020) highlights how during a significant exogenous shock like a pandemic, individuals – particularly women - who would have lost their jobs may not classify themselves as being "unemployed", but may report themselves as being out of the labour force. These studies stress the important point that during a pandemic, the normal classifications of employment and unemployment may not capture the full reality of work loss and its impact on income, earnings and well-being. While these criticisms of standard definitions of work status is important, we refrain from widening the ambit of the category "unemployment": our aim is to analyse the factors driving changes in the measured unemployment rate - as understood by the standard notation - over a longer time period that does not just include the pandemic.

The Pandemic and Job-Loss

The imposition of the lockdown in 2020 led to output shrinking by 23.9% in the April-June quarter of 2020 and by 7.3% during the period 2020-21[5][6]. Using data from the Centre for Monitoring Indian Economy (CMIE), employment numbers declined by roughly 26 million between the quarters September-December 2019 and January-April 2020, with unemployment rates rising to 11.6% during the quarter May-August 2020 (Roychowdhury et al, 2022). Using PLFS data in comparison, Kannan and Khan (2022) estimate a reduction in urban employment of 17.51 million when comparing the second quarter of 2020 – covering April to June 2020 - with quarter 2 of 2019. An early survey conducted by researchers at the Azim Premji University outlined the extent of the reduction in earnings and food security as a result of the pandemic: nearly 60% of households reported difficulties in affording a week's worth of essentials (Kesar et al, 2021.[7]

The first wave of the pandemic saw an increase in informal employment and a movement from formal salaried employment into self-employment and daily wage work. Households saw rising debt and food insecurity, with a significant proportion of households reporting food insecurity even 6 months after the pandemic[8]. In 2021, CMIE data revealed significant signs of weakness in Indian labour markets: youth unemployment and agricultural unemployment had increased, with women's labour force participation reducing (CEDA-CMIE 2022).

An important trend highlighted by many authors was the gendered impact of the pandemic. During the first wave, urban women, who made up 3% of total employment, suffered 39% of total job losses (IWWAGE, 2021)[9]. As outlined by Deshpande (2020), while more men lost jobs in absolute terms, the probability of women regaining employment was lesser than that of men. Men appeared to have moved across industries and different employment arrangements, while women tended to move out of the workforce, revealing the lack of suitable "fallback" options for women. Women experienced higher probabilities of losing work as well as not returning to work

[5] https://www.hindustantimes.com/india-news/india-s-gdp-growth-rises-falls-by-23-9-per-cent-in-april-june-quarter/story-Yj1GGTR7fuHAQ6QNL0jpBL.html

[6] https://www.thehindu.com/business/Economy/indias-gdp-grows-16-in-january-march-shrinks-73-in-2020-1/article34690310.ece

[7] See Jha and Kumar (2020) for an extensive discussion of findings from field surveys.

[8] https://www.hindustantimes.com/business/the-poorest-have-been-worst-hit-by-pandemic-101611781491571.html

[9] The study notes that in the second wave, the brunt of job losses was experienced by urban men.

compared to men (Abraham, Basole and Kesar, 2022). Permanent job losses were seen more in the case of women than men (Azim Premji University, 2021), indicating heightened insecurities for a demographic cohort already beset by low labour force participation and adverse conditions of work. Women's work worldwide was hit disproportionately as a result of the pandemic, with women's employment-to-population ratios falling more than men's (ILO, 2021). Given the multiple axes of discrimination faced by women, some authors have urged for policy interventions directed specifically at women to ameliorate the harms of the pandemic (Mitra and Sinha, 2021).

There have been a number of studies that have utilised new datasets – both public and private – to analyse the broad trends in the Indian labour market in the wake of the pandemic. Das (2023) and Singh (2023) point to the high rates of job loss for women and younger workers in the pandemic, while Sengupta (2023) notes a significant reduction in earnings of urban households during the lockdown and the presence of a significant earnings gap between urban men and women. Both of these studies utilised the rotational panel schema of the PLFS. Chatterjee and Dev (2023) use CMIE data to examine the impact of the pandemic on access to full-time and part-time work, finding significant differences in the ability of men and women to access full-time work across educational groups.

Data and Methodology

In contrast to the 5-yearly Employment and Unemployment Surveys (EUS) undertaken by the NSSO, the PLFS is conducted yearly, allowing for a more detailed look at changes in labour markets in India. Secondly, the PLFS allows for the construction of longitudinal panels. Each individual in the urban sample is followed once every quarter for four quarters, enabling for a truly dynamic analysis of labour in India, as opposed to the cross-sectional data of the EUS.

The National Statistics Office has been publishing regular Quarterly Bulletins since June 2020, outlining important statistics on urban employment. The reports span the period from April 2018 to September 2022, data being recorded for each three-month period (or quarter). Table 5 in each report contains information on labour market flows between each pair of subsequent quarters. For instance, these reports track the total share of individuals who were employed in the first quarter who have moved into either employment, unemployment or non-participation (out of the labour force) in the subsequent quarter. Similarly, the reports record such movements from unemployment and non-participation. The reports quantify these measures of labour market flows by estimating the total shares of individuals – as a share of the total population – surveyed between two adjacent quarters who have moved between any two labour market categories across those quarters.

Using these figures as tabulated by the PLFS Quarterly reports, we calculate labour market transition probabilities. Our methodology is as follows. We adopt the Current Weekly Status (CWS) classification of the PLFS, classifying individuals into three statuses: employed E – comprising statuses 11 to 72 – unemployed U – statuses 81 and 82 – and out of the labour force O (or non-participation - statuses 91 to 98). We do not make a difference as to the kinds of work undertaken; our measure of the employed E includes the self-employed, those in casual labour and those regularly employed. Similarly, we classify as unemployed all those available for work, whether they actively sought it or not. We define transition probabilities as measuring the probability that any individual initially in status i in the initial quarter transitions to status j by the next quarter. Thus, the transition probability l_t^{ij} measures the number of individuals in status i at time t (i = E,U,O) transitioning to status j in time *(t+1)* (j = E,U,O) as a proportion of those in status i in time t. There are 9 such transitions possible for any individual in any quarter, and hence 9 transition probabilities calculated each quarter. The method of labour market transitions has been utilised for the study of gender gaps in unemployment for the developed economy (Azmat. Guëll and Manning, 2006, Albanesi and Sahin, 2018); this analysis could not be done for the Indian economy for periods prior to 2017 owing to the lack of data.

The Quarterly Reports of the PLFS records these movements as proportions of the entire population, and separately for employment categories (i.e. self-employed, regular wage workers and casual workers). We aggregate the different employment categories into one category we term the Employed (for ease of analysis), and convert the population proportions into transition probabilities. The data is recorded for all persons, men and women from the quarter of April-June 2018 to July-September 2022. In this paper, we classify the quarters in the following way: Q1 covers the quarter January-March, Q2 covers April-June, Q3 July-September and Q4 October-December.

There are some significant problems with regard to the data collected. Given the structure of the PLFS, where individuals are interviewed once every quarter, it is hard to completely isolate the impact of the different waves of the pandemic and the lockdown. The nationwide lockdown was imposed on March 24, 2020, and lasted till May of that year, while the process of opening up or "unlocking" began from June 2020. Thus, the full impact of the lockdown can be seen in the quarter April-June 2020

(Q2 2020), even though this quarter covers the lockdown as well as the beginning of the process of opening up. Similarly, the second wave's impact can be seen in Q1 2021, covering the period from January to March 2021.

Furthermore, the impact of the lockdown and the pandemic imposed significant difficulties with respect to the conduct of the survey itself. Field work for the collection of data was suspended from 18th March 2020 to 1st June 2020. When fieldwork resumed, information for the intervening period was collected in a retrospective manner. Moreover, revisit interviews were collected telephonically for all quarters up till September 2022. The reports also state that there existed some hesitation with regard to providing such information and meeting enumerators physically owing to concerns about the pandemic, but that respondents were "…sensitised and motivated to provide information" (NSO, 2022, pg 2)" All these factors – the conduct of telephonic interviews, retrospective interviews and the fears of respondents – may have introduced bias to responses. We do not undertake any attempt to correct for these biases in this work, leaving it open to future research to investigate and correct for these biases, if they are found to be significant.

Our methodology of estimating and decomposing worker flows is largely taken from Elsby et. al. (2011). The numbers of the unemployed increase (decrease) if individuals move from employment to unemployment (unemployment to employment), or if they move from non-participation to unemployment (unemployment to non-participation). The flow measure E-U, which measures the transition probability of moving from employment in any quarter to unemployment in the next quarter gives us the job-loss rate, while the flow measure U-E gives us the job-finding or employment generation rate. Thus, the change in the numbers of the unemployed across any two periods *t* and *t+1* can be given by:

$$\Delta U_t = l_t^{EU}.E_t + l_t^{OU}.O_t - (l_t^{UE} + l_t^{UO}).\ U_t$$

Where l_t^{ij} measures the transition probability between states i *and* j from period t to period *t+1*, and E_t, U_t and O_t stand for the numbers of those employed, unemployed and out of the labour force at time t respectively.

