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ISSN: 2365-9793

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ABSTRACT

Motherhood and Labour Market Outcomes: Penalty or Premium?*

Using nationally representative longitudinal data from the Consumer Pyramids Household Survey, we examine the effect of childbirth on female labour market outcomes in India. Contrary to findings from similar studies in developed countries, we do not observe any motherhood penalty in earnings, employment or work hours post-childbirth, after accounting for unobserved individual heterogeneity. Interestingly, we find that the birth of a child leads to a 27.4% and 32.6% increase in women's average earnings in urban and rural regions, respectively, relative to non-mothers. This motherhood premium seems to arise partly due to higher employment after childbirth. Further, we find that the increase in the likelihood of employment is predominantly observed among women from lower caste, Hindu religion, lower income quartiles, those with primary education, and higher order births in urban regions. In rural regions, the effect is restricted to women from the lowest income quartiles. We find that the presence of older siblings in the household increases the likelihood of women's employment by 3.7 percentage points. These findings underscore the role of socio-economic factors in shaping the labour market outcomes of women in India.

JEL Classification: J13, J21, J31

Keywords: childbirth, female labour market, motherhood penalty, employment, earnings, event study, India

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* We thank Melanie Luhrmann, Christoph Kronenberg, Marius Opstrup Morthorst, Farzana Afridi, Jyotsna Jalan, Mrinalini Jha, Abhiroop Mukhopadhyay, Nikita Sangwan, Michele Di Maio, and the participants at the Essen Health Conference 2025, IHEA 2025 Congress, International Conference on Reflections in Development Economics (2024) at Presidency University, Kolkata, Conference on Contemporary Issues in Labor Economics (2025) at Centre for Studies in Social Sciences (CSSS), Kolkata, for helpful discussions and comments. Any errors or omissions are the sole responsibility of the authors.

1 Introduction

The wide disparity between male and female labour market outcomes has remained a damaging reality in many developing and emerging economies. Despite increasing economic growth, rising educational attainment, and lowering fertility rates, women have been unable to bridge the gender gap in the labour market. The Global Gender Gap Report (2025) demonstrated the unfavourable condition of women in the labour market based on the economic participation and opportunity sub-index, revealing that a gender gap of 39.3% still exists in the labour force participation rates, wages, income, and other labour market indicators. One of the significant factors that has been widely discussed in developed countries such as Denmark, Sweden, U.S., Russia, and Italy in influencing women’s labour market decision is ‘childbirth’, an event, that is often associated with - popularly known as ‘motherhood penalty’ or ‘child penalty’ (Angelov et al., 2016; Casarico and Lattanzio, 2023; Kleven et al., 2019; Berniell et al., 2021; Zhang et al., 2024; Lundborg et al., 2017). Motherhood penalty is defined as the negative impact on mothers’ labour market outcomes, such as earnings, labour force participation, employment, and work hours, resulting from the disproportionate burden of child care falling exclusively upon them and thus detrimentally affecting their job market prospects. It also increases the likelihood of women’s employment in more informal and flexible jobs so that they can manage their childcare responsibilities along with the workplace responsibilities (Berniell et al., 2021, 2023a; Bertrand, 2018).

The Indian labour market has consistently exhibited low labour force participation of women. In 1993-1994, the female labour force participation rate was 33.0% in rural and 16.5% in urban regions, which rose to 35.5% and 22.3% by 2023-2024, respectively. In contrast, the participation rate for men has remained relatively stable over time - 57.9% in rural and 59.0% in urban regions in 2023-2024. Given the poor female labour market outcomes, the existing literature has attempted to identify numerous demand- and supply-side factors that adversely affect female labour market decisions, such as, mechanization of agriculture, lower levels of human capital, social norms and stigma, household chores and domestic responsibilities, lower bargaining power within the household, increasing household income, and socio-cultural identities such as belonging to upper caste and Muslim religion (Afridi et al., 2020; Mahajan, 2017; Sahoo and Klasen, 2018; Srija and Vijay, 2020; Heath and Jayachandran, 2016; Ghosh and Thomas, 2022; Mehrotra and Parida, 2017). Childcare responsibility is another crucial aspect that shapes women’s labour market decisions and choice of economic activities. Since childcare responsibilities are predominantly borne by women, they have fewer opportunities to gain work experience, which limits them from achieving their full potential in the labour market (Bhalla and Kaur, 2011). Managing childcare responsibilities alongside workplace duties causes many mothers to either leave the workforce or reduce their work hours from full-time to part-time. There exists an extensive literature in the developed countries, where the impact of childbirth has been researched and found to have a negative effect (Goldin et al., 2024; Kleven et al., 2019; Lundberg and Rose, 2000; Angelov et al., 2016). More recently, there has been an increasing interest in examining this relationship in developing and less developed countries as well, owing to their distinct socio-economic structures and

labour market dynamics, with results showing both negative effects and, in some cases, little to no impact (Berniell et al., 2023a; Aaronson et al., 2021; Aguilar-Gomez et al., 2026; Querejeta and Bucheli, 2023; Kleven et al., 2024). However, it has received little attention in the Indian context. There exists scant research focusing explicitly on the link between childbirth and female labour market outcomes, particularly the dynamic effects as a child grows up. This aspect has received limited attention, primarily due to the unavailability of high-frequency panel data with a large number of cross-sectional units and a long time horizon. Previous studies have analyzed the relationship between maternal parity and labour market outcomes using pooled cross-sectional data, but fall short of providing a rigorous analysis focusing on childbirth (Das and Žumbyté, 2017; Klasen and Pieters, 2015).

Our study fills this research gap and aims to estimate the effects of childbirth on labour market outcomes such as labour force participation (LFP), employment, earnings, and work hours, separately in urban and rural regions, by comparing the outcomes of women with children with those without children, utilizing the high-frequency longitudinal data from the Consumer Pyramids Household Survey (CPHS) in India. We use a staggered difference-in-differences research design and use data from 2016-2023. We also examine the heterogeneous effect of childbirth based on various household and individual characteristics, such as women’s education, household income, caste, religion, and birth order. In addition, we provide evidence on potential mechanisms that may explain the observed effects.

This study contributes to multiple strands of the existing literature. First, we advance the understanding of how childbirth affects women’s labour market outcomes in the context of a developing country, characterized by socio-economic and cultural dynamics that differ markedly from those of developed nations. Second, the panel nature of the data enables us to observe the same women over time, thereby allowing us to control for time-invariant unobserved individual characteristics. This represents a key advantage over studies based on cross-sectional data, which are unable to account for such unobserved individual heterogeneity. Although Tiwari et al. (2022) utilizes the panel nature of the two waves (2004-2005 and 2011-12) of the India Human Development Survey (IHDS) to investigate the impact of the change in reproductive burden on female labour market outcomes, the study has not specifically focused on childbirth. Third, an important distinction of our study from the related research is the focus on intensive margins as well, such as earnings and work hours, along with the binary indicator of LFP and employment in contrast to Deshpande and Singh (2021) and Abraham et al. (2021) that has only examined LFP. These are the only studies, to the best of our knowledge, that have studied the impact of childbirth on women’s labour market outcomes in India. Abraham et al. (2021) estimates the impact of first childbirth in Karnataka and Rajasthan (primarily the rural population) and found no immediate effect but a marginal increase in the likelihood of mothers’ LFP, four years after childbirth. Similarly, Deshpande and Singh (2021) also finds no decline in mothers’ LFP just after a new childbirth, but an increase, a year later. Finally, we provide a comprehensive view by examining the effect of both first and higher order births, as they may have very different implications for mothers’ labour market outcomes. We also isolate the effect of motherhood itself,

avoiding the confounding influence of broader gender-based disparities, that arise when using men as the comparison group.

In contrast to the findings observed in developed countries, our main results suggest an increase of 27.4% and 32.6% in the average earnings of mothers, after a new childbirth in urban and rural regions, respectively, once we account for unobserved individual heterogeneity. Notably, this motherhood premium seems to arise from an increase in the likelihood of mothers' employment. Further, we observe that childbirth has differential effects on women belonging to different socio-economic background, and the motherhood premium is primarily restricted to women belonging to lower caste, Hindu religion, lower income quartiles, those with primary education, and with higher order births in urban regions, while in rural regions, the effect is evident only among women belonging to the lowest income quartile. Our findings also suggest that the presence of older siblings in the household may serve as a plausible mechanism facilitating the increase in mothers' likelihood of employment.

The rest of the paper is organized as follows. Section 2 provides a review of the related literature. Section 3 describes the data and empirical strategy utilised in the study. Section 4 reports the results obtained from the event study specification. Section 5 explores possible mechanisms. Section 6 presents the robustness analysis followed by discussion and conclusion in section 7.

2 Literature Review

We categorize the extant literature into two sections: (i) Evidence from Developed countries, and (ii) Evidence from Developing and Less Developed countries.

2.1 Evidence from Developed Countries

There exists an extensive literature investigating the impact of having an additional child on female labour supply in developed countries. More commonly, studies have relied on the instrumental variable estimation using twin birth and sex composition of first two children as instruments for the third birth and found a negative impact of having an additional child on female labour supply ([Angrist and Evans, 1998](#); [Bronars and Grogger, 1994](#)). So far, only a few studies have focused on the impact of childbirth at the extensive margin- specifically, the impact of first childbirth on female labour market outcomes ([Cristia, 2008](#); [Lundborg et al., 2017](#); [Adda et al., 2017](#); [Kleven et al., 2019](#); [Zhang et al., 2024](#)). Using an instrumental variable strategy based on in vitro fertilization (IVF), [Lundborg et al. \(2017\)](#) found that women with a successful first IVF treatment earn less compared to women who failed the first treatment and this penalty is mainly driven by working fewer hours rather than by reducing labour supply. In another study, [Cristia \(2008\)](#) used a sample of childless women, seeking assistance to achieve pregnancy, and found a significant decline in employment among women having child below one year compared to those women who did not become pregnant. In addition to the limited studies

utilizing natural experiments, recent studies have adopted an event study approach to examine the labour market impacts of first childbirth (Kleven et al., 2019; Casarico and Lattanzio, 2023; Zhang et al., 2024; Cortés and Pan, 2023; Angelov et al., 2016; Koopmans et al., 2024). Kleven et al. (2019) examined the impact of first childbirth on women’s earnings in Denmark by comparing them to those of men and non-mothers. The study found that women’s earnings dropped immediately by 30% following childbirth, while there was no comparable decline in the earnings of men or non-mothers. The earnings impact is found to stem from a corresponding decline in women’s labour supply, work hours, and wage rates. These labour market outcomes have not been observed to converge to their pre-child levels even 10 years after childbirth. Moreover, the study also highlights the role of childcare responsibilities in lowering the likelihood of women’s employment on higher occupational rank and increasing the likelihood to opt for more flexible and family friendly jobs, which ultimately has an adverse effect on women’s labour market outcomes. Cortés and Pan (2023) observed that almost two-thirds of the existing gender gap in the U.S. labour market can be attributed to the childcare burden carried out significantly by women relative to men. The role played by gender norms in influencing the effect of childbirth in China has been highlighted by Zhang et al. (2024). The study concludes that social norms and stigma further widen the divergence between men’s and women’s labour market performance and push women towards household chores and informal employment while showing no impact on men. The dominant role played by the gender norms regarding women’s employment has also been elucidated by Galván (2022), where the breadwinner norms of men negatively impacting both the quantity and quality of the jobs that women are engaged in are highlighted. In the context of Sweden, Angelov et al. (2016) assess the impacts of parenthood on the gender pay gap and focus particularly on the within-couple gender differences after first childbirth. The study found the gender pay gap to increase by 28 percentage points 15 years after childbirth relative to the pre-child level.

Bertrand et al. (2010) notes that the career interruption caused by the first childbirth and the corresponding loss of job experience leads many women to work for shorter hours and more in part-time jobs and self-employment. The shift towards part-time or self-employment have huge negative implication on the earnings dynamics of women compared to men. The study further observed that the penalty imposed on these women is greatly affected by their spousal income, leading to a modest and temporary impact, if the spouse’s income is low. Goldin et al. (2024) studied the impact on earnings as children grow up and childcare demand reduces by estimating the parental gender gap in earnings in the U.S. The study concludes that the work hours of mothers increase as the children grow up, leading to reduction of the motherhood penalty. Kwak (2022) observed a decline in the wage gap between mothers and non-mothers in the U.S, suggesting that over the past few decades, differences in unobserved factors such as productivity and career commitment between the two groups have significantly diminished. The study also finds the existence of motherhood premium at the upper wage quantiles. In a recent study, Kleven et al. (2024) investigated the child penalties in employment in 134 countries, including India. The study finds a decline in the likelihood of mothers’ employment post-childbirth compared to men, but with huge variation in magnitude across different regions of the world, underscoring the presence of different economic, cultural, political, and social institutions.

Moreover, the study also observed that child penalty does not play a crucial role at low levels of economic development, but as the economies develop and transition from traditional agricultural sector to industrial and services sectors, it becomes a dominant factor contributing to existing gender inequality. [Aaronson et al. \(2021\)](#) observed a negative relationship between fertility and women’s labour market outcomes only at higher levels of economic development using 441 censuses and surveys from various countries.

