Ashoka University Economics Discussion Paper 65

Dropping Out, Being Pushed out or Can't Get In? Decoding Declining Labour Force Participation of Indian Women

July 2021

Ashwini Deshpande, Ashoka University

Jitendra Singh, Ashoka University

https://ashoka.edu.in/economics-discussionpapers

Plot No. 2, Rajiv Gandhi Education City,
National Capital Region,
P.O.Rai, Sonepat, Haryana 131029

Dropping Out, Being Pushed Out or Can't Get In? Decoding Declining Labour Force Participation of Indian Women*

Ashwini Deshpande† Jitendra Singh‡

August 10, 2021

Abstract

The stubbornly low and declining level of labor force participation rate (LFPR) of Indian women has prompted a great deal of attention with a focus on factors constraining women's labour supply. Using 12 rounds of a high frequency household panel survey, we demonstrate volatility in Indian women's labour market engagement, as they exit and (re)enter the labor force multiple times over short period for reasons unrelated to marriage, child-birth, or change in household income. We demonstrate how these frequent transitions exacerbate the issue of measurement of female LFPR. Women elsewhere in the world face a "motherhood penalty" in the form of adverse labour market outcomes after the first childbirth. We evaluate the motherhood penalty in the Indian context and find that mothers with new children have a lower base level of LFPR, but there is no sharp decline around the time of childbirth. Blinder-Oaxaca decomposition of determinants of female LFPR suggests that none of the total fall (10 percentage points) in our study period is explained by a change in supply-side demographic characteristics. We suggest that frequent transitions, as well as fall in LFPR, are consistent with the demand-side constraints, *viz.*, that women's participation is falling due unavailability of steady gainful employment. The high unemployment rate and industry-wise composition of total employment provide suggestive evidence that women's participation is falling as women are likely to be displaced from employment by male workers. We show that women's employment is likely to suffer more than men's due to negative economic shocks, as was seen during the fallout of demonetisation of 86 percent of Indian currency in 2016. Our analysis contests the prominent narrative that

*We would like to thank Farzana Afridi and Anisha Sharma for suggestions and comments on a preliminary outline of the research plan, and Mahesh Vyas of Centre for Monitoring Indian Economy (CMIE) for clarifying queries in real time. All errors are our own.

†Department of Economics, Ashoka University, Rajiv Gandhi Education City, Sonipat, Haryana 131029, India. Email: ashwini.deshpande@ashoka.edu.in

‡PhD Candidate, Department of Economics, Ashoka University. Email: jitendra.singh_phd18@ashoka.edu.in

women are voluntarily dropping out of the labor force due to an increase in household income and conservative social norms. Our results suggest that India needs to focus more on creating jobs for women to retain them in the labor force.

JEL Classification Codes: J23; J710; J160; O53

Keywords: Female labour force participation rate; Employment; Social norms; India; labour demand

1 Motivation

The stubbornly low and declining level of female labour force participation (FLFP) in India has prompted a great deal of academic attention (Mazumdar and Neetha, 2011; Neff et al., 2012; Chaudhary and Verick, 2014; Chatterjee et al., 2015; Das et al., 2015; Klasen and Pieters, 2015; Dubey et al., 2017; Dhanaraj and Mahambare, 2019; Sarkar et al., 2019; Afridi et al., 2020; Siddique, 2021; Afridi et al., 2021b, among others). The focus on a binary indicator – in or out – implicitly leads us to think about labour force participation as a labour supply issue. Women typically report lower rates unemployment compared to men; therefore, when they are not employed, the default assumption is that they must have voluntarily chosen to exit the labour force. The persistently low level of FLFP in India over the decades indicates a state of permanence or stationarity in women's LFP status. Additionally, the decline since 2004 suggests a transition in one direction (exit out of the labour force from an already low level), but not in the other direction (entry into the labour force).

International media has drawn attention to this issue by focusing on cultural norms that keep Indian women at home[1], with a recent analysis concluding that "hardly any women in India are in paid employment".[2] The role of social norms in shaping women's engagement with the labout market has received prominent attention in the academic literature too. Jayachandran (2021) discusses the role of cultural norms in explaining large differences in female employment across countries with the same level of economic development. Cultural norms do matter: the social norm of being predominantly responsible for domestic chores is an important constraint to Indian women's ability to participate in paid work (Deshpande and Kabeer, 2021).

However, national level survey data has repeatedly documented Indian women's willingness to work if work was available either at or near their homes. We know that in developed countries, women transition in and out of the labour market more than once in their lifetimes. For instance, women are observed to drop out of the work force for child birth or child rearing reasons. If/when women re-enter the workforce, they do so at lower positions than the men in their age cohort, and correspondingly earn less. This is the infamous "motherhood penalty" (Bronars and Grogger, 1994; Angrist and Evans, 1998; Lundborg et al., 2017; Kleven et al., 2019a,b, among others).

In this paper we investigate whether Indian women's engagement with the labour market might also be marked by transitions as they enter and exit the labour market at different points of time, as opposed to a continuous and prolonged state of withdrawal. The absence of large N longitudinal data in countries such as India makes it difficult to observe if there

[1] https://www.economist.com/briefing/2018/07/05/culture-and-the-labour-market-keep-indias-women-at-home

[2] https://www.economist.com/asia/2021/02/18/hardly-any-women-in-india-are-in-paid-employment

are life cycle-related patterns of entry and exit in women's labour force participation. Sarkar et al. (2019) examine entry and exit of Indian women from the workforce across time based on a two-wave India Human Development Survey (IHDS) panel. They find that more than 10 percent women dropped out of the labor force in a period of seven years between two waves. They interpret this to suggest that women have very low attachment to the labor market. However, if women changed their labour market status frequently in the interim period between the two waves, they would not be able to observe that and this conclusion would not be valid. Dhanaraj and Mahambare (2019), using the same data, show that changes in family structure affect women's entry and exit probabilities into rural non-farm employment; specifically, residing in a joint family set up is associated with a lower probability of being in non-farm employment.

Access to the high-frequency nationally representative longitudinal data from the Consumer Pyramids Household Survey (CPHS) of Centre for Monitoring Indian Economy (CMIE) allows us to demonstrate a less-known fact about Indian women. Working age women transition in and out of the labour force, not just once but multiple times (Figure 5). The bulk of the literature, reviewed below, focuses on supply-side constraints that prevent women from entering the labour force, ranging from sexual violence to stigma to conservative social norms. However, if women enter and exit several times, none of these explanations appear convincing, as stigma and social norms do not oscillate over short intervals. This suggests that the transitions in women's labour force participation status might be shaped by demand for their labour.

The CPHS observes each household member every four months (called a "wave"), with three waves each calendar year. The survey collects data on employment status, household consumption, expenditure, assets and several other socio-economic characteristics. We analyse daily employment status of more than 350,000 working age women (15 years and older) using 12 waves between 2016-2019 and make five major contributions.

1.1 Main Contributions

Our paper makes several contributions to the vast literature on women's LFP in India by providing fresh evidence on three broad themes. One, we document frequent transitions in and out of the labour force as well as factors responsible for these transitions; two, we evaluate whether the motherhood/child penalty is responsible for women dropping out of the labour force. In doing so, we suggest that motherhood penalty be evaluated through a method more suited for a developing country context; and three, we provide multiple strands of evidence to argue that the fall in Indian women's LFP is more likely to be a consequence of low and declining demand for female labour, rather than supply-side constraints keeping women indoors.

Our main results can be summarised as follows. First, by documenting the repeated transitions in women's labour force status even over a short period of four years, we provide novel empirical evidence on women's labour force participation rate (LFPR) that questions the conventional wisdom of the decline in FLFP reflecting (rising?) conservative social norms or stigmatisation of working women, and/or fear of sexual violence.

During the period under examination, the average labour force participation rate of women was close to 14.5 percent, which is lower than the estimates from the official statistics, as the CMIE definition of measuring work is more stringent than the official National Sample Survey (NSS). Over the period, female labour force participation rate fell from 22 percent to 12.8 in rural and 11 percent in urban areas. However, within the overall declining trend, we observe that a large proportion of women frequently change their labor force participation status between "In the labor force (ILF)" and "Out of labor force (OLF)", as they drop out of labor force in a given wave to sometimes rejoin in later waves. We examine how transitions differ by age, education levels, urban-rural residence and social group identity.

We also make a contribution to the measurement question: there is ample evidence to demonstrate that women's labour force statistics consistently underestimate their actual involvement in productive work. We show how the irregular and short-term engagement of women in the labour force leads to underestimation of female LFPR. The average FLFP rate using CPHS dataset stands at around 14.5 percent for the study period. However, around 44 percent of women (more than thrice the FLFP rate) were part of labor force in at least one of the waves, with only two percent of women remaining in the labor force in each of the 12 waves. These transitions over a short span of four years indicate that a) actual proportion of women engaged in economically productive work is much higher than revealed by any point estimate from cross-sectional data, and b) women are not held back from productive work due to cultural factors, but are probably unable to find continuous employment which they take up when possible.

Second, we examine the extent to which the transitions are permanent in nature and what factors explain these transitions. We find that a large proportion of these transitions are temporary: women exit the labor force and rejoin in next few waves. More than 50 percent of women who were in the labor force in at least one wave made more than two transitions (exit to entry or entry to exit). This phenomenon of frequent and temporary transition between ILF and OLF contests the narrative that women are voluntarily dropping out of the labor force due to stigma against women's work or fear of sexual violence or conservative social norm, as these factors are structural and not prone to rapid and multiple oscillations.

The temporary dropping out of the labor force, both in urban and rural areas, suggests unavailability of regular and steady employment opportunities for women. It is possible that this is a manifestation of widespread informalisation and precarity of labor markets where men are working out of compulsion but women are able to join the work force only when it is compatible with reproductive labour (domestic chores, child care, elderly care). These tasks are predominantly under the purview of women everywhere, but even more strongly in South Asia, where the gender norms of sharing housework are markedly more unequal than the rest of the world, barring the Middle East and North African (MENA) region.

We examine to what extent these transitions can be explained by individual and household level time-varying characteristics. Specifically, we estimate the impact of a change in other household members' income and change in number of unemployed male members in the households. We estimate a panel regression model controlling for individual and wave (time) fixed effects. We find that an increase in other household members' income leads to a statistical significant fall in the probability of entry and rise probability of exit. Similarly, a presence (or increase) in unemployed male member in the household increases (decreases) the probability of entry (exit) out of labor force. However, the magnitude is relatively small to provide the major explanation for frequent entries and exits among women.

Third, in contrast to studies for developed countries, where child penalty is typically defined as a wage penalty to new mothers, we propose a different method of examining child penalty for India, given the low proportions of workers, especially women, in regular wage and salaried work. We estimate whether child birth induces women to transition out of the labor force. We use a sub-sample of parents with a new child birth in the study period and match them to individuals with similar demographic and socioeconomic characteristics using the methodology of Entropy Balancing (EB). Thus, the only difference between the two groups of parents is whether parents have additional childcare responsibilities. We find that women with a new child have a significantly lower level of LFPR relative to the women from comparison group across all waves, but not around the time of the child birth. We use two-way fixed effect estimation in event study design setting to gauge the pattern in women's LFPR before and after the child birth. In contrast to the literature from developed countries, we do not find any immediate effect (negative or positive) of child birth. We interpret this to suggest that child penalty operates in a very different way in Indian context. Women leave the labor force early in the anticipation of child birth and continuously remain outside the labor force for a longer period, rather than drop-out around child birth.

Fourth, we use Blinder-Oaxaca decomposition analysis to show that the supply-side demographic characteristics explain none of the fall in FLFPR in the study period. Between January-April 2016 and September-December 2019, the FLFPR fall by 10 percentage points from 22 percent to 12 percent. We use various specifications by using exogenous variables such as age, caste, religion and endogenous variables such as education level, highest education level of any male member in the household, household income, share of young child in household etc as explanatory variables. We find that none of these demographic characteristics explain the fall in FLFP. This provides additional validation of our argument that the fall in women's labor market participation is due to unidentified – most likely demand-side– causes and not due to supply side demographic characteristics.

Fifth, we provide suggestive evidence that the fall in FLFP rate is likely to be a manifestation of low labor demand. Our study period is marked by almost negligible employment creation compared to growth in the working-age population in India. In the period of 12 waves, total male employment increased by 12 million, which was accompanied by a fall in female employment of 9 million. Disaggregating the change in total employment at the broad industry level shows that this possible displacement is not the outcome of change in the industry composition of total employment, but as a result of the fact that the share of women has fallen in almost all the industries. Further, female unemployment rate in January to April 2016 was approximately 50 percent and has fallen sharply over the our study period. But the fall in unemployment has been a result of women moving from unemployment to OLF. We argue that such a large unemployment level in the initial waves may have discouraged women from continuing to seek work, and made them drop out of the labor force.

We dig deeper into this displacement by focusing on how a negative economic shock disproportionately affects the female LFPR. We estimate the impact of a sharp and sudden unanticipated negative shock of "demonetisation", where the Government of India declared 86 percent of currency in circulation as illegal tender from midnight of November 9, 2016. This resulted in sharp decline in cash in circulation for several months across India resulting in a sharp contraction in economic activity: employment level fell by three percentage points and economic growth by two percentage points (Chodorow-Reich et al., 2020). Using the CPHS data for six waves (January 2016 to December 2017), we shows that women were disproportionately affected by the demonetisation shock and female LFPR dropped by two percentage points compared to male.

Our paper makes a significant contribution to the literature on low female LFPR in India by revealing recurrent inter-temporal movements in women's labour force participation status. Our analysis suggests that the fall in FLFP rate in recent decades could be the outcome of low demand of women's work. Our findings have important policy implications, as we argue that women are not unwilling to join the labour force, but are unable to continue in paid employment. This indicates that retaining women continuously in the labor force needs to be specially targeted, in addition to policies targeted towards bringing new women into the labor force.

1.2 Context and Existing Literature

Historically and elsewhere in the world, rising female education levels and a decline in fertility rates have been positively associated with greater entry of women in the labour force. India is an exception with low and falling FLFP rates associated with long periods of high rates of growth, low fertility and rising education levels. Rural India witnessed a secular decline in FLFP: participation rate of women fell by 25 percentage points between 2004-2018, whereas FLFP rate remained nearly stagnant at around 20 percent in urban India according to NSS data.

The decline could possibly reflect the fact that India is on the declining part of the U-shaped pattern hypothesized by (Boserup, 1970; Goldin, 1995) who suggested that that female labor force participation follows a U-shaped relationship with economic growth. However, the evidence on this hypothesis is mixed and varies with geographical and temporal contexts (Tam, 2011; Lahoti and Swaminathan, 2013; Gaddis and Klasen, 2014).

The literature discusses the income effect: women dropping out because their families are getting richer, as can be expected with long periods of high growth such as the Indian economy witnessed in last three decades. Rising education can also lower LFP rates, as women stay longer in educational institutions. Indeed, there is some evidence on both these counts. Afridi et al. (2018) show that an increase in education level (of both men and women) and household income level can explain a large part of decline in married women's participation in rural India. Klasen and Pieters (2015) shows the similar reasons for stagnant LFP rate in urban India. Neff et al. (2012) and Mehrotra and Parida (2017) also shows suggest that a substantial share of fall in LFP rate can be attributed to negative income impact.

A strand of the literature (Borker, 2017; Chakraborty et al., 2018; Chakraborty and Lohawala, 2021; Siddique, 2021) focuses on sexual violence or fears for personal safety, as well as a rise in conservative sentiments or traditional values stigmatizing women's work outside the home. Indeed, Indian women have to face high levels of violence both inside and outside the home. A ranking accords India the dubious distinction of "the most dangerous country to be a woman".[3]

Stylised facts about the decline in FLFP put a question mark on several of the explanations offered for the decline. The decline in the last two decades has been driven by a fall in LFP of rural women, especially rural ST women. There is no evidence to suggest that incomes of rural ST families have risen more compared to other groups in the population. There is no data to suggest that the rise in sexual violence was disproportionately greater against rural ST women compared to other categories of women. Similarly, there is no compelling quantitative or ethnographic evidence, that we are aware of, suggesting that rural

[3] https://edition.cnn.com/2018/06/25/health/india-dangerous-country-women-survey-intl/index.html

ST (Adivasi) women had to encounter a disproportionate surge in conservative social norms compared to other categories of women. Finally, the Employment-Unemployment Survey (EUS) and the Periodic Labour Force Survey (PLFS) data from the NSS document substantial unmet demand for work. When women who declare themselves to be "not working" outside the home are asked if they would be willing to work if work was available at or near their home, an overwhelming majority respond positively.

The unavailability of adequate work compatible with household duties, family structure, education level and employment preferences is an important factor contributing to the low FLFP rates as well as the decline (Das and Desai, 2003; Chowdhury, 2011; Kannan and Raveendran, 2012; Kapsos et al., 2014; Chatterjee et al., 2015; Desai, 2017; Desai and Joshi, 2019; Deshpande, 2019; Dhanaraj and Mahambare, 2019; Deshpande and Kabeer, 2021). Deshpande and Kabeer (2021) find a large unmet demand for paid work among women in West Bengal. Women, who report themselves as out of labor force, are actually willing to work depending on the nature of work and compatibility with household chores.This literature suggests that social norms do affect women's ability to work outside the home; it is not stigma or sexual violence but norm of high gender inequality in sharing of domestic chores and reproductive labour.

Chatterjee et al. (2015) argue that decline in agricultural jobs without commensurate increase in non-farm jobs is the prominent explanation for the fall in FLFPR. Desai (2017) suggests that the annual number of working days performed by women has declined due to a lack of demand and not the proportion of economically active women. Afridi et al. (2020) find that mechanisation in agriculture disproportionately affected the women's employment opportunities and explain a large part of decline in rural FLFPR. Similarly, Sanghi et al. (2015) argues that unavailability of well paid job for educated women in rural India may be the primary reason of fall in participation.In addition to the paucity of jobs, there are other constraints that affect women's ability to access the jobs that exist. Lei et al. (2019) highlight transportation as a major constraint. They show that increase in paved roads and more frequent bus services increases probability of working in rural non-farm employment for both men and women but the effect is larger for women. They also show that improved transportation infrastructure has a stronger effect on women's non-farm employment in communities with more egalitarian gender norms.

Measurement is also a key factor underlying both low levels as well as the recent decline. FLFPR statistics, which are usually estimated using the NSS survey in India, underestimate women's participation in economic activity (Sudarshan and Bhattacharya, 2009; Hirway and Jose, 2011). In the South Asian context, women's role can not be merely captured by a dichotomous variable - either participating in the labor force or not - since a large section of women fall between these two extremes (Deshpande, 2019). Women's domestic responsibilities extend far beyond care work and include economic production as unpaid family worker. Deshpande and Kabeer (2021) find that a significant number of women are engaged in economic activities that can be classified as "expenditure saving", but their work is not recognised as conventional economic production activity. These women are involved in family business, livestock rearing, farming, etc. but do not get counted as workers, unlike their male counterparts doing similar work; instead get reported as economically inactive. The NSS estimates also do not capture the economic participation adequately in case of irregularity of employment and occasional work in multiple occupations (Desai, 2017).

Our paper fills a lacuna in the literature by documenting the transitions in women's labour force status over a relatively short period of four years, suggesting that most of the conventional supply side explanations are inadequate. The transitions are partly explained by negative income shocks. The most likely explanation would the be the unavailability of steady gainful employment.

The rest of the paper is organised as follows. Section 2 explains the data and presents summary statistics. Section 3 documents the transitions in labour force participation. Section 4 presents the estimates of the determinants of the transitions. Section 5 investigates the child penalty in the context of labour force participation in India. Section 6 presents a decomposition analysis. Section 7 discusses the demand for women's work. Section 8 offers concluding comments.

2 Data and Summary Statistics

We use the Consumer Pyramids Household Survey (CPHS) conducted by the Centre for Monitoring Indian Economy (CMIE) for our analysis. CPHS is a representative longitudinal survey of households in India and collects data from all the major states of India. The data set includes details on household demographics, employment status, income, expenses, amenities, assets, etc. on a panel of more than 150,000 households and approximately 350,000 working-age women. CPHS is a wave-based panel survey where each household is surveyed every four months. Therefore, we have three points of response in each calendar year. Each household is visited three times a year once in each of month slots January-April, May-August, and September-December with roughly a gap of four months. We use data from 12 waves beginning January-April 2016 (Wave 7) to September-December 2019 (Wave 18) for the analysis. CMIE began conducting the CPHS survey in January 2014. However, the employment status of household members is collected only after January 2016. We limit our analysis till September-December 2019 wave to exclude the exceptionally unusual impact of the Covid-19 pandemic.

The CPHS provides the daily employment status of each household member of age 15 years or above on the day of the survey or the day preceding the survey. CPHS classifies the employment status in four categories: 1) employed 2) unemployed, willing and looking for a job, 3) unemployed, willing but not looking for a job, 4) unemployed, not willing and not looking for a job. We consider the second and third category as "unemployed" and fourth as "out of the labor force". An individual is considered as employed if that person "is engaged in any economic activity either on the day of the survey or on the day preceding the survey, or is generally regularly engaged in an economic activity".

Table 1 shows the employment status in the 12 waves between 2016-2019. The female labor force participation rate (sum of employed and unemployed) fell from 22 percent to 12.8 percent during the study period in rural areas; while the female LFPR in urban areas dropped from 22 percent to 11 percent. There exist a differential trend within ILF where the share of employed women is greater in rural than in urban; while the unemployment rate is higher in urban areas. We should note that due to differences in sampling and definition of employment, in CPHS data, we see both urban and rural FLFP declining over time, whereas NSS data show a decline in rural FLFP and a low but steady urban FLFP over the last two decades.[4]

One striking feature of this fall in FLFP rate is that it is primarily due to a fall in the unemployment rate (see Figure 1). The share of unemployed women declined from 9.6 percent to 2.8 percent in rural and 11.3 percent to 4.1 percent in urban areas. In January -April 2016, the unemployment rate among women was more than 50 percent; only less than half of women could find paid employment opportunities. The fall in the unemployment rate over time might be due to discouraging effect of unemployment (Menon, 2019). Male LFPRs also declined over the period, but the magnitude was lower: five percentage points. Also, the major component of the fall in male LFPR is the fall in employed men.