In order to focus only on labour flows, define a steady-state unemployment rate $u*$ where $\Delta U_t = 0$. This steady-state unemployment rate should not be seen as an expression of any inherent equilibrium potential of the economy, given the relatively short period of quarter-to-quarter changes estimated here, but as a method to identify and analyse the extent of labour market flows and its impact on unemployment.

Using similar equations for changes in the numbers of the employed and those out of the labour force respectively, the steady-state unemployment rate may be derived as:

$$u^* = \frac{s_t}{s_t + f_t} \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

where s_t and f_t are the inflow and outflow rates respectively at time t, where:

$$s_t = l_t^{EU} + l_t^{EO} . \frac{l_t^{OU}}{l_t^{OU} + l_t^{OE}} \text{ and } f_t = l_t^{UE} + l_t^{UO} . \frac{l_t^{OE}}{l_t^{OU} + l_t^{OE}}$$

The inflow and outflow rates can be expressed as a simple sum of direct and indirect labour market flows affecting unemployment. The direct components of inflow and outflow rates are given by l_t^{EU} and l_t^{UE} respectively, where l_t^{EU} measures the job-loss rate and l_t^{UE} the job-finding rate. The indirect components (l_t^{EOU} and l_t^{UOE}) measure the rates of movement from employment (unemployment) to unemployment (employment) through non-participation.

Our final set of decompositions involve decomposing changes in the inflow and outflow rates as follows:

$$\Delta \ln . s_t = w_t^s \Delta \ln . l_t^{eu} + (1 - w_t^s) . \Delta \ln . l_t^{eou} \quad \ldots\ldots\ldots\ldots \text{(2)}$$

$$\text{And } \Delta \ln . f_t = w_t^f \Delta \ln . l_t^{ue} + (1 - w_t^f) . \Delta \ln . l_t^{uoe} \quad \ldots\ldots\ldots\ldots \text{(3)}$$

Where $w_t^s = \frac{l_t^{eu}}{s_t}$ and $w_t^f = \frac{l_t^{ue}}{f_t}$

Aggregate Unemployment Rates

Table 1 presents yearly unemployment rates according to the UPSS and CWS status over the last four PLFS annual rounds. As expected, the CWS records a higher unemployment rate, since the probability of being engaged in some work varies positively with the length of the reference period, the CWS adopting a shorter reference period of a week compared to one year used for the UPSS. The CWS unemployment rate for all individuals is roughly constant till 2019-20, before falling in 2020-21. While men's unemployment increases in 2019-20, women's unemployment shows a constant fall throughout.

Table 2 disaggregates unemployment rates by gender and sector. Three main findings emerge. Firstly, CWS unemployment rates are universally higher than UPSS rates, within sectors (rural and urban), for both genders and across all years. Secondly, urban unemployment rates are universally higher than rural rates, for both genders and both statuses (the gap is smallest for men's CWS unemployment). Third, while urban men's CWS unemployment rose from 2017-18 to 2020-21, urban women experienced the highest unemployment rates compared to any other cohort across all years. Urban men saw their unemployment rate rise from 8.8% in 2017-18 to 9.4% in 2020-21, while urban women's unemployment rate in 2020-21 was 12.2%, a marginal reduction from that experienced in 2017-18 (12.8%).

Table 1: Aggregate Unemployment Rates

	Male		**Women**		**Persons**	
	UPSS	**CWS**	**UPSS**	**CWS**	**UPSS**	**CWS**
2017-18	6.2	8.8	5.7	9.1	6.1	8.9
2018-19	6	8.8	5.2	8.7	5.8	8.8
2019-20	5.1	9.3	4.2	7.3	4.8	8.8
2020-21	4.5	7.8	3.5	6.6	4.2	7.5

Source: Various Annual PLFS reports

The difference in reference periods explains why urban men's CWS unemployment rates rose, but not the UPSS. Imagine an individual who had steady employment over the previous year, but lost their job during the lockdown. They would be counted as employed according to the UPSS status, but unemployed according to the CWS status. While this explains the difference in trends for urban men's CWS and UPSS unemployment rates, it does not explain why women's unemployment rates across both statuses fell.

Moreover, the CWS status, when aggregated across the entire year, may present a misleading picture. If a majority of the individuals rendered unemployed during the lockdown were to find employment in the subsequent quarters, the CWS unemployment rate might be high during the period of the lockdown, and would fall in following quarters. The yearly CWS rate, when averaged across all quarters, would thus incorporate both these effects. The urban CWS unemployment rate in Table 2 indicates that unemployment rate rose from 9.5% to 11% across 2018-19 and 2019-20, a rise that incorporates both the loss in jobs during the lockdown and the subsequent recovery.

Table 2: Unemployment Rates across sectors

	Male				Women				Persons			
	UPSS		CWS		UPSS		CWS		UPSS		CWS	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
2017-18	5.8	7.1	8.8	8.8	3.8	10.8	7.7	12.8	5.3	7.8	8.5	9.6
2018-19	5.6	7.1	8.7	8.9	3.5	9.9	7.3	12.1	5	7.7	8.4	9.5
2019-20	4.5	6.4	8.7	10.6	2.6	8.9	5.5	12.4	4	7	7.9	11
2020-21	3.9	6.1	7.2	9.4	2.1	8.6	4.8	12.2	3.3	6.7	6.5	10.1

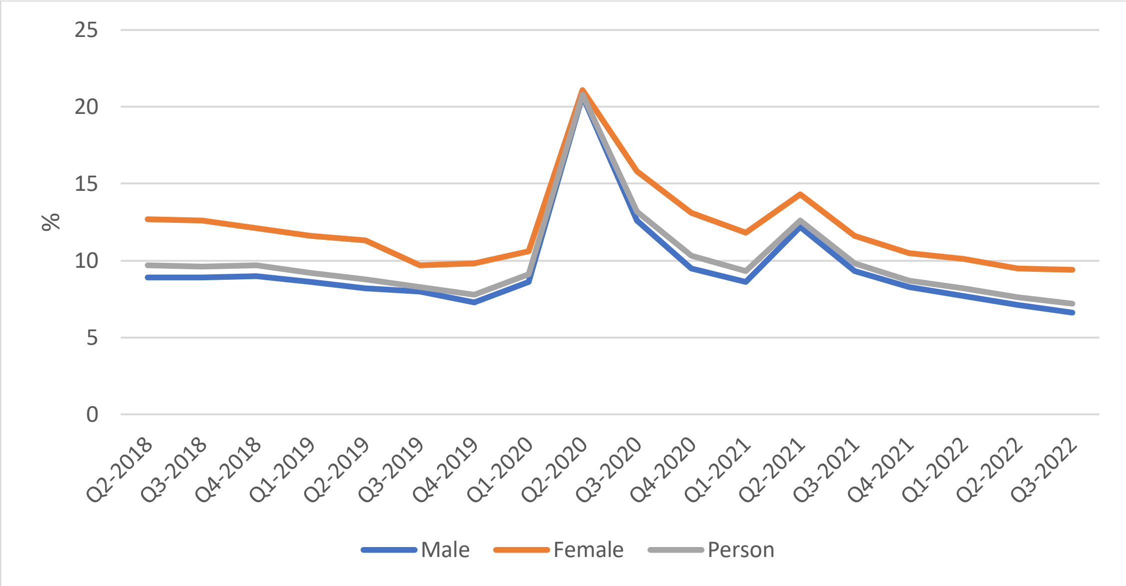
Source: Various Annual PLFS reports

To fully account for changes in unemployment during the pandemic, a quarter-to-quarter analysis is important. Figure 1 shows the quarterly unemployment rates disaggregated by gender from the period April-June 2018 to July-September 2022, as taken from the Quarterly Bulletins of the PLFS. The CWS unemployment rates here measure unemployment within each quarter.

In the quarter April-June 2020 - the quarter covering the lockdown period - the unemployment rate rose to 20.8%, as compared to 7.8% in October-December 2019. The rise in the unemployment rate in January-March 2020 incorporates the loss in unemployment during the last week of March 2020, when the lockdown was announced. The unemployment rate fell in the quarters following the lockdown, before rising again one year hence, in April-June 2021, and then showing a subsequent reduction. The rise in unemployment rates during the first half of 2021 may indicate the effect of the second wave.