2.2 Evidence from Developing and Less Developed Countries

Studies examining the motherhood penalty in the context of developing countries include [Heath \(2017\)](#); [Lebedinski et al. \(2023\)](#); [Azimi \(2015\)](#); [Cruces and Galiani \(2007\)](#); [Ebenstein \(2009\)](#); [Querejeta and Bucheli \(2023\)](#); [Aguilar-Gomez et al. \(2026\)](#). [Heath \(2017\)](#) assess the effect of fertility on the labour market outcomes in urban Ghana and note that the presence of young children may increase the work hours of women if they prioritize the monetary investment in children over the time investment required for child-rearing. Furthermore, the study highlights the role of adult females and older siblings in the household, who contribute to childcare and household chores, thereby freeing up the mothers’ time to manage her work-related responsibilities. [Lebedinski et al. \(2023\)](#) found no significant impact of childbirth on hours worked and hourly wage rates but only a decline in employment and earnings in Russia. [Querejeta and Bucheli \(2023\)](#) also examined the phenomenon of motherhood penalty on women’s formal employment and earnings in Uruguay and observed a 22% decline in mothers’ earnings, one year after childbirth. This decline results from the corresponding decline in women’s formal employment. Furthermore, [Azimi \(2015\)](#) found no impact of having additional children on female LFP in Iran while [Cruces and Galiani \(2007\)](#) observed a negative impact of an additional child in Mexico and Argentina. Using infertility shock as an instrument for the family size, [Agüero and Marks \(2011\)](#) examined the causal relationship between children and female LFP in 26 developing countries and found no significant effect on mothers’ likelihood of participation or work intensity but observed a negative impact on their likelihood of paid work. These studies provide mixed evidence on women’s labour market outcomes associated with childbirth.

In the Indian context, the studies examining the association of childcare burden and female LFP include [Sarkar et al. \(2019\)](#); [Sorsa et al. \(2015\)](#); [Mehrotra and Parida \(2017\)](#); [Klasen and Pieters \(2015\)](#); [Das and Žumbyté \(2017\)](#); [Bhalla and Kaur \(2011\)](#); [Kapsos et al. \(2014\)](#). Examining the determinants of low female LFP, several studies have included the presence or number of children under five years old in a household as a control variable to represent the childcare burden. These studies consider this factor to be a key determinant affecting women’s labour market participation. The findings consistently show a negative effect of young children on female LFP. For example, [Sarkar et al. \(2019\)](#) explored the factors influencing women’s labour market transitions using the IHDS data. They identified the birth of a newborn between 2004-2005 and 2011-2012 as a significant factor influencing women’s labour market dynamics. The study found that the presence of a newborn between the two survey periods was associated with a 3 percentage points higher likelihood of women exiting the labour force in rural areas.

Child-rearing plays a significant role in maintaining the gender wage gap, as highlighted by [Bhalla and Kaur \(2011\)](#). The study finds that this wage gap primarily results from women losing work experience due to child-rearing responsibilities. Even when women have the same age, education, and enter the labour market at the same time as men, career breaks related to childcare lead to lower earnings for women compared to their male counterparts. [Das and Žumbytė \(2017\)](#) examined the relationship between women’s employment and childcare responsibilities in urban India using the Employment and Unemployment Survey (EUS) conducted by the National Sample Survey Organization (NSSO) from 1983 to 2011. The study found that the gap in labour force participation rates between women with young children (under 6 years of age) and non-mothers increased from 4.7 percentage points in 1983 to 7.5 percentage points in 2011. This widening gap reflects the lack of formal or informal childcare facilities, as well as the decline of the joint family structure, which previously helped share childcare responsibilities and mitigated the trade-off between child rearing and labour supply. The presence of young children can also have different implications for rural and urban regions ([Sorsa et al., 2015](#)). Urban areas have experienced a sharper decline in female LFP compared to rural areas. This is due to the limited availability of childcare facilities and the dominance of nuclear families in urban areas, which place a greater share of childcare responsibilities on women. In contrast, rural women’s participation is often supported by older household members who can share caregiving responsibilities. The differential effects observed across geographies has also been emphasized by [Gautham \(2022\)](#) using the Indian Time Use Survey (TUS) conducted by the NSSO. The study compared the LFP and time spent in paid work between married non-mothers and those with their first child. It found that the decline in participation was smaller in rural areas than in urban areas, which could be attributed to the greater temporal and spatial flexibility of rural jobs that are more compatible with childcare responsibilities. More recently, [Mukherjee and Sarkhel \(2025\)](#) propose an alternative measure of motherhood, defined as the gap between actual and desired fertility, termed ‘fertility shock’. Drawing on IHDS data, they demonstrate that fertility shocks exert a negative effect on mothers’ earnings, work hours, and employment, with substantial heterogeneity across geographic regions and socio-familial contexts. Notably, the study identifies a positive association between fertility shocks and women’s employment in Southern states, in regions with higher female-to-male ratios, and in areas with greater female LFP, attributing this pattern to the heightened financial responsibilities accompanying childbearing.

To the best of our knowledge, only two studies — [Abraham et al. \(2021\)](#) and [Deshpande and Singh \(2021\)](#) — have examined the effect of childbirth on women’s labour market outcomes in India. [Abraham et al. \(2021\)](#), using primary data from the Indian Working Survey (2020–2021) conducted in Karnataka and Rajasthan, employed the Life History Calendar (LHC) method to collect long-term retrospective information on labour market trajectories. Their findings suggest a positive effect of childbirth on women’s LFP four years post-childbirth, primarily through increased informal employment, although the analysis is limited due to violation of the parallel trends assumption. Our study is more closely related to [Deshpande and Singh \(2021\)](#), which used CPHS data (2016–2019) and reported a positive effect of childbirth on mothers’ LFP, relative to non-mothers’, one year after childbirth. However, our analysis departs in several important ways: (i) we examine outcomes at the extensive

as well as intensive margins, which allows us to capture mothers' labour market entry and exit along with changes in their earnings and work hours, as a result of childbirth, (ii) we employ a different control group, which is more appropriate and cleaner to isolate the effect of childbirth¹, (iii) we provide specific attention to the effects of first childbirth, because the effect could be very different for first and subsequent births, and (iv) we offer evidence for potential mechanisms to explain the observed effects.

Taken together, the limited existing evidence highlights a gap in the literature on the dynamics of women's labour market outcomes around childbirth and as children grow up. Since the impact of childbirth may differ in the short and medium term, our study leverages the longitudinal structure of the CPHS data to offer a more comprehensive account, capturing both immediate and medium-term effects across the extensive and intensive margins. In addition, we identify the key factors underlying these changes and provide evidence on the possible mechanisms at work.

3 Data and Empirical Strategy

3.1 Data

We use panel data from the CPHS conducted by the Centre for Monitoring Indian Economy (CMIE) over the period 2016 to 2023. This high-frequency nationwide household-level panel data involves surveying and collecting data from households three times annually (referred to as waves) at four-month intervals, beginning with the first wave from January to April, 2014. Each wave includes approximately 800,000 individuals from 170,000 households. It provides extensive information on socio-economic and demographic indicators at both the individual and household levels. It includes four databases - People of India, Aspirational India, Income Pyramids, and Consumption Pyramids. We use the People of India and Income Pyramids database for our analysis, restricting the time period to 2016 (wave 7: January to April) - 2023 (wave 30: September to December) due to the unavailability of employment data for the earlier waves. The People of India file provides information about the employment status and work hours of an individual along with other socio-demographic characteristics such as age, education, caste, religion, relationship with head of the household (HOH), health status etc., while the Income Pyramids file provides details of individual as well as household income from various sources.

The CPHS asks about the employment status of respondents who are 15 or older. The possible responses are: (i) employed; (ii) unemployed, willing and looking for a job; (iii) unemployed, willing but not looking for a job; and (iv) unemployed, not willing and not looking for a job. We consider individuals in the first category as employed, those in the second and third categories as unemployed, and those in the fourth category as out of the labour force. Thus, we define LFP as a binary indicator,

¹Deshpande and Singh (2021) defines non-mothers as working-age women from households who did not have any children under the age of five at any point during the study period.

taking the value 1 for individuals belonging to either first, second or third category, and 0, otherwise. Similarly, employment is also a binary indicator, equal to 1, if an individual belongs to first category, and 0, otherwise. Work hours is the average daily hours of work performed by the individual over the week preceding the day of the survey.² Earnings include income from wages, salary earned by the salaried people, overtime payments, bonuses, and income from business for self-employed individuals. Earnings of individuals who are not working are reported as zero. Following the existing literature (Kleven et al., 2019; Zhang et al., 2024; Cortés and Pan, 2023; Lebedinski et al., 2023), our measure of earnings is unconditional on employment status, thereby retaining zeros that arise due to non-participation.

Since our main goal is to examine the effect of childbirth on mothers' labour market outcomes, and the CPHS does not directly provide information on parent and child relationships, we first identify mothers and non-mothers during the study period. We identify mothers with new childbirth following Deshpande and Singh (2021), which comprise our treatment group and non-mothers (control group) as those women who have never had a child during the study period (see Appendix I, section A1 for details about identification of the treatment and control groups). We do not include women with multiple childbirths during the study period to isolate the effect of a single childbirth, without potential influence from subsequent births. Unlike several prior studies that focus exclusively on the first birth (Kleven et al., 2019; Angelov et al., 2016; Cortés and Pan, 2023; Abraham et al., 2021; Koopmans et al., 2024), we include new childbirths that occur during the study period, regardless of birth order. This is primarily because restricting the analysis to first birth would significantly reduce our sample size.³ Lebedinski et al. (2023) has also adopted a similar approach. Moreover, higher-order births are particularly relevant in the Indian context, where multi-child families remain common and subsequent births may have distinct implications for women's labour market trajectories.

Our initial sample consists of 5,654,413 observations on women. However, we are able to identify mothers and non-mothers only when the individual is either HOH or spouse of the HOH. This restriction reduces the sample size to 320,101 (94.34% of the observations get dropped). After merging the employment data with income file, we end up with 177,415 observations. Further, we narrowed the sample to include only women between the ages of 15 to 35 years when they are observed for the first time in the data. This restriction ensures that both groups are observed during their prime childbearing years and are similarly at risk of childbirth. Additionally, it helps mitigate the concern related to potential confounding due to underlying health condition and delayed fertility among older women. Finally, we consider the time span of 9 waves (3 years) before and 21 waves (7 years) after childbirth in order to have considerable number of observations at each time period relative to childbirth, because as we move further away from the event of childbirth, the sample size shrinks. Our

²The information on work hours is available from 2019 (wave 18) and for those who are employed.

³We define a first birth as a case where no other household member is identified as an older sibling of the child. Consequently, a birth is classified as a higher-order birth if the child has at least one older sibling in the household, indicating that they are not the firstborn.

final sample comprises 88,530 observations.⁴

3.2 Empirical Strategy

We estimate the effect of new childbirth on mothers’ labour market outcomes - earnings, LFP, employment, and work hours. Since different individuals received the “treatment” (childbirth) at different points in time, we use the Difference-in-Differences (DiD) estimator developed by [Callaway and Sant’Anna \(2021\)](#), which is robust to staggered treatment adoption and treatment effect heterogeneity.^{5,6} This approach allows us to estimate the effect of childbirth on mothers’ labour market outcomes based on the assumption that, without childbirth, the trends in the potential outcomes would be the same for both the treatment and control groups (parallel trends). We estimate the effect of childbirth by comparing mothers (treatment group) to non-mothers (control group) throughout the same period. Given that women in the treatment and control groups are between ages 15 and 35 when they are observed for the first time in the data, the control group represents an appropriate counterfactual (not-yet treated), as they are likely to be subject to similar labour market conditions and life-cycle dynamics as the treated women, but have not yet experienced the event of childbirth.⁷

The empirical specification of the model is given as follows:

$$Y_{it} = \alpha_i + \beta_t + \sum_{l=-k}^{-4} \gamma_l \mathbf{1}\{t - G_i = \ell\} + \sum_{l=-2}^L \mu_l \mathbf{1}\{t - G_i = \ell\} + X'_{it} \delta + \epsilon_{it}, \quad (1)$$

where Y_{it} represents the dependent variable (earnings, LFP, employment, and work hours) for individual i in wave t . We transform earnings and work hours by taking natural logarithm to account for the skewed nature of these variables. α_i denotes the individual fixed effects, β_t the wave fixed effects, and ϵ_{it} is the error term. G_i represents the group, defined as the time period in which individual i is first treated, i.e., when they experience the childbirth. $\{t - G_i = \ell\}$ is an indicator taking value 1 for individual i being l waves away from the initial treatment time G_i at time t . The event time l ranges from -9 waves to 19 waves, indicating 9 waves (3 years) before and 19 waves (≈ 6 years) after childbirth. The post-childbirth effects, estimated up to 19 waves (≈ 6 years) reflect the period over which the effects can be identified using the [Callaway and Sant’Anna \(2021\)](#) estimator.⁸ The event time $l=0$ denotes the wave when the child is observed for the first time in the data. We

⁴We provide a sample construction table in Appendix I, Table A1, highlighting the steps undertaken to arrive at the analytical sample.