We should note that the FLFPR is lower in magnitude than estimates in other nationally representative surveys such as NSS because of comparability issues between daily employment status in CPHS survey with NSS surveys. The NSS Employment and Unemployment Survey (NSS-EUS) surveys use three different reference periods of time to measure the employment status: annual, weekly, and daily. CPHS's daily employment status definition is closer to the definition of Current Weekly Status (CWS) and Current Daily Status (CDS).[5] A person is considered as working in CWS definition is he/she was worked for at least one hour in seven days preceding the day of the survey. The CDS status is determined using daily activity pursued by individuals on each day of the preceding week.

The CPHS estimates for male LFPR are similar to NSS, but female LFPR estimates are lower than NSS estimates (Abraham and Shrivastava, 2019; Afridi et al., 2021a). Afridi et al. (2021a) compare the Periodic Labor Force Survey (PLFS) conducted in July 2017-June

[4] https://ceda.ashoka.edu.in/are-indian-women-quitting-paid-work-because-of-increased-sexual-violence/

[5] see Abraham and Shrivastava (2019) for detailed discussion on comparability between NSS and CPHS.

2018 to the CPHS survey for the same period and find that the employment rate in CPHS is half (three-fourth) of PLFS estimates using CWS (CDS). One possible reason of discrepancy could be the framing of the question as female LFPR is usually sensitive to that (Bardasi et al., 2011). Also, there is an argument that CPHS under-represents poorer households in which female LFPR is historically observed to be high.[6] However, the CPHS definition is useful in our analysis to observe the short-term transitions in the women's participation, in addition to the advantage of being able to observe the same individuals over a period of time.

3 Documenting Transitions in Labour Force Participation

This section discusses women's labor force status transitions across various demographic characteristics. We define the labor force participation transitions based on their Labor force participation status (LFP status) in any given period and comparing that with their LFP status in the previous period. LFP status takes the value 1 in period t if the individual is in the labor force (ILF) and takes the value 0 if the individual is out of the labor force (OLF).

The variable *entry* (transition from OLF to ILF) is defined for only those individuals who were out of the labor force in period t. The variable *entry* takes value 1 if the individual changes her status to "in the labor force" in period $t+1$ and 0 if she does not change her status. Similarly, we define the *exit* (transition from ILF to OLF) for the individuals who are part of the labor force in period t. The variable *exit* takes the values 1 if the individual leaves workforce in period $t+1$ and 0 otherwise. In our data, an individual can change their status a maximum of 11 times in 12 waves. If an individual is not observed in period $t+1$, then the *entry* or *exit* is estimated by using the LFP status of the period whenever she is observed next in the data. Our results and pattern of transitions are consistent if we define the entry and exit only for individuals observed in 2 consecutive waves.

$$\text{entry (transition from OLF to ILF)}_{t,t+1} = \begin{cases} 1 \text{ if } LFP_{t+1} = 1 \ \& \ LFP_t = 0 \\ 0 \text{ if } LFP_{t+1} = 0 \ \& \ LFP_t = 0 \end{cases}$$

$$\text{exit (transition from ILF to OLF)}_{t,t+1} = \begin{cases} 1 \text{ if } LFP_{t+1} = 0 \ \& \ LFP_t = 1 \\ 0 \text{ if } LFP_{t+1} = 1 \ \& \ LFP_t = 1 \end{cases}$$

[6] https://economictimes.indiatimes.com/opinion/et-commentary/view-the-new-barometer-of-indias-economy-fails-to-reflect-the-deprivations-of-poor-households/articleshow/83696115.cms

Figure 2 shows the wave-wise pattern of exit by gender for the study period. The female LFPR was around 14.6 percent over the period of four years. The average exit rate among women is approximately 30 percent ; i.e. 30 percent women leave the labor force in each wave, and 70 percent of women remain in the labor force. The wave-average male LFPR declined from 78 percent to 73 percent in the four years. The exit rate is almost six times higher among women compared to men. On average, five percent (four out of 74) of men from the labor force exit in each wave and 95 percent remain in the labor force. The exit rate has declined in the recent waves and it is under 24 percent for women and four percent for men since May-August 2018.

Figure 3 shows the entry rate in each wave of the study period. As the entry rate is defined for individuals who were out of the workforce, it shows the percentage of individuals who join the labor force in the next wave. The figure indicates that the entry rate is four times higher among men than women. Approximately four percent women join the labor force in each wave, while around 15 percent men join the labor force in the next wave if they were out of the labor force. Similar to the exit rate, the entry rate was also higher in initial waves and it stands approximately nine percent for women in January-April 2016, showing that a large number of women entering the labor force in each wave. The entry rate has declined to 2.8 percent in the most recent wave of our study period.

Looking at Figures 2 and 3 together, we note that women are six times more likely than men to exit the labor force and four times less likely than men to enter the labor force. The entry rate fluctuates around four percent and the exit rate around 24-30 percent across waves for women. We would like to point out that the base population for which the transitions are defined are very different for entry and exit. The base population for entry rate (i.e. OLF) is much larger than the base for exit (i.e. ILF) for women, whereas for men, the size of the base population is the opposite (higher for exit compared to entry). Therefore, the difference between absolute number of entries and exits will be relatively less stark. These transitions between ILF and OLF resulted in a fall in female LFPR of approximately 10 percentage points in the study period of 12 waves, with an average 0.9 percentage points fall in the female LFPR rate in each wave. It indicates that in terms of absolute numbers, a large number of women are joining in each wave, but an even larger number of women are leaving the workforce. The difference in entry-exit rate between men and women could be due to the gendered nature of the labor market as well as the disproportionately higher burden of household work that restricts women's ability to work outside the home. It is possible that this is a manifestation of widespread informalisation and precarity of labor markets where men are working out of compulsion but women are able to join the workforce only when it is compatible with reproductive labor (domestic chores, childcare and elderly care).

Appendix A1 discusses the trend of LFPR, entry and exit rates among women across demographic characteristics in detail. We provide a quick summary here. We find that the entry rate decreases with age. The entry (exit) rate is relatively high (low) among women with education levels above undergraduate. If we check by marital status, the entry rate is highest among unmarried women, and the exit rate is lowest among divorced/widowed. Further, the exit rate is lowest among white-collar and managerial occupations and in the service sector industries.

What is the implication of the high frequency of entry and exit on measurement of female labor force participation rate in India? Figure 4 shows the number of individuals who were part of the labor force at least once in the 12 waves, the mean of LFPR in 12 waves, and the fraction of individuals who were always in the labor force. For simplicity, the figure includes only those individuals whose employment status was reported in all 12 waves. The wave-average female LFPR for the study period stands at 14.6 percent. We find that more than 44 percent of women were in the labor force at least once during the four years. However, only a small share of women (approximately two percent) were in the labor force in all the waves. This shows that percentage of women who were "working" at some point in the four years was almost three times the average FLFPR estimates over the period. Further, if we break down this 44 percent into employed and unemployed, approximately 30 percent of women were employed in at least one wave, additional six percent were actively looking for a job and eight percent were willing to work in at least one wave. These 44 percent women do not appear to be hindered by supply-side factors and/or conservative social norms. Also, we observe only a fraction of these 44 percent women as part of the labor force in each wave. This is the reason that cross-sectional estimates for female LFPR show a substantially lower FLFP rate than the percentage of women who could be considered in the labor force, but may appear OLF in any give wave.

3.1 Actual transition or a change in self-reporting?

One concern might be that these transitions could be driven by the transition between reported unemployed and OLF without any change in the proportion of employed women. Transitions between ILF to OLF can be of two types: (a) transition between employed and OLF, (b) transition between unemployed and OLF. The boundary between unemployment and OLF for women is often fuzzy, as women might not be actively looking for work in any given wave, even if they are unemployed. Thus, it is possible that it might be difficult to distinguish between the self-reported OLF unemployed status, and can be reported interchangeably by the same individual in different waves without any actual change in employment status. For instance, women reported as "not looking for a job but willing to work" are considered ILF and women reported as "not looking for a job and not willing to work" are considered OLF in our analysis. The difference between these two responses is not sharp, as both are "not looking for a job". As a matter of fact, unlike our classification, CMIE itself considers women reporting "not looking for a job but willing to work" as OLF. If a large number of transitions are occurring between "not looking for a job but willing to work" (ILF in our scheme) and "not looking for a job and not willing to work" (OLF), it is not really about entry or exit, but instead a reflection of reporting without actual change in employment level. However, we find that these transitions are not driven by only this possibility. If we examine the transition between "employed" to "not employed" (includes both unemployed and OLF), we find the trends similar to LFP transitions. In each period, around three percent of women from "not employed" are found "employed" in the next wave. Also, more than 18 percent of the "employed" women are found to be "not employed" in the next wave. Therefore, women are frequently joining and leaving jobs and not just the labor force.

Another concern might be that (a part of) these entry and exit may be seasonal in nature in rural areas and women might be leaving and joining the workforce may depend on job availability for women at different stages of the agriculture cycle. As the entry rate should be higher at the beginning of the harvesting season and the exit rate should be higher at the end of it. However, we can not exactly pinpoint the month when an individual made an entry or exit. As we observe the same individual every four months, the LFP status can change (multiple times) at any time between this period. Alternatively, we can check the month-wise female and male LFPR rates in rural areas. However, we do not find any considerable systematic difference in LFPR across months for both men and women.

3.2 Total Number of Transitions

We examine the number of total transitions (exit and entry). Some of the exits can be permanent (or for a longer period) in nature when women leave the workforce for reasons such as due to child care, permanent rise in household income, old age etc. Similarly, younger women might be joining the workforce permanently for the first time. The permanent or longer absences from the labour force most likely indicate primarily supply-side constraints or factors, while temporary or shorter term absences from the workforce are likely to indicate irregular demand for women's employment. We check the total number of transitions between ILF and OLF in 12 waves to get a sense of the nature of transitions. A lower frequency of transition indicates continuity in labor force participation status. An individual with frequent transitions shows her willingness to join the labor force but is unable to remain there, most likely due to a shortage of demand.

Figure 5 shows the number of transitions across gender and rural-urban. For easier interpretation, we restrict the sample to all the individuals who were observed in all the 12 waves and were ILF in at least one wave. This leaves out individuals who are OLF in all the twelve waves, as these might be individuals possibly permanently out of the labor force. We see that more than 70 percent men were part of the labor force in all the waves. Around 20 percent men made more than two transitions (entry-exit or exit-entry). Compared to that, only a small proportion of women (5 percent) were part of the labor force in all the waves, and 95 percent of women made at least one transition in 12 waves. Approximately 34 percent women made one transition, 36 percent women made two transitions, and 25 percent women made more than three transitions between OLF and ILF in 12 waves in rural areas, with a similar pattern in urban areas. Approximately 60 percent women made at least three transitions. This clearly indicates a large unmet demand for work where half the women could not remain continuously in the workforce and made frequent transitions between ILF and OLF.

4 Determinants of Entry and Exit

In this section, we estimate determinants of women's exit and entry at different points of time. Particularly, we check whether and how much of these entries and exits can be explained by time-varying supply-side factor. The existing literature suggests that women's labor force participation is dependent on time-varying factors and change in such characteristics can lead to a change in LFP status (entry or exit). For example, a rise in household income is negatively associated with the FLFP rate. Similarly, childbearing and child care responsibilities also depress the female LFPR. We focus on a few possible factors which can be tested using the CPHS dataset. We estimate the following two equations to measure the determinants of entry and exit respectively-

$$Entry_{i(t,t-1)} = \alpha + \boldsymbol{X}_{i(t,t-1)}\beta + \gamma_i + \tau_t + \epsilon_{it} \tag{1}$$

$$Exit_{i(t,t-1)} = \alpha + \boldsymbol{X}_{i(t,t-1)}\beta + \gamma_i + \tau_t + \epsilon_{it} \tag{2}$$

where binary variable $Entry_{i(t,t-1)}$ is defined for women who were OLF in period $t-1$ and takes value 1 for women i in period t if she switches to ILF and takes value 0 if she remains OLF. Similarly, $Exit_{i(t,t-1)}$ takes value 1 if a woman switches from ILF in $t-1$ to OLF in t and takes value 0 she remains ILF. γ_i and τ_t are the individual and wave fixed effects, respectively. $X_{i(t,t-1)}$ are time-varying individual and household characteristics, which include change or presence of unemployed male members in the households, change in the total income of other household members, and a measure of child care responsibilities. The entry equation with fixed effects compares the outcome in different periods of the same women who were OLF in at least two waves. Since CPHS data do not report the birth history of mothers, we use change in total number of children below five years of age in the household as a measure of change in child care responsibility.

We use reported incomes of the previous calendar month corresponding to the employment status on the day of the survey for the analysis due to the following reason. CPHS reports the monthly income of the household and its members for the previous four calendar months to the date of the survey. Therefore, it is not always possible to get the income for the month corresponding to that individual's employment status due to non-response and attrition of households in some waves. For example, if a household is surveyed on 21st May 2016, then the surveyor will ask for the daily employment status of that day and income-related information will be asked for the previous four months (January-April, 2016). If the same household is not surveyed again in September due to non-response, then we would not know the income in May. To circumvent this issue, we use the previous month's income instead of the month in which a household is surveyed. Since a single survey visit captures that day's employment status and previous four months' income, we are able to link all individuals with member income and household income. We use the monthly CPI index (base year=2011-12) separately for rural and urban to convert the nominal income into real income.

Table 2 shows the results from estimating equations (1) and (2). Columns (1)-(3) show the results for entry rate and include controls for individual fixed effects and wave fixed effects. First, we find that increase in the income of other members leads to a small fall in the probability of entry (Column 1). Even after controlling for male unemployed members in the household, the income effect remains almost the same (Columns 2 & 3). Second, an increase in unemployed male members in the household is highly correlated with the entry of women into the labor force. One additional unemployed male member increases the probability of entry by 2.7 percentage points. In Column (3), we take another measure "any unemployed male member in HH in period t," we find the impact of unemployment (5.4 percentage points) is twice to the measure in Column (2). Since the measure of unemployed male members in Column (3) also includes the situation where male members could be unemployed in the previous wave $(t-1)$, in addition to the current wave, the impact in this scenario should be larger. Third, the sign of the coefficient for change in total number of children below five in the household is opposite to the expected sign. We discuss the possible explanation of this in the next section where we discuss the child penalty in detail.

Columns (4)-(6) show the results from estimating Equation (2) for exit rate among women. Similar to the entry, we find that an increase in income of other members is positively associated with the probability of exit. We find that the exit rate is negatively affected by an increase (Column 5) or the presence of any unemployed male member (Column 6) in the household. The presence of any unemployed male member decreases the probability of exit by 22 percentage points. Similar to entry, we do not find any negative impact of change in child care burden on exit out of labor force.

Column (7) and (8) report the impact of income level, unemployment of male members, and child care duties on FLFP (instead of exit and entry). The regression results show that an increase in male unemployed members in the household is associated with an increase in women's labor force participation in both specifications without (Column 7) and with (Column 8) fixed effects. The presence of unemployed male members increases the probability of being in labor force by 11 percentage points. Second, the income of other household members is negatively associated with the probability of being in the labor force. One percent increase in other members' income decreases the probability of being in the labor force by 1.3 percentage points. Third, if we do not control for individual fixed effects, child care duties are negatively associated with labor force participation. The results are similar to the estimates using cross-section data in India by Das and Žumbytė (2017). They use NSS data and find that women without younger children have a 1.4 times higher probability of being in the labor force compared to women with younger children. Controlling for individual fixed effects makes childcare insignificant as a determinant of FLFP.

We use our regression coefficients for a back-of-the-envelope, rough calculation to gauge the relative contribution of two factors, *viz.*, the presence of unemployed male members in the household and change in other household members' income in the total entry and exit rates of women. As we discuss in the previous section, on average, the entry rate for women in our study period is four percent and the exit rate is approximately 30 percent. Our regression results show that the presence of male unemployed members in the household increases the probability of entry by 5.4 percentage points and decreases the probability of exit by 22 percentage points. The probability that working-age women have at least one male unemployed member in the household in our data is 0.074. Combining these two, it appears that only 0.4 percent (5.4×0.074) of entry rate and 1.6 percent (22×0.074) of exit rate in each period can be explained by the presence of unemployed members. Similarly, the mean value of the change in the log income of other household members is 0.04. One unit increase in log income increases the probability of entry and exit by approximately 0.35 and 0.63 percentage points, respectively. Therefore, on average 0.01 percent (0.35×0.04) of entry rate and 0.025 percent (0.63×0.04) of exit rate in each wave can be explained by the income effect. In summary, the change in income and unemployment of male members in the household explain a small part of the entry and exit rates of women.

Change in income of household members is not the only reason for women to enter or exit the workforce. Marriage is one of the chief reasons why women either do not enter or exit the workforce (Afridi et al., 2018). However, we do not observe the same women before and after marriage, as the probability that a woman's natal and marital households are in the sample is very low; besides, even if both households are present, matching marital households to natal households is not possible. Therefore, the documentation of entry and exit rate excludes the transitions due to marriage. We should note that marriage can not explain neither entry nor frequent transitions.

5 Motherhood or Child Penalty for Indian Women

Motherhood or child penalty is defined as a negative labor market outcome such as labor force participation, wage, earning, occupation for women due to childbearing and child care compared to men ((Bertrand, 2020)). In developed country labour markets, conditional on various wage-earning characteristics, mothers earn less than childless women (Bronars and Grogger, 1994; Lundborg et al., 2017), and less than their husbands. In fact, studies show that new fathers earn a wage premium, whereas new mothers earn a wage penalty (Lundberg and Rose, 2000). This aggravates the existing male-female wage gap in almost all countries. Feminist economists have convincingly argued that labour markets are gendered institutions. While the productive economy cannot function without the unpaid and invisible contribution of reproductive labour, women (who are disproportionately represented in the latter) are penalised in the labour market, whereas men are rewarded (Folbre, 1994).

In mainstream economic analyses, the earnings gap between women with children and women without children can be a result of two processes- role of adverse selection and causal role of having children. According to the first explanation, women who chose to have children might earn less even in the event they did not have children, e.g. some women may prefer to have children instead of compete in the labour market either due to their preferences or due to unobservable characteristics. The second explanation focuses on the possibility that childcare responsibilities could have a negative causal role on labor market performance for mothers (Lundborg et al., 2017).

There are many possible channels for the motherhood/child penalty. Women may leave the labor market or reduce their work hours by moving to part-time work. They can also choose to find a job with flexible work (for example, switching from private to public sector or self-employment) or closer to their residence to invest more time in child care (Mas and Pallais, 2017; Lundborg et al., 2017; Le Barbanchon et al., 2021). All these mechanism can reduce their hourly earnings due to reduced labor supply. Further, this short-run supply shock can have a large negative impact on long-term wages in the labor market due to lower accumulation of human capital such as work experience and skill acquisition. Additionally, employers can also discriminate in hiring if they believe that women with potential childcare duties may cause interruption in workplace. A recent correspondence study found that employers discriminate in hiring of married women who are in the childbearing cycle in part-time jobs (Becker et al., 2019).

The early empirical literature on motherhood/child penalty relies primarily on instrumental variable estimation to separate the causal role from adverse selection. There are two prevalent exogenous fertility shocks which are used as instruments in the literature- twin birth and sibling sex composition (Bronars and Grogger, 1994; Angrist and Evans, 1998) . However, both of these instruments are useful to estimate the impact at intensive margin, which is the labor market impact of an additional child on parents' labour market outcomes. The impact at the extensive margin, which is the impact of having the first child, is difficult to estimate causally. The literature relies on some other exogenous (policy or health) shock and event study design for estimating the impact at extensive margins (Angelov et al., 2016; Lundborg et al., 2017; Kleven et al., 2019a,b) .

The bulk of the evidence on motherhood/child penalty comes from developed countries. The evidence is relatively scarce from developing countries due to unavailability of panel data. Developing country labour markets are characterised by a large proportion of workers in the informal sector and a lower share of regular wage/salaried workers. In this context, a wage penalty is not the best metric to evaluate the motherhood penalty.

We use the CPHS panel data to estimate if the addition of a new child in the household impacts women's labor force participation in India. Since, CPHS data do not provide the birth history of all children of surveyed members. We use a small sample of households in which we can identify new births and link them with their parents. We primarily use variables "relationship with household head," "age of the household member," and period when each member of the household observed first time in the data to identify new births.

We identify mothers with a new child birth only in cases when women are either *head of household* (HOH) or *spouse of HOH*; and, daughter or son of the HOH are potential new births for these women. We define a new child birth when a child is observed later than the household in the dataset and with reported age less than 12 months.[7] We exclude mothers with multiple child births for simplicity. In our data set, there are approximately 3000 mothers with new child birth. We define our comparison group as women without any child care burden. The comparison group includes all working age women from those households who never had any children below 5 years during the study period of 12 waves. Finally, we limit the sample to women between 15-50 years when they are observed first time in the data. Thus, we have we have approximately 3000 new mothers and more than 1,93000 women in comparison group.

In most of the literature on child penalty, researchers are interested in the labor market outcomes before and after the *first* child birth instead of each child birth irrespective of the birth order. Unsurprisingly, they find the relatively large negative impact at first child birth compared to next births in order. However, we repeat the same exercise with each birth

[7] The age of each individual does not increase exactly by four months after each wave in the survey. Therefore in this section, we use the age of each member when she was observed for the first time in the dataset and impute the age in following waves by adding 4 months for each wave.

(including first) to understand whether child penalty can explain frequent transitions.

5.1 Matching Mothers with Comparable Non-mothers

Since new mothers can be different from the comparison group of not-new-mothers because of self-selection, and also because child birth is non-random event, therefore, the treatment (new child birth) would be correlated with other covariates which are related to FLFP as well. To correct for non-random assignments, researchers widely use matching methods. The matching methods compare the outcome of treated unit with nearest matched (on covariates) comparison unit to estimate the treatment impact. We use one such recent estimation method, namely Entropy Balancing (EB) developed by Hainmueller (2012). EB essentially reassigns weights to each units in comparison groups to balance the covariates on desired statistical moments. This re-weighted sample is matched on covariates across treatment and control groups.