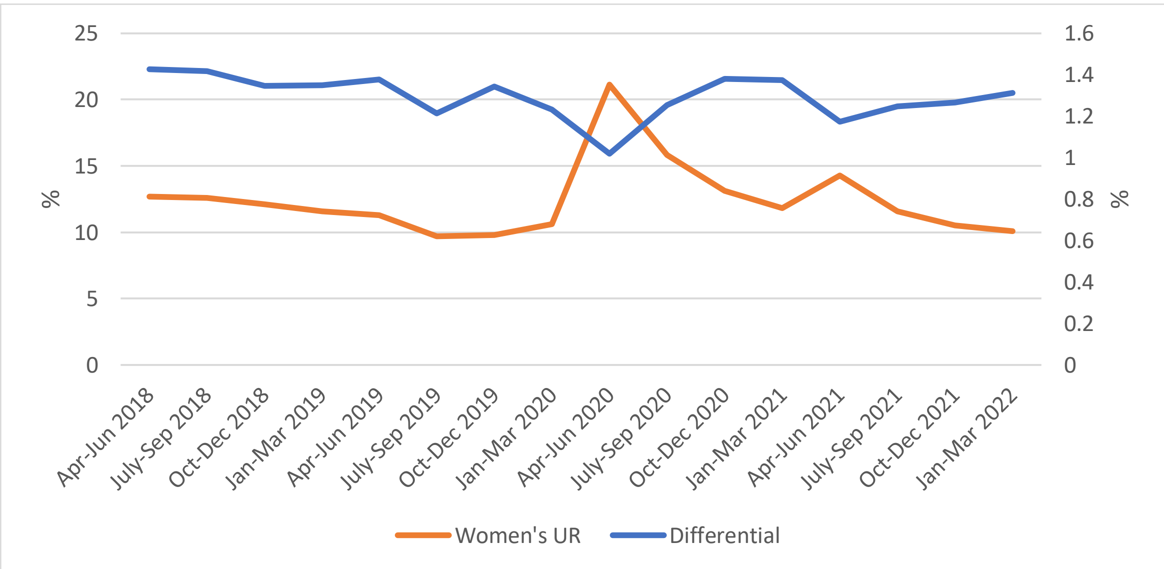
Two features are of interest. First, women's unemployment rates are consistently higher than men's rates. The second feature relates to the narrowing of the gender unemployment gap during the first lockdown, with both men's and women's unemployment rates roughly converging (20.7% and 21.1% respectively). Given that men's unemployment rates were lower in the previous quarter (8.6% for men and 10.6% for women), it indicates a greater impact of the lockdown on men's unemployment than women. However, during the second period of rising unemployment, there is no convergence, with women's unemployment rates (14.3%) higher than that of men's (12.2%).

Figure 1: Quarterly Unemployment Rates



Source: PLFS Quarterly Bulletins, various reports

Figure 2: Women's Unemployment Rate and Unemployment Differences



Source: PLFS Quarterly Bulletins, various reports

Note: Women's unemployment rate (Women's UR) is measured on the left-hand axis. Differential indicates the ratio of women's to men's unemployment rate, measured on the right-hand axis.

Figure 2 outlines the gender differential (the ratio of women's to men's unemployment rate) and women's unemployment rates. The differential in early 2022 is lower than what it was in 2018. Before the first wave, both women's unemployment rates and the differential showed signs of a gradual reduction. During the first and second waves, when women's unemployment rates rose, the differential reduced, indicating a faster rise in men's unemployment rates during the two waves. Following the second wave, however, even though women's unemployment rates reduced, the differential increased, indicating a faster *reduction* of men's unemployment rates.

The unemployment rate at time *t* can be written as:

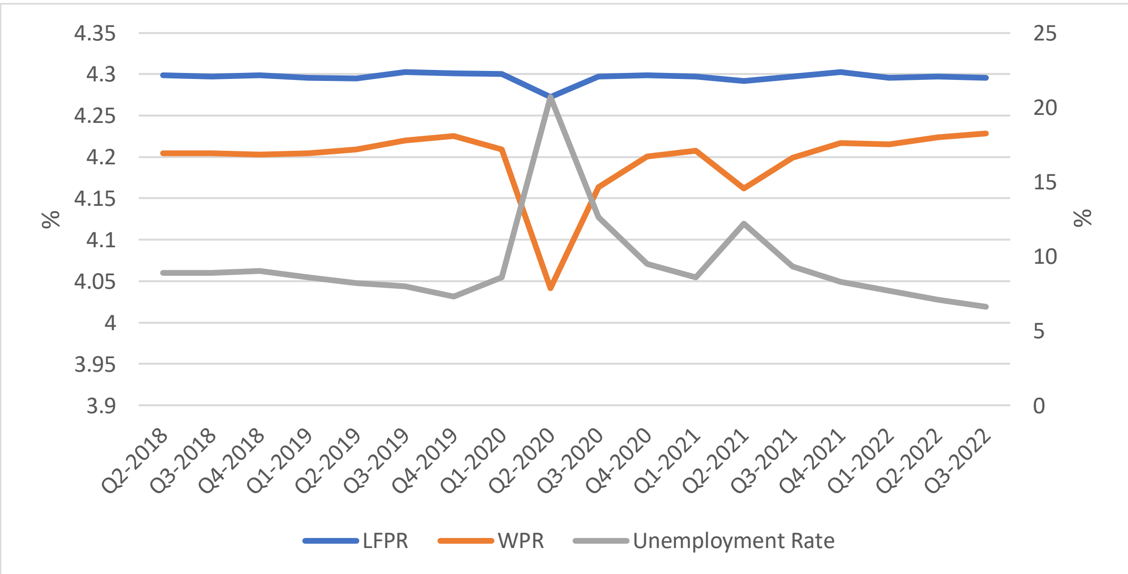
$u_t = 1 - \frac{WPR_t}{LFPR_t}$ where u_t is unemployment rate, $LFPR_t$ is the labour force participation rate and $WPR_t$is the worker-to-population ratio at time *t*.

The change in the unemployment rate between *t* and *(t+1)* can be approximated to:

$\Delta u_t = (1 - u_t).(d.\log(LFPR_t) - d.\log(WPR_t))$ ………….(3)

Figures 3 and 4 plots the LFPR, WPR and the unemployment rate for men and women, with the LFPR and WPR plotted in logs. The increase in the unemployment rate during the first lockdown is clearly visible, with the WPR and LFPRs showing a significant fall during that period, for both men and women.

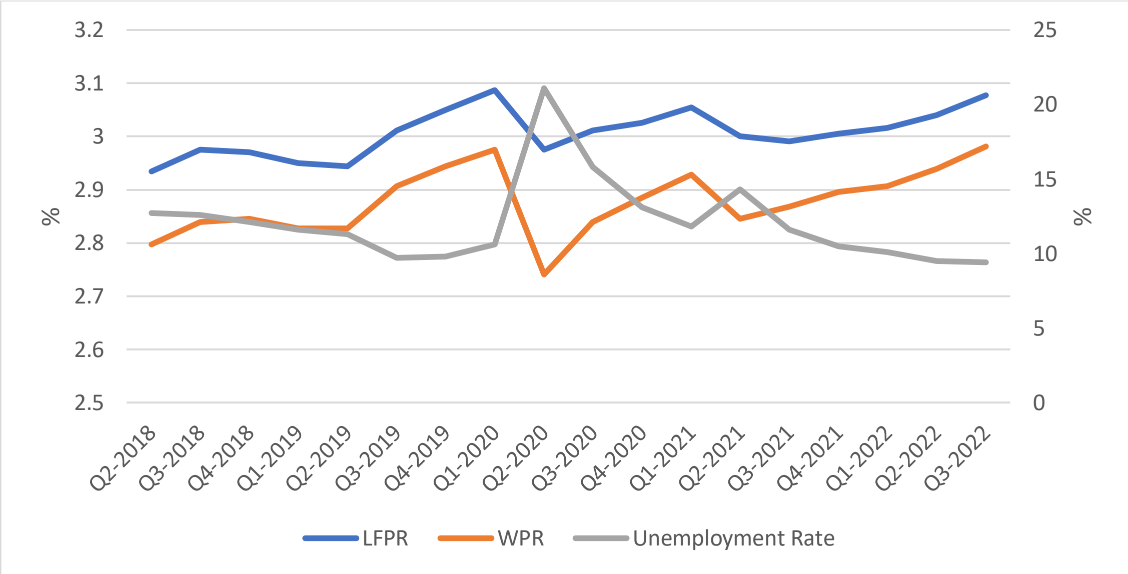
Figure 3: LFPR, WPR and Unemployment Rates: Men



Source: PLFS Quarterly Bulletins, various reports

Note: LFPR and WPR measured in logs on the left-hand axis, Unemployment rates measured in basis points on the right-hand axis.

Figure 4: LFPR, WPR and Unemployment Rates: Women



Note: Same as Figure 2

The first lockdown (Q2-2020) saw a significant reduction in the WPR, falling by 15.4% for men and 21% for women. However, women's LFPR fell by more as compared to men, resulting in a larger rise in men's unemployment rates even though women faced a larger reduction in the WPR. Following the lockdown, unemployment rates reduced for both genders accompanied by sustained increases in both WPRs and LFPRs, indicating a greater increase in employment generation as compared to labour force participation.

During the second wave (Q2-2021), men's WPR fell by 4.5% while women's fell by 8%. The difference lies in labour force participation: men's LFPR remained largely constant, while women's fell by 5.2%. While men's unemployment rates did register a higher rise than women's, the gap remains due to women's unemployment rates being comparatively higher in the quarter prior to the lockdown. Men's unemployment rate falls to 8.6% in Q1-2021 following the lockdown – similar to its level in Q1-2020 – while women's unemployment rate is 11.8% in this period, as compared to 10.6% a year prior. The slower pace of women's unemployment reduction between the two waves contributed to the re-emergence of the gap in the second wave. Following the second wave, women's LFPRs and WPRs have shown a consistent increase, ending at higher levels in Q3-2022 compared to Q2-2018, resulting in unemployment rates at lower levels as compared to the initial period – 6.6% for men, 9.4% for women as compared to 8.9% and 12.7% in the beginning of 2018.