⁵Particularly, we use the doubly robust DiD estimator based on inverse probability weighting and ordinary least squares.

⁶We are unable to implement the empirical strategy adopted by [Kleven et al. \(2019\)](#) due to the lack of rich and long-term panel data. Moreover, we cannot assign placebo birth events to non-mothers, as in [Kleven et al. \(2019\)](#), because our data do not allow us to follow individuals consistently throughout their childbearing years.

⁷CPHS records marital status only from 2019 onwards, and directly incorporating this variable would substantially reduce the sample size. However, since approximately 80% of women in the dataset are identified as the spouse of the household head—implicitly indicating that they are married—the risk of confounding by marital status is largely mitigated.

⁸We are not able to estimate the effects up to 19 waves (≈ 6 years) for work hours since the information on work hours is available from 2019 (wave 18) and for those who are employed, resulting in insufficient number of observations.

have omitted the event time -3 (one year before childbirth) as the base (reference) period, and each coefficient is interpreted with respect to this period. Finally, the coefficient μ_l for $l > -3$ shows the effect of childbirth relative to the year before the birth on mothers' labour market outcome compared to non-mothers'. Notably, we also estimate the coefficients for the pregnancy period, specifically at $l = -1$ and $l = -2$, because women's labour market outcomes may be affected even before the actual event of childbirth. The coefficient γ_l for $l < -3$, exhibit the pre-trend, i.e., the difference in average outcome between the treatment and the control group prior to pregnancy. Since we do not observe the counterfactual outcomes for the treatment group, as a work-around, we tested for the joint significance of the pre-treatment interaction coefficients for each of the outcome variables to test the parallel trends assumption. We use the monthly Consumer Price Index (CPI) with base year 2011-2012 for both rural and urban regions, separately, to adjust nominal earnings to real earnings.

Since most of the individual-level control variables are either time-invariant or endogenous to fertility decisions, we estimate equation (1) using only covariates that are exogenous and measured prior to any potential treatment anticipation, thereby mitigating concerns of using bad controls. X'_{it} is a vector of covariates, including individual's age, quadratic term of age, and household income (excluding the individual's own earnings). We account for the excessive number of zeroes present in the earnings variable due to individuals being unemployed or out of the labour force by estimating a Tobit regression model for the censored sample which models the observed outcome variable (Y_{it}) in terms of an underlying latent variable (Y_{it}^*).^{9,10} It is formally expressed as:

$$Y_{it}^* = \alpha_i + \beta_t + \sum_{l=-k}^{-4} \gamma_l \mathbf{1}\{t - G_i = \ell\} + \sum_{l=-2}^L \mu_l \mathbf{1}\{t - G_i = \ell\} + X'_{it} \delta + \epsilon_{it}, \quad (2)$$

$$Y_{it} = \begin{cases} Y_{it}^* & \text{if } Y_{it}^* > 0, \\ 0 & \text{if } Y_{it}^* \leq 0 \end{cases} \quad (3)$$

We also report the weighted average of all available group-time average treatment effects on the treated (ATT for all groups across all waves) using the aggregation provided by [Callaway and Sant'Anna \(2021\)](#).

Our identification strategy is not without concerns. First, women's labour market outcomes may simultaneously influence their fertility decisions, potentially biasing the estimates. However, in the Indian context, decisions regarding childbirth are shaped predominantly by family preferences and cultural norms rather than individual career considerations. Consequently, the timing of childbirth is less likely to be a strategic response to labour market conditions. Second, unobserved factors may jointly affect fertility and labour market outcomes. Yet, as emphasized by [Zhang et al. \(2024\)](#) and [Kleven et al. \(2019\)](#), such factors are unlikely to perfectly determine the timing or occurrence of childbirth, thereby limiting the extent of bias. Third, concerns of sample selection may arise, since

⁹We also estimate positive earnings.

¹⁰Additionally, we employ the trimmed least absolute deviation estimator proposed by [Honoré \(1992\)](#), which allows for the inclusion of fixed effects while addressing censoring in the dependent variable.

work hours are observable only for those who are employed. However, we are not able to account for this potential selection issue because of sample size considerations.

To underscore the crucial role of time-invariant unobserved individual heterogeneity, we show the estimates with and without individual fixed effects, to enable meaningful comparisons. Finally, we perform a heterogeneity analysis based on various individual and household characteristics using different sub-samples to identify the primary factors affecting the dynamics of childbirth and mothers' labour market outcomes. These characteristics include education (No Education, Primary Education [1st to 8th std.], Secondary Education [9th to 12th std.], and Higher Education [Graduation and above]), household income quartiles (First, Second, Third, and Fourth), religion (Hindu and Muslim), caste (Upper [General and Intermediate] vs Lower [OBC's, SC's, and ST's]), birth order (First and Higher). Additionally, we provide suggestive evidence on potential mechanisms that could explain the results.

We conducted a number of robustness checks. First, we perform a sub-sample analysis, restricting the sample to the first birth to ensure comparability with prior studies. Second, we restrict the sample to include only those observations where we have consistent information on both the mother and the child. Third, to ensure that our results are not driven by the COVID pandemic, we provide a separate analysis for pre- (2016-2019) and post-COVID (2021-2023) periods. Fourth, we restricted the age of mothers and non-mothers to 15 - 30 when they are observed for the first time in the survey to further ensure the comparability of our treatment and control groups. Finally, we present the results after incorporating survey weights provided by the CPHS data. Our results remain largely consistent across all these checks.

4 Results

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics of the key variables used in the study for mothers and non-mothers at the base period (the wave when the individual has been observed for the first time in the data). It highlights the differences between mothers' and non-mothers' labour market outcomes in urban and rural regions. It shows that in the urban regions 13.6% of mothers are part of the labour force in contrast to 16.1% of non-mothers. In rural regions, the corresponding figures are approximately 13.4% and 19.8%, respectively. Similarly, earnings and employment are also significantly higher for non-mothers compared to mothers in both regions, while the average daily work hours are higher for mothers compared to non-mothers in rural regions, with no significant difference in urban regions. On average, non-mothers are younger than mothers in both regions. Moreover, a significantly higher proportion of mothers have at least a secondary education compared to non-mothers in rural regions. Additionally, a significantly higher percentage of mothers (72.1% vs 66.1%) belong to the upper caste compared to non-mothers in the urban regions.

Table 1. Summary statistics of the key study variables at base period

	Urban			Rural		
	Mothers (N=3503)	Non-mothers (N=1716)	p-value [§]	Mothers (N=2144)	Non-mothers (N=996)	p-value [§]
LFP	0.136 (0.343)	0.161 (0.368)	0.017	0.134 (0.341)	0.198 (0.399)	<0.001
Employment	0.059 (0.235)	0.114 (0.317)	<0.001	0.075 (0.264)	0.154 (0.361)	<0.001
Earnings [†]	477.271 (3047.087)	781.489 (3136.506)	<0.001	243.254 (1311.111)	506.177 (1582.296)	<0.001
Daily Work hours [‡]	7.040 (1.790)	6.690 (1.310)	0.420	7.030 (1.260)	5.950 (2.060)	0.040
Age (years)	26.495 (3.894)	23.728 (4.483)	<0.001	25.955 (4.191)	23.956 (4.755)	<0.001
Education						
No education	0.086 (0.281)	0.088 (0.283)	0.840	0.215 (0.411)	0.273 (0.446)	<0.001
Primary education	0.312 (0.464)	0.406 (0.491)	<0.001	0.417 (0.493)	0.501 (0.500)	<0.001
Secondary education	0.443 (0.497)	0.356 (0.479)	<0.001	0.311 (0.463)	0.192 (0.394)	<0.001
Graduation and above	0.158 (0.365)	0.150 (0.357)	0.420	0.058 (0.233)	0.034 (0.181)	0.005
Religion						
Hindu	0.825 (0.380)	0.866 (0.341)	<0.001	0.849 (0.358)	0.906 (0.292)	<0.001
Muslim	0.133 (0.339)	0.093 (0.291)	<0.001	0.115 (0.319)	0.074 (0.262)	<0.001
Christian	0.017 (0.130)	0.019 (0.136)	0.660	0.016 (0.125)	0.006 (0.078)	0.020
Other [*]	0.025 (0.155)	0.022 (0.148)	0.620	0.020 (0.141)	0.014 (0.118)	0.210
Caste						
Upper caste (General)	0.721 (0.449)	0.661 (0.474)	<0.001	0.795 (0.404)	0.785 (0.411)	0.520
Lower caste (OBCs/SCs/STs)	0.279 (0.449)	0.339 (0.474)	<0.001	0.205 (0.404)	0.215 (0.411)	0.520
Household income ^{**}	12266.780 (10513.050)	12559.310 (11156.790)	0.350	7932.218 (7580.338)	6926.042 (6718.068)	<0.001

Notes: Weighted mean and standard deviation (in parenthesis) of the key study variables at the base period (the wave when the individuals are observed for the first time in the data) for mothers and non-mothers in urban and rural regions. Except earnings, daily work hours, age, and household income, other variables are categorical.

[†]Earnings (monthly, in INR) are unconditional on employment status.

[‡]Information on daily work hours is available from 2019 (wave 18) and for those who are employed.

^{*}‘Other’ category under religion includes Jain, Sikh, Buddhist, Parsi, Khasi, and others.

^{**}Household income (monthly, in INR) excludes the individual’s own earnings.

[§]*p*-values are reported using t-test for continuous variables and proportion test for categorical variables.

4.2 Parallel Trends Results

The key identifying assumption underlying the DiD framework is that of parallel trends, which states that in the absence of the treatment, the outcomes for the treatment and control groups would have followed similar trends. This assumption is not testable since it requires data on counterfactuals. Instead, we check whether the treatment and control groups had similar trend before the treatment (childbirth). The event study plots presented in the following section provide evidence that the trends across groups were similar for earnings, LFP, and employment, with p -values ranging from 0.18 to 0.58 in urban and 0.17 to 0.79 in rural regions. The only exception is work hours, where the parallel trends assumption is not satisfied ($p < 0.001$ in both regions).

4.3 Effects on Earnings, LFP, Employment, and Work hours: Urban Regions

Figure 1 shows the effect of childbirth on various labour market outcomes of mothers compared to non-mothers for 9 waves (3 years) before and 19 waves (≈ 6 years) after childbirth, relative to 3 waves (1 year) before childbirth in urban regions, estimated using equation (1). The standard errors are robust to heteroskedasticity and clustered at the individual level. The vertical dashed line at wave -3 indicates the omitted base (reference) period. Panel A shows an increase of almost 24% in the average earnings of mothers, one year (3 waves) after childbirth, and it increases to approximately 66% by the 5th year (15 waves) after childbirth. We do not find any significant effect on the likelihood of mothers' LFP, as evident in Panel B, but we do observe an increase in the likelihood of employment by almost 3 percentage points one year post-childbirth, which increases to about 7.6 percentage points by the 5th year (15 waves) post-childbirth. Panel D demonstrates the effect on work hours conditional on employment. We find reduction in work hours by about 36% at the time of childbirth and about 12%, one wave post-childbirth; however, these findings should be interpreted with caution due to data limitations. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a substantial reduction in sample size ($N=335$). While we are unable to examine the potential contribution of changes in work hours or wage rates to the motherhood premium in earnings, Panels B, C, and D suggest that the observed earnings effect is at least partly driven by an increase in the mothers' likelihood of employment, one year after childbirth.

We observe very similar findings for earnings based on the Tobit model estimated using equation (2). It also shows a positive and significant effect a year after childbirth, although the magnitude is smaller (Appendix I, Figure A1: Panel A).¹¹

¹¹We find qualitatively similar results using trimmed least absolute deviation estimator proposed by Honoré (1992).