We use a number of individual and household level covariates for Entropy Balancing. For the male sample, we include: age (in years), relationship with household head, social identity (caste, tribe, religion), rural-urban, level of education, and total number of members in the households. In addition to these, we use highest level of male education in the household as a covariate for female sample. We use these covariates separately in each wave to generate balanced weights for comparison units. We constrain the covariates on mean and standard deviation.

Table A.3 (in Appendix) shows the mean and variance of covariates before and after the balancing in Wave 7 for female sample. Indeed, there is a large difference between mean values of covariates such as age, share of rural, size of household and education level of male member (Panel A). The mean age in treated group (new mothers) is 28.5 years; while it 32.2 years in comparison group. The size of household (number of members) is smaller for treated women. The treated women are relatively more rural and less educated than the comparison group. The highest level of male education is lower among treated women. Panel (B) shows the summary statistics after EB. The mean and variance of all the covariates are statistically similar between new mothers and comparison group women after EB.

Figure 6 shows the trend of FLFP among new parents and comparison groups between January-April 2016 (Wave 7) to September-December 2019 (Wave 18). Figure 5 presents the FLFP rate trend for comparison group using EB generated weights. As we discussed previously, FLFP rate is falling over the study period; therefore we find a falling trend among comparison group. New mothers are those with a child birth in any one of the wave between wave 7 and wave 18. Surprisingly, we find that new mothers' trend of labor force participation is parallel to the comparison group with a large difference in base. The difference between FLFP rate among new mothers and the comparison group is approximately 3 to 6 percentage points. Women in the comparison group have 1.3 (Wave 18) to 1.4 (Wave 7) times the probability of being in the labor force compared to new mothers. Contrary to women, men possibly get a premium in labor market as a result of child birth. New fathers have a positive level effect as they have a higher LFPR compared to men from the comparison group. The LFPR for new fathers is more than 97 percent.

5.2 Effect of Child Birth on Mother's LFP

We estimate the effect of child birth on female LFPR using Two-way Fixed Effect (TWFE) estimation in event study setting. We estimate the following equation:

$$LFP_{it} = \alpha_i + \gamma_t + \sum_{\tau=-K}^{L} \delta_\tau D_{it}^{\tau} + \epsilon_{it} \tag{3}$$

Where, LFP_{it} is dependent variable which takes value 1 if women i was ILF in period t and 0 otherwise. α_i is individual fixed effect and γ_i is individual wave effect. D_{it}'s are dummies for τ waves after and before the child birth for women i (example: $\tau = -K, \ldots, -3, -2, -1, 0, 1, 2, 3, \ldots, L$). Each of these dummies take value zero for all women in comparison group. One of the coefficients is fundamentally unidentified; therefore we take $\tau = -3$ (one year before the child birth) as base category. All coefficients δ_τ measure the effect relative to period $\tau = -3$. The coefficient δ_τ shows the effect of child birth on probability of labor force participation τ waves before/after the child birth relative to the women with no child in the household.

Figure 7(a) shows the results from estimating Equation (3). We use the weights generated using Entropy Balancing. The X-axis represents τ (waves before/after the child birth) and Y-axis represents the coefficients δ_τ. The blue dots are point estimates and blue lines are 95% confidence interval. We report the coefficients for nine waves before and nine waves after the child birth. Because the significance level falls as we move away from $\tau = 0$ due to decrease in sample size. We find very surprising results for positive values of τ; we do not see any fall in FLFP during or immediately after the child birth unlike the literature from developed countries. There exists a weak trend of increase in FLFP one year after the child birth. Also, we do not find parallel trend before the child birth. In contrast, we find that FLFP was increasing till one year (three waves) before child birth and converging towards towards the (higher) FLFP level of comparison group women. The only possible explanations of this trend could be: women with future child expectations exit the labor market years before the child birth and their FLFP remains constant for next few years at a lower level. We conduct this analysis on the balanced panel by considering only those individuals which were observed in all 12 waves in the survey. Figure 6(b) shows the results from estimating the Equation (3) using balanced panel and our results similar to that from the unbalanced panel.

Combining Figures 6 and 7 suggest that women with child care responsibilities might be leaving the labor force earlier than the actual time they are bearing the child and they remain out of the labour force for a longer time. In contrast to this, the pattern of women's employment from developed countries shows that mothers leave the labor force few months before the child birth and a large share of them re-join after the birth. Therefore, we find a level impact where women continue to remain out of labor force with a small increase in FLFP years after the child birth. Our results are consistent with motherhood penalty estimates by Das and Žumbytė (2017). They use NSS cross-section data and find that women without any young children (age below 6 years) have 1.4 times more probability of being employed compare to women with young children. Our trend in figure 13 shows the similar level effect.

5.3 Stacked D-I-D estimates

A nascent literature on TWFE estimation with staggered event design shows that the coefficients obtained from TWFE model may be biased and not be causally interpretable if there exists heterogeneity in treatment effect across units (Goodman-Bacon, 2019; Callaway and Sant'Anna, 2020; Sun and Abraham, 2018; De Chaisemartin and d'Haultfoeuille, 2020; Baker et al., 2021). The problem appears because TWFE estimation uses early treated units as comparison groups for late treated units. The literature suggest some alternate estimators which circumvent this problem. We use one of them, i.e. Stacked Difference-in-differences (DID), similar to Cengiz et al. (2019) and Deshpande and Li (2019). Stacked DID compares treated units (new mothers) to comparison units and does not compare the late treated units to early treated units.

Stacked DID primarily requires creating cohort datasets and arranging them. As the first step, we create 11 cohort datasets for each wave from 8 to 18. Each cohort includes treated units and comparison units. The comparison units in each cohort dataset include all the comparison group women in whose households we never observed any child, whereas the treatment units include women in whose households we observe a child birth in the respective wave. For example, Cohort 9 dataset will include the women who observed a child birth in Wave 9 and all the comparison women as treated and comparison units respectively. We create variable *treated* which takes value 1 if the unit is treated in that cohort and 0 for comparison units. As the second step, we assign event-wave (τ) to each observation in cohort datasets, which is time order of each observation relative to the wave when a child birth is observed. For example in the Cohort 9 dataset, each observation in wave 7, 8, 9, 10 ... will take values τ=-2, -1, 0, 1.... Next we append these 11 cohort dataset and create dummies for each value of τ denoted as D^{τ}_{ct}. We estimate following equation:

$$LFP_{it} = \alpha_{ic} + \gamma_{ct} + \delta_0(Treated)_{ic} + \sum_{\tau} D^{\tau}_{ct} + \sum_{\tau} \delta_{\tau}(Treated_{ic} \times D^{\tau}_{ct}) + \epsilon_{ict} \quad (4)$$

Where LFP_{ict} is labor force participation status of women i in period t. α_{ic} is individual $\times$ cohort fixed effect and γ_{ct} is wave$\times$cohort fixed effect. $(Treated)_{ic}$ is dummy which takes value 1 for treated units in cohort c. The coefficient of interest are δ_{τ}s. We take τ=-3 as base category. The interpretation of each coefficient δ_{τ} is similar to the interpretation in Equation (3). Figure 8 shows the results from Stacked DID estimates for unbalanced panel (sub-figure 8a) and balanced panel (sub-figure 8b). The results using Stacked DID are similar to TWFE estimates.

We also estimate child penalty separately for mothers of the *first* newborn child and mothers of a newborn child in the study period other than the first child (Appendix Figure A.2). We create comparison groups for the two sub-samples separately analogous to our main estimate using the Entropy Balancing method. The impact of the *first* child birth on mothers' LFPR is similar to our main estimates, i.e. mothers' workforce participation does not drop around the first child birth (Appendix Figure A.2(a)). We do not find any trend of increase in LFPR in the years following the first child birth. Appendix Figure A.2(b) shows the estimates for motherhood/child penalty for mothers with a new child in our study period but where the child is not the first one. We find a significant increasing trend of FLFP a year after child birth and converging towards the (higher) FLFP level of comparable women without any child care responsibilities. These results confirm our interpretation that women expecting their first child remain out of the labor force in the medium term both before and after the child birth but the actual event of the child birth does not mark a structural break in their LFPR.

6 Decomposition Analysis

The idea behind this section is to provide the evidence for our suggestion that the recent fall in FLFPR may not be caused by predominantly or only by supply-side factors. The high frequency of entry and exit notwithstanding, the FLFP rate declined by 10 percentage points from 22 percent in January-April 2016 to 12 percent September-December 2019 over a period of 12 wave (4 years). We use the Blinder-Oaxaca decomposition method to gauge how much of the fall in FLFPR can be explained by supply side factors. We use two waves of CPHS survey: Wave 7 (the first wave with details of employment status) and Wave 18 (the last wave before the Covid-19 Pandemic). The variation in demographic characteristics in our data over the 12 waves arises from addition of new sample households between waves, re-assigning of survey weights, changes in family composition or individuals residing in the house, and change in the ages of surveyed members as some younger household members enter the labour market in later waves to be eligible for questions related to employment status.

6.1 Methodology

We use the Blinder-Oaxaca decomposition method to decompose the change in FLFPR into two components: one, explained by covariates or labour market characteristics and two, the change that cannot be explained by covariates. The unexplained component captures the change in labour force participation that is not explained by changes in individual (supply-side) characteristics. To apply this method, first we estimate the following linear regression equation for both Waves 7 and 18:

$$\hat{Y}_i^t = \mathrm{X}_i^t \beta^t + u_i^t \tag{5}$$

where, Y_i^t is a binary variable which takes value 1 if women i is "In the labor force (ILF)" in wave t and 0 otherwise. X_i^t includes household and individual demographic characteristics. β^t are parameters estimated from equation (4) for wave t. And, u_i^t is error term. Next, we estimate the following decomposition equation:

$$\bar{Y}^{18} - \bar{Y}^{7} = \underbrace{\sum^{j} \beta_j^7 (\bar{\mathrm{X}}_j^{18} - \bar{\mathrm{X}}_j^{7})}_{\text{explained}} + \underbrace{\sum^{j} \bar{\mathrm{X}}_j^{18} (\beta_j^{18} - \beta_j^{7})}_{\text{unexplained}} \tag{6}$$

The first term shows the change in FLFPR due to change in explanatory variables (determinants of labour market participation) and the second term shows the change in FLFPR not similarly explained.

6.2 Data and Results

We use the CPHS data for two waves: January-April 2016 (Wave 7) and September-December 2019 (Wave 18) for the decomposition analysis to estimate the extent to which the supply side individual and household characteristics can explain the fall in female labor force participation (FLFPR) between these waves. Table 3 shows the summary statistics for Waves 7 and 18 as well as for the combined sample. The sample size is larger in Wave 18 as CPHS has increased the sample size over the time. The FLFPR dropped from 22 percent in Wave 7 to 12.2 percent in Wave 18. The age composition changed slightly with a higher proportion of women below the age of 35 years in Wave 18. Women's own education level and the highest level of education of any male in household has increased over time in the sample. We observe a fall in child care responsibilities over the two waves, captured by share of child below 5 years in the household. Thus, there are some changes in average supply-side characteristics of women in our sample.

Table A.4 (in the Appendix) shows the results from estimating the reduced form Equation (5) for the rural sample. Specification 1 includes all the exogenous explanatory variables such as dummies for rural, age groups and caste and religion. We see that after controlling from own education, age, caste and religion, the coefficient of *Wave18* remains around 0.10; showing a fall in FLFPR of approximately 10 percentage points. Columns (2) and (3) show the results from estimating Equation (5) separately for both Wave 7 and Wave 18. Specification 2 includes all exogenous and potentially endogenous variables such as dummies for highest education level of any male member in household, household income deciles and share of children below 5 years of age in total household members. The coefficient size of *Wave18* remains at almost same level even after the inclusion of the endogenous variables. Appendix Table A.5 show the results from estimating Equation (5) for urban sample.

Table 4 shows the results from estimating Equation (6) using Blinder-Oaxaca (B-O) decomposition separately for urban and rural samples. The table reports the B-O decomposition using coefficients from Wave 7 as reference coefficients. Specification 1 includes exogenous variables and Specification 2 includes all the explanatory variables including endogenous variables. The results from the decomposition exercise shows that almost none of the change (9.4 percentage points) in rural FLFP rate between Wave 7 and Wave 18 can be explained by supply-side individual and household characteristics in either of the specifications. The negative significant value of the explained portion shows that if the return to each characteristics in labor force participation would have remained same, then the female LPFR would be higher in Wave 18 compared to Wave 7 (at 22 percent). In urban areas, FLFPR dropped by 11 percentage points and only a small portion of that drop (one percentage point) can be explained by explanatory variables.

Figure 9 shows the contribution of each explanatory variables in the explained and unexplained components for the rural sample. The unexplained portion is high for OBCs (1.4 percentage points) and SCs (1.1 percentage points). Further, there is a significant unexplained part (approximately one percentage point) each for below primary and middle school educated women; and 0.5 percentage points for higher secondary school educated women. This indicates that a large portion of women with relatively lower education level are not able to find employment opportunities compared to Wave 7. In the exogenous Specification 1, women at all education levels (except postgraduate and above) show a large unexplained component. Further, a large share of the total unexplained component is coming from the highest education level of male members in the household. Other household members' income do not explain the change in female LFPR over the period. Figure 10 shows the contribution of each variable in explained and unexplained components for the urban sample. The results for urban women show a slightly greater explained part compared to rural, i.e. a fall in FLFP explained by change in characteristics over time. The contribution of individual covariates to the unexplained part is similar to the rural areas.

7 Demand for women's work

In the previous sections, we demonstrate two noteworthy attributes of women's employment which contest the narrative that female LFPR are low and falling in India due to supply-side reason. One, women frequently enter and exit the labour force over short intervals of time, due to reasons unrelated to the supply side factors widely studied in the literature. Two, while female LFPR dropped by 10 percentage points in the study period, almost none of it can be explained by supply side demographic characteristics. In this section, we discuss suggestive evidence than that both of these attributes can be outcome of large unmet demand for women's work.

We believe that the literature on the demand-side constraints offers compelling explanations for these two factors. It appears that women are dropping out of the labor force because of the nature of the growth process that has not been employment intensive and during which female workers are being displaced by male workers. Table 5 shows the change in total working age population (older than 14 years) and total employment level in India over the study period. The working age population increased by approximately nine percent from 944 million to 1029 million. However, the total employment level increased only by two million (0.7 percent growth in employment) from 404 million to 407 million. This demonstrates the Indian economy's employment crisis, which could not generate enough employment opportunities for the rising population, which is manifested in a high unemployment rate. In such a case, there is a possibility that the rising number of men in the working age population are displacing women from employment. Our data shows that the total male employment increased by approximately 12 million, with a similar number of women (nine million) of women dropping out from employment over the 12 waves.

A large fall in female employment and an almost equal rise in male employment indicates that men are displacing women at a time when the Indian economy created almost negligible new jobs. However, this stylised fact is compatible with the possibility that the share of different industries in total employment also changed over the period, and employment fell in industries that had a relatively higher share of women workers, whereas it rose in industries with lower share of female workers. If this is true, it would imply that men are not displacing women but the traditional avenues that employed women are shrinking. Table 6 shows the employment level (in millions) in broad industry levels in January-April 2016 (Wave 7) and September-December 2019 (Wave 18). We do not see any trend to suggest that total employment is disproportionately falling in industries where women are relatively better represented. Also, we observe that the relative share of women in total employment has fallen in all the broad industries except the food industry (including hotel and restaurants).

Total employment in agriculture and allied activities (relevant for rural areas) has increased by two percent over the period. However, we see a fall in female employment in agriculture of 2.8 million (amounting to 11 percent). This suggests that the share of women is falling in agriculture as men are replacing women. A part of this fall in women's employment in agriculture sector is the outcome of displacement of women due to mechanisation in agriculture (Afridi et al., 2020). The total employment has fallen over time in manufacturing and construction by 26 percent and 15 percent respectively. The aggregate employment in these industries has fallen both for men and women, but it has disproportionately affected women as female employment has fallen by more than 40 percent in both.

Most surprisingly, while total employment has increased in the education sector, but women's (absolute) employment has declined in this industry where women are assumed to have a comparative advantage and have been traditionally better represented. The total employment increased by seven percent in education but women's employment registered a sharp fall of 25 percent. Almost, two million fewer women are employed in the education sector over a period of less than four years. Total employment of women increased in trade, food industry, personal and care services. However, the level of employment in these industries is too small to absorb women who are unable to get employment in larger industries such as agriculture, manufacturing, construction and education. In summary, the industry-level employment level data indicates that women are displaced by men in large industries.

Second, it is often seen that a high unemployment rate discourages women from joining the labor force (Menon (2019)). Figure 1 shows the LFPR, employment and unemployment rates. We see that in January-April 2016, almost half of the women looking for employment could not find any employment opportunities and remained unemployed. The unemployment rate is particularly high in urban areas. Such a high rate of unemployment rate seems consistent with Deshpande and Kabeer (2021), where they find that more than 70 percent of women ready to accept work if it can be made available at or in the vicinity of their homes. The unemployment rate is falling in later periods but for wrong reasons; women are not moving from unemployed to employed but out of the labor force altogether. We argue that the inability to find paid employment might have discouraged women and pushed them out of labor force. Almost negligible new job creation, unavailability of jobs accommodating women's domestic work requirements, and possible displacement by men has led to a large unmet demand for women's work. This large unmet demand, further, discourages women to join the labor force in the future.

7.1 Negative economic shock and FLFP

In this context, how does a negative large economy-wide shock affect female labor force participation? In our study period, the "demonetisation" exercise took place, which was a random unanticipated negative shock. In a sudden move, India declared 86 percent of currency in circulation as illegal tender from the midnight of November 9, 2016. This announcement took everyone by surprise and resulted in a sharp decline in cash currency for upcoming months across India with adverse effects on economic activity, as the Indian economy is heavily cash-dependant. Chodorow-Reich et al. (2020) study the impact of demonetisation on economic activity and employment. They find that demonetisation led to a fall in economic growth by two percentage points and three percentage points fall in employment level.

We show that the demonetisation disproportionately affected female LFPR and discouraged them to join the labor force. Figure 11 shows the monthly LFPR trends between January 2016 and December 2017 separately for men and women. As we discussed earlier, women's participation has been falling over time. Additionally, we see that India witnessed a a significant shift in level of female LFPR around November 2016. If we see the difference between fitted lines, LFPR dropped by 4 percentage points in both rural as well as urban areas. We should note that a bulk of this fall is due to women moving from unemployed to out of labor force, which indicates that the fall in economic activity due to the demonetisation shock discouraged women from joining the labor force. To estimate the disproportionate impact of demonetisation on female LFPR, we estimate the following regression equation:

$$ILF_{it} = \alpha_i + \gamma_t + \beta_1(post)_t + \delta(female \times post)_{it} + \beta_2(wave)_t + \beta_3(female \times wave)_{it} + \epsilon_{it} \quad (7)$$

Where, i is individual and t is wave. ILF_{it} takes value 1 if individual i was in the labor force in wave t and 0 is she was out of labor force. α_i is individual fixed effect and γ_t is wave fixed effect. $(wave)_t$ and $(female \times wave)_{it}$ controls for linear time trends. Variable *post* takes value 1 for observations from November 2019 and 0 for the period before that. The coefficient of interest is δ which shows the different impact of demonetisation on labor force participation of women compare to men. We use the data from six waves beginning from January-April 2016 to September-December 2019.

Table 7 shows the regression results from estimating Equation (7) for combined sample and separately for rural and urban sample. We find that, demonetisation had a large significant negative impact of 1.9 percentage points on female LFPR. Demonetisation led to a fall in female LFPR by 1.5 percentage points in rural and 2.8 percentage points in urban areas. The negative coefficient of (female$\times$ wave) shows secular decline in female LFPR by approximately one percentage points in each wave.

These results are qualitatively similar to Afridi et al. (2021b) and Deshpande (2021) that demonstrate the disproportionate impact of exogenous negative economic shocks, *viz.*, drought and the Covid-19 pandemic, respectively, on women's employment.

8 Discussion and Concluding Comments

Our paper presents new evidence on the low and declining level of female labor force participation in India using high-frequency longitudinal data from CMIE. During 2016-2019, the average labour force participation rate of women was close to 14.5 percent in our data. Over the period, female labour force participation rate fell from 22 percent to 12.8 in rural and 11 percent in urban areas. However, within the overall declining trend, we observe that a large proportion of women frequently change their labor force participation status between "In the labor force (ILF)" and "Out of labor force (OLF)", as they drop out of labor force in a given wave to sometimes rejoin in later waves. We examine how transitions differ by age, education levels, urban-rural residence and social group identity.

There is ample evidence to demonstrate that women's labour force statistics consistently underestimate their actual involvement in productive work. We show how the irregular and short-term engagement of women in the labour force leads to underestimation of female LFPR. The average FLFP rate using CPHS dataset stands at around 14.5 percent for the study period. However, around 44 percent of women (more than thrice the FLFP rate) were part of labor force in at least one of the waves, with only two percent of women remaining in the labor force in each of the 12 waves. These transitions over a short span of four years indicate that a) actual proportion of women engaged in economically productive work is much higher than revealed by any point estimate from cross-sectional data, and b) women are not held back from productive work due to cultural factors, but are probably unable to find continuous employment which they take up when possible.

The existing vast literature discusses both supply-side and demand-side explanations. Using panel data over four years, our analysis demonstrates that contrary to the narrative of a steady decline and/or the state on continuous withdrawal from the labour force, Indian women's LFP status is marked by volatility and exhibits frequent transitions. To the best of our knowledge, our paper is the first to document the frequent short-term entry and exit of women from the labor force for reasons unrelated to marriage, child-birth, and change in household incomes. This pattern is inconsistent with the idea that women are voluntarily dropping out of the labor force; instead, it suggests that supply-side reasons can not be the primary explanation for the fall in labor force participation of women. Our results also suggest that frequent transitions in and out of the labour force exacerbate the issue of underestimation of female LFPR.