Faster employment generation in the face of rising LFPRs has no doubt contributed to this fall. Yet this does not automatically imply that this is an unambiguously beneficial outcome. There has been a shift in the nature and character of employment, especially for women, as shown in Table 3. When comparing Q2-2018 with Q3-2022, women have experienced a reduction in regular wage work and casual labour, and an increase in self-employment. Within self-employment, while own-account workers and employers have increased, there has also been an increase in unpaid family helpers, from 9.9% of the female workforce to 11.5%. Moreover, there has been an increase – from 6.7% to 8.9% - in the share of urban working women engaged in the primary sector, a reversal of trends normally expected from an economy undergoing structural transformation. These outcomes clearly point to a spread of distress employment (Kannan and Khan, ibid, Dhamija and Chawla, 2023).

Table 3: Forms of Employment

	Men		**Women**	
	April-June 2018	**July-September 2022**	**April-June 2020**	**July-September 2022**
Own Account Worker, Employer	34.6	35.3	23.3	25.5
Unpaid helper	4.2	4.3	9.9	11.5
Regular Wage Worker	46.4	46.9	56.1	55
Casual Labour	13.6	12.8	9.4	7.3
Agriculture	5.1	4.8	6.7	8.9
Manufacturing	35.6	35.1	29.1	27.1
Services	59.4	60.1	64.2	64.1

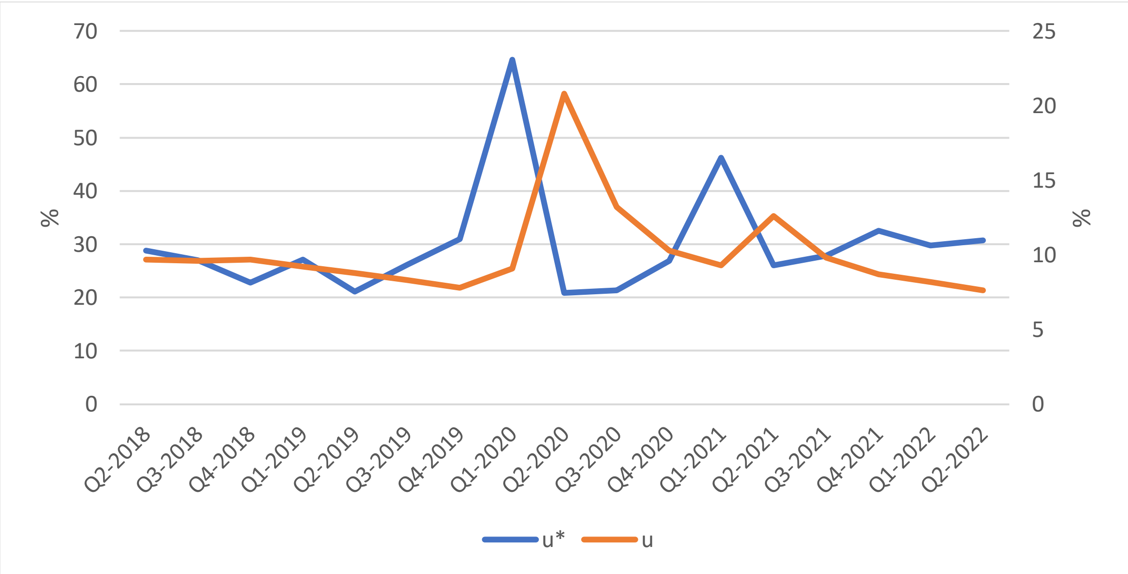
Source: PLFS Quarterly Bulletins, various reports

Labour market transitions and unemployment

The above analysis looks at changes in stocks over time, and does not look at movements within these categories. For instance, is the rise in LFPR due to individuals moving into the labour force in greater numbers or because individuals remain in the labour force for longer periods? The analysis of labour market transitions allows for a clearer analysis of these dynamics[10]. The steady-state unemployment rate acts as a leading indicator of the actual unemployment rate, as shown in figure 5. We calculate u* using inflow and outflow rates (as defined in equation (1)) and compare it with the actual unemployment rate as recorded in the PLFS Quarterly Bulletins. While there does exist a significant difference in the values of u and u*, trends in u* predict future changes in actual unemployment.

Figure 6 outlines steady-state unemployment rates for men and women, indicating the clear gulf between genders, evidence of urban women's greater unemployment rates being a structural feature of the urban economy. The comparison of steady-state rates shows a clear widening of the gap between genders following the second wave.

Figure 5: Unemployment and Steady State Unemployment Rates

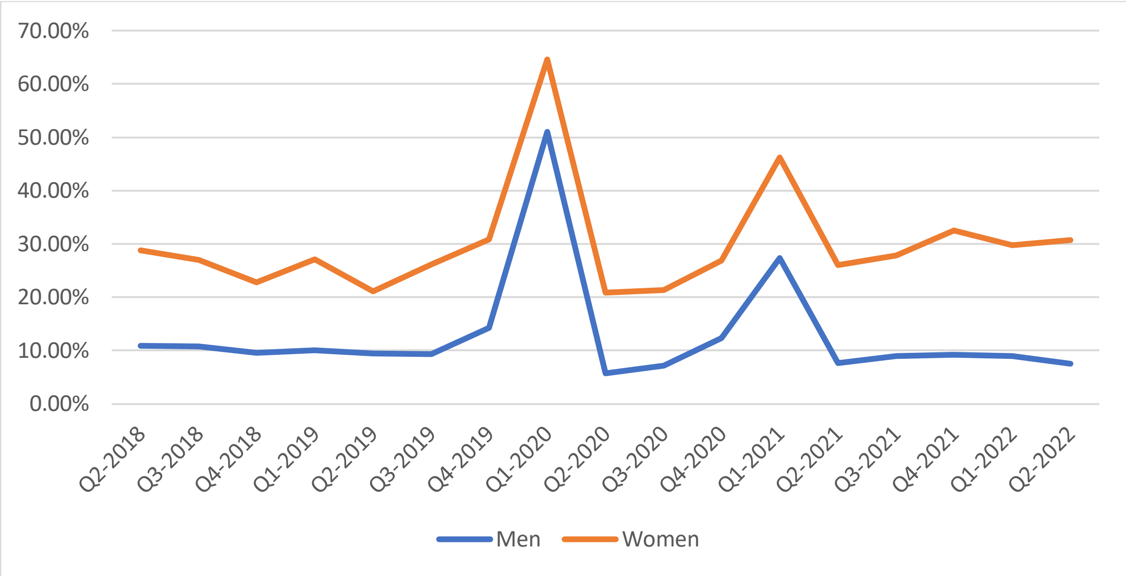


Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

Note: u is measured on the right-hand axis. Figures in % terms

[10] A note of caution with regard to the use of the steady-state unemployment rate: we do not attempt to analyse the behaviour of the economy outside of the steady-state and its possible adjustments to equilibrium, and make no comment on whether an economy can actually reach a steady-state equilibrium within a period as short as a quarter. We use simply use the concept as a framing device so we may focus our attention on different labour market flows and its impact on changes in unemployment rates.

Figure 6: Steady-state unemployment rates of men and women

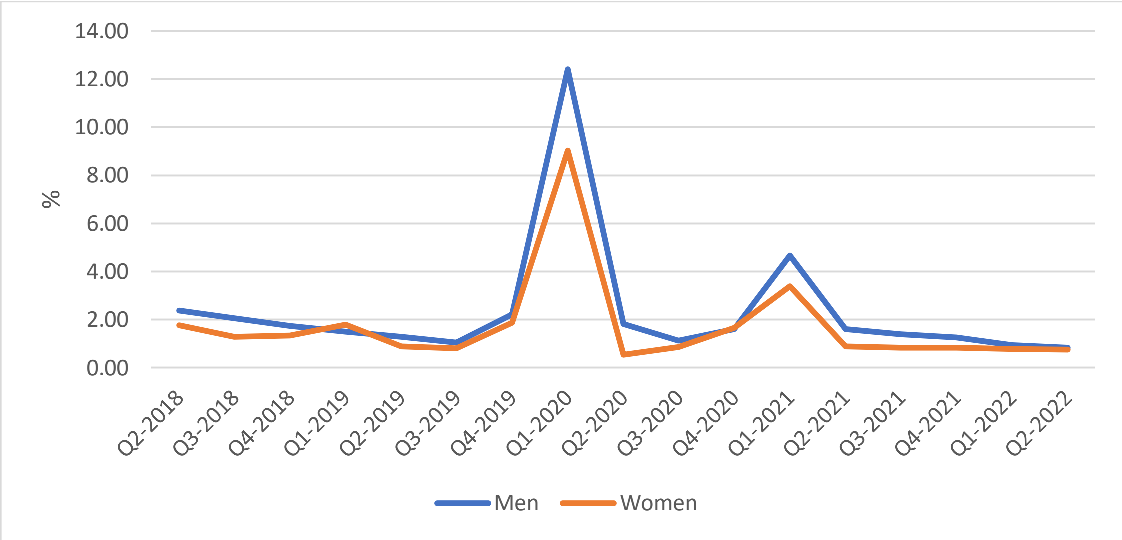


Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

As outlined above, u* can be expressed as a combination of inflow and outflow rates, each of which can be decomposed into direct and indirect components. Movements from employment to unemployment comprise the direct inflow into unemployment, also termed as the *job-loss* rate. Direct outflows from unemployment comprise movements from unemployment to employment, also termed as the *job-finding* rate, a measure of employment generation. These direct flows are shown in Figures 7a and 7b below. Even though women's unemployment rates are higher, they experience lower rates of both job-loss and job-finding.