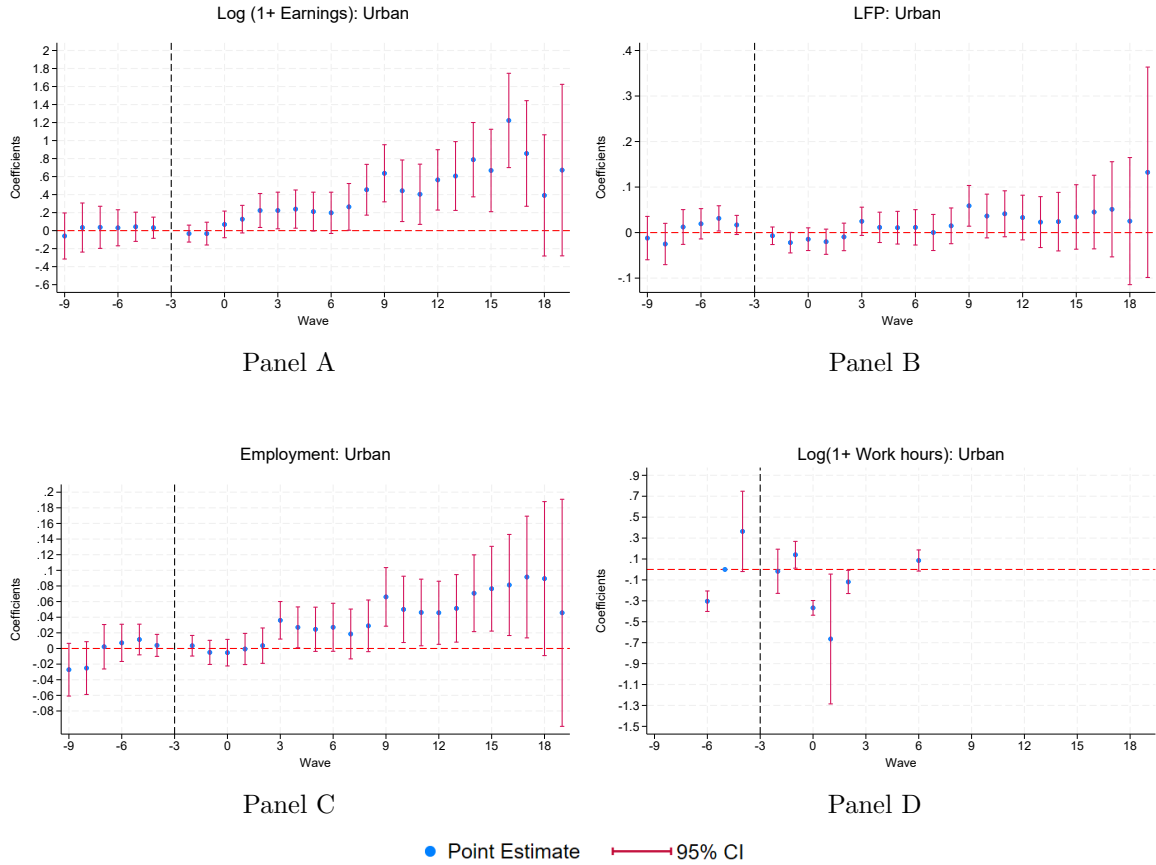


Figure 1. Effect of childbirth on labour market outcomes: Urban regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for various labour market outcomes in urban regions. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), employment (Panel C), and work hours (Panel D). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted base (reference) period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=335$). The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

We provide the weighted average of all group-time ATT of childbirth on mothers' various labour market outcomes compared to non-mothers' in Table 2. We find a significant increase in the average earnings of mothers by 27.4% post-childbirth compared to non-mothers. We do not find any significant effect on the likelihood of mothers' LFP, but we do observe an increase in the likelihood of employment by 2.4 percentage points post-childbirth. Examining the effect of childbirth on mothers' earnings, conditional on having positive earnings (Table 2, column (5)), we do not observe any significant effects.

Table 2. Effect of childbirth on mothers’ labour market outcomes: Urban regions

	(1)	(2)	(3)	(4)	(5)
	Log (1+Earnings)	LFP	Employment	Log (1+Work hours)	Log (Earnings [†])
ATT	0.2739*** (0.082)	0.0084 (0.013)	0.0244** (0.010)	-0.041 (0.084)	-0.074 (0.175)
Controls	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effect	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	27,302	27,302	27,302	335	1,057

Notes: This table shows the weighted average of all group-time ATT of childbirth on mothers’ unconditional earnings, LFP, employment, work hours, and earnings (conditional on positive earnings) using Callaway and Sant’Anna (2021) estimator in urban regions. The control variables include age, quadratic term of age, household income (excluding the individual’s own earnings), along with individual and time fixed effects. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size. Heteroskedasticity robust standard errors, clustered at the individual level, are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. [†] Positive earnings are reported.

4.4 Role of Unobserved Individual-level Heterogeneity: Urban regions

The time-invariant unobserved individual characteristics play a crucial role in explaining the effect of childbirth on mothers’ labour market outcomes. The earlier studies in the Indian context (Gautham, 2022; Das and Žumbytė, 2017) were based on cross-sectional data and could not account for such unobserved heterogeneity. Although Tiwari et al. (2022) and Mukherjee and Sarkhel (2025) address such heterogeneity by leveraging the panel nature of the IHDS data, these studies do not specifically focus on childbirth. Furthermore, Deshpande and Singh (2021) also utilizes the panel nature of the CPHS data, our study differs from theirs in several important aspects (see section 2.2). In this section, we show that ignoring these unobserved characteristics can lead to substantial bias. Here, we present results using four different specifications of equation (1): (i) no fixed effects, (ii) only wave fixed effects, (iii) wave and individual fixed effects (Two-Way Fixed Effects (TWFE)), and (iv) Callaway and Sant’Anna (2021) estimator with both FEs. The primary motivation for this analysis is to examine the importance of accounting for individual unobserved heterogeneity, a dimension that has received little attention in the Indian context. Addressing this gap also facilitates a more robust comparison with the existing body of literature on India. Second, it contributes to the growing literature on TWFE estimators in settings with staggered treatment adoption and heterogeneous treatment effects.

We provide these results for all four outcomes considered in the study, namely, earnings, LFP, employment, and work hours in Figure 2, Figure 3, Figure 4, and Figure 5, respectively, for urban regions. In each of the figures, Panel A reports the results with no fixed effects, Panel B with wave fixed effects, Panel C with TWFE, and Panel D, using Callaway and Sant’Anna (2021) estimator. Notably, we are

able to estimate the post-childbirth effects up to 21 waves (7 years) in all the specifications (Panels A-C) with the only exception being Panel D, which is estimated using Callaway and Sant’Anna (2021) estimator in each figure. When we do not control for any of the fixed effects (Figure 2: Panel A), we find a negative effect of childbirth on mothers’ earnings compared to non-mothers’, with significant pre-trends before childbirth. When we account for the wave fixed effects in Figure 2: Panel B, the results broadly remain the same. A striking difference emerges once individual fixed effects are accounted for in Figure 2: Panel C. The inclusion of these fixed effects not only renders the coefficients positive but also ensures that the parallel trends assumption is satisfied. As shown in Panel C, controlling for individual fixed effects produces the most substantial change, yielding a positive effect of childbirth on mothers’ average earnings relative to non-mothers’.

Furthermore, recent literature has highlighted that TWFE estimators may generate biased estimates, primarily because early-treated units are inappropriately used as controls for late-treated units (Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant’Anna, 2021). Sun and Abraham (2021) shows that the coefficients in the event study specification is contaminated by the effects of the other relative time indicators as well. Using the Callaway and Sant’Anna (2021) estimator (Figure 2: Panel D), the results reveal a greater increase in earnings, suggesting that the motherhood premium in urban areas may be stronger than what is captured by the TWFE estimator.

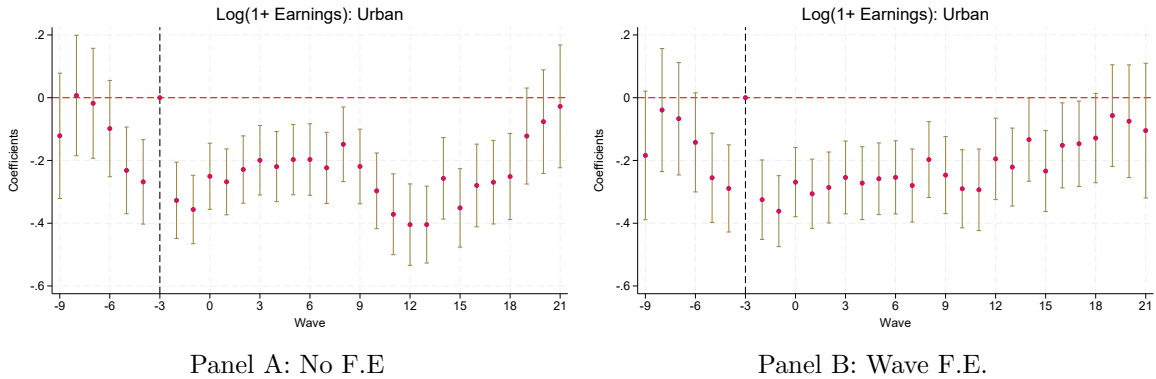


Figure 2. Effect of childbirth on Earnings: Urban regions

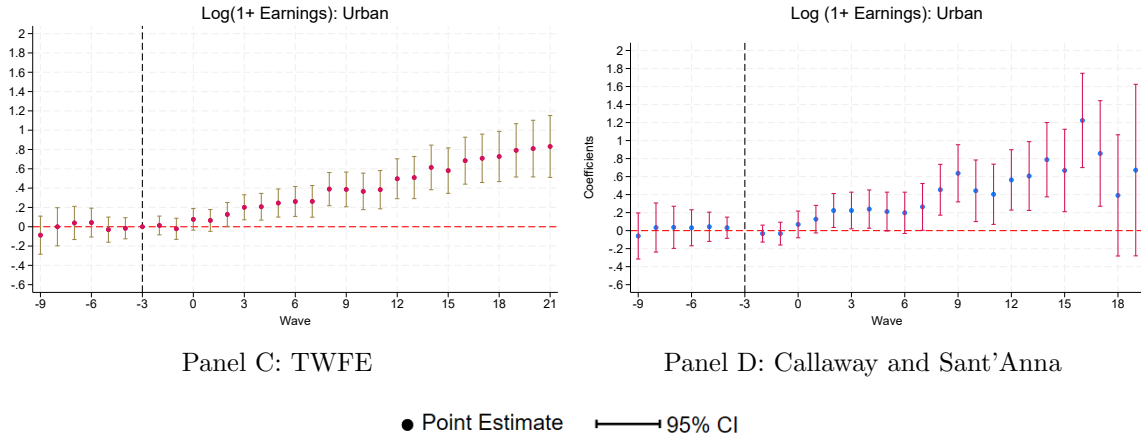
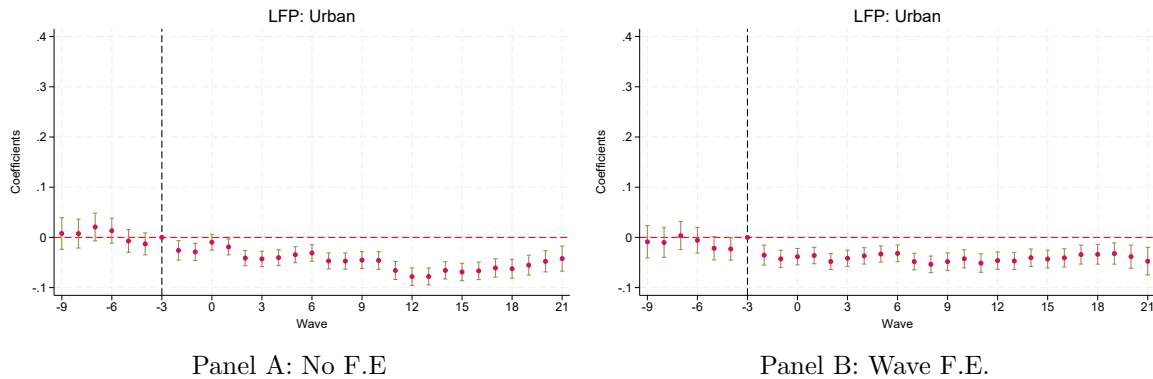


Figure 2. Effect of childbirth on Earnings: Urban regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for mothers' unconditional earnings in urban regions with different specifications. Panel A reports the coefficients without controlling for any fixed effects, Panel B accounts for wave fixed effects, Panel C includes TWFE, and Panel D shows the coefficients estimated using Callaway and Sant'Anna (2021) estimator. The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event-time $l=0$ denotes the time when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted base (reference) period. Each coefficient shows the effect of childbirth on mothers' average earnings compared to non-mothers', relative to three waves (one year) before childbirth. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

Figure 3 presents the estimated effects of childbirth on mothers' LFP across the four empirical specifications. Prior to accounting for individual fixed effects, the coefficients are negative with significant pre-trends (Figure 3: Panels A and B). However, once individual fixed effects are included, the coefficients indicate a positive (but insignificant) effect after wave 11 and no longer violate the parallel trends assumption (Figure 3: Panel C). Estimates based on the Callaway and Sant'Anna (2021) estimator also yield positive but insignificant effects (Figure 3: Panel D).