The literature on the measurement of women's work in India correctly focuses on the inability of survey data to capture women's unpaid economic work in household enterprises and several attempts have been made to correct for this source of under-counting or measurement error, as discussed in Deshpande and Kabeer (2021). We demonstrate that in addition to the more commonly discussed issue of under-counting, the volatility in women's labour force status also exacerbates the measurement problem. Our results show that even with a restrictive definition of employment, without counting women's productive work in household enterprises, 44 percent of women were in the labour force at least once during the four-year period, which is far higher than any official estimate. This lends credence to the argument that the number of women in the labour force has not declined but the duration that they work for has become shorter, which registers as a decline in their labour force participation (Desai and Joshi, 2019).

The frequent transitions in the labour force status of women, and their repeated and temporary exits out of the labor force, both in urban and rural areas, suggest the unavailability of regular and steady employment opportunities for women. This may be a manifestation of widespread informalization and precarity of labor markets where men work as main breadwinners, but women are able to join the workforce only when there is work available that is compatible with reproductive labor (domestic chores, child care, elderly care). Especially for our study period, when the unemployment rate is very high and the rate of new job creation has been low, women are disproportionately hit.

Choithani et al. (2021) document the lack of diversification of employment opportunities in census towns, i.e. erstwhile villages being reclassified as urban settlements, as the proportion of male breadwinners with agriculture as the primary source has fallen over time. Men either migrate to cities in search of livelihood opportunities or work in, say construction, centres within daily commuting distance. In their fieldwork sites, they find that alternative local livelihoods are very limited and reliance on remittances from migration is very common. For women, this presents very few choices. Women either work on family enterprises, mostly agriculture; landless lower-caste families worked on others' farms for cash incomes.

Afridi et al. (2021b) also highlight the lack of diversification of employment opportunities in the non-farm sector. They show that when a drought occurs, women's workdays fall by 11 percent more than men's as women are less likely to migrate or work outside the village compared to men during times of agricultural distress.

The first-order issue related to employment in India over the last three decades is lack of adequate job opportunities for men and women, described as "jobless growth"[8], as well as

[8] Choithani et al. (2021) summarizes recent literature on the subject.

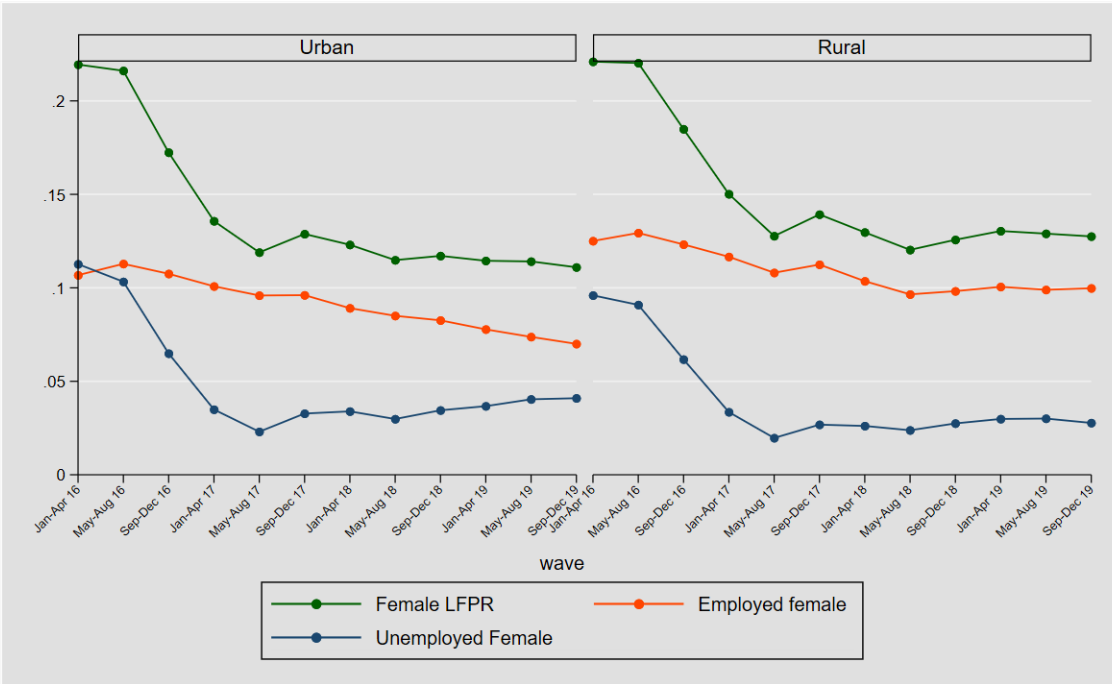
precarity and informality of labour markets. The post-1991 economic growth was driven by sectors such as information and technology (IT) which are not labour intensive. Since 2016, there has been deceleration of economic growth, which means that both growth (jobless or not) as well as jobs are matters of concern. During a period of three decades marked by extensive structural transformation of the Indian economy, it is both a puzzle and a source of worry that demand for women's work has steadily declined. While the mainstream explanations have centred on on women dropping out of paid work due to adverse social norms, we have tried to demonstrate in this paper that the demand-side narrative, summarized in Section 1.2, is more compelling. There is plenty of evidence of gender discrimination or employer bias against female employees who are seen as either less capable or are presumed to have lower attachments to their jobs relative to their domestic engagements. Feminist scholarship has demonstrated how women are penalised for their reproductive labour that actually provides the vital safety net when a crisis hits – a phenomenon we are witnessing around the globe during the Covid-19 pandemic which is underway at the time of writing. We need deep-dive research specifically rooted in the Indian context in order to understand the precise combination of factors that shape demand for women's labour.

We also need more research to identify accurate and effective policy responses. The most substantive policy response at the macro-level would be a combination of policies to boost employment-intensive growth. Additionally, Lei et al. (2019) highlight the importance of augmenting transportation infrastructure. Deininger et al. (2020) examine the effects of female reservation in village local government in the context of the National Rural Employment Guarantee Scheme (NREGS) and find that women's labour force participation, number of days worked per year and total earnings is higher in "ever" versus "never" reserved villages. While achieving the appropriate macro-policy framework might be more challenging as it needs a broader political consensus, there is considerable space in the existing policy arena that can be exploited to promote women's desire to be engaged in paid economic work.

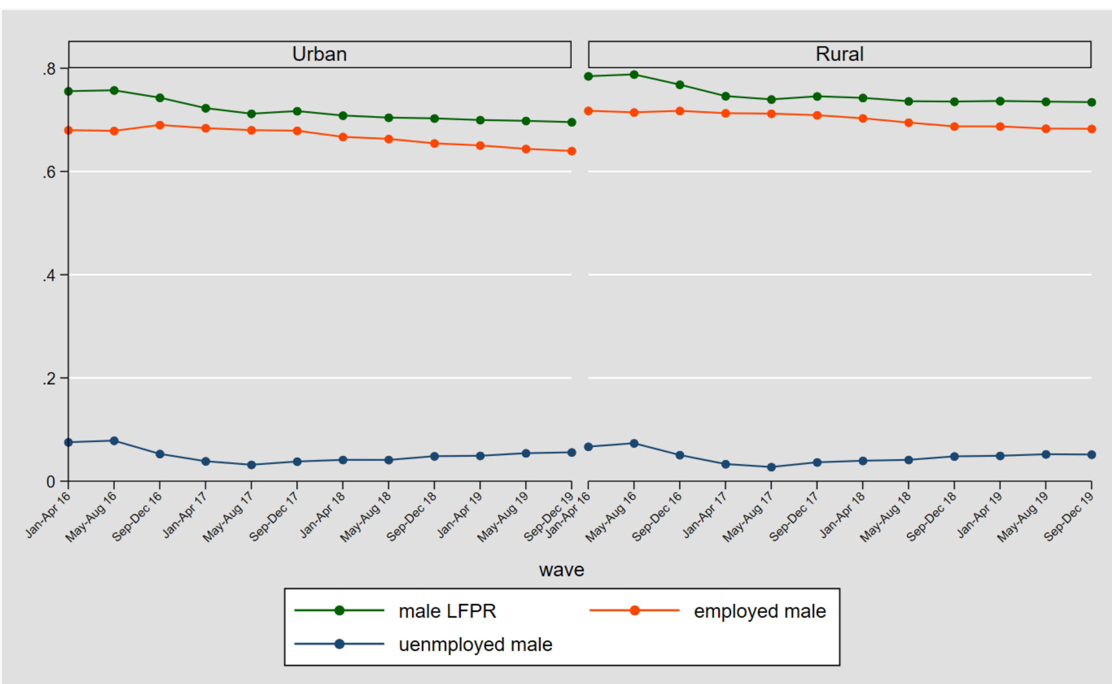
Figures and Tables

Figure 1: Employment Status

(a) Female

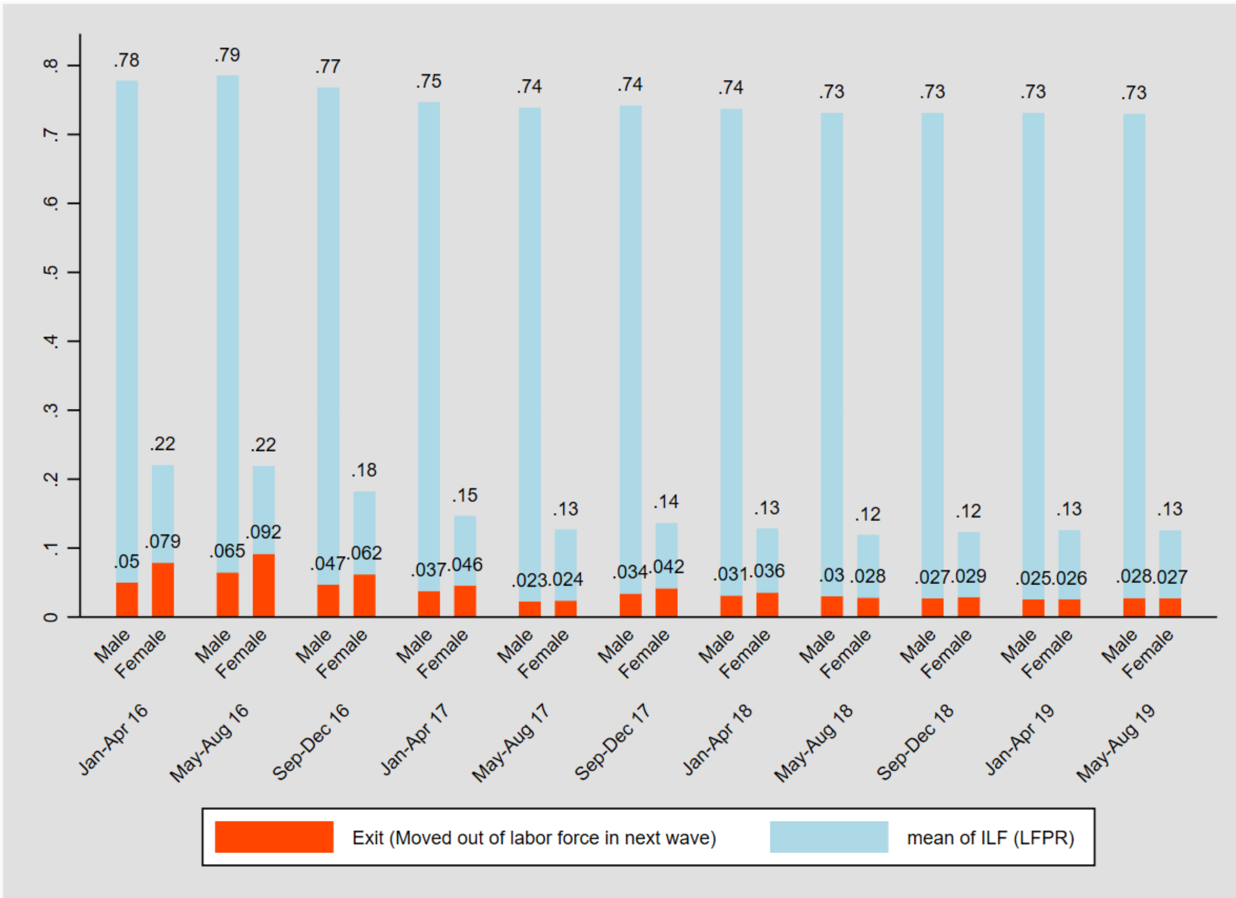


(b) Male



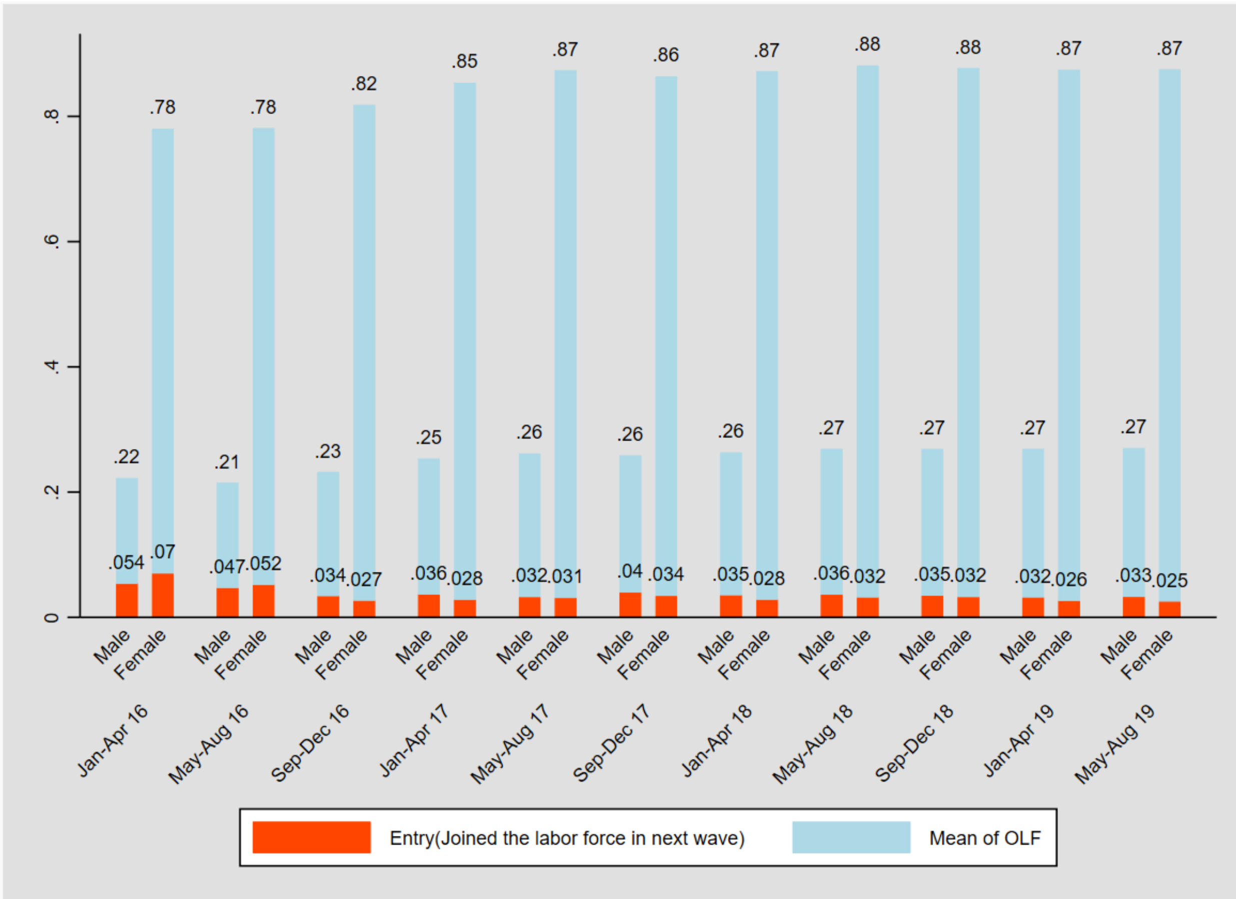
Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: This figure Labor force participation (in green), employment percent (in orange) and unemployment percent (in blue) of all the individuals above 14 years of age separately for urban and rural. We use survey weights for workforce population provided by CPHS.

Figure 2: Exit (transition from ILF to OLF) rate by wave



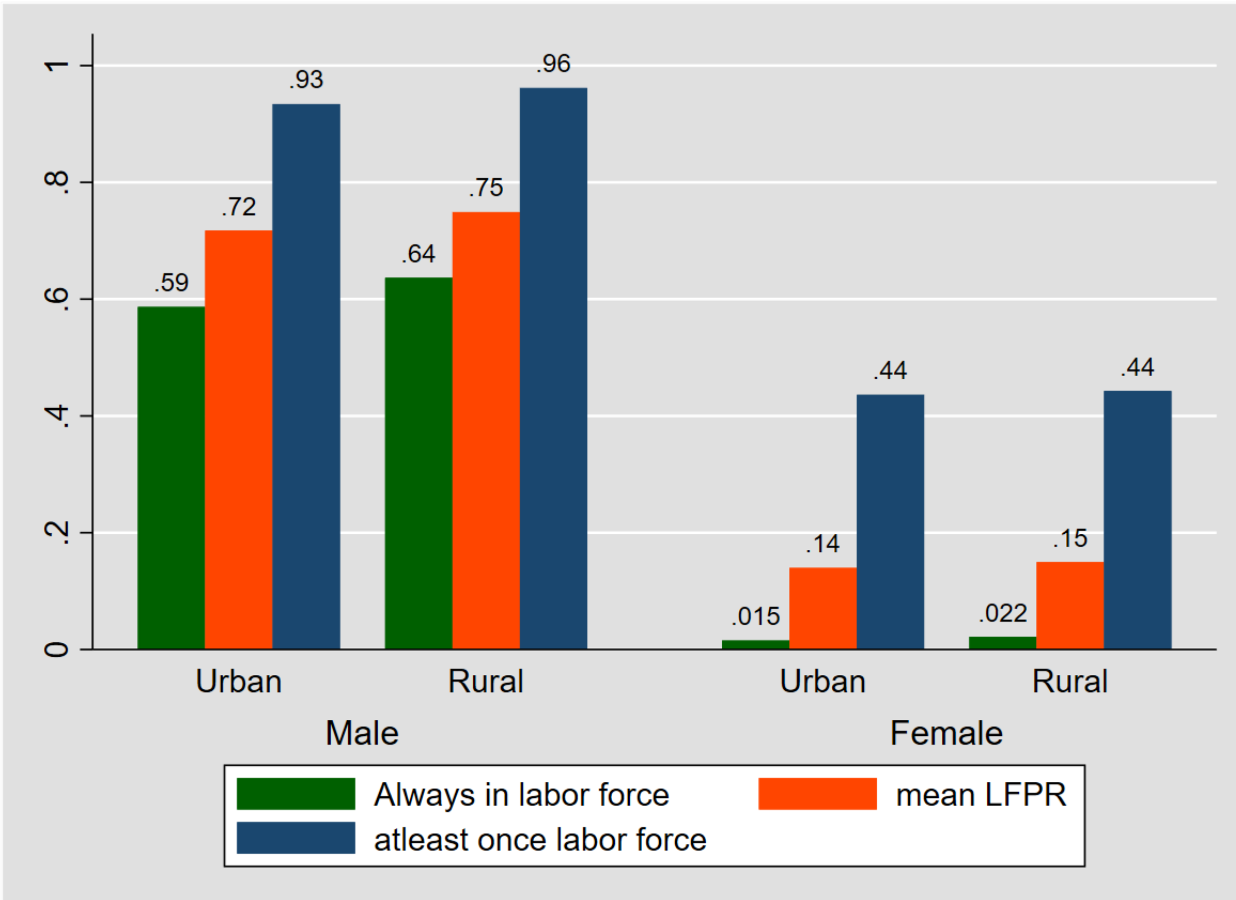
Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: The figure is drawn using employment status of all the individuals above age 14 years. Interpretation: The FLFPR was 22% in January-April 2016. Out of them 36% (0.79 of 0.22) left the labor force when they were observed in next wave.

Figure 3: Entry (transition from OLF to ILF) rate by wave



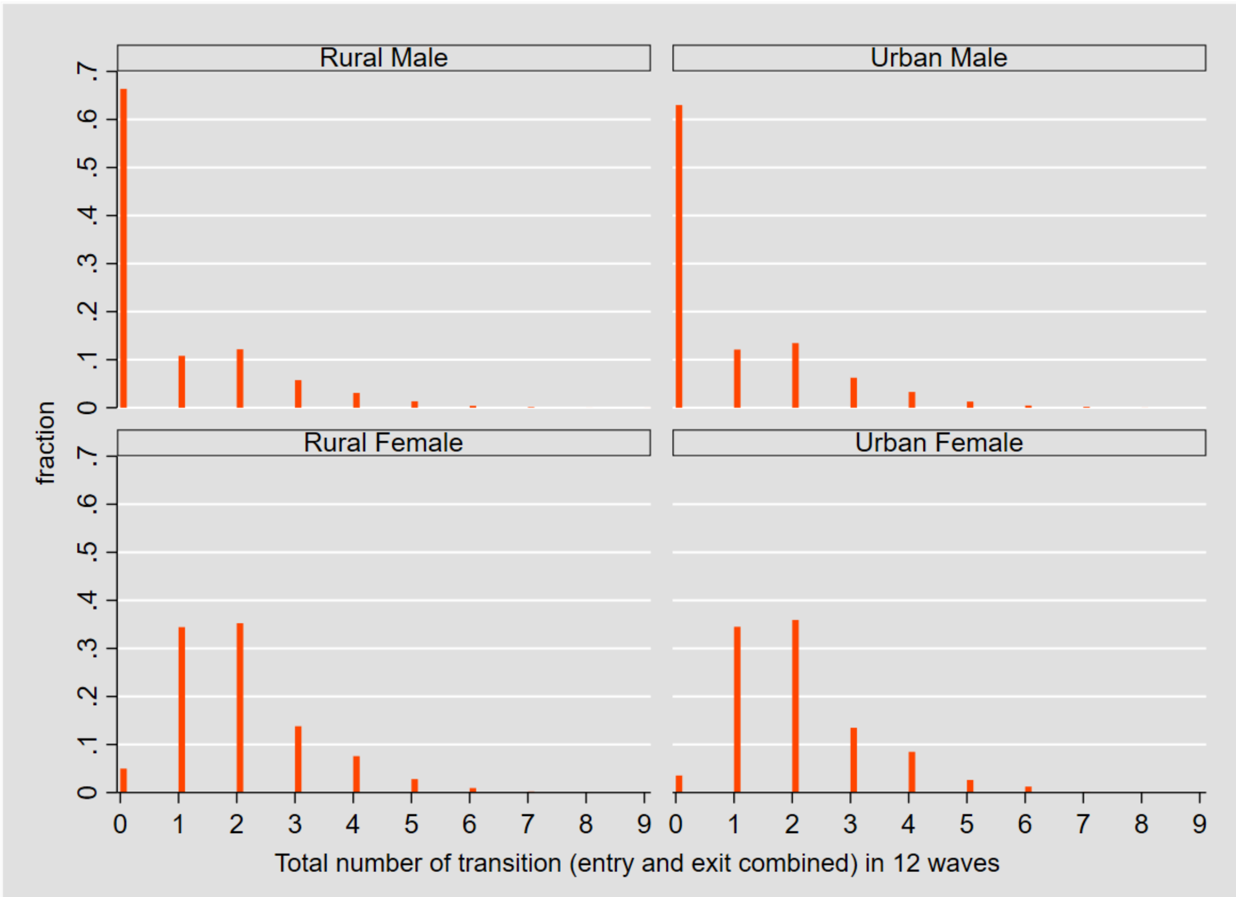
Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: The figure is drawn using employment status of all the individuals above age 14 years. Interpretation: 78% of working age women were out of labor force in January-April 2016. Out of them 9% (0.07 of 0.78) joined the labor force when they were observed in next wave.