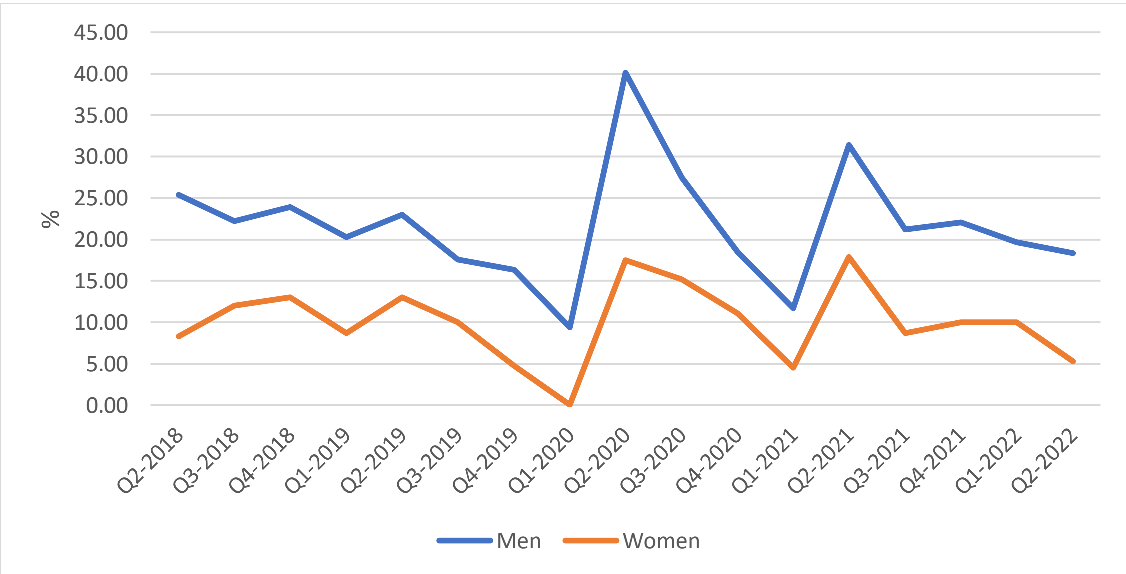
Consider the job-loss rate. The job-loss rates show two large spikes, during the first and second waves. Outside of these two periods, the job-loss rate is low for India, largely staying below 2% at the aggregate level, for both men and women. The largest variations are seen with respect to the job-finding rate, which rose significantly in the quarters immediately after the first and second wave. These high increases in job-finding rates are the reason why the rise in unemployment rates did not persist over quarters. However, the increases in job-finding were short-lived, reducing in subsequent quarters. This suggests that the rise in job-finding rates were primarily indicative of labour demand rising to make up for the cessation of economic activity during lockdowns, rather than any sustained dynamism on the part of the economy.

Figure 7a: Job-loss rates



Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

Figure 7b: Job-finding rates

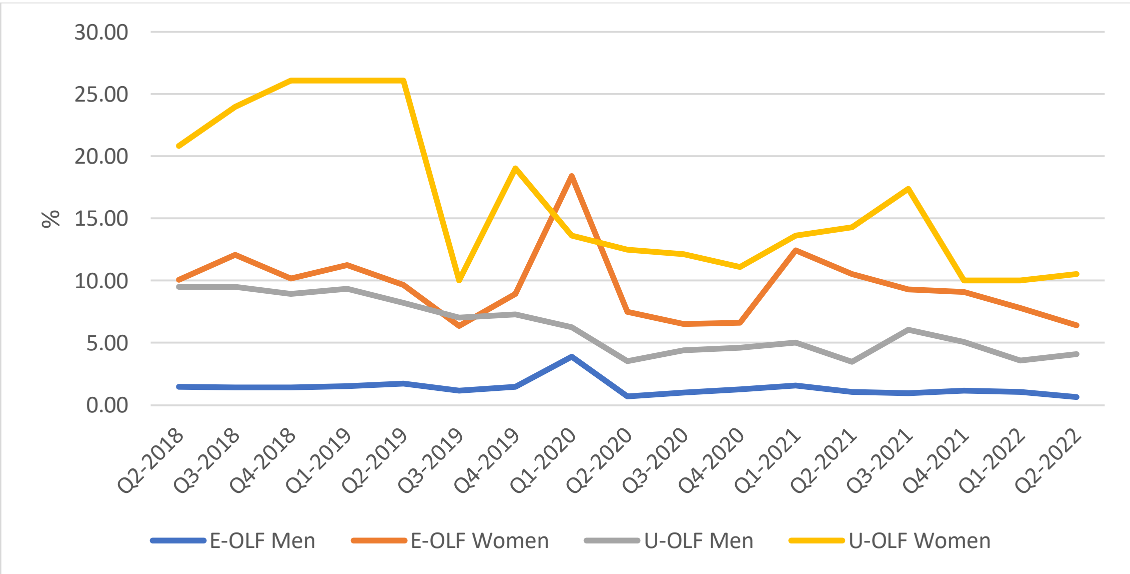


Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

An examination of the trends in job-finding rates throws up several disquieting observations. Women's job-finding rates are worryingly low, averaging only around 10% in the quarters before the first lockdown, and registering a steady downward trend outside of the two waves. In contrast, men's employment generation rates were around 10% during the lockdown quarter, which is equal to the *average* job-finding rates of women in the previous quarters. This represents a serious weakness for a developing economy, that cannot ensure adequate employment generation even with the presence of a widespread informal sector, and one in which prospects for women's employment are even lower.

Indirect flows have differing impacts on the unemployment rate depending on the direction of flows. An increase in the U-OLF flow, which implies unemployed individuals leaving the labour force, unambiguously reduces the unemployment rate, since it reduces the LFPR without affecting the WPR. An increase in the E-OLF flow increases the unemployment rate, since it reduces the WPR by a greater proportion than the LFPR. Figure 8 presents flows from the labour force to non-participation, disaggregated by gender. The magnitude of flows for women are much larger than that for men, in contrast to the magnitude of direct flows[11]. Furthermore, when compared to the initial period of Q2-2018, all flows have reduced in magnitude by Q3-2022.

Figure 8: Transitions from the labour force to non-participation



Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

Between 2018-2019, the average magnitude of the U-OLF flow for women was 21.7%, implying that almost 22% of unemployed women left the labour force across any two quarters[12]. Large flows from unemployment to non-participation kept the

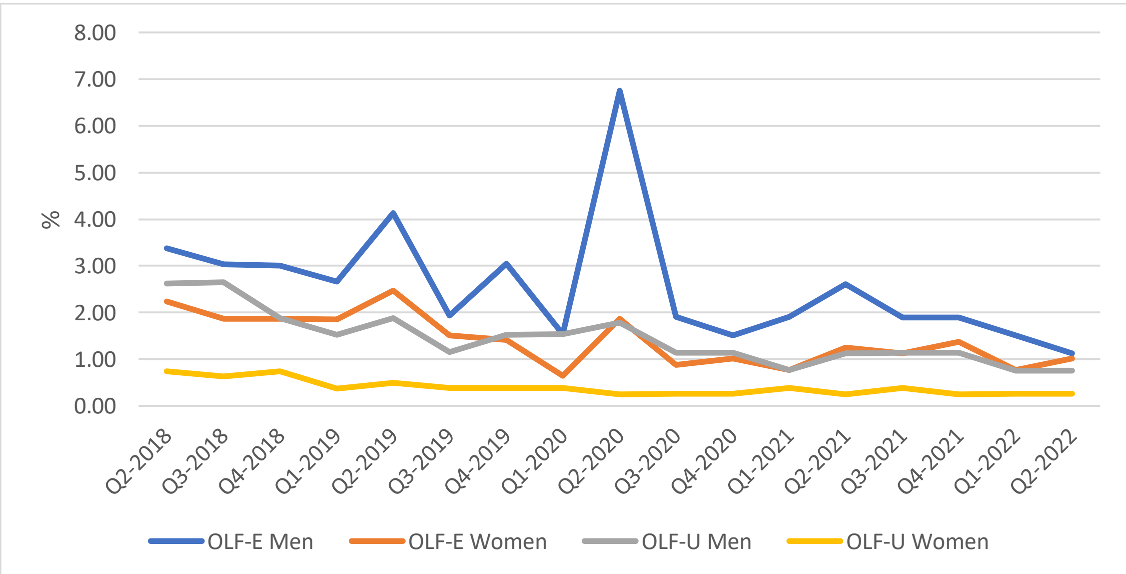
[11] This gender differential in flows out of the labour market remain significant even after demographic characteristics like age and education are controlled for, as shown in Menon and Nath (2022).