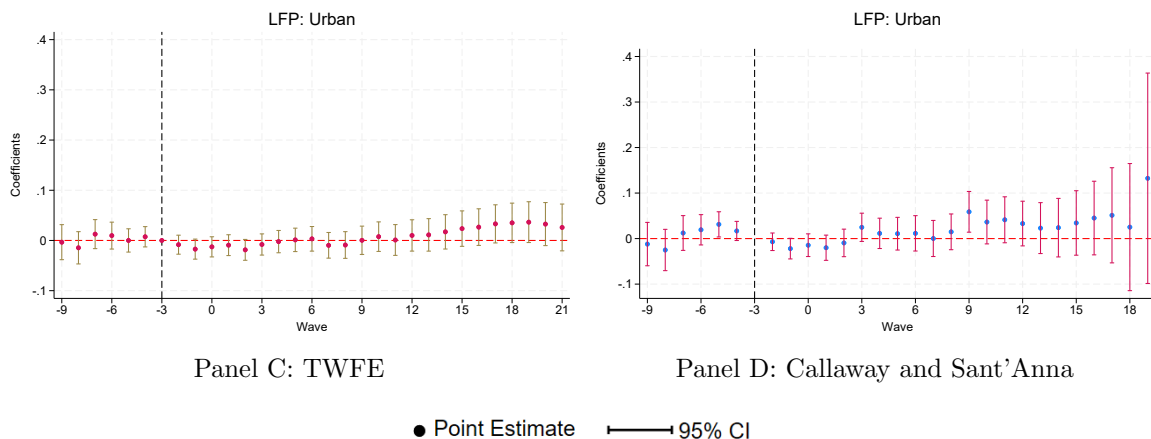


Figure 3. Effect of childbirth on LFP: Urban regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for mothers' likelihood of LFP in urban regions with different specifications. Panel A reports the coefficients without controlling for any fixed effects, Panel B accounts for wave fixed effects, Panel C includes TWFE, and Panel D shows the coefficients estimated using [Callaway and Sant'Anna \(2021\)](#) estimator. The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event-time $l=0$ denotes the time when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted base (reference) period. Each coefficient shows the effect of childbirth on mothers' likelihood of LFP compared to non-mothers', relative to three waves (one year) before childbirth. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

Similarly, [Figure 4](#) shows the effect of childbirth on mothers' likelihood of employment. It is again evident that prior to accounting for individual fixed effects, the coefficients are negative, with significant pre-trends ([Figure 4](#): Panels A and B), but once we control for it, the coefficients are positive and significant after wave 6 ([Figure 4](#): Panel C) and also satisfy the parallel trends assumption. The estimates based on [Callaway and Sant'Anna \(2021\)](#) estimator show a positive and significant trend wave 9 onward and are generally higher compared to the TWFE estimates although the confidence intervals are much wider ([Figure 4](#): Panel D).

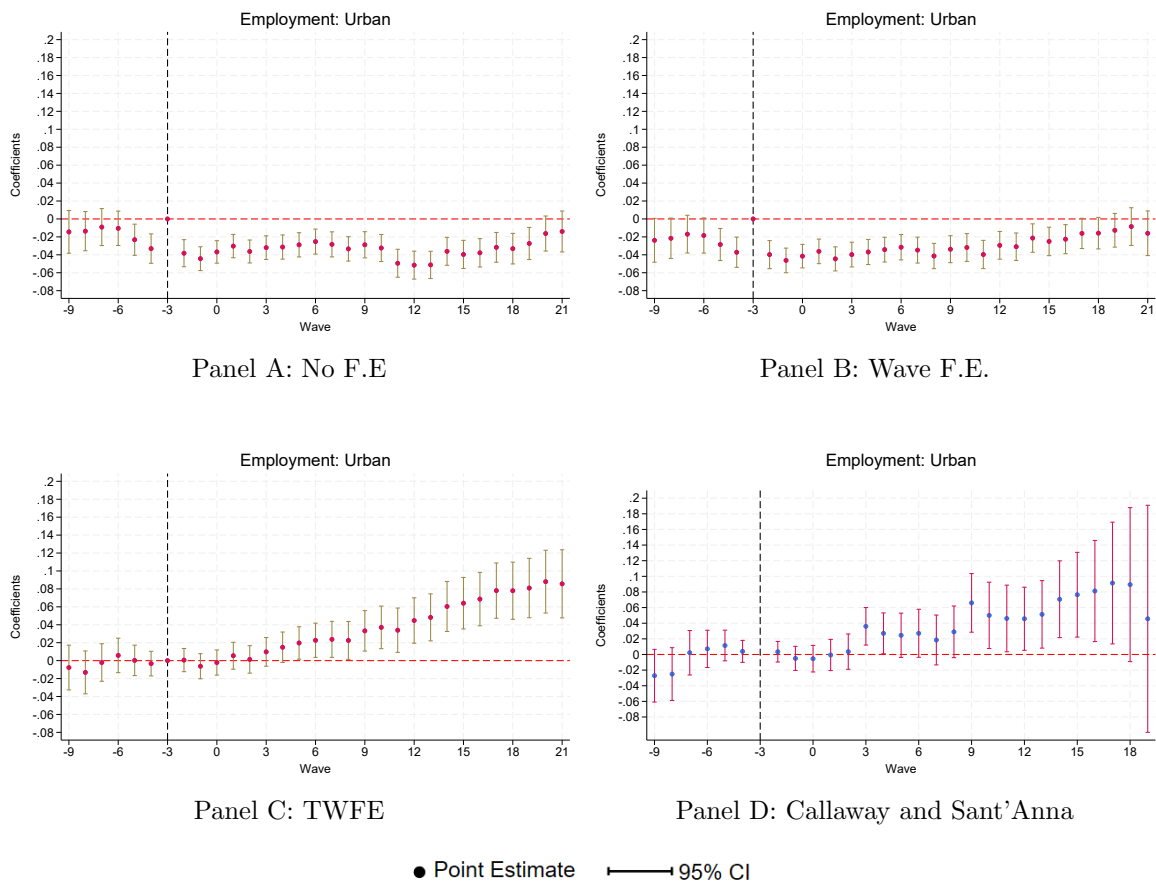


Figure 4. Effect of childbirth on Employment: Urban regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for mothers' likelihood of employment in urban regions with different specifications. Panel A reports the coefficients without controlling for any fixed effects, Panel B accounts for wave fixed effects, Panel C includes TWFE, and Panel D shows the coefficients estimated using [Callaway and Sant'Anna \(2021\)](#) estimator. The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event-time $l=0$ denotes the time when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted base (reference) period. Each coefficient shows the effect of childbirth on mothers' likelihood of employment compared to non-mothers', relative to three waves (one year) before childbirth. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

[Figure 5](#) presents the coefficients on work hours, which largely indicates negative or null effects, although the coefficients are not statistically significant (Panels A and B). Once we control for individual fixed effects, the coefficients exhibit a positive effect after childbirth but remain insignificant (Panel C). Using the [Callaway and Sant'Anna \(2021\)](#) estimator, we were unable to estimate the coefficients precisely due to lack of sufficient number of observations ($N=335$).

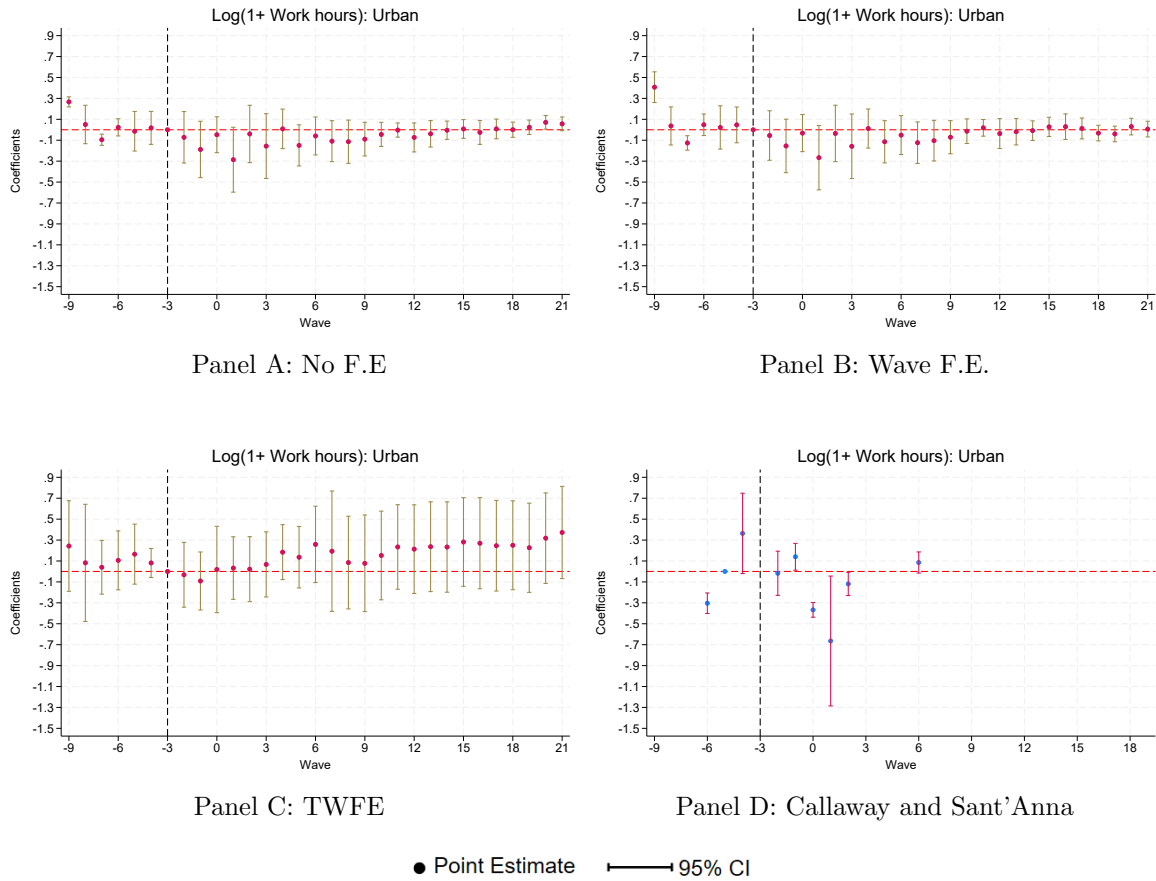


Figure 5. Effect of childbirth on Work hours: Urban regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for mothers' work hours in urban regions with different specifications. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=335$). Panel A reports the coefficients without controlling for any fixed effects, Panel B accounts for wave fixed effects, Panel C includes TWFE, and Panel D shows the coefficients estimated using [Callaway and Sant'Anna \(2021\)](#) estimator. The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event-time $l=0$ denotes the time when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted base (reference) period. Each coefficient shows the effect of childbirth on mothers' average work hours compared to non-mothers', relative to three waves (one year) before childbirth. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

As we have shown, controlling for unobserved time-invariant individual heterogeneity is critical. It is plausible that women who are more family oriented and/or less inclined to work may be more likely to have children earlier. If such (unobserved) characteristics are not adequately controlled for, the estimates from cross-sectional analyses may be biased.

Additionally, an individual’s susceptibility to prevailing social norms - such as traditional gender roles or cultural expectations around motherhood - may also remain stable over time and influence both fertility and labour market decisions. For example, the expectation of having a child soon after marriage, coupled with the belief that a woman should prioritize childcare responsibilities over labour market participation, can significantly shape these decisions.

The results presented above underscore the importance of controlling for such stable individual characteristics. Once these are accounted for using individual fixed effects, the estimated effect of childbirth on labour market outcomes is positive. This highlights that in the absence of individual fixed effects, our findings would align with the existing literature in the Indian context which has documented negative associations between childbirth or the presence of young children (typically under five years of age) and women’s LFP (Das and Žumbyté, 2017; Gautham, 2022). These studies have utilized repeated cross-sectional data from the EUS, and a single cross-sectional data from the Indian TUS. Moreover, the violation of the parallel trends assumption when unobserved heterogeneity is not accounted for raises concerns about the validity of the estimates obtained from cross-sectional data.

4.5 Effects on Earnings, LFP, Employment, and Work hours: Rural Regions

Figure 6 illustrates the effect of childbirth on mothers’ labour market outcomes in rural regions, estimated using equation (1). Panel A shows the results on earnings, where we observe a positive effect on the average earnings of mothers of about 54% one year after childbirth, which increases to 75% by the 4th year (12 waves) post-childbirth compared to non-mothers. Panel B, Panel C, and Panel D exhibit mothers’ likelihood of LFP, employment, and work hours, respectively. We do not observe any significant effect on the likelihood of mothers’ LFP, and employment. Since we do not have sufficient statistical power to estimate the effect on work hours and wage rates, due to lack of observations (N=441), we can only speculate that, in the absence of any employment effect, the observed motherhood premium in earnings is likely driven by an increase in work hours, wage rates, or a combination of both. Also, the Tobit results for earnings align with the main finding of having positive effects after childbirth (Appendix I, Figure A1: Panel B).¹²

¹²We find qualitatively similar results using trimmed least absolute deviation estimator proposed by Honoré (1992).