Figure 4: Estimation of labor force participation rate



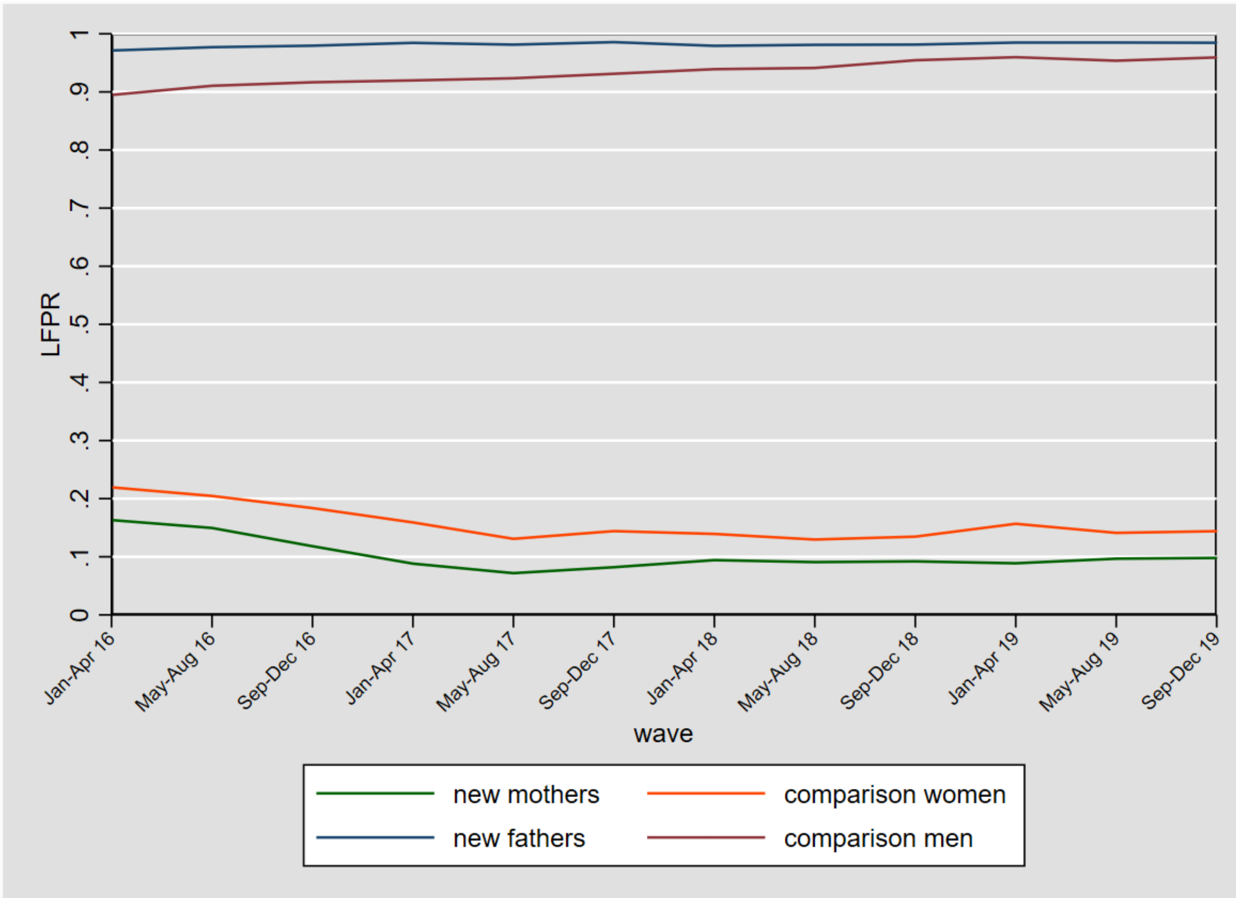
Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: The green bar shows the percentage on individuals who were part of labor force in each wave. Orange bar shows the mean LFPR in 12 waves. And, blue bar shows the percentage of individuals who were at least once part of labor force in 12 waves. The green and blue bars are drawn using data of all the individuals above age 14 years in each wave and were observed in all 12 waves. We use survey weights for estimation of LFPR and mean of survey weights of individual across 12 waves to estimate the “atleast once labor force” and ”always in labor force”.

Figure 5: Total number of transition in 12 waves



Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: The figure is drawn using data of all the individuals who were above age 14 years and were observed in all 12 waves. X-Axis shows the number of transitions (including both entry and exits) and Y-axis shows the fraction of individuals with x number of transitions. We use mean of survey weights of individual across 12 waves.

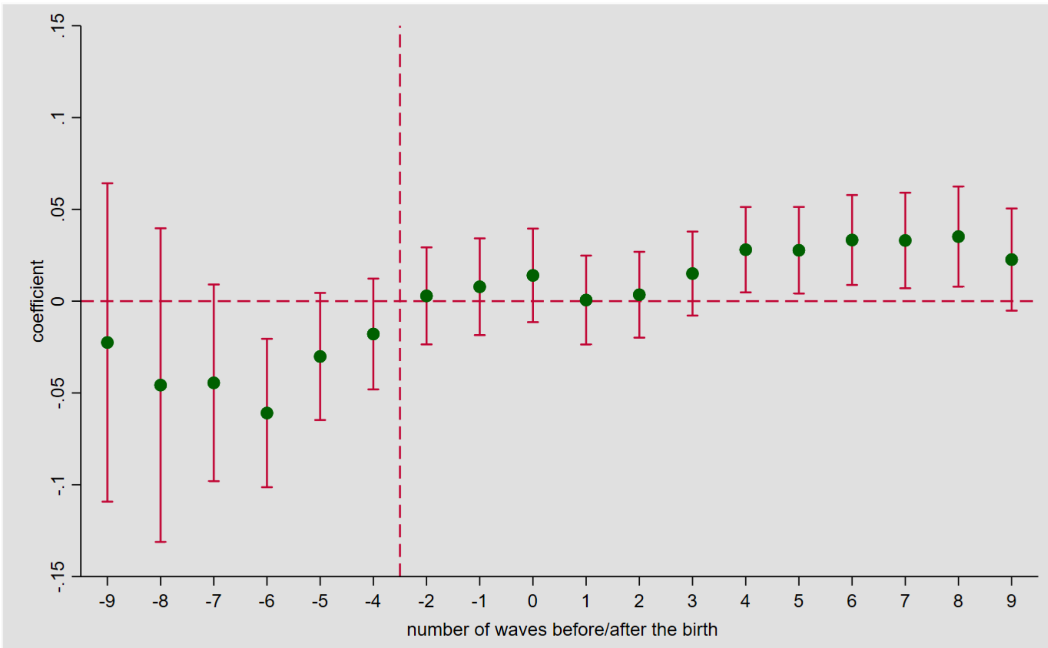
Figure 6: Labor force participation rate: Parents of new born child v/s comparison group



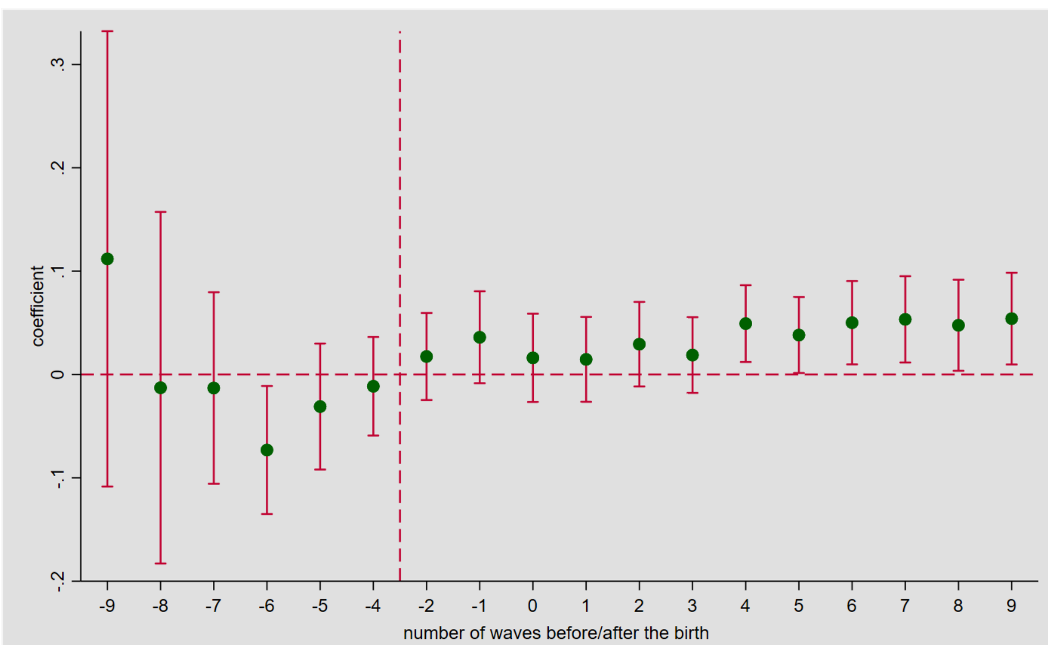
Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: The figure shows wave-wise labor force participation rate among 1) new mothers (plotted in green color), 2) comparison women (plotted in orange color) 3) new fathers (plotted in blue color), 4) comparison men (plotted in maroon color). We define new mothers and fathers as those individuals who reported any new child of age below 1 year between May-August 2016 (wave 8) and September-December 2019 (wave 18). While, the comparison groups include the women and men with no child below 5 years in the household in the study period and age below 50 years in each wave. The LFPR numbers are estimated by using Entropy balancing method generated weighted. The figure utilizes 3089189 observation points of 2995 new mothers, 193865 comparison women, 2932 new fathers and 209668 comparision men across 12 waves.

Figure 7: Child Penalty: TWFE estimates

(a) Unbalanced Panel



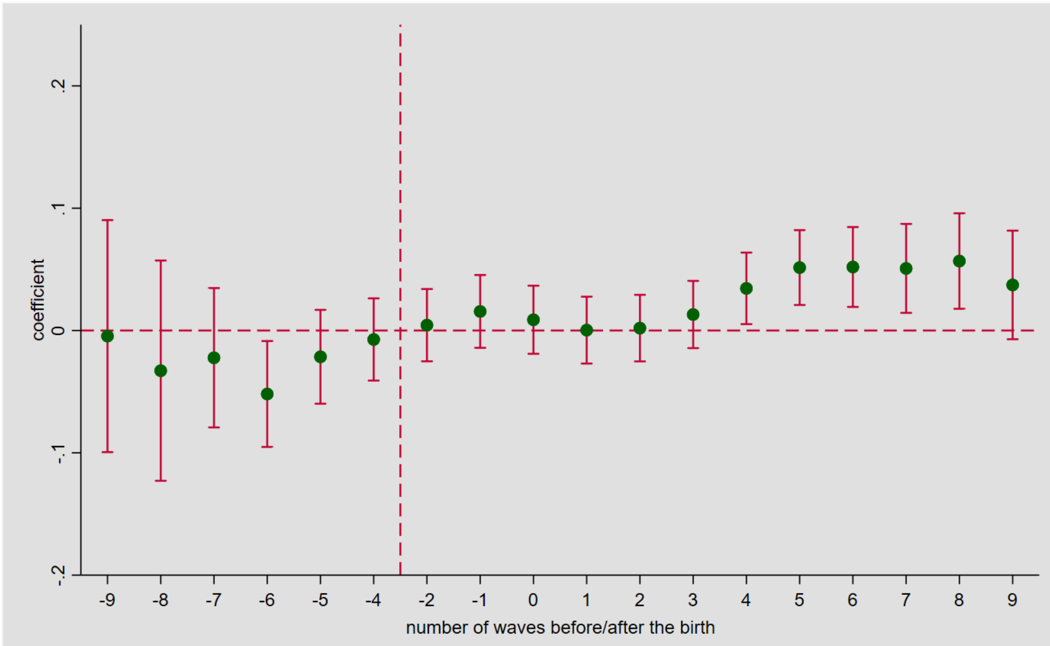
(b) Balanced Panel



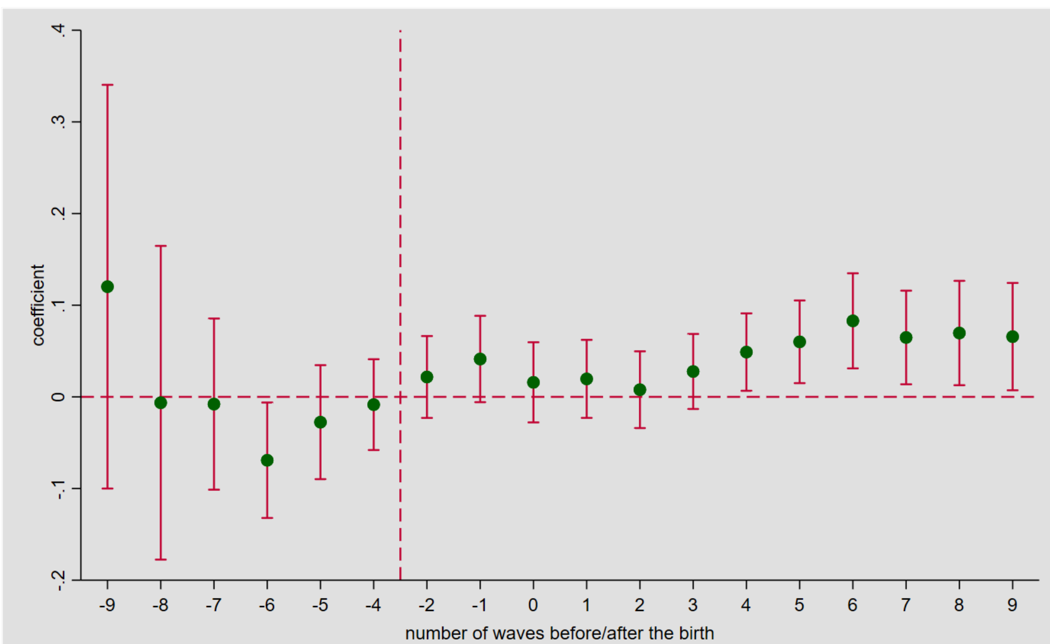
Note: This figure corresponds to the estimation of regression Equation (3). Sub-figure (a) uses the full unbalanced sample and Sub-figure (b) uses only balanced sample. $\tau = 0$ represents the a child birth. The reference period is $\tau = -3$ (12 months before the childbirth) and each coefficients should interpreted with respect to that. Each green color dot in the figure corresponds to a a regression coefficient. Standard errors are robust and the bars shows 95% confidence interval. We report the coefficients only for 9 waves before the violence and 19 waves after the child birth.

Figure 8: Child Penalty: Stacked DID estimates

(a) Unbalanced Panel

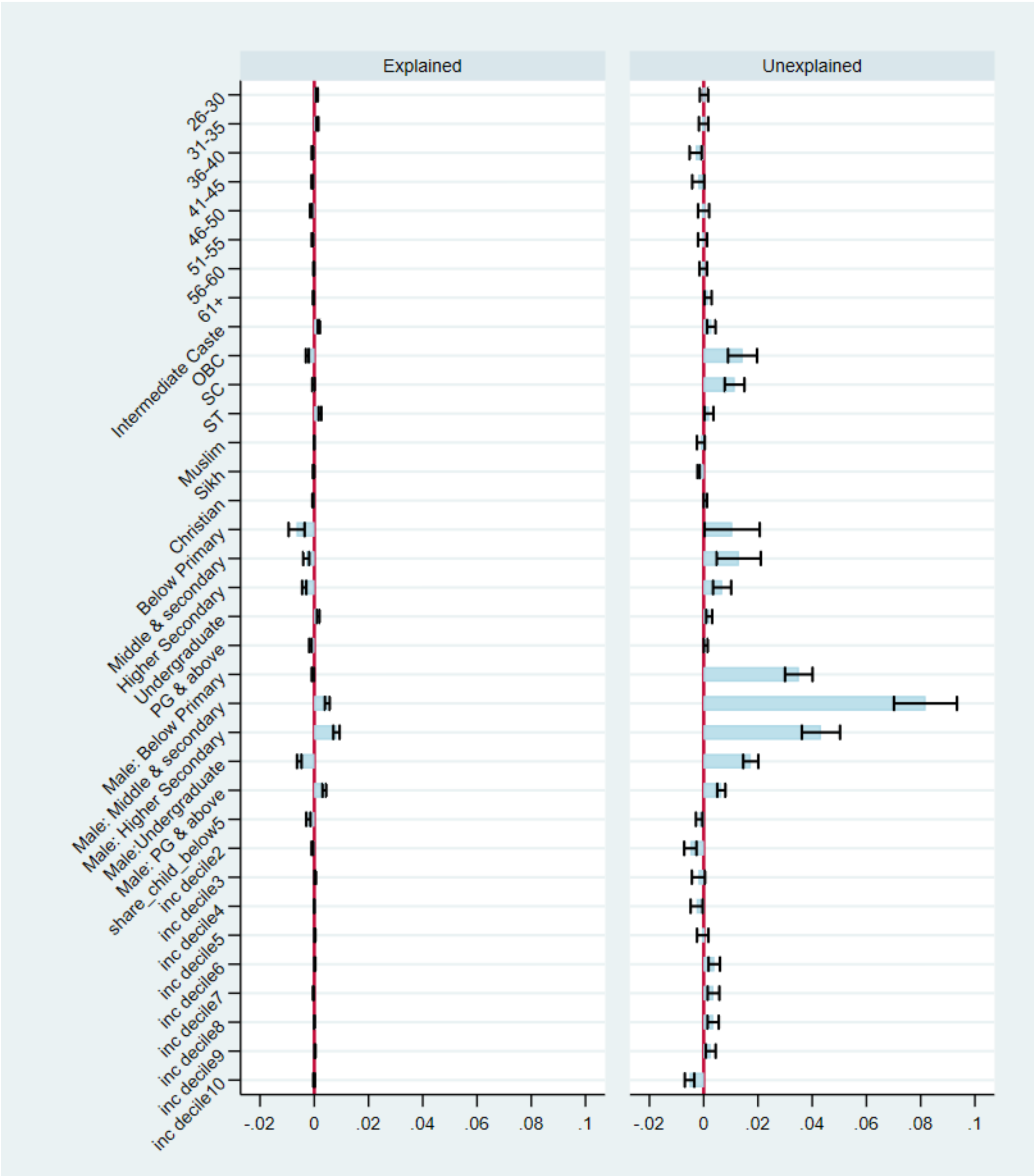


(b) Balanced Panel



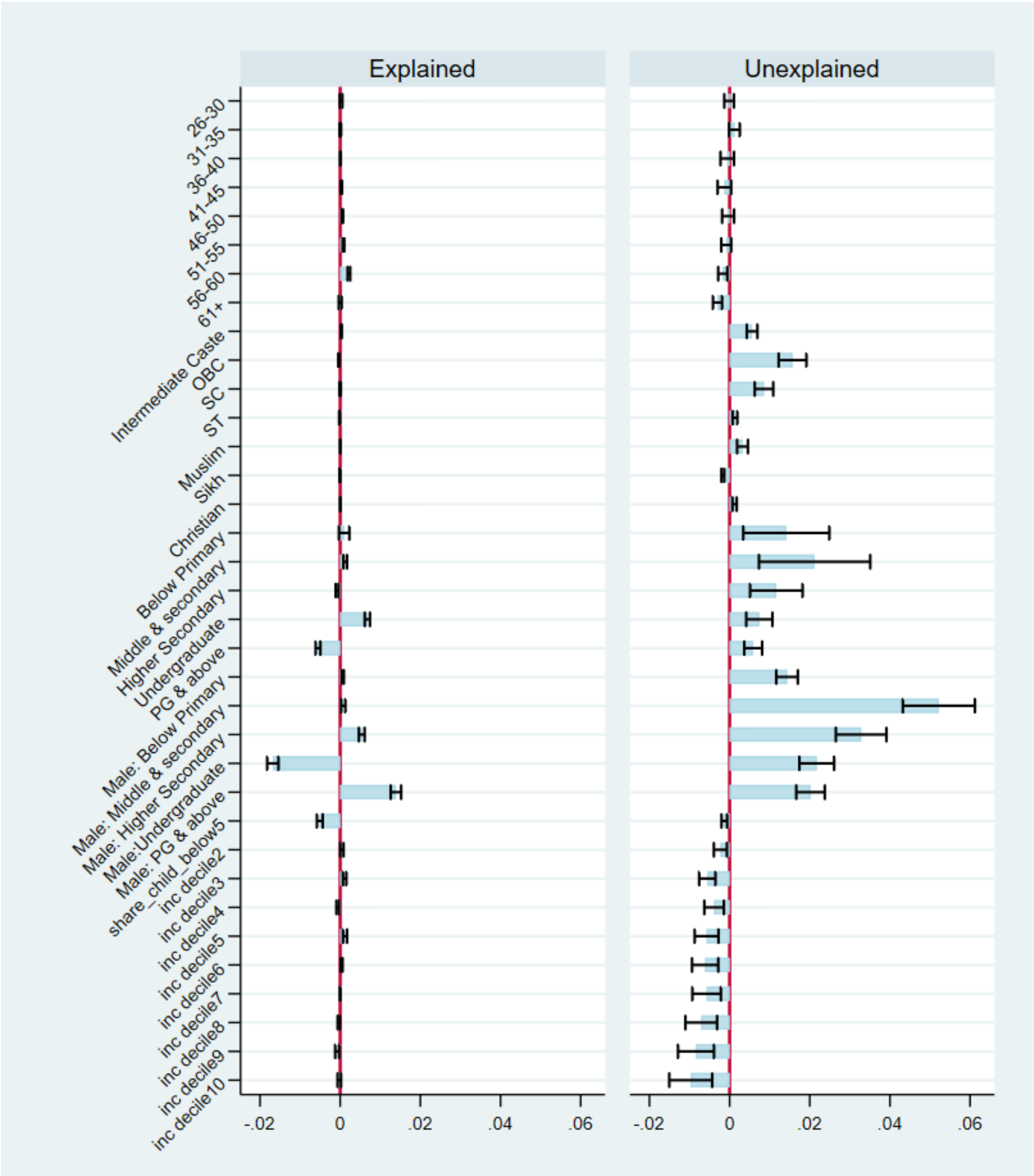
Note: This figure corresponds to the estimation of regression Equation (4). Sub-figure (a) uses the full unbalanced sample and Sub-figure (b) uses only balanced sample. $\tau = 0$ represents the a child birth. The reference period is $\tau = -3$ (12 months before the childbirth) and each coefficients should interpreted with respect to that. Each green color dot in the figure corresponds to a a regression coefficient. Standard errors are robust and the bars shows 95% confidence interval. We report the coefficients only for 9 waves before the violence and 19 waves after the child birth.