[12] This is not to imply that these unemployed women *permanently* leave the labour force, just that in every quarter, a fifth of unemployed women leave the labour force, possibly returning in later periods. As shown by Deshpande and Singh (2021), women make multiple entries and exits to the labour force. Since this study

unemployment rate lower than what it would otherwise have been. However, these flows have reduced over time, falling to 10.5% in Q3-2022, half the average value in the initial quarters. The E-OLF flows for women average at 10% across 2018-19, rising to 18.4% during the lockdown, and to 12.5% in the second wave. This too, has shown a significant fall over time, falling to 6.4% in Q3-2022. While high flows from employment to non-participation increase the unemployment rate (relative to U-OLF flows), the reduction in these flows would put downward pressure on the unemployment rate. The net effect would be determined on the strengths of each flow relative to each other.

Men's flows are extremely low in comparison, the E-OLF flow falling from 1.49% to 0.63% over the entire period, while U-OLF flows, averaging around 8.6% in 2018-19, falls to 4.08% in Q3-2022. Figure 9 outlines flows in the opposite direction, from non-participation into the labour force. The relative magnitudes are reversed, with men showing larger magnitudes of these flows. All flows show a downward trend over time; the only large increase is in the direction from non-participation to employment for men in the quarter after the lockdown, indicating the rise in labour demand that would have brought some men back into the labour force. Such a rise is not seen for women.

Figure 9: Transitions from non-participation into the labour force



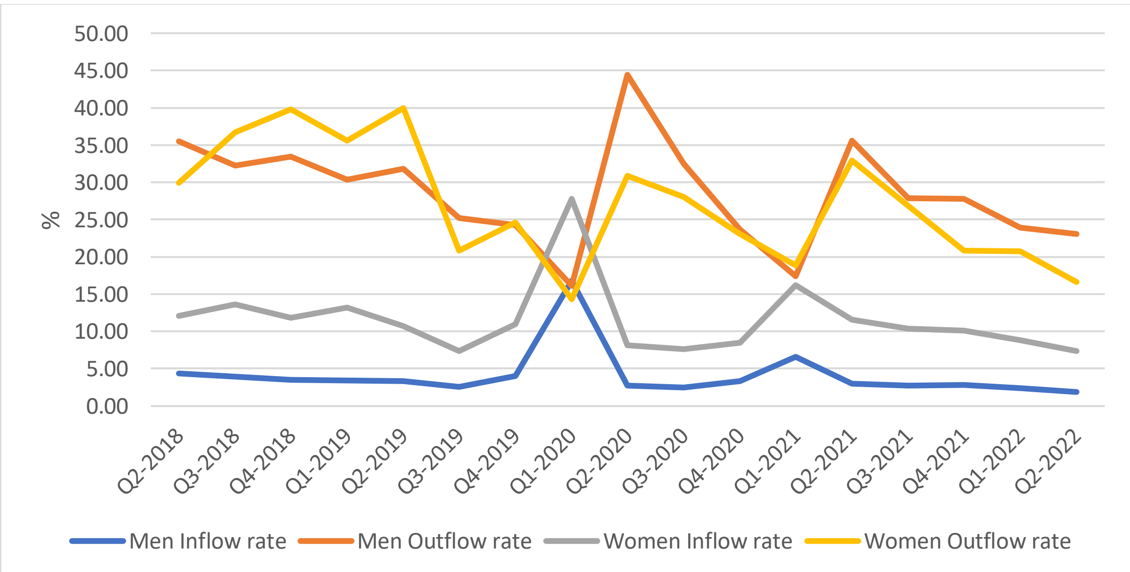
Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

deals with aggregate transitions and is not an individual-level analysis, we do not deal with the question of whether these moves are permanent or only temporary.

Putting these flows together resolves some puzzles and throws up significant questions. Low rates of women's labour force participation are not just due to low rates of entry, but also high rates of exit from the labour force. The subsequent *rise* in women's labour force participation is occurring not due to increased women's entry into the labour force, but because of reduced exits, with women in the labour force tending to stay for longer. The reduction in indirect flows since the lockdown, seen in conjunction with the increase in precarious forms of employment, may indicate greater distress in the labour market, with individuals holding onto employment no matter its nature. Moreover, the fact that the U-OLF transition has fallen by a greater proportion than E-OLF flows for women – the former has halved, while the latter has fallen by roughly 36.5% - indicates upward pressures on the unemployment rate for women.

Putting all flows together, we calculate inflow and outflow rates (as defined above) and display them according to gender in Figure 10. Inflows into unemployment rise during both waves – with a higher spike during the first – while outflows rise in the quarters after the waves. Seen in conjunction with the graphs above, the importance of women's indirect flows is being highlighted here. Even though women's job-loss rates are lower relative to men, the high rates of flows from employment to non-participation result in a higher aggregate inflow rate. Similarly, even though women's job-finding rates are lower, their outflows match that of men's due to the higher U-OLF flow. While women's outflows were higher than men before the lockdown, the reduction in the U-OLF flow have now led to men's outflows being slightly higher.

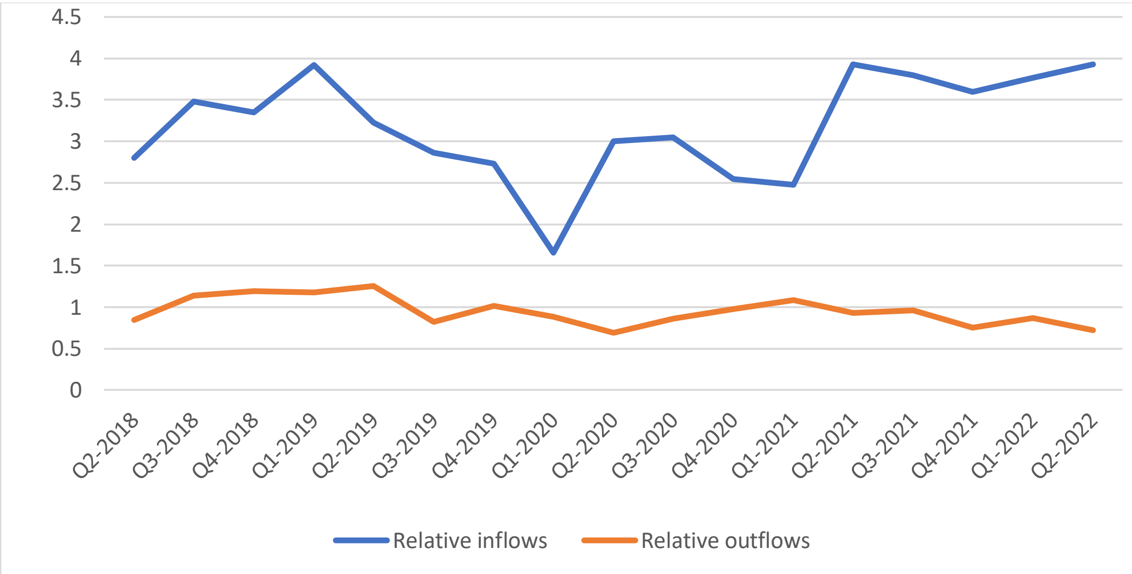
Figure 10: Inflow and Outflow Rate of Men and Women



Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

Unlike in the United States, where women's rising labour force participation rates have seen a reduction in the unemployment rate differential between men and women (Albanesi and Sahin, 2018), the opposite has happened in India. Rising LFPRs of women have seen a reduction in women's unemployment rates, but the differential has shown a rising trend. The condition for women's steady-state unemployment rate to be higher than that of is $\frac{s_w}{s_m} > \frac{f_w}{f_m}$, i.e. relative inflows into unemployment should be greater than relative outflows. Figure 11 charts women's inflows and outflows relative to men over the entire period. Women's relative inflows remain higher than men throughout, explaining higher unemployment rates. While relative outflows remain roughly constant, the largest fluctuations are seen in relative inflows, which explains much of the patterns of divergence in unemployment rates.

Figure 11: Relative inflows and outflows



Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

The convergence in unemployment rates during the lockdown can be largely explained by falling relative inflows. Relative inflows showed a falling trend even before the lockdown, with men's high rates of direct job loss causing the ratio to fall to its lowest level during the lockdown. However, following the lockdown, there has been a steady increase in relative inflows, widening the gap between relative inflows and outflows. Relative inflows do not reduce as much during the second wave as during the lockdown, explaining why unemployment rates converge during lockdown and not during the later period. This increase in relative inflows explains why the gender differential in unemployment rates have risen following the second lockdown even when unemployment rates of both men and women have reduced.

Are women's unemployment rates understated?

The E-OLF flow presents a particular problem of evaluating women's unemployment rates, especially during the lockdown. Even though women's job-loss rates are lower, women's E-E flows – or the proportion of employed women who retain employment every quarter – are considerably lower, with the falls in women's E-E flows during the first and second waves significantly more than men (Figure 12). This implies that though more men moved from employment to unemployment during the lockdown, lesser women remain employed. A simple answer is that more women moved straight from employment to non-participation during the lockdown. But without a proper understanding of what these flows actually indicate, we may run the danger of under-estimating the actual impacts of economic slowdown on women's unemployment.