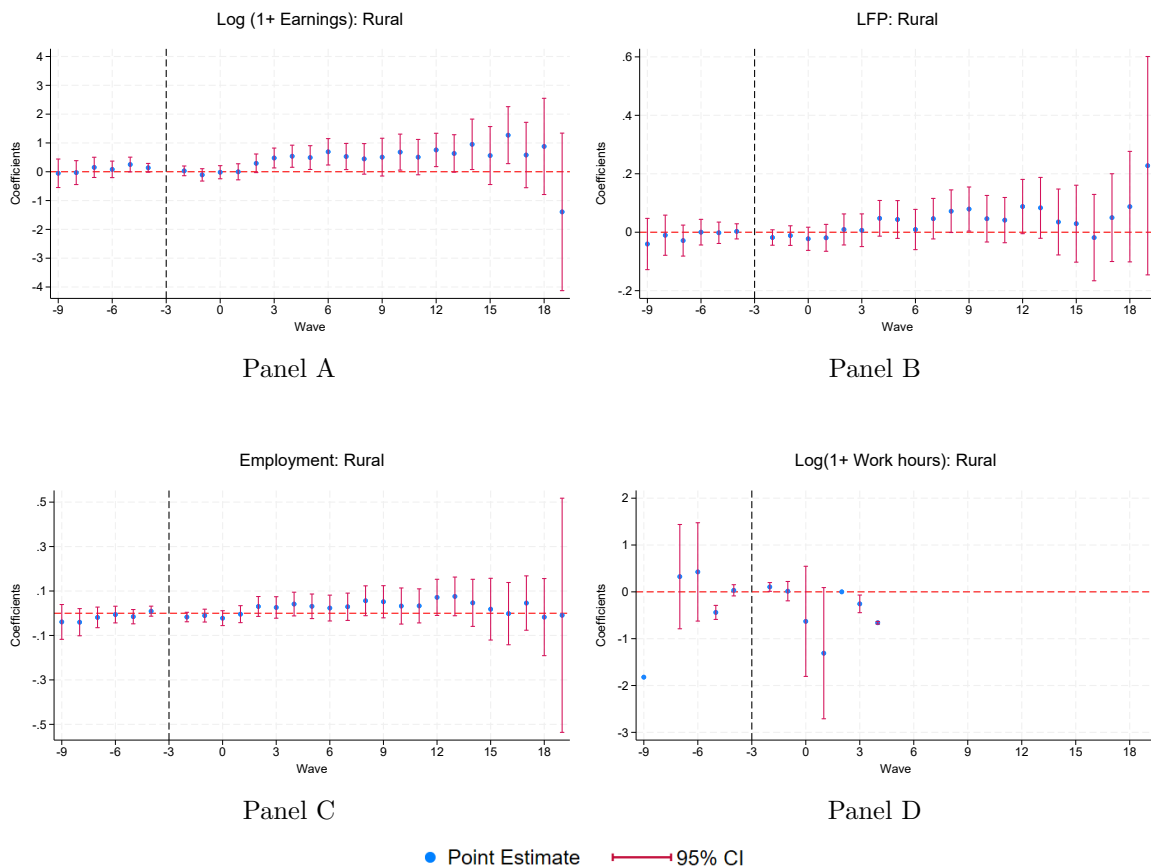


Figure 6. Effect of childbirth on labour market outcomes: Rural regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for various labour market outcomes in rural regions. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), employment (Panel C), and work hours (Panel D). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted base (reference) period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=441$). The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

We also provide the weighted average of all group-time ATT of childbirth on mothers' various labour market outcomes compared to non-mothers' in Table 3. We find a significant increase of 32.6 % in the average earnings of mothers post-childbirth compared to non-mothers. We do not find any significant effect on the likelihood of mothers' LFP, employment, and work hours as evident in columns (2)-(4). Additionally, we do not observe any significant effect of childbirth on mothers' earnings conditional on having positive earnings (column (5)).

Table 3. Effect of childbirth on mothers’ labour market outcomes: Rural regions

	(1)	(2)	(3)	(4)	(5)
	Log (1+Earnings)	LFP	Employment	Log (1+Work hours)	Log (Earnings [†])
ATT	0.3257*** (0.130)	0.017 (0.019)	0.0168 (0.017)	-0.19 (0.141)	-0.037 (0.171)
Controls	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effect	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	14,244	14,244	14,244	441	1,038

Notes: This table shows the weighted average of all group-time ATT of childbirth on mothers’ unconditional earnings, LFP, employment, work hours, and earnings (conditional on positive earnings) using Callaway and Sant’Anna (2021) estimator in rural regions. The control variables include age, quadratic term of age, household income (excluding the individual’s own earnings), along with individual and time fixed effects. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size. Heteroskedasticity robust standard errors, clustered at the individual level, are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. [†] Positive earnings are reported.

4.6 Role of Unobserved Individual-level Heterogeneity: Rural regions

We replicate the whole analysis to examine how the inclusion of individual fixed effects affect the results in rural regions. The results on earnings, LFP, employment, and work hours are reported in Figure 7, Figure 8, Figure 9, and Figure 10, respectively. In each of the figures, Panel A reports the coefficients without controlling for any fixed effects, Panel B includes wave fixed effects, Panel C accounts for TWFE, and Panel D presents coefficients estimated using Callaway and Sant’Anna (2021) estimator. As before, we are able to estimate the the post-childbirth effects for up to 21 waves (7 years) in all the specifications (Panels A-C) with the only exception being Panel D, estimated using Callaway and Sant’Anna (2021) estimator in each figure. Figure 7 demonstrates a negative effect of childbirth on mothers’ earnings compared to non-mothers’ along with significant pre-trends, when we do not control for any fixed effects (Panel A) and when we include only wave fixed effects (Panel B). However, once the individual fixed effects are accounted for (Panel C), the parallel trends assumption are satisfied and the effect of motherhood on earnings is positive and significant. The Callaway and Sant’Anna (2021) estimates also show a positive effect on earnings, although, the results suggest greater variation across treatment cohorts, and the confidence intervals are wider (Panel D).

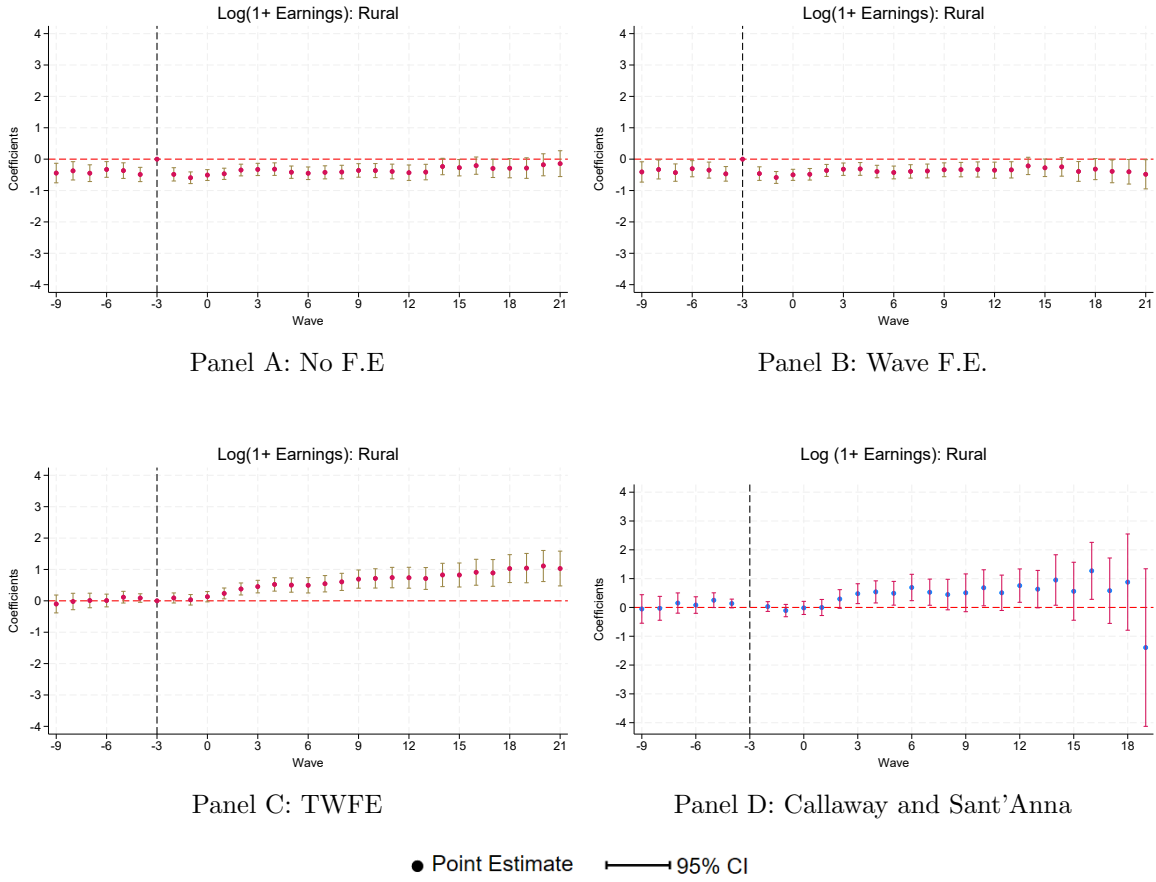


Figure 7. Effect of childbirth on Earnings: Rural regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for mothers' unconditional earnings in rural regions with different specifications. Panel A reports the coefficients without controlling for any fixed effects, Panel B accounts for wave fixed effects, Panel C includes TWFE, and Panel D shows the coefficients estimated using [Callaway and Sant'Anna \(2021\)](#) estimator. The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event-time $l=0$ denotes the time when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted base (reference) period. Each coefficient shows the effect of childbirth on mothers' average earnings compared to non-mothers', relative to three waves (one year) before childbirth. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

[Figure 8](#) reports the effects on LFP, where we observe negative effects in Panels A and B with significant pre-trends, but after controlling for individual fixed effects, we note a significant and positive effect 7 waves after childbirth. However, once we account for the treatment effect heterogeneity in Panel D, the findings are no longer significant.

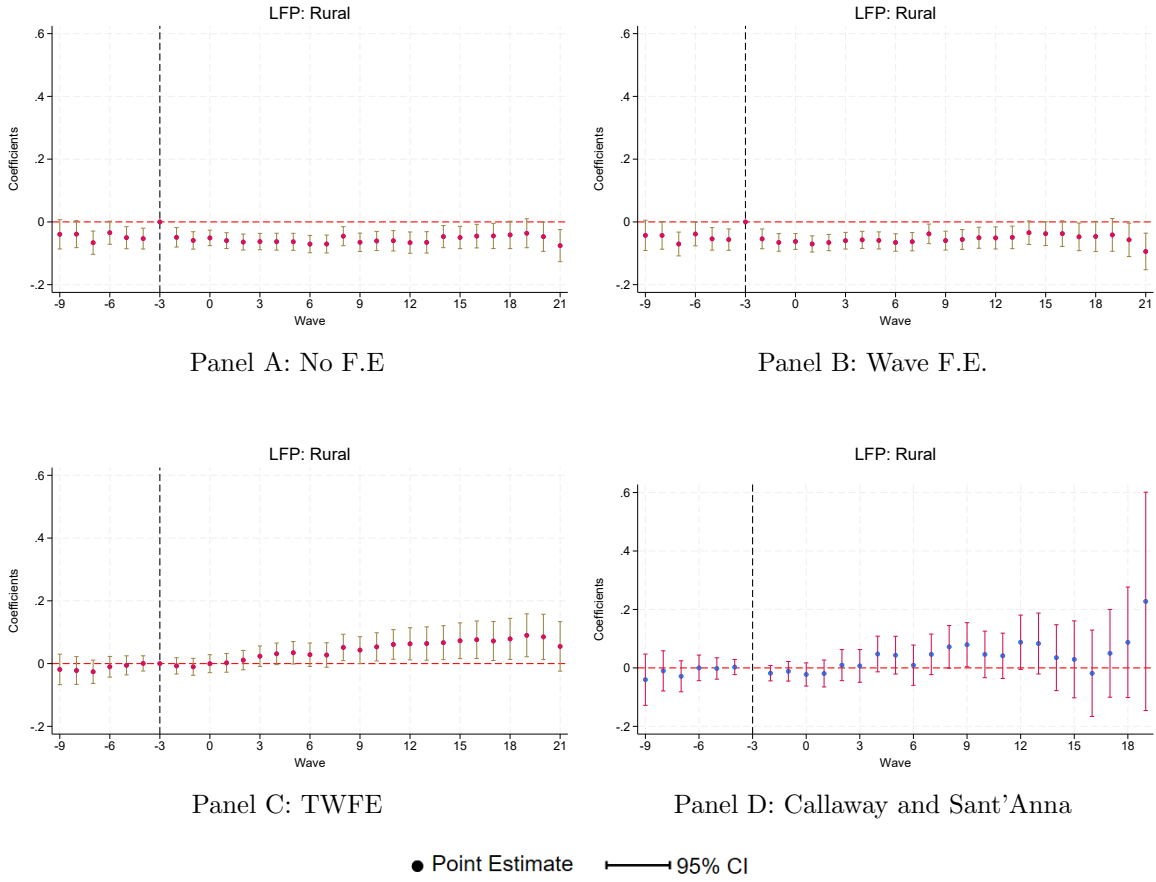


Figure 8. Effect of childbirth on LFP: Rural regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for mothers' likelihood of LFP in rural regions with different specifications. Panel A reports the coefficients without controlling for any fixed effects, Panel B accounts for wave fixed effects, Panel C includes TWFE, and Panel D shows the coefficients estimated using Callaway and Sant'Anna (2021) estimator. The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event-time $l=0$ denotes the time when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted base (reference) period. Each coefficient shows the effect of childbirth on mothers' likelihood of LFP compared to non-mothers', relative to three waves (one year) before childbirth. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

Figure 9 reports the results of the effect of childbirth on mothers' likelihood of employment. Panel A and B demonstrates the negative effect of childbirth with significant pre-trends. Once individual fixed effects are accounted for, the parallel trends assumption is satisfied and we find positive effects almost 7 waves after childbirth (Panel C). Finally, once treatment effect heterogeneity is accounted for, we no longer find any significant effects on employment (Panel D).