Figure 9: Blinder-Oaxaca decomposition results: Rural sample



Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: This figure plots explained and unexplained component of each predictor in B-O decomposition for rural sample.

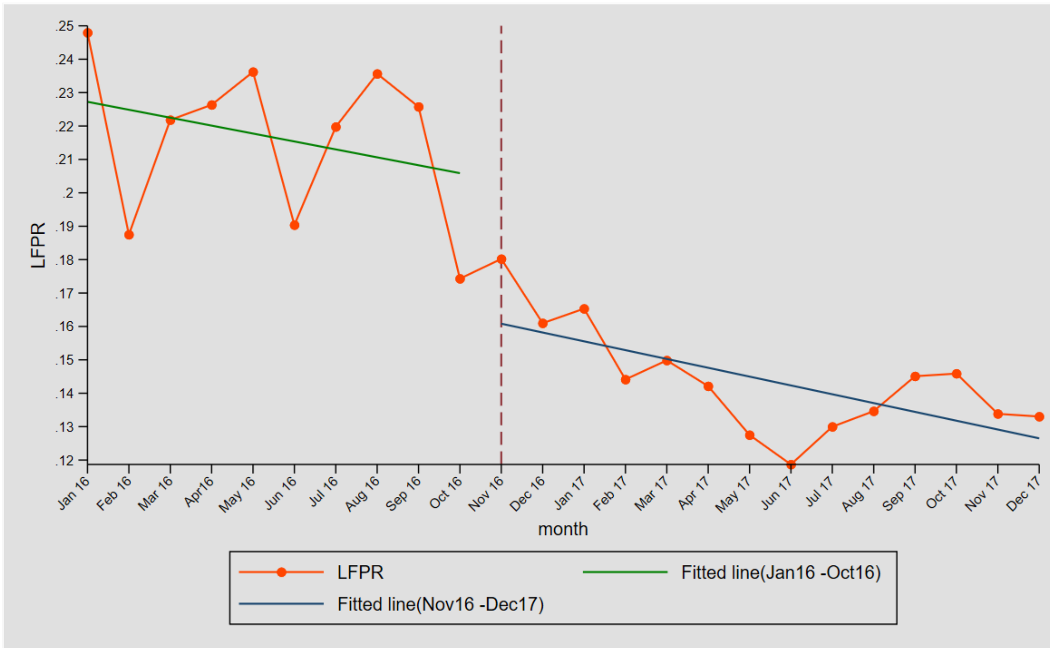
Figure 10: Blinder-Oaxaca decomposition results: Urban sample



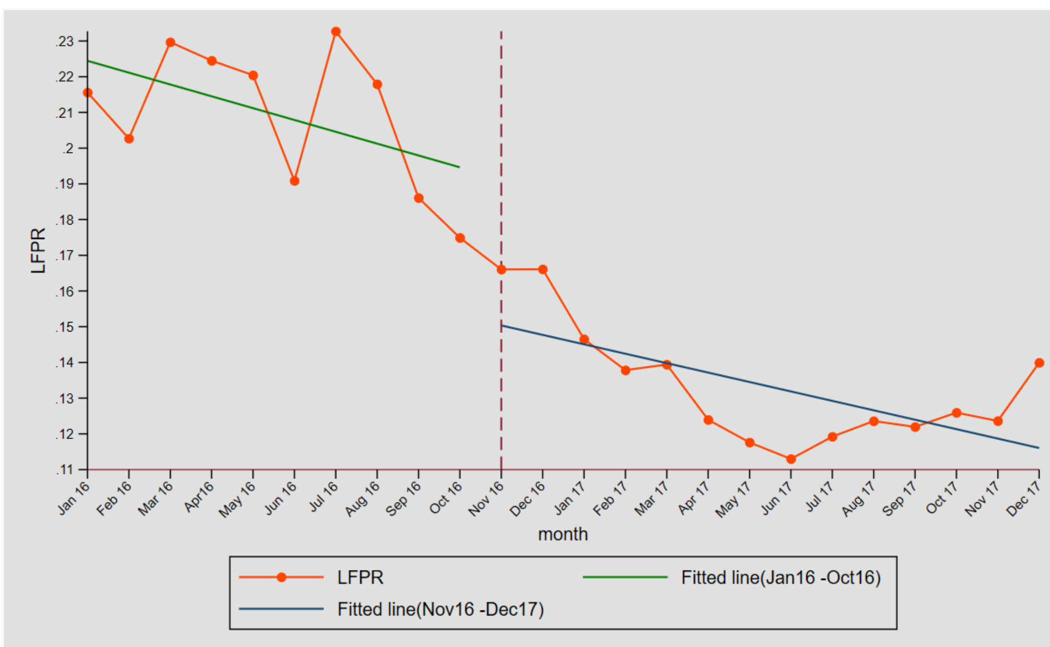
Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: This figure plots explained and unexplained component of each predictor in B-O decomposition for rural sample.

Figure 11: Month wise female labor force participation rate

(a) Rural



(b) Urban



Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: This figure plots monthly labor force participation (in orange color), fitted line for the period of January 2016 to October 2016 (in green color), and fitted line for period of November 2016 to December 2017 (in blue color) for the age group above 14 years separately for urban and rural.

Table 1: Labor force participation rate

	Jan-Apr 16	May-Aug 16	Sep-Dec 16	Jan-Apr 17	May-Aug 17	Sep-Dec 17	Jan-Apr 18	May-Aug 18	Sep-Dec 18	Jan-Apr 19	May-Aug 19	Sep-Dec 19
Rural Female												
employed	0.125	0.129	0.123	0.117	0.108	0.112	0.104	0.097	0.098	0.101	0.099	0.100
	(0.331)	(0.336)	(0.329)	(0.321)	(0.310)	(0.316)	(0.305)	(0.295)	(0.298)	(0.301)	(0.299)	(0.300)
unemployed	0.096	0.091	0.062	0.034	0.020	0.027	0.026	0.024	0.027	0.030	0.030	0.028
	(0.295)	(0.287)	(0.241)	(0.180)	(0.139)	(0.162)	(0.159)	(0.152)	(0.163)	(0.170)	(0.171)	(0.164)
olf	0.779	0.780	0.815	0.850	0.872	0.861	0.870	0.880	0.874	0.870	0.871	0.872
	(0.415)	(0.414)	(0.388)	(0.357)	(0.334)	(0.346)	(0.336)	(0.325)	(0.332)	(0.337)	(0.335)	(0.334)
N	62970	64278	62902	64454	62548	72762	79468	83047	80160	81338	80234	79173
Urban Female												
employed	0.107	0.113	0.108	0.101	0.096	0.096	0.089	0.085	0.083	0.078	0.074	0.070
	(0.309)	(0.316)	(0.310)	(0.301)	(0.294)	(0.295)	(0.285)	(0.279)	(0.275)	(0.268)	(0.261)	(0.255)
unemployed	0.113	0.103	0.065	0.035	0.023	0.033	0.034	0.030	0.034	0.037	0.040	0.041
	(0.316)	(0.304)	(0.246)	(0.184)	(0.150)	(0.178)	(0.181)	(0.170)	(0.183)	(0.188)	(0.197)	(0.198)
olf	0.781	0.784	0.828	0.864	0.881	0.871	0.877	0.885	0.883	0.886	0.886	0.889
	(0.414)	(0.412)	(0.378)	(0.342)	(0.324)	(0.335)	(0.328)	(0.319)	(0.322)	(0.318)	(0.318)	(0.314)
N	142821	141918	140731	143380	139400	135494	142223	147692	148497	146357	145750	145892
Rural Male												
employed	0.718	0.715	0.718	0.713	0.712	0.709	0.703	0.695	0.687	0.687	0.683	0.683
	(0.450)	(0.452)	(0.450)	(0.452)	(0.453)	(0.454)	(0.457)	(0.460)	(0.464)	(0.464)	(0.465)	(0.465)
unemployed	0.067	0.074	0.051	0.033	0.028	0.037	0.040	0.041	0.048	0.049	0.052	0.052
	(0.250)	(0.261)	(0.220)	(0.179)	(0.164)	(0.188)	(0.195)	(0.199)	(0.214)	(0.216)	(0.222)	(0.221)
olf	0.215	0.212	0.232	0.254	0.260	0.254	0.257	0.264	0.264	0.263	0.265	0.266
	(0.411)	(0.409)	(0.422)	(0.435)	(0.439)	(0.435)	(0.437)	(0.441)	(0.441)	(0.440)	(0.441)	(0.442)
N	71279	72756	70957	72541	70423	82117	89105	93119	89388	91177	90568	89283
Urban male												
employed	0.680	0.679	0.690	0.684	0.680	0.679	0.667	0.663	0.655	0.651	0.644	0.640
	(0.466)	(0.467)	(0.462)	(0.465)	(0.466)	(0.467)	(0.471)	(0.473)	(0.476)	(0.477)	(0.479)	(0.480)
unemployed	0.076	0.079	0.053	0.039	0.032	0.038	0.041	0.041	0.048	0.049	0.054	0.056
	(0.264)	(0.269)	(0.224)	(0.193)	(0.176)	(0.191)	(0.199)	(0.199)	(0.215)	(0.216)	(0.227)	(0.230)
olf	0.244	0.243	0.257	0.277	0.288	0.283	0.292	0.296	0.297	0.300	0.302	0.304
	(0.430)	(0.429)	(0.437)	(0.448)	(0.453)	(0.450)	(0.454)	(0.456)	(0.457)	(0.458)	(0.459)	(0.460)
N	155980	154474	152765	156167	152203	148529	155837	162347	162988	161845	162547	163199

Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: The table reports mean and standard deviation (in parenthesis) of variables employed, unemployed and olf(out of the labor force) and number of observation in each wave. The sample includes all the household members of age 15 years and older. The values are estimated using survey weights for working age population provided by CPHS.

Table 2: Regression results: Probability of entry and exit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Entry ($t-1$ to t)			Exit ($t-1$ to t)			LFP (t)	
change in log income of other HH member ($income_t$-$income_{t-1}$)	-0.0036*** (0.0005)	-0.0034*** (0.0005)	-0.0035*** (0.0005)	0.0070*** (0.0011)	0.0063*** (0.0011)	0.0063*** (0.0011)		
change in total unemployed male in HH ($tot\_unemp\_male_t$- $tot\_unemp\_male_{t-1}$)		0.0269*** (0.0020)			-0.0984*** (0.0085)			
change in number of children below 5yrs ($total\_children_t$-$total\_children_{t-1}$)	0.0020** (0.0009)	0.0019** (0.0009)	0.0020** (0.0009)	0.0115 (0.0101)	0.0126 (0.0099)	0.0129 (0.0099)		
any unemployed male in HH (t)			0.0541*** (0.0038)			-0.2195*** (0.0158)	0.0810*** (0.0057)	0.1080*** (0.0059)
log income of other HH members (t)							-0.0389*** (0.0022)	-0.0128*** (0.0011)
number of children below 5yrs (t)							-0.0147*** (0.0027)	0.0017 (0.0026)
Constant	0.0714*** (0.0047)	0.0709*** (0.0046)	0.0660*** (0.0045)	0.0952*** (0.0230)	0.0949*** (0.0224)	0.1258*** (0.0210)	0.5590*** (0.0241)	0.3169*** (0.0127)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,899,691	1,899,691	1,899,691	327,139	327,139	327,139	2,593,489	2,593,489
R-squared	0.3465	0.3480	0.3492	0.5015	0.5048	0.5081	0.0455	0.5669

Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: This table corresponds to regression results from estimating Equation (1) and (2). Column (1)-(3) report the results from estimating equation (1) with dependent variable $entry_{t,t-1}$ and include the sample of women who were out of the labor force in period $t-1$. Column (4)-(6) report the results from estimating equation (2) with dependent variable $exit_{t,t-1}$ and include the sample of women who were part of the labor force in period $t-1$. The dependent variable is LFP status (0 or 1) in Column (7) and (8) Standard errors are robust and clustered at district level in parentheses*** p<0.01, ** p<0.05, * p<0.1

Table 3: Summary statistics for decomposition analysis

	(1) Pooled sample		(2) Wave 7		(3) Wave 18	
	mean	sd	mean	sd	mean	sd
ILF	0.169	0.375	0.220	0.415	0.122	0.327
rural	0.661	0.473	0.659	0.474	0.662	0.473
Age group(in years)						
15-25	0.259	0.438	0.266	0.442	0.252	0.434
26-30	0.095	0.293	0.107	0.309	0.084	0.277
31-35	0.102	0.303	0.111	0.314	0.094	0.292
36-40	0.117	0.321	0.112	0.316	0.120	0.326
41-45	0.112	0.315	0.105	0.307	0.117	0.322
46-50	0.094	0.291	0.085	0.279	0.101	0.302
51-55	0.074	0.262	0.067	0.251	0.081	0.272
56-60	0.063	0.243	0.057	0.232	0.069	0.254
61+	0.085	0.278	0.089	0.284	0.081	0.273
Caste groups						
Upper Caste	0.205	0.404	0.209	0.407	0.202	0.401
Intermediate Caste	0.100	0.300	0.108	0.311	0.093	0.290
OBC	0.399	0.490	0.383	0.486	0.413	0.492
SC	0.226	0.418	0.225	0.418	0.227	0.419
ST	0.069	0.254	0.074	0.262	0.065	0.247
Religious groups						
Hindu	0.861	0.346	0.861	0.346	0.861	0.346
Muslim	0.099	0.299	0.100	0.300	0.099	0.298
Sikh	0.020	0.141	0.021	0.142	0.020	0.139
Christian	0.014	0.116	0.012	0.110	0.015	0.120
Education level						
Illiterate	0.180	0.384	0.353	0.478	0.021	0.144
Below Primary	0.297	0.457	0.178	0.382	0.406	0.491
Middle & secondary	0.325	0.469	0.286	0.452	0.362	0.480
Higher Secondary	0.122	0.327	0.103	0.304	0.139	0.346
Undergraduate	0.058	0.233	0.068	0.252	0.048	0.214
PG & above	0.018	0.132	0.012	0.109	0.023	0.150
Highest edu level of male member						
Male: Illiterate	0.034	0.181	0.067	0.250	0.004	0.062
Male: Below Primary	0.149	0.356	0.150	0.357	0.148	0.355
Male: Middle & secondary	0.383	0.486	0.370	0.483	0.396	0.489
Male: Higher Secondary	0.221	0.415	0.196	0.397	0.244	0.429

Male:Undergraduate	0.140	0.347	0.166	0.373	0.116	0.321
Male: PG & above	0.050	0.217	0.031	0.174	0.066	0.249
income deciles						
inc decile 1	0.070	0.255	0.061	0.239	0.079	0.269
inc decile 2	0.091	0.287	0.093	0.290	0.089	0.284
inc decile 3	0.088	0.284	0.080	0.272	0.096	0.294
inc decile 4	0.097	0.296	0.098	0.298	0.096	0.294
inc decile 5	0.097	0.296	0.097	0.296	0.098	0.297
inc decile 6	0.100	0.300	0.100	0.299	0.101	0.301
inc decile 7	0.105	0.307	0.103	0.304	0.107	0.309
inc decile 8	0.112	0.316	0.115	0.318	0.110	0.313
inc decile 9	0.113	0.317	0.118	0.323	0.108	0.310
inc decile 10	0.126	0.332	0.135	0.342	0.117	0.322
share of child below 5yrs	0.028	0.080	0.038	0.092	0.019	0.065
Observations	430856		205791		225065	

Source: Consumer Pyramids Household Survey. January 2016 to December 2019.

Table 4: Blinder-Oaxaca decomposition of labor force participation

	(1)	(2)	(3)	(4)
	Rural		Urban	
	Specification 1	Specification 2	Specification 1	Specification 2
overall				
Wave 7	0.221***	0.221***	0.220***	0.220***
	(0.002)	(0.002)	(0.001)	(0.001)
Wave 18	0.127***	0.127***	0.110***	0.110***
	(0.001)	(0.001)	(0.001)	(0.001)
difference	0.094***	0.094***	0.110***	0.110***
	(0.002)	(0.002)	(0.002)	(0.002)
explained	-0.008***	-0.006**	0.011***	0.007***
	(0.002)	(0.002)	(0.001)	(0.001)
unexplained	0.102***	0.100***	0.099***	0.103***
	(0.003)	(0.003)	(0.002)	(0.002)
N	140641	140641	284051	284051

Source: Consumer Pyramids Household Survey. January-April 2016 and September-December 2019. Note: This table corresponds to regression results from estimating Equation (6). Standard errors are robust and in parentheses*** p<0.01, ** p<0.05, * p<0.1

Table 5: Total employment (in millions)

	(1) Working-age Population	(2) Tot employed population	(3) Male Employed	(4) Female employed
Jan-Apr 2016	944	404	351	53
May-Aug 2016	951	408	353	56
Sep-Dec 2016	959	411	358	53
Jan-Apr 2017	966	409	358	51
May-Aug 2017	974	408	360	48
Sep-Dec 2017	982	411	361	50
Jan-Apr 208	989	406	359	46
May-Aug 2018	997	402	359	44
Sep-Dec 2018	1005	401	356	44
Jan-Apr 2019	1013	404	360	45
May-Aug 2019	1021	405	361	44
Sep-Dec 2019	1029	407	363	44

Source: Consumer Pyramids Household Survey. January 2016-December 2019. Note: Working age population corresponds to all the individuals above 14 years in age. All the values in table are in millions.

Table 6: Industry-wise total employment (in millions) and growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Jan-Apr 2016 (wave 7)				Sep-Dec 2016 (wave 18)				Employment Growth	
Industry	tot emp	male emp	female emp	female share	tot emp	male emp	female emp	female share	tot emp	female emp
Agri & allied	146.59	121.54	25.05	0.17	149.28	127.07	22.21	0.15	0.02	-0.11
Manufacturing & Mining	26.65	25.71	0.94	0.04	19.67	19.11	0.56	0.03	-0.26	-0.40
Construction & Real estate	79.09	74.44	4.65	0.06	67.54	65.17	2.37	0.04	-0.15	-0.49
Textile & handicraft	12.19	9.63	2.56	0.21	8.17	7.19	0.98	0.12	-0.33	-0.62
Retail & wholesale Trade	42.53	39.78	2.75	0.06	59.64	56.46	3.18	0.05	0.40	0.16
Food Industry	11.10	8.88	2.21	0.20	10.36	8.01	2.35	0.23	-0.07	0.06
Health & personal services	25.41	19.28	6.13	0.24	37.20	30.36	6.85	0.18	0.46	0.12
Education	13.70	8.43	5.28	0.39	14.65	11.21	3.44	0.23	0.07	-0.35
Others & services	46.20	43.28	2.92	0.06	39.78	38.16	1.62	0.04	-0.14	-0.45
Total	404.45	350.97	52.48	0.13	406.29	362.74	43.55	0.11	0.01	-0.17

Source: Consumer Pyramids Household Survey. January-April 2016 and September-December 2019. Note: Agri & allied also includes fishing, forestry, plantation, poultry and animal husbandry. Manufacturing also includes. Other & services includes Defence, Communication, Post & Courier, Entertainment and Sports, Financial Services, IT & ITES, Media and Publishing, Public Administrative Services,Travel and Tourism, and Utilities. Column (9) and (10) shows the growth in employment between Wave 7 and Wave 18.