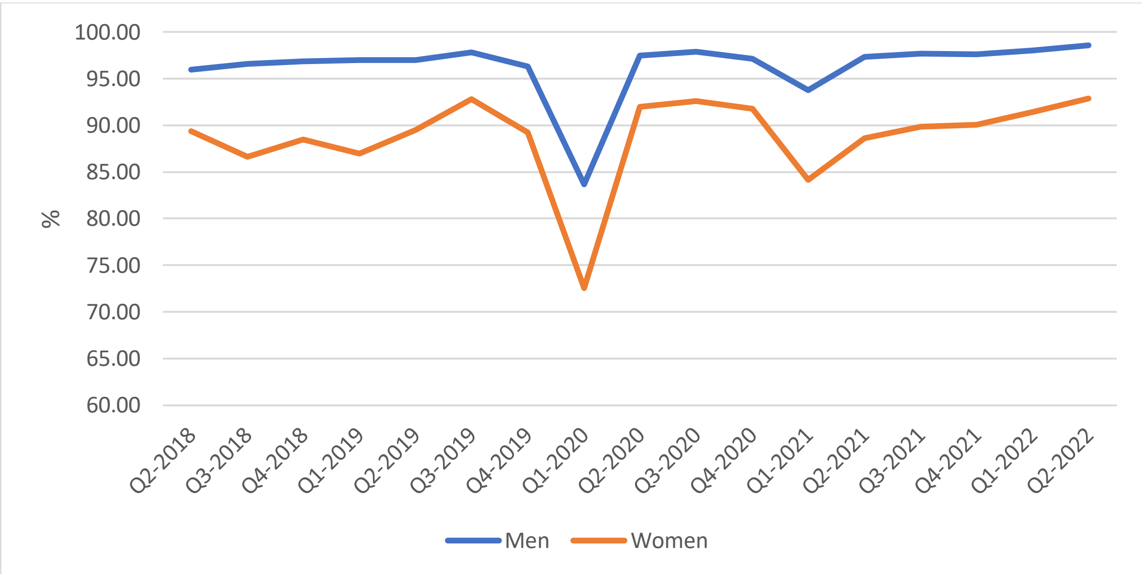
As discussed by Bhalotia et al (ibid) and Abraham (2020), a situation where a woman loses her job and does not indicate that she is willing to work would *not* be counted as a rise in *unemployment*, only an increase in non-participation. Thus, measured unemployment rates that rely on self-identification of labour force status may under-estimate the extent of unemployment. However, the timing of interviews may also under-estimate the extent of unemployment if the time spent by women in job-search is lesser than the time between interviews.

The PLFS interviews women once every three months. Consider a situation where an employed woman is interviewed in January, yet is fired from her job in February. Assume she spends a short time searching for a new job (a period lesser than three months) before exiting the labour force, either due to social norms or other constraints. When interviewed the next quarter in April, her transition would be recorded as E-OLF, even though she spent some time in unemployment. The interview structure of the PLFS may thus lead to an under-estimation of job-loss (strictly defined as the E-U flow) for women.

This would have implications for the determination of the unemployment rate. Based on the definitions of inflows and outflows, direct flows have a greater impact on the unemployment rate as compared to indirect flows: the E-OLF flow is multiplied by a fraction lesser than 1. Thus, if women were fired from jobs and spent lesser than a minimum of three months searching for employment before exiting to non-participation, the classification of E-U flows as E-OLF would understate the actual unemployment rate.

This may go some way in explaining the puzzle of the convergence of unemployment rates during the lockdown. The studies cited above have highlighted the disproportionate impact of the pandemic on women, with more women losing employment. However, the increase in unemployment rates was greater for men. It may be the case that more women lost jobs, but because social norms or other factors may limit their stay in the labour force, their exits were seen as a direct flow to non-participation rather than job-loss; the E-OLF flow for women spiked during the lockdown. This would result in an under-estimation of women's unemployment rates. What convergence was seen may simply be an artefact of the ways in which interviews are carried out in the PLFS.

Figure 12: E-E flows



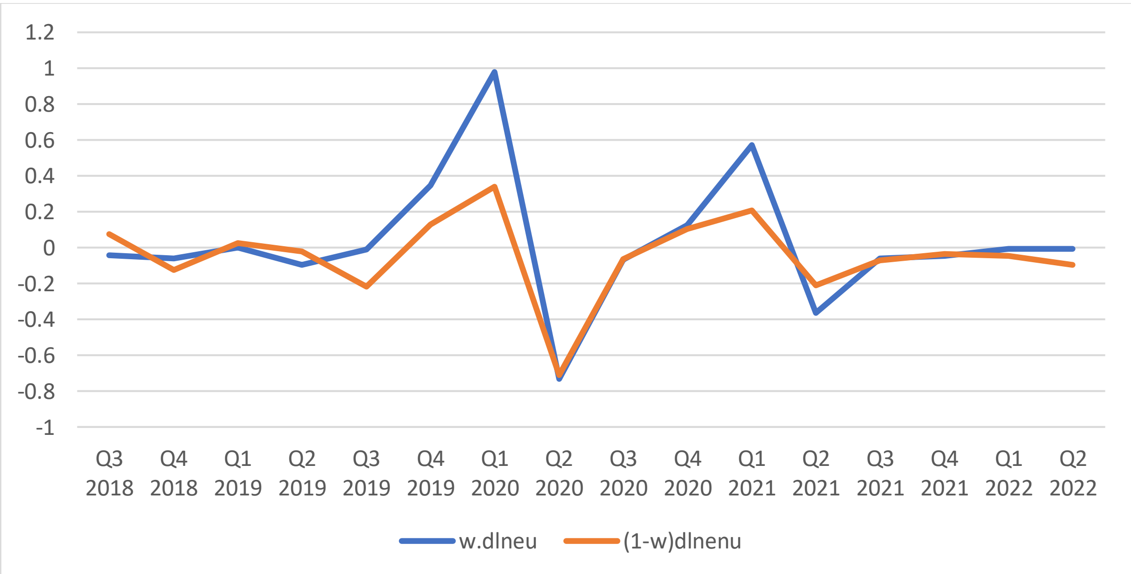
Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

Decomposing changes in the unemployment rate

Figures 13a and 13b decomposes changes in inflows and outflows respectively into their direct and indirect components, utilising equation (2). While both direct and indirect flows contributed significantly to the rise in inflows – and hence the unemployment rate - during the first and second waves, it was largely direct outflows that brought the unemployment rate down in the quarters immediately after, with indirect outflows playing a very minor role (at the level of the aggregate economy). As seen in Figure 13b, apart from the two waves, falling employment generation rates have imparted upward pressures on the unemployment rates, which have been outweighed by the effect of falling inflows.

The results for men look similar to those derived at the aggregate level (owing to the large presence of men in the labour force). We focus on the results for women. We focus only on three flows, the direct and indirect component of inflows, and the indirect component of outflows. This is because the U-E flow is recorded as being statistically insignificant during the first lockdown, and hence the impact of U-E flows on changes in women's unemployment cannot be adequately estimated. The rise in employment generation after the first lockdown did significantly reduce the unemployment rate, but given the fact that its value during the lockdown quarter was not considered statistically significant, it is difficult to estimate its precise impact on changes in unemployment rates.

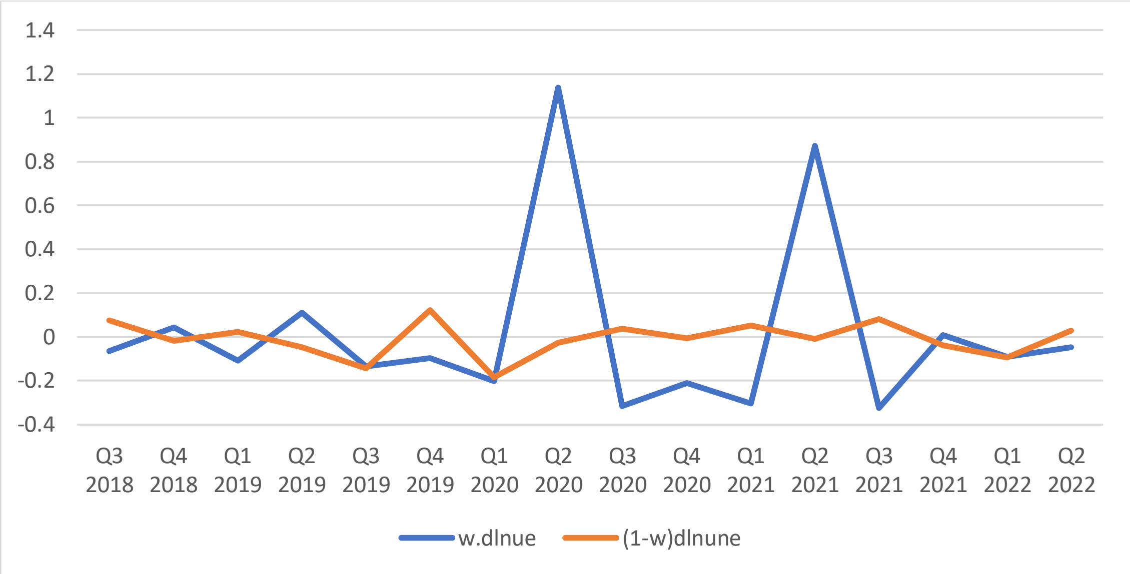
Figure 13a: Decomposition of inflows: All Persons



Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

In contrast to the experience of men, women's indirect flows play a larger role in determining changes in inflows and outflows, and hence the aggregate unemployment rate. During the first lockdown, the impact of indirect inflows – driven largely by the E-OLF flow – on rising unemployment is quantitatively as much as direct rates of job-loss. As outlined above, it is unclear whether this accurately measures flows from employment out of the labour force or whether a major part of it is comprised of actual job-losses for women. The fall in E-OLF rates immediately after the lockdown was responsible, in part, for the significant reduction in the unemployment rate.