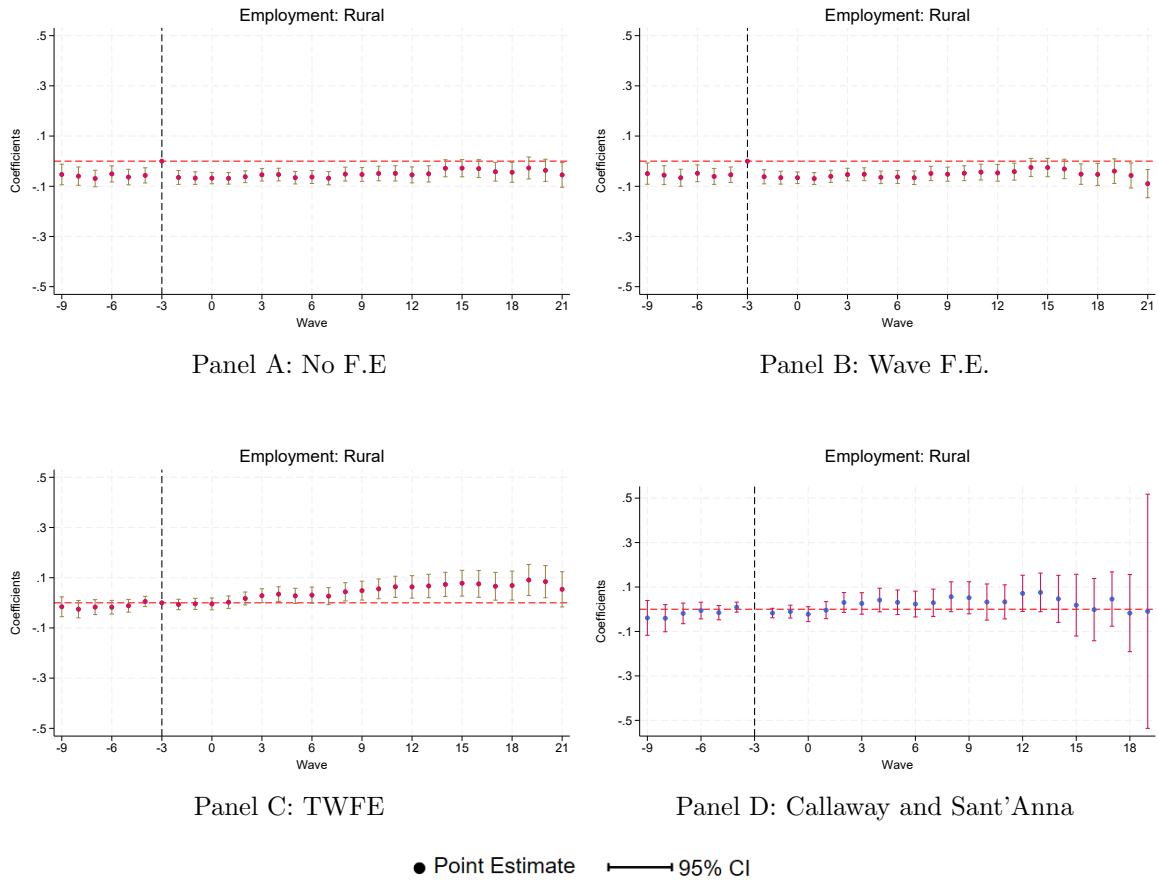


Figure 9. Effect of childbirth on Employment: Rural regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for mothers' likelihood of employment in rural regions with different specifications. Panel A report the coefficients without controlling for any fixed effects, Panel B accounts for wave fixed effects, Panel C includes TWFE, and Panel D shows the coefficients estimated using [Callaway and Sant'Anna \(2021\)](#) estimator. The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event-time $l=0$ denotes the time when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted base (reference) period. Each coefficient shows the effect of childbirth on mothers' likelihood of employment compared to non-mothers', relative to three waves (one year) before childbirth. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

[Figure 10](#) reports the results on the effect of childbirth on mothers' work hours. We do not observe any significant effects across the different specifications (Panels A-D).

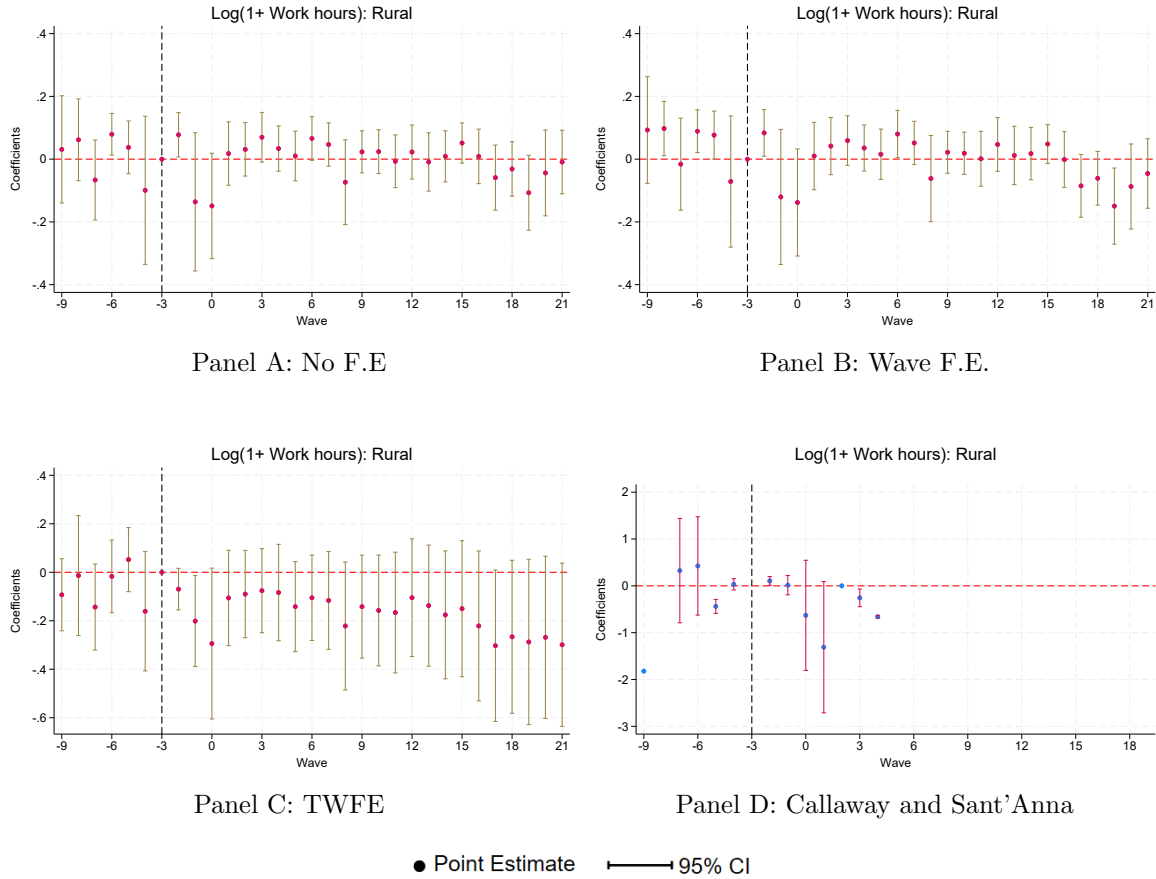


Figure 10. Effect of childbirth on Work hours: Rural regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for mothers' work hours in rural regions with different specifications. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=441$). Panel A reports the coefficients without controlling for any fixed effects, Panel B accounts for wave fixed effects, Panel C includes TWFE, and Panel D shows the coefficients estimated using [Callaway and Sant'Anna \(2021\)](#) estimator. The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event-time $l=0$ denotes the time when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted base (reference) period. Each coefficient shows the effect of childbirth on mothers' average work hours compared to non-mothers', relative to three waves (one year) before childbirth. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

4.7 Heterogeneity Analysis

The crucial role of socio-economic factors such as education, household income, caste, and religion in affecting female labour market outcomes have been widely discussed in the existing literature, revealing a wide range of heterogeneous effects across these characteristics ([Abraham, 2013](#); [Chatterjee et al.](#),

2018; Das, 2006; Goldin, 1994; Klasen and Pieters, 2015; Deshpande et al., 2018). Unlike men, women’s decision to participate in the labour market is often shaped not only by economic factors but also by a complex interplay of socio-cultural aspects. To examine the heterogeneous effects of childbirth on mothers’ employment across these characteristics, we conduct several sub-sample analyses for urban and rural regions, separately.¹³ Additionally, we also look into the heterogeneous effects by birth order, which has been found to play an important role in shaping mothers’ employment decisions (Lebedinski et al., 2023).¹⁴ Except caste and religion, all the other characteristics are time-varying and hence we have taken their base period values.¹⁵ Moreover, since the effects could be very different during pregnancy and first year of childbirth vs after first year of childbirth, we carry out the analysis separately for two time periods: (i) during pregnancy and first year of childbirth, and (ii) after first year of childbirth. We present the weighted average of all the group-time ATT based on Callaway and Sant’Anna (2021) estimator. The control variables include age, quadratic term of age, and household income (excluding the individual’s own earnings). The results are presented in Figure 11 and Figure 12 for urban and rural regions, respectively. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

Figure 11: Panel A shows the heterogeneous effects of childbirth on mothers’ employment compared to non-mothers’ in urban regions during pregnancy and first year of childbirth. The top row shows the effect on all urban women and the subsequent rows shows the effects by various socio-economic characteristics of women. We do not find any significant effects overall and across any of these characteristics. On the other hand, Figure 11: Panel B illustrates the heterogeneous effect on mothers’ employment after the first year of childbirth. On average, the probability of mothers’ likelihood of employment increases by almost 4.7 percentage points in urban regions. Panel B also demonstrates that the effects vary across these socio-economic characteristics after first year of childbirth. We find a positive and significant effect of almost 5.6 percentage points for mothers who have primary education. We do not find any significant effects for the other educational categories. We also explore how the effects vary with household income level. We divide household income (excluding the individual’s own earnings) into four quartiles: the first quartile represents the lowest income group and the fourth the highest income group. We find a positive effect of almost 6.5 percentage points on the likelihood of employment of mothers belonging to the lowest income quartile and a 10.8 percentage points increase for mothers belonging to the second income quartile. However, both of these coefficients are not statistically different from each other. On the contrary, we do not observe any significant effects for mothers belonging to higher income quartiles. Interestingly, we find a positive and significant effect of 6.4 percentage points for mothers belonging to the lower caste and a 4.7 percentage points increase for mothers belonging to the Hindu religion. Finally, we note a 3.7 percentage points increase in the likelihood of employment for mothers with higher birth order but no significant effect for those with

¹³We are unable to conduct the heterogeneity analysis for earnings, as the limited number of observations with positive earnings does not permit further sub-sample analyses.

¹⁴We define a first birth as a case where no other household member is identified as an older sibling of the child. Consequently, a birth is classified as a higher-order birth if the child has at least one older sibling in the household, indicating that they are not the firstborn.

¹⁵We take the values when the individual are observed for the first time in the data.

first birth.