Table 7: Regression results: Impact of demonetisation

VARIABLES	(1) Total	(2) Rural	(3) Urban
post× female	-0.020***	-0.015**	-0.028***
	(0.006)	(0.007)	(0.006)
post	-0.008	-0.012	0.002
	(0.006)	(0.009)	(0.006)
wave	-0.001	0.000	-0.004**
	(0.002)	(0.002)	(0.002)
female× wave	-0.010***	-0.011***	-0.009***
	(0.002)	(0.003)	(0.002)
Constant	0.548***	0.547***	0.551***
	(0.017)	(0.022)	(0.018)
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Observations	2,593,849	829,987	1,763,862
R-squared	0.812	0.814	0.808

Source: Consumer Pyramids Household Survey. January 2016 to December 2017.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

References

Abraham, R. and Shrivastava, A. (2019). How comparable are india's labour market surveys? *CSE Working Paper*.

Afridi, F., Bishnu, M., and Mahajan, K. (2020). Gendering technological change: Evidence from agricultural mechanization. *IZA Discussion Paper No. 12666*.

Afridi, F., Dinkelman, T., and Mahajan, K. (2018). Why are fewer married women joining the work force in rural india? a decomposition analysis over two decades. *Journal of Population Economics*, 31(3):783–818.

Afridi, F., Mahajan, K., and Sangwan, N. (2021a). Employment guaranteed? social protection during a pandemic. *IZA Discussion Paper No. 14099*.

Afridi, F., Mahajan, K., and Sangwan, N. (2021b). The gendered effects of climate change: Production shocks and labor response in agriculture. *IZA Discussion Paper No. 14568*.

Angelov, N., Johansson, P., and Lindahl, E. (2016). Parenthood and the gender gap in pay. *Journal of Labor Economics*, 34(3):545–579.

Angrist, J. and Evans, W. (1998). Children and their parents' labor supply: Evidence from exogenous variation in family size. *American Economic Review*, 88:450–77.

Baker, A. C., Wang, C. C., and Larcker, D. F. (2021). How much should we trust staggered differences-in-differences estimates? Technical report, Working paper.

Bardasi, E., Beegle, K., Dillon, A., and Serneels, P. (2011). Do labor statistics depend on how and to whom the questions are asked? results from a survey experiment in tanzania. *The World Bank Economic Review*, 25(3):418–447.

Becker, S. O., Fernandes, A., and Weichselbaumer, D. (2019). Discrimination in hiring based on potential and realized fertility: Evidence from a large-scale field experiment. *Labour Economics*, 59:139–152.

Bertrand, M. (2020). Gender in the twenty-first century. In *AEA Papers and proceedings*, volume 110, pages 1–24.

Borker, G. (2017). Safety first: Perceived risk of street harassment and educational choices of women. *Job Market Paper, Department of Economics, Brown University*, pages 12–45.

Boserup, E. (1970). *Woman's role in economic development*. Earthscan.

Bronars, S. and Grogger, J. (1994). The economic consequences of unwed motherhood: Using twin births as a natural experiment. *American Economic Review*, 84(5):1141–56.

Callaway, B. and Sant'Anna, P. H. (2020). Difference-in-differences with multiple time periods. *Journal of Econometrics*.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The Effect of Minimum Wages on Low-Wage Jobs*. *The Quarterly Journal of Economics*, 134(3):1405–1454.

Chakraborty, T. and Lohawala, N. (2021). Women, violence and work: Threat of sexual violence and women's decision to work. Technical report, Institute of Labor Economics (IZA).

Chakraborty, T., Mukherjee, A., Rachapalli, S. R., and Saha, S. (2018). Stigma of sexual violence and women's decision to work. *World Development*, 103:226–238.

Chatterjee, U., Murgai, R., and Rama, M. (2015). Job opportunities along the rural-urban gradation and female labor force participation in india. *World Bank Policy Research Working Paper*.

Chaudhary, R. and Verick, S. (2014). *Female labour force participation in India and beyond*. ILO New Delhi.

Chodorow-Reich, G., Gopinath, G., Mishra, P., and Narayanan, A. (2020). Cash and the economy: Evidence from india's demonetization. *The Quarterly Journal of Economics*, 135(1):57–103.

Choithani, C., van Duijne, R. J., and Nijman, J. (2021). Changing livelihoods at india's rural-urban transition. *World Development*, 146:105617.

Chowdhury, S. (2011). Employment in india: What does the latest data show? *Economic and Political Weekly*, 46(32):23–26.

Das, M. and Desai, S. (2003). *Why are educated women less likely to be employed in India?: Testing competing hypotheses*. Social Protection, World Bank Washington, DC.

Das, M. B. and Žumbytė, I. (2017). *The motherhood penalty and female employment in urban India*. The World Bank.

Das, M. S., Jain-Chandra, M. S., Kochhar, M. K., and Kumar, N. (2015). *Women workers in India: why so few among so many?* International Monetary Fund.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

Deininger, K., Jin, S., Nagarajan, H. K., and Singh, S. K. (2020). Political reservation and female labor force participation in rural india. *Policy Research Working Papers, World Bank, No. 9350*.

Desai, S. (2017). Declining female labour force participation in rural india: The demand side. *Ideas for India*.

Desai, S. and Joshi, O. (2019). The paradox of declining female work participation in an era of economic growth. *The Indian Journal of Labour Economics*, 62(1):55–71.

Deshpande, A. (2019). The visible and invisible barriers to indian women working. *The India Forum*.

Deshpande, A. (2021). The covid-19 pandemic and gendered division of paid work, domestic chores and leisure: evidence from india's first wave. *Economia Politica*.

Deshpande, A. and Kabeer, N. (2021). Norms that matter: Exploring the distribution of women's work between income generation, expenditure-saving, and unpaid domestic responsibilities in india. *WIDER Working Paper/2021/070-2*.

Deshpande, M. and Li, Y. (2019). Who is screened out? application costs and the targeting of disability programs. *American Economic Journal: Economic Policy*, 11(4):213–48.

Dhanaraj, S. and Mahambare, V. (2019). Family structure, education and women's employment in rural india. *World Development*, 115:17–29.

Dubey, A., Olsen, W., and Sen, K. (2017). The decline in the labour force participation of rural women in india: Taking a long-run view. *The Indian Journal of Labour Economics*, 60(4):589–612.

Folbre, N. (1994). *Who pays for the kids?: Gender and the structures of constraint*. New York: Routledge.

Gaddis, I. and Klasen, S. (2014). Economic development, structural change, and women's labor force participation. *Journal of Population Economics*, 27(3):639–681.

Goldin, C. (1995). The u-shaped female labor force function in economic development and economic history. In Schultz, T. P., editor, *Investment in women's human capital*, pages 61–90. University of Chicago Press.

Goodman-Bacon, A. (2019). Difference-in-differences with variation in treatment timing. Working Paper 25018, National Bureau of Economic Research.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political analysis*, pages 25–46.

Hirway, I. and Jose, S. (2011). Understanding women's work using time-use statistics: The case of india. *Feminist Economics*, 17(4):67–92.

Jayachandran, S. (2021). Social norms as a barrier to women's employment in developing countries. *IMF Economic Review*, pages 1–20.

Kannan, K. and Raveendran, G. (2012). Counting and profiling the missing labour force. *Economic and Political Weekly*, pages 77–80.

Kapsos, S., Bourmpoula, E., Silberman, A., et al. (2014). Why is female labour force participation declining so sharply in india? Technical report, International Labour Organization.

Klasen, S. and Pieters, J. (2015). What explains the stagnation of female labor force participation in urban india? *The World Bank Economic Review*, 29(3):449–478.

Kleven, H., Landais, C., Posch, J., Steinhauer, A., and Zweimuller, J. (2019a). Child penalties across countries: Evidence and explanations. *AEA Papers and Proceedings*, 109:122–26.

Kleven, H., Landais, C., and Sogaard, J. E. (2019b). Children and gender inequality: Evidence from denmark. *American Economic Journal: Applied Economics*, 11(4).

Lahoti, R. and Swaminathan, S. (2013). Economic growth and female labour force participation in india (working paper no 414). *Bangalore: Indian Institute of Management Bangalore*.

Le Barbanchon, T., Rathelot, R., and Roulet, A. (2021). Gender differences in job search: Trading off commute against wage. *The Quarterly Journal of Economics*, 136(1):381–426.

Lei, L., Desai, S., and Vanneman, R. (2019). The impact of transportation infrastructure on women's employment in india. *Feminist Economics*.

Lundberg, S. and Rose, E. (2000). Parenthood and the earnings of married men and women. *Labour Economics*, 7(6):689–710.

Lundborg, P., Plug, E., and Rasmussen, A. W. (2017). Can women have children and a career? iv evidence from ivf treatments. *American Economic Review*, 107(6):1611–37.

Mas, A. and Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, 107(12):3722–59.

Mazumdar, I. and Neetha, N. (2011). Gender dimensions: Employment trends in india, 1993-94 to 2009-10. *Economic and Political Weekly*, 46(43):119.

Mehrotra, S. and Parida, J. K. (2017). Why is the labour force participation of women declining in india? *World Development*, 98:360–380.

Menon, R. (2019). Never done, poorly paid, and vanishing: female employment and labour force participation in india. *Economic and Political Weekly*, 54(19).

Neff, D. F., Sen, K., and Kling, V. (2012). The puzzling decline in rural women's labor force participation in india: a reexamination.

Sanghi, S., Srija, A., and Vijay, S. S. (2015). Decline in rural female labour force participation in india: A relook into the causes. *Vikalpa*, 40(3):255–268.

Sarkar, S., Sahoo, S., and Klasen, S. (2019). Employment transitions of women in india: A panel analysis. *World Development*, 115:291–309.

Siddique, Z. (2021). Media reported violence and female labor supply. *Economic Development and Cultural Change*, forthcoming.

Sudarshan, R. M. and Bhattacharya, S. (2009). Through the magnifying glass: Women's work and labour force participation in urban delhi. *Economic and Political Weekly*, pages 59–66.

Sun, L. and Abraham, S. (2018). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Available at SSRN*, 3158747.

Tam, H. (2011). U-shaped female labor participation with economic development: Some panel data evidence. *Economics Letters*, 110(2):140–142.

Appendices

A1. Entry and Exit: Demographic Characteristics

In this section, we discuss the trend of entry and exit across demographic characteristics. Appendix Table A.1 shows the entry and exit rates among women in rural areas for various demographic characteristics: age groups, education level, marital status, caste, and religion. Column (1) shows the weighted mean of ILF (labor force participation rate) for working-age women between Wave 7 and Wave 17. Column (2) shows the mean OLF (out of labor force). Column (3) shows the entry rate which is the fraction of women from OLF who joined the labor force in the next wave. Since entry is possible only when an individual is OLF in a wave and depends on whether she changes her LF status in the next wave, the entry rate is defined for the base population of OLF (column 2). Column (4) presents the exit rate which is the share of women from ILF who left the Labor force in the next observed wave.[9] The exit rate is defined for the base population of ILF (column 1). Female LFPR rate stands at 15.4 percent between Wave 7 and Wave 17 in rural areas. The average entry rate was 4.1 percent and the exit rate was 28.5 percentage. In other words, four percent of OLF women join the labor force, and 28.5 percent of ILF women leave the labor force in the next observed waves.

Panel (A) shows the entry and exit rate by age groups in rural areas. There exists a large variation in female LPFR where women from the younger age group (below 25 years) and older age group (above 55 years) have relatively lower participation rates. The entry rate is more than than 4 percent for all age groups below 55 years and around three percent for women above 55 years. The exit rate is relatively low among the 26-45 year age group. 25 percent of women leaving the labor force in the 41-55 age-group does not seem to be explained by supply-side factors. The exit rate is high among young (age below 25 years) and older women (above 55 years) and stands at 39 percent and 34.5 percent, respectively. A part of the high exit rate in the older age group can be explained by the fact that many of these women are likely to be leaving the workforce permanently. And, high exit rate among younger age cohort can be attributed to dropping from the labor force for education or marriage. Men in the middle age group have only one percent exit rate; showing almost all men remain in the labor force in prime working age.

[9] The table estimates the weighted average of LFP status and entry-exit rate in all waves by using the individual weight of members in each wave. We should note that the recent waves correspond to the increased population in the country and therefore, the summation of survey weights will be relatively larger in the recent waves compared to the initial waves. So, the wave average estimates using survey weights will be biased towards recent waves. Since the entry and exit rates were smaller in recent waves, the wave-average estimates in the table are biased toward zero. Alternatively, we can revise the weights in such a way that summation of weights across the waves remains the same. However, the difference between the two will not be not sizeable and relative interpretation of entry-exit rate across demographic characteristics remains the same.

Female LFPR has a U-shaped relationship with education level in rural areas. FLFPR is highest among women with education levels more than postgraduate (40 percent) and lowest among middle and secondary school-educated women (13 percent). The entry rate is also high among college-educated women, where more than 8 percent of women from OLF join the labor force in the next wave. Women with education levels of post-graduates and above have the lowest exit rate (18 percent), while women with middle or higher secondary schooling have an almost double probability of exit than postgraduate women.

Next, we discuss the entry and exit rate by marital status. The marital status of household members is available for the last three waves only, therefore the numbers are estimated using two possible transitions only. Widowed and separated women have a higher probability (25.3 percent) of being in the labor force compare to unmarried (10.7 percent) and married (12.7 percent). The entry rate is higher for unmarried (3.7 percent) and widowed/separated (3.6 percent) compare to married women (2.6 percent). The exit rate is lowest among widowed/separated women (14 percent) compare to married (20 percent) and unmarried (23.4 percent) women.

Panel (D) and (E) shows the transitions for social caste groups and religious groups respectively. The FLFP rate is highest among Scheduled Tribes (ST) (23.8 percent) and lowest among Upper Caste (9.4 percent) in rural areas. The entry rate is also high for ST women (7 percent). The exit rate is low among Scheduled Caste (SC) (24.6 percent) and ST (27.3 percent) women, relative to other caste categories (more than 30 percent OBC, intermediate caste and Upper caste). Next, both LFPR and entry rate are lower among Muslims and Sikhs relative to Hindus in rural areas; while the exit rate is low among Sikh and Christian minorities compare to Hindus and Muslims.

Appendix Table A.2 shows the entry and exit rate among women in urban areas. The overall entry rate is similar to the rural areas (four percent), but the exit rate at 31.7 percent is higher than in rural areas. The entry rate among women continuously declines with age in urban areas. The entry rate for young women (below 25 years) in urban areas is approximately six percent compared to 4 percent in the rural area. It falls below two percent for women above age 55 years. The exit rate is low among the age group of 26-45 years. LFPR and entry rates follow a U-shaped relationship with education level in urban areas as well. The entry rate is more than 5 percent for illiterate women and college-educated women; while it is approximately three percent for education level secondary level. The exit rate is approximately 20 percent in postgraduate women and as high as 35 percent in middle to higher secondary school educated women.

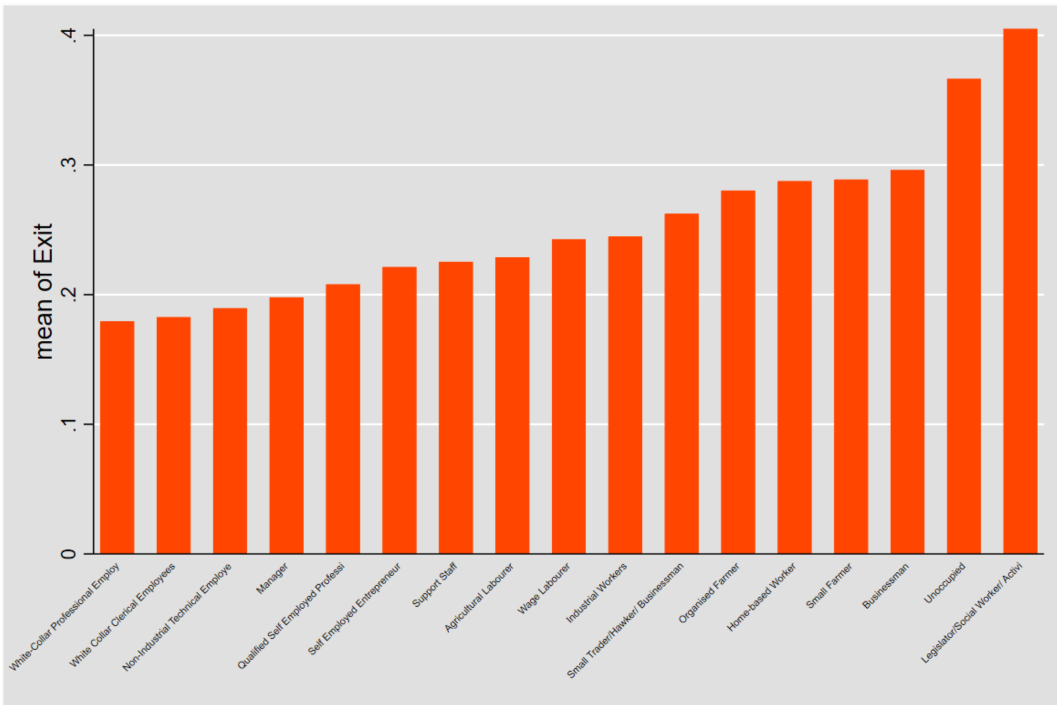
The entry rate is more than six percent for unmarried women compared to 2.3 percent and 3.2 percent among married and widowed/separated women respectively. The exit rate is smaller (17.7 percent) among widowed/separated women compare to others. The entry rate and LFPR are high among SC and ST women compare to others. The exit rate does not vary much by caste category with relatively low among SC and ST women. The exit rate is higher among Hindus and Muslims relative to other religious minorities.

We also investigated whether some industries and occupations are better than others in terms of providing continuous employment opportunities to women. Appendix Figure A.1 shows the exit rate among women working in different occupations and industries. We see that all occupations have a high exit rate among women, which vary between 18 to 40 percent. As expected, the rate is lowest among white-collar and managerial occupations and it is high among farmers, small self-employed businesses. The exit rate is lower among service sector industries and higher among agriculture and allied activities and manufacturing industries. In summary, the exit rate is higher among women in informal work and agriculture. Since we do not observe industry and occupation when women were OLF (reference level for to define entry), we can not define the entry rate.

Appendix Figures and Tables

Figure A.1: Exit rate by nature of occupation and industry

(a) Nature of occupation



(b) Industry

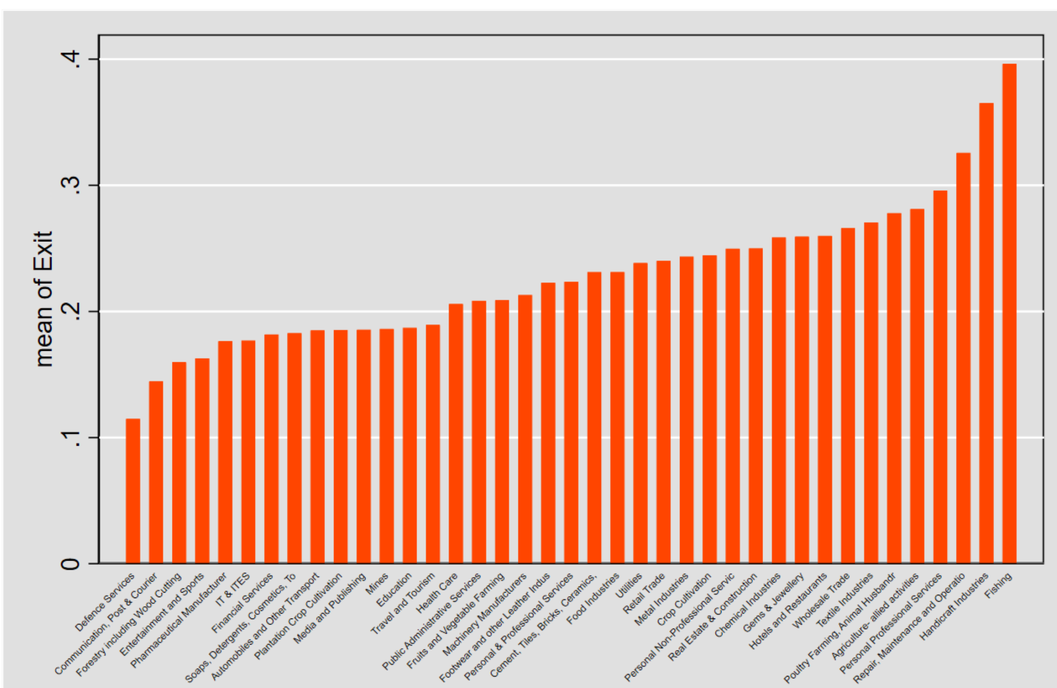
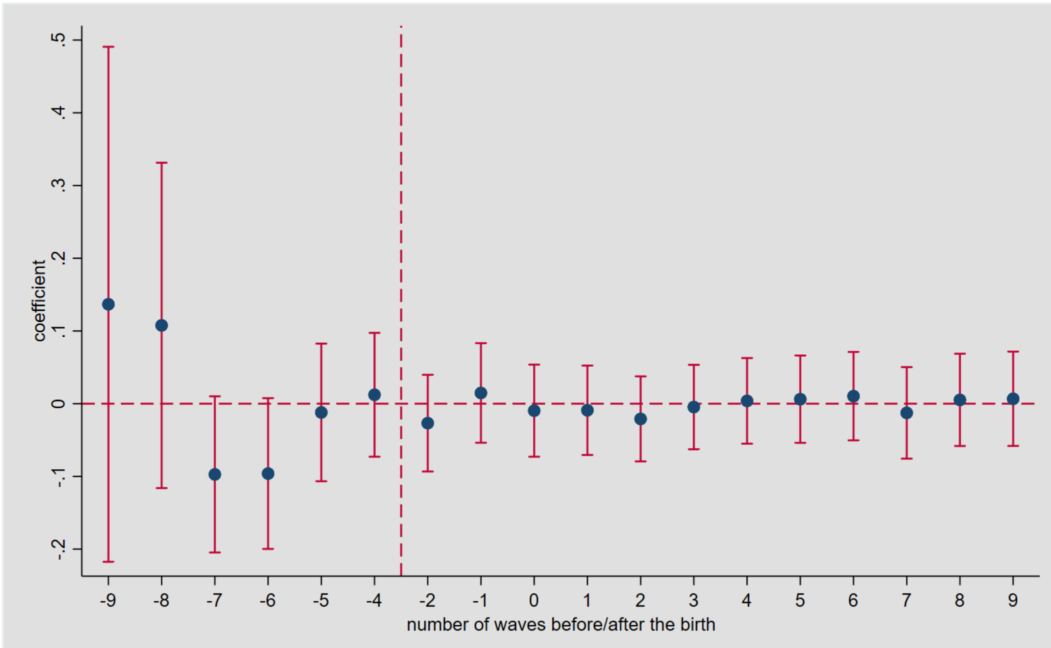
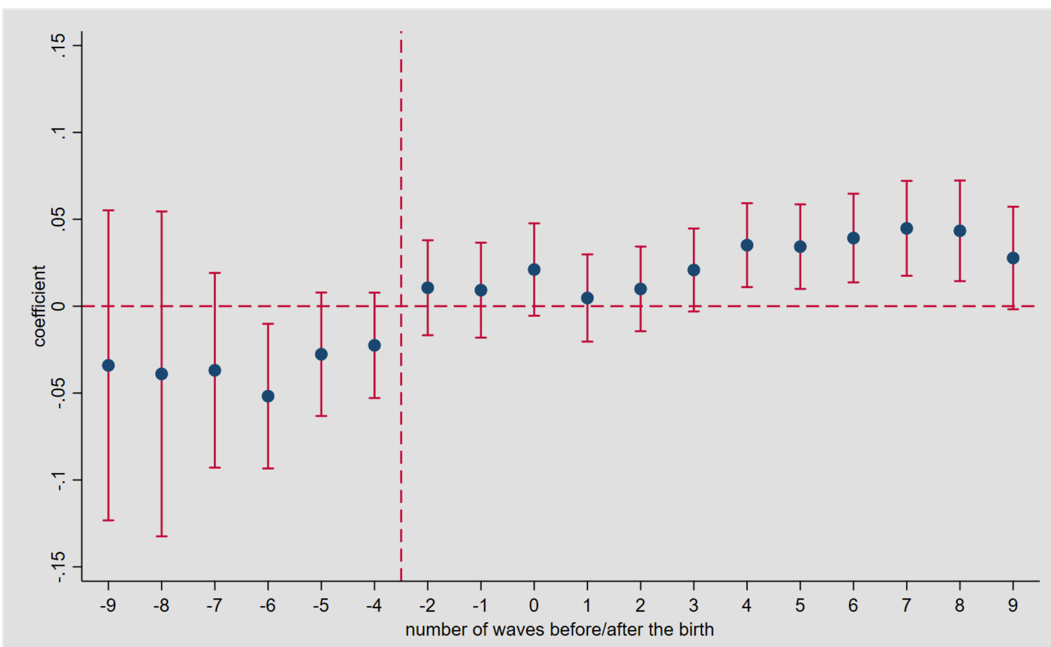


Figure A.2: Child Penalty: TWFE estimates

(a) First child birth only



(b) Other than first child birth



Note: This figure corresponds to the estimation of regression Equation (3) with unbalanced panel. Sub-figure (a) includes all the mothers with first childbirth in the study period and Sub-figure (b) includes all the mothers with other than first childbirth in the study period. EB weights are generated for comparison groups separately for both the sub-figures. $\tau = 0$ represents the a child birth. The reference period is $\tau = -3$ (12 months before the childbirth) and each coefficients should interpreted with respect to that. Each green color dot in the figure corresponds to a a regression coefficient. Standard errors are robust and the bars shows 95% confidence interval. We report the coefficients only for 9 waves before the violence and 19 waves after the child birth.