Figure 13b: Decomposition of outflows: All persons



Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

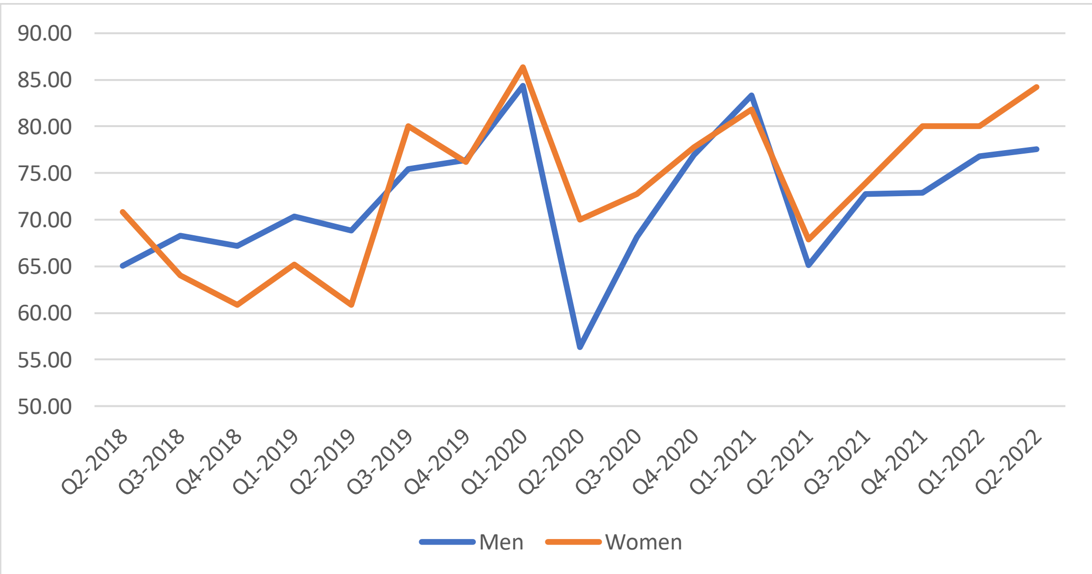
The rise in E-OLF rates during the second wave contributed more to the rise in unemployment rates than direct job loss. Following the second wave, the sustained reduction in the E-OLF flow has meant consistent reductions in the unemployment rate. In fact, for women, a significant contributor to falling unemployment rates has been the falling E-OLF flow, and not rising employment generation. Falls in the U-OLF flows, on the other hand, imply rising pressure on the unemployment rate. As seen in fig 14, apart from periods around the two waves, indirect outflows have either increased the unemployment rate or, at the very least, contributed to ever-decreasing reductions in the unemployment rate.

These changes in women's flows out of the labour force imply contradictory trends for the unemployment rate, yet both hold out significant problems that deserve serious attention. Falling U-OLF flows imply women may be staying for longer in the labour force searching for jobs, implying upward pressures on the unemployment rate, and the slow persistence of unemployment. As shown in Figure 15, the share of the unemployed who remain unemployed across quarters – i.e. the U-U flow - has been rising, with the share higher for women than for men. Falling E-OLF flows reduce the unemployment rate, and imply greater participation of women in the workforce. But if this is being done at the cost of rising precarity and informalisation, it does not imply an unambiguously positive outcome.

Figure 14: Decomposition of flows: Women

Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

Figure 15: The U-U transition



Source: Author's calculation from the PLFS Quarterly Bulletins, various reports

Note: y-axis starts from 50.

Conclusion

Our results present a comprehensive analysis of the factors differentially affecting unemployment rates for men and women, an original contribution to the study of urban labour markets in India. The overall reduction in unemployment rates following spikes during the first and second waves was largely due to one-period increases in employment generation, indicating a re-absorption of labour rather than sustained dynamism. Falling rates of employment generation implies that unemployment rates may not continue to fall for much longer. Reductions in the E-OLF flow of women have also contributed to falling unemployment rates at the aggregate level.

Women's unemployment rates have been higher than men's due to higher – and rising – relative inflows as compared to roughly constant relative outflows. In contrast to developed economies, rising labour force participation of women has not led to a reduction in the gap between men's and women's unemployment rates. Employment generation is even lower for women than men, and has been falling since the pandemic, indicating worsening conditions for urban women. Women's LFPRs have been rising due to a reduction in outward flows rather than an increase in entry, with signs pointing to increasing distress employment. The Indian urban labour market displays signs of significant vulnerabilities that urgently requires policy attention.

References

Abraham, R. (2020, October). What the Numbers Don't Tell Us: Looking Beyond Standard Measures of Employment During an Economic Lockdown. *Centre for Sustainabl Employment Blogpost*.

Abraham, R., Basole, A., & Kesar, S. (2022). Down and Out? The Gendered Impact of the Covid-19 Pandemic on India's Labour Market. *Economia Politica, 39*, 101-128.

Albanesi, S., & Sahin, A. (2018). The Gender Unemployment Gap. *Review of Economic Dynamics, 30*, 47-67.

Azmat, G., Guell, M., & Manning, A. (2006). Gender Gaps in Unemployment Rates in OECD Countries. *Journal of Labor Economics, 24*(1), 1-37.

Azim Premji University (2021) State of Working India 2021: One year of Covid-19, Centre for Sustainable Employment, Azim Premji University.

Bhalotia, S., Dhingra, S., & Kondirolli, F. (2020). City of Dreams no More: The Impact of Covid-19 on Urban Workers in India. *Centre for Economic Performance Paper No 008*.

CEDA-CMIE. (2022). *The Impact of the Covid-19 Pandemic on People's Economic Lives.*

Chatterjee, P., & Dev, A. (2023). Labour Market Dynamics and Worker Flows in India: Impact of Covid-19. *Indian Journal of Labour Economics*.

Das, P. (2023). Creation and Destruction of Jobs in Urban Labour Market: Role of Gender, Caste and Religion in India . *Indian Journal of Labour Economics*.

Deshpande, A. (2022). The Covid-19 Pandemic and Gendered Division of Paid Work, Domestic Chores and Leisure: Evidence from India's First Wave. *Economia Politica, 39*, 75-100.

Deshpande, A., & Singh, J. (2021). Dropping Out, Being Pushed Out or Can't Get In? Decoding Declining Labor Force Participation of Indian Women. *IZA DP No 14639*.

Dhamija, D., & Chawla, A. (2023, March 20). Growth in Female Labour Force Participation in India now Seems to be Stagnating. *The Wire*.

Elsby, M. W., Smith, J. C., & Wadsworth, J. (2011). The Role of Worker Flows in the Dynamics and Distribution of Unemployment. *Oxford Review of Economic Policy, 27*(2), 338-363.

ILO. (2021). *An Uneven and Gender-Unequal Covid Recovery: Update on Gender and Employment Trends 2021.* International Labour Organisation.

IWWAGE. (2021). *Women and Work: How India Fared in 2021.*

Jha, P., & Kumar, M. (2020). Labour in India and the Covid-19 Pandemic. *The Indian Economic Journal, 68*(3), 417-437.

Kannan, K., & Khan, M. I. (2022). Loss of Job, Work and Income in the Time of Covid-19: An Analysis of PLFS data. *Economic and Political Weekly, 57*(2), 37-41.

Kesar, S., Abraham, R., Lahoti, R., Nath, P., & Basole, A. (2021). Pandemic, Informality and Vulnerability; Impatc of COVID-19 on Livelihoods in India. *Canadian Journal of Development Studies, 42*(1-2), 145-164.

Menon, R., & Nath, P. (2022). A Dynamic Analysis of Women's Labour Force Participation in Urban India. *The Economic and Labour Relations Review, 33*(4), 766-785.

Mishra, P., & Das, S. (2022). An Estimation of Rise in Unemployment and Income Loss Due to Covid-19 Lockdown in India: An Analysis Based on PLFS Data (April to June 2020). *Manpower Journal, 56*(1 & 2), 25-40.

Mitra, S., & Sinha, D. (2021). Covid-19 and Women's Labour Crisis: Reiterating an Inclusive Policy Response. *Economic and Political Weekly, 56*(17), 44-51.

Organisation, I. L. (2017). *World Employment Social Outlook: Trends for Women 2017.* Geneva: International Labour Office.

Roychowdhury, A., Bose, M., & Roy, S. D. (2022). The Great Indian Lockdown 1.0: Exploring the Labour Market Dynamics. *Canadian Journal of Development Studies, 43*(4), 550-574.

Sengupta, A. (2023). Effect of Covid-19 Pandemic on Employment and Earnings in Urban India during the First Three Months of Pandemic Period: An Analysis with Unit-Level Data of Periodic Labour Force Survey. *Indian Journal of Labour Economics.*

Singh, J. (2023). Unenployment Fluctuations in Urban Labour Market in India. *Indian Journal of Labour Economics.*

University, A. P. (2021). *State of Working India 2021: One Year of Covid-19.* Bengaluru: Centre for Sustainable Employment, Azim Premji University.