Table A.1: Entry and Exit Rate: Rural

	(1) ILF	(2) OLF	(3) Entry (from OLF)	(4) Exit (from ILF)	(5) Obs
Total	0.154	0.846	0.041	0.285	745,458
			Panel (A)		
age_group					
15-25	0.112	0.888	0.042	0.389	190,589
26-40	0.187	0.813	0.045	0.250	240,081
41-55	0.177	0.823	0.042	0.249	204,605
55+	0.107	0.893	0.030	0.345	110,183
			Panel (B)		
ed_level					
illiterate	0.184	0.816	0.048	0.300	137,520
primary & below	0.145	0.855	0.034	0.249	258,647
middle & sec school	0.127	0.873	0.037	0.315	236,592
higher sec	0.152	0.848	0.052	0.317	80,809
UG	0.267	0.733	0.081	0.264	26,505
PG & above	0.399	0.601	0.091	0.177	5,385
			Panel (C)		
marital_status_grp					
Married	0.127	0.873	0.026	0.199	102,054
Unmarried	0.107	0.893	0.037	0.234	27,675
Widowed/Separated	0.253	0.747	0.036	0.141	11,425
			Panel (D)		
caste_cat					
UC	0.094	0.906	0.027	0.318	103,580
IC	0.160	0.840	0.049	0.315	92,942
OBC	0.143	0.857	0.039	0.303	293,886
SC	0.176	0.824	0.042	0.246	172,392
ST	0.238	0.762	0.070	0.273	72,937
			Panel (E)		
religion_grp					
Hindu	0.159	0.841	0.043	0.285	645,569
Muslim	0.108	0.892	0.032	0.324	60,702
Sikh	0.062	0.938	0.013	0.218	24,352
Christian	0.254	0.746	0.052	0.213	11,331
Other/not stated	0.304	0.696	0.095	0.229	3,504

Source: Consumer Pyramids Household Survey. January 2016 to December 2019. Note: Column (1) shows the weighted mean of ILF (labor force participation) of women between wave 7 and wave 17 and were observed in next wave (i.e. for whom entry and exit can be defined). Column (2) show the weighted percentage of OLF. Column (3) shows the share of women out of OLF who joined the labor force in next wave. Column (4) shows the share of women out of ILF who left the labor force in next wave. Column (5) shows number of observations. The sample includes all the household members of age above 14 years in rural areas. The mean values are estimates using survey weights.

Table A.2: Entry and exit rate: Urban

	(1) ILF	(2) OLF	(3) Entry (from OLF)	(4) Exit (from ILF)	(5) Obs
Total	0.141	0.859	0.041	0.317	1,482,049
			Panel (A)		
age group					
15-25	0.148	0.852	0.059	0.365	354,945
26-40	0.179	0.821	0.048	0.285	464,304
41-55	0.141	0.859	0.034	0.293	426,190
55+	0.059	0.941	0.018	0.432	236,610
			Panel (B)		
education level					
illiterate	0.175	0.825	0.052	0.343	143,476
primary & below	0.119	0.881	0.033	0.313	359,370
middle & sec school	0.109	0.891	0.034	0.358	522,241
higher sec	0.136	0.864	0.049	0.352	232,932
UG	0.231	0.769	0.065	0.261	161,508
PG & above	0.280	0.720	0.058	0.198	62,522
			Panel (C)		
marital status					
Married	0.084	0.916	0.023	0.289	184,098
Unmarried	0.155	0.845	0.062	0.223	53,400
Widowed/Separated	0.211	0.789	0.032	0.177	25,502
			Panel (D)		
caste category					
UC	0.119	0.881	0.034	0.306	439,632
IC	0.134	0.866	0.040	0.340	130,394
OBC	0.141	0.859	0.042	0.332	562,112
SC	0.168	0.832	0.050	0.306	282,864
ST	0.204	0.796	0.064	0.300	40,543
			Panel (E)		
religious group					
Hindu	0.146	0.854	0.043	0.315	1,237,485
Muslim	0.109	0.891	0.034	0.371	165,463
Sikh	0.095	0.905	0.023	0.241	38,470
Christian	0.169	0.831	0.036	0.258	24,797
Other/not stated	0.167	0.833	0.062	0.312	15,834
Total	0.141	0.859	0.041	0.317	1,482,049

Source: Consumer Pyramids Household Survey. January 2016 to December 2019. Note: Column (1) shows the weighted mean of ILF (labor force participation) of women between wave 7 and wave 17 and were observed in next wave (i.e. for whom entry and exit can be defined). Column (2) show the weighted percentage of OLF. Column (3) shows the share of women out of OLF who joined the labor force in next wave. Column (4) shows the share of women out of ILF who left the labor force in next wave. Column (5) shows number of observations. The sample includes all the household members of age above 14 years in rural areas. The mean values are estimates using survey weights.

Table A.3: Entropy Balancing: women sample in Wave 7

Panel (A)	Before Entropy Balancing			
	(1)		(2)	
	Treated		Comparison	
	mean	sd	mean	sd
age (in yrs)	28.511	6.462	32.233	10.576
rural	0.759	0.428	0.649	0.477
HH size	2.232	0.630	3.176	1.246
HOH	0.014	0.116	0.038	0.191
Parent of HOH	0.002	0.044	0.003	0.050
Spouse of HOH	0.897	0.304	0.545	0.498
Daughter of HOH	0.011	0.106	0.277	0.448
DIL of HOH	0.069	0.253	0.110	0.313
OBC/IC	0.441	0.497	0.486	0.500
SC/ST	0.372	0.483	0.295	0.456
Muslim	0.155	0.362	0.098	0.298
Christian	0.004	0.064	0.012	0.108
Sikh	0.008	0.087	0.022	0.146
Primary & below	0.178	0.383	0.173	0.378
Middle & Sec	0.298	0.457	0.333	0.471
Higher Sec	0.118	0.322	0.124	0.330
UG	0.041	0.198	0.079	0.270
PG & above	0.008	0.090	0.013	0.111
Male:Primary & below	0.252	0.435	0.148	0.355
Male: Middle & Sec	0.329	0.470	0.389	0.487
Male: Higher Sec	0.137	0.344	0.204	0.403
Male: UG	0.094	0.292	0.159	0.366
Male: PG & above	0.020	0.139	0.029	0.169
Observations	1837		120811	

Panel (B)	After Entropy Balancing			
	Treated		Comparison	
	mean	sd	mean	sd
age (in yrs)	28.511	6.462	28.436	6.725
rural	0.759	0.428	0.756	0.430
HH size	2.232	0.630	2.278	0.732
HOH	0.014	0.116	0.014	0.119
Parent of HOH	0.002	0.044	0.002	0.044
Spouse of HOH	0.897	0.304	0.879	0.326
Daughter of HOH	0.011	0.106	0.029	0.166

DIL of HOH	0.069	0.253	0.068	0.252
OBC/IC	0.441	0.497	0.442	0.497
SC/ST	0.372	0.483	0.370	0.483
Muslim	0.155	0.362	0.155	0.362
Christian	0.004	0.064	0.004	0.066
Sikh	0.008	0.087	0.008	0.090
Primary & below	0.178	0.383	0.177	0.381
Middle & Sec	0.298	0.457	0.302	0.459
Higher Sec	0.118	0.322	0.119	0.324
UG	0.041	0.198	0.042	0.201
PG & above	0.008	0.090	0.008	0.090
Male:Primary & below	0.252	0.435	0.249	0.432
Male: Middle & Sec	0.329	0.470	0.330	0.470
Male: Higher Sec	0.137	0.344	0.139	0.346
Male: UG	0.094	0.292	0.097	0.296
Male: PG & above	0.020	0.139	0.020	0.140
Observations	1837		120811	

Source: Consumer Pyramids Household Survey. January 2016 to December 2019. Note: The table reports mean and standard deviation of variables for treated units (new mothers) and comparison group women, before (Panel A) and after (Panel B) the entropy balancing for Wave 7 (January-April 2016) only. We do the similar the exercise for each wave to generate the entropy balanced weights.

Table A.4: OLS estimates for rural sample: pooled and wave-wise

	(1)	(2)	(3)	(4)	(5)	(6)
		Spec 1			Spec 2	
VARIABLES	Pooled	Wave7	Wave18	Pooled	Wave7	Wave18
Wave 18	-0.102***			-0.098***		
	(0.002)			(0.002)		
Age group dummies (in Years)						
26-30	0.038***	0.035***	0.040***	0.043***	0.043***	0.044***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)
31-35	0.068***	0.068***	0.069***	0.073***	0.074***	0.073***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)
36-40	0.098***	0.085***	0.108***	0.105***	0.091***	0.114***
	(0.004)	(0.007)	(0.005)	(0.004)	(0.007)	(0.005)
41-45	0.082***	0.069***	0.093***	0.090***	0.076***	0.097***
	(0.004)	(0.007)	(0.005)	(0.004)	(0.007)	(0.005)
46-50	0.066***	0.063***	0.070***	0.073***	0.069***	0.074***
	(0.004)	(0.007)	(0.005)	(0.004)	(0.007)	(0.005)
51-55	0.052***	0.050***	0.054***	0.056***	0.054***	0.056***
	(0.004)	(0.008)	(0.005)	(0.004)	(0.008)	(0.005)
56-60	0.029***	0.023***	0.034***	0.030***	0.021**	0.031***
	(0.005)	(0.008)	(0.005)	(0.004)	(0.008)	(0.005)
61+	-0.034***	-0.028***	-0.040***	-0.036***	-0.032***	-0.047***
	(0.004)	(0.007)	(0.004)	(0.004)	(0.007)	(0.004)
Caste group dummies						
Intermediate Caste	0.066***	0.091***	0.044***	0.062***	0.084***	0.040***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)
OBC	0.050***	0.076***	0.028***	0.044***	0.067***	0.025***
	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.003)
SC	0.079***	0.113***	0.051***	0.071***	0.101***	0.046***
	(0.003)	(0.005)	(0.004)	(0.003)	(0.005)	(0.004)
ST	0.149***	0.164***	0.134***	0.140***	0.154***	0.128***
	(0.004)	(0.007)	(0.006)	(0.004)	(0.007)	(0.005)
Religious group dummies						
Muslim	-0.013***	-0.013**	-0.013***	-0.021***	-0.022***	-0.018***
	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)
Sikh	-0.114***	-0.170***	-0.080***	-0.118***	-0.181***	-0.083***
	(0.004)	(0.007)	(0.005)	(0.004)	(0.007)	(0.005)
Christian	0.169***	0.118***	0.183***	0.157***	0.114***	0.165***
	(0.010)	(0.021)	(0.011)	(0.010)	(0.021)	(0.011)
Education level dummies						
Below Primary	0.017***	0.015***	-0.002	0.036***	0.027***	0.026***
	(0.003)	(0.005)	(0.008)	(0.003)	(0.005)	(0.008)
Middle & secondary	0.011***	0.015***	-0.011	0.036***	0.032***	0.023***
	(0.004)	(0.005)	(0.008)	(0.004)	(0.005)	(0.008)
Higher Secondary	0.058***	0.071***	0.032***	0.088***	0.095***	0.069***
	(0.005)	(0.007)	(0.009)	(0.005)	(0.008)	(0.009)
Undergraduate	0.177***	0.185***	0.150***	0.214***	0.216***	0.195***

	(0.007)	(0.011)	(0.012)	(0.008)	(0.011)	(0.012)
PG & above	0.274***	0.275***	0.250***	0.321***	0.323***	0.301***
	(0.016)	(0.030)	(0.020)	(0.016)	(0.031)	(0.020)
higest edu level of male member						
Male: Below Primary				-0.164***	-0.109***	-0.303***
				(0.006)	(0.007)	(0.011)
Male: Middle & secondary				-0.193***	-0.141***	-0.328***
				(0.006)	(0.007)	(0.011)
Male: Higher Secondary				-0.199***	-0.155***	-0.328***
				(0.006)	(0.007)	(0.011)
Male:Undergraduate				-0.229***	-0.177***	-0.362***
				(0.006)	(0.008)	(0.011)
Male: PG & above				-0.257***	-0.204***	-0.390***
				(0.008)	(0.014)	(0.012)
share of child below 5yrs				-0.088***	-0.141***	-0.026
				(0.013)	(0.018)	(0.017)
income decile dummies						
inc decile 2				-0.022***	-0.053***	0.000
				(0.004)	(0.008)	(0.005)
inc decile 3				-0.007	-0.024***	0.006
				(0.004)	(0.008)	(0.005)
inc decile 4				0.020***	0.010	0.028***
				(0.004)	(0.008)	(0.005)
inc decile5				0.022***	0.021***	0.023***
				(0.004)	(0.008)	(0.005)
inc decile 6				0.041***	0.067***	0.019***
				(0.004)	(0.008)	(0.005)
inc decile 7				0.034***	0.059***	0.014***
				(0.004)	(0.008)	(0.005)
inc decile 8				0.023***	0.042***	0.008
				(0.004)	(0.008)	(0.005)
inc decile 9				0.042***	0.056***	0.030***
				(0.004)	(0.008)	(0.005)
inc decile 10				0.034***	0.008	0.053***
				(0.004)	(0.008)	(0.005)
Constant	0.110***	0.091***	0.044***	0.260***	0.203***	0.318***
	(0.004)	(0.007)	(0.009)	(0.007)	(0.010)	(0.014)
Observations	140,641	61,993	78,648	140,641	61,993	78,648
R-squared	0.051	0.029	0.050	0.066	0.046	0.076

Source: Consumer Pyramids Household Survey. January 2016 to December 2019. Note: This table corresponds to regression results from estimating Equation (5) for rural sample. The dependent variable is LPF status which takes value 1 if a women is ILF and 0 otherwise. Standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1.

Table A.5: OLS estimates for urban sample: pooled and wave-wise

	(1)	(2)	(3)	(4)	(5)	(6)
		Spec 1			Spec 2	
VARIABLES	Pooled	Wave7	Wave18	Pooled	Wave7	Wave18
Wave18	-0.099***			-0.100***		
	(0.001)			(0.002)		
age groups dummies (in years)						
26-30	-0.016***	-0.024***	-0.004	-0.006**	-0.014***	0.003
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
31-35	-0.025***	-0.019***	-0.032***	-0.021***	-0.016***	-0.026***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
36-40	-0.021***	-0.022***	-0.018***	-0.016***	-0.019***	-0.012***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
41-45	-0.034***	-0.036***	-0.030***	-0.027***	-0.029***	-0.024***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
46-50	-0.051***	-0.055***	-0.044***	-0.043***	-0.046***	-0.040***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
51-55	-0.077***	-0.082***	-0.071***	-0.070***	-0.073***	-0.068***
	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.003)
56-60	-0.104***	-0.113***	-0.096***	-0.100***	-0.107***	-0.095***
	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.003)
61+	-0.151***	-0.168***	-0.133***	-0.153***	-0.167***	-0.141***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)
caste group dummies						
Intermediate Caste	0.029***	0.060***	-0.003	0.023***	0.055***	-0.010***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
OBC	0.020***	0.038***	0.002	0.014***	0.033***	-0.004**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
SC	0.043***	0.062***	0.024***	0.034***	0.053***	0.016***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
ST	0.083***	0.097***	0.068***	0.070***	0.086***	0.055***
	(0.005)	(0.008)	(0.006)	(0.005)	(0.008)	(0.006)
religious group dummies						
Muslim	-0.010***	0.006*	-0.027***	-0.019***	-0.002	-0.035***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)
Sikh	-0.051***	-0.091***	-0.016***	-0.056***	-0.098***	-0.017***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)
Christian	0.049***	0.065***	0.036***	0.039***	0.057***	0.021***
	(0.006)	(0.010)	(0.007)	(0.006)	(0.010)	(0.007)
education level dummies						
Below Primary	-0.019***	-0.024***	-0.077***	-0.001	-0.008**	-0.057***
	(0.003)	(0.003)	(0.011)	(0.003)	(0.003)	(0.011)
Middle & secondary	-0.048***	-0.046***	-0.109***	-0.021***	-0.022***	-0.080***
	(0.003)	(0.003)	(0.011)	(0.003)	(0.003)	(0.011)
Higher Secondary	-0.009***	-0.004	-0.072***	0.026***	0.029***	-0.036***
	(0.003)	(0.004)	(0.011)	(0.003)	(0.004)	(0.011)
Undergraduate	0.093***	0.101***	0.024**	0.132***	0.137***	0.064***

	(0.004)	(0.004)	(0.012)	(0.004)	(0.005)	(0.012)
PG & above	0.144***	0.180***	0.060***	0.190***	0.215***	0.112***
	(0.005)	(0.008)	(0.012)	(0.005)	(0.008)	(0.012)
higest edu level of male member						
Male: Below Primary				-0.164***	-0.108***	-0.267***
				(0.005)	(0.006)	(0.008)
Male: Middle & secondary				-0.200***	-0.143***	-0.301***
				(0.005)	(0.006)	(0.007)
Male: Higher Secondary				-0.216***	-0.162***	-0.314***
				(0.005)	(0.006)	(0.008)
Male:Undergraduate				-0.245***	-0.189***	-0.342***
				(0.005)	(0.006)	(0.008)
Male: PG & above				-0.265***	-0.193***	-0.372***
				(0.005)	(0.007)	(0.008)
share of child below 5yrs				-0.203***	-0.228***	-0.141***
				(0.010)	(0.013)	(0.014)
income decile dummies						
inc decile2				-0.015**	-0.046***	0.014*
				(0.006)	(0.011)	(0.007)
inc decile3				-0.048***	-0.087***	-0.005
				(0.006)	(0.010)	(0.007)
inc decile4				-0.041***	-0.075***	-0.005
				(0.006)	(0.010)	(0.007)
inc decile5				-0.039***	-0.068***	-0.006
				(0.006)	(0.010)	(0.007)
inc decile6				-0.030***	-0.066***	0.009
				(0.006)	(0.010)	(0.007)
inc decile7				-0.018***	-0.056***	0.022***
				(0.006)	(0.010)	(0.007)
inc decile8				-0.029***	-0.074***	0.017***
				(0.006)	(0.010)	(0.007)
inc decile9				-0.028***	-0.069***	0.015**
				(0.006)	(0.010)	(0.007)
inc decile10				0.005	-0.037***	0.046***
				(0.006)	(0.010)	(0.007)
Constant	0.240***	0.226***	0.214***	0.453***	0.426***	0.482***
	(0.003)	(0.004)	(0.012)	(0.007)	(0.011)	(0.014)
Observations	284,051	140,048	144,003	284,051	140,048	144,003
R-squared	0.059	0.037	0.044	0.078	0.051	0.079

Source: Consumer Pyramids Household Survey. January 2016 to December 2019. Note: This table corresponds to regression results from estimating Equation (5) for urban sample. The dependent variable is LPF status which takes value 1 if a women is ILF and 0 otherwise. Standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1.