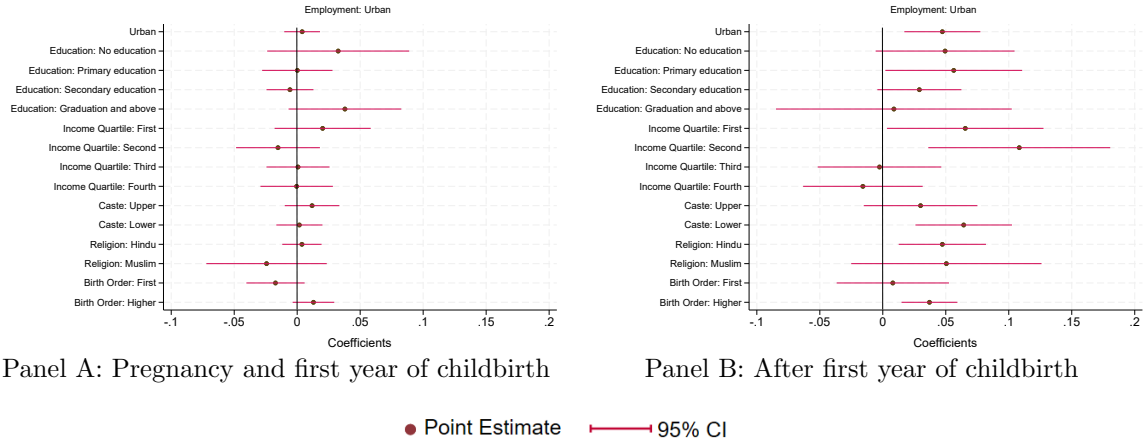


Figure 11. Heterogeneous effects of childbirth on Employment: Urban regions

Notes: The figure shows the heterogeneous ATT of childbirth on mothers' likelihood of employment compared to non-mothers' using Callaway and Sant'Anna (2021) estimator in urban regions. Panel A demonstrates the heterogeneous effect during pregnancy and first year of childbirth while Panel B demonstrates for after first year of childbirth. The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The top row shows the effect on all urban women and the subsequent rows shows the effects by various socio-economic characteristics of women such as education (No Education, Primary Education [1st to 8th std.], Secondary Education [9th to 12th std.], and Graduation and above), household income quartiles (First, Second, Third, and Fourth), caste (Upper caste [General and Intermediate caste], Lower caste [SC's, ST's, and OBC's]), religion (Hindu and Muslim), and birth order (First and Higher). Except caste and religion, the other characteristics are time-varying and hence we have taken their base values (when the individuals are observed for the first time in the data). We define a first birth as a case where no other household member is identified as an older sibling of the child. A birth is classified as a higher-order birth if the child has at least one older sibling in the household, indicating that they are not the firstborn. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

Figure 12 demonstrates the heterogeneous effects in rural regions. Figure 12: Panel A shows the results for the period including pregnancy and first year of childbirth; we do not observe any significant effects overall and across the different socio-economic groups. Figure 12: Panel B presents the coefficients for the period after first year of childbirth. Surprisingly, we see a positive effect on the likelihood of employment for mothers belonging to the lowest income quartile. The other socio-economic characteristics, such as household income, mothers' education, caste, religion, and birth order do not show any significant effects.

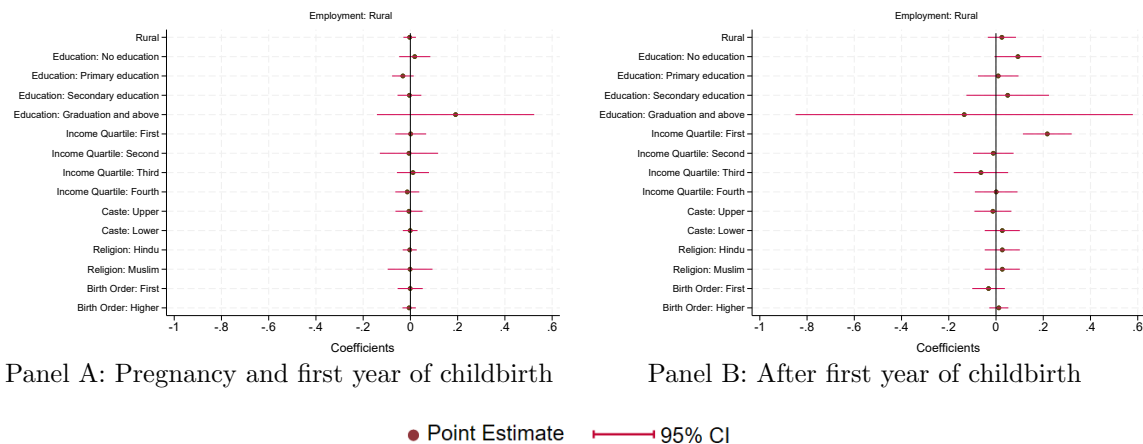


Figure 12. Heterogeneous effects of childbirth on Employment: Rural regions

Notes: The figure shows the heterogeneous ATE of childbirth on mothers' likelihood of employment compared to non-mothers' using Callaway and Sant'Anna (2021) estimator in rural regions. Panel A demonstrates the heterogeneous effect during pregnancy and first year of childbirth while Panel B demonstrates for after first year of childbirth. The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The top row shows the effect on all urban women and the subsequent rows show the effects by various socio-economic characteristics of women such as education (No Education, Primary Education [1st to 8th std.], Secondary Education [9th to 12th std.], and Graduation and above), household income quartiles (First, Second, Third, and Fourth), caste (Upper caste [General and Intermediate caste], Lower caste [SC's, ST's, and OBC's]), religion (Hindu and Muslim), and birth order (First and Higher). Except caste and religion, the other characteristics are time-varying and hence we have taken their base values (when the individuals are observed for the first time in the data). We define a first birth as a case where no other household member is identified as an older sibling of the child. A birth is classified as a higher-order birth if the child has at least one older sibling in the household, indicating that they are not the firstborn. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

5 Mechanisms

One potential enabling mechanism through which mothers may increase their labour supply is the availability of alternative caregivers within the household who can substitute for or assist in childcare responsibilities. These caregivers may include in-laws, adult female household members, or the child's older siblings. In the absence of affordable childcare services, families in India often rely on informal care arrangements, such as the support of relatives and household members. Their support can alleviate the mothers' burden of childcare and domestic duties, thereby enabling greater engagement in the labour market. As highlighted by Das and Žumbyté (2017), a large proportion of women in India are engaged in informal and unregulated forms of employment, where access to institutional childcare services is either minimal or entirely absent, even in cases where such services do exist. In this context, the support of co-residing household members becomes not only helpful, but often

essential, in enabling mothers to participate in the labour market. Existing literature has consistently underscored the importance of household-level factors in influencing women's labour market decisions. The presence of in-laws can have different effects on mothers' ability to engage in paid work. On the one hand, in-laws may provide direct assistance with childcare and domestic responsibilities, thereby reducing the time burden on mothers and supporting their LFP. On the other hand, their presence can also reinforce traditional gender roles and expectations that prioritize women's roles as caregivers over economic engagement, thereby discouraging or even preventing them from seeking employment (Sorsa et al., 2015; Chatterjee et al., 2015; Sarkar et al., 2019; Khanna and Pandey, 2024). Presence of any adult female and older siblings in the household may also affect the employment decision of women (Sorsa et al., 2015; Das and Žumbyté, 2017; Heath, 2017; Hallman et al., 2005; Connelly et al., 1996; Wong and Levine, 1992). Sorsa et al. (2015) did not find any significant effect of the presence of children between 6-14 years age on women's LFP in urban and rural regions, while Das and Žumbyté (2017) reports positive significant effects of the presence of 6-15-year-old girls and 6-9-year-old boys on mothers' employment in urban regions.

While examining the impact of children on women's labour market outcomes in urban Ghana, Heath (2017) finds that some mothers prioritize financial contributions over time investments in childcare. As a result, they tend to increase their work hours as the number of children rises. This response is largely facilitated by the presence of older children or other adult household members, who take on caregiving responsibilities and thereby allow mothers to substitute their time with income generating work. Connelly et al. (1996) highlights the crucial role played by the household composition in influencing mothers' labour supply decision in Brazil and finds that the number of daughters aged 10-14 positively affects mothers' employment by substituting her time for childcare and household chores, while the effect for boys are not significant, providing evidence that girls are more likely to alleviate mothers' domestic burden. Hallman et al. (2005) also emphasized that in developing countries, the presence of young girls of even 6 years old in the household increase the probability of mothers' employment when there is younger children present who needs care.

Table 4. Effect of childbirth on mothers' employment by household composition and region¹⁶

Panel A: Urban regions			
	(1)	(2)	(3)
	Presence of Adults	Presence of Older Siblings	None are present
Employment	-0.039 (0.037)	0.037*** (0.013)	0.008 (0.013)
Controls	Yes	Yes	Yes
Wave Fixed Effect	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes
Observations	13,939	20,335	16,387
Panel B: Rural regions			
	(1)	(2)	(3)
	Presence of Adults	Presence of Older Siblings	None are present
Employment	-0.534 (0.610)	0.037** (0.018)	-0.052 (0.038)
Controls	Yes	Yes	Yes
Wave Fixed Effect	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes
Observations	7,208	10,872	8,225

Notes: This table shows the weighted average of all group-time ATT of childbirth on mothers' likelihood of employment by household composition using Callaway and Sant'Anna (2021) estimator in urban and rural regions. The controls variables include age, quadratic term of age, household income (excluding the individual's own earnings), along with individual and time fixed effects. Column 1 shows the effect on employment in the presence of adults, where adults include presence of in-laws or any adult female (18 years and above at the time of childbirth) in the household. Column 2 reports the coefficients in the presence of older siblings (we identify siblings when they hold the relation of either son or daughter of the HOH and is older than the newborn), while Column 3 presents the coefficients when none of them are present. Heteroskedasticity robust standard errors, clustered at the individual level, are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To examine whether the presence of alternative caregivers increase mothers' likelihood of employment, we conduct a series of sub-sample analyses (Table 4) for urban (Panel A) and rural (Panel B) regions. First, we assess whether the presence of in-laws¹⁷ or any adult female household member aged 18 years or older (at the time of childbirth) affects mothers' likelihood of employment. These individuals are grouped into a single category, referred to as the presence of adults, to capture the potential support provided by older household members. We find no significant effect of the presence of adults in the household in either urban (Panel A, column(1)) or rural (Panel B, column(1)) regions. Second, we examined the effect of childbirth on mothers' employment in the presence of older siblings in

¹⁶We have estimated columns (1)-(3) separately in urban (Panel A) as well as in rural (Panel B) regions.

¹⁷In-laws are identified based on their reported relationship to the HOH.

the household.¹⁸ We find a positive and statistically significant effect of 3.7 percentage points on the mothers' likelihood of employment in both urban (Panel A, column(2)) and rural (Panel B, column(2)) regions when older siblings are present in the household. This suggests that older siblings may play a facilitative role by alleviating some of the mothers' responsibilities related to childcare and household chores, thereby freeing up time and allowing her to engage more actively in the labour market. Their presence can act as an informal support mechanism, particularly in contexts where formal childcare services are either unavailable or unaffordable. To further examine the importance of household support structures, we also estimate the effect of childbirth on mothers' employment in households where none of these potential caregivers are present; we do not observe any significant effects either in urban (Panel A, column(3)) or rural (Panel B, column(3)) regions. This contrast highlights the enabling role of intra-household caregiving arrangements, particularly the contribution of older siblings, in supporting mothers' post-childbirth economic engagement. While our findings point to the positive relationship between the presence of older siblings and mothers' likelihood of employment, it is important to note that we do not directly observe whether this support is provided through active childcare, supervisory roles, or assistance with household chores.

To better understand the potential nature of this support, we further disaggregated our analysis based on the age of the older siblings present in the household, since children of different age groups may contribute in different ways; for example, very young children may be less capable of providing care, while older siblings may be more likely to assist with care or chores.¹⁹ We divide the sibling's age into three age-groups: 1-3 years, 4-8 years, and 9-18 years. Moreover, since the effect of the presence of older siblings in the household is almost identical in both rural and urban regions (see Table 4, column (2), Panels A and B), we combine both regions in this analysis to take advantage of a larger sample size and improve the precision of our estimates. We find no significant effect on mothers' employment when the oldest sibling is in the 1-3 years age group (Table 5, column(1)). This finding reinforces the idea that children in this age group are likely too young to contribute meaningfully to household responsibilities or provide any form of support in caring for a newborn, and therefore do not alleviate the caregiving burden on mothers in a way that would increase their labour supply. We find a positive and statistically significant effect of 3.8 percentage points (Table 5, column (2)) and 4.3 percentage points (Table 5, column (3)) on the mothers' likelihood of employment when the oldest sibling belongs to the 4-8 years and 9-18 years age groups, respectively. These findings suggest that even relatively young siblings in the 4-8 years age group may provide some degree of informal support to the mother, such as playing with the newborn, keeping the infant engaged, or occupying themselves without requiring constant attention. While their contribution may be limited, it can nevertheless ease the mothers' caregiving burden to a small extent, thereby enable their labour market participation. The larger effect observed for the 9-18 years age group likely reflects their greater capacity to actively assist in the household chores. Older siblings in this age group are more capable of taking care of younger children, performing simple domestic tasks, and supporting the mother in daily routines.

¹⁸We identify a sibling based on their relationship as either son or daughter of the HOH.

¹⁹We consider the age of the oldest sibling in the household (when more than one is present) at the time of childbirth to avoid the possibility that their age may have direct consequences for mothers' employment.

This kind of assistance can significantly ease the mothers’ workburden and free up her time, making it more feasible for her to take up employment. Overall, the increasing impact with age suggests that as siblings grow older, their ability to meaningfully support the mother strengthens, contributing to her greater likelihood of participating in the labour market.

Table 5. Effect of childbirth on mothers’ employment by age group of the older siblings in the household (Urban + Rural)

	(1) 1–3 years	(2) 4–8 years	(3) 9–18 years
Employment	0.042 (0.037)	0.038*** (0.014)	0.043*** (0.014)
Controls	Yes	Yes	Yes
Wave Fixed Effect	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes
Observations	21,268	25,925	24,667

Notes: This table shows the weighted average of all group-time ATT of childbirth on mothers’ likelihood of employment by age group of the older siblings in the household using [Callaway and Sant’Anna \(2021\)](#) estimator for the combined sample (Urban+Rural). The control variables include age, quadratic term of age, household income (excluding the individual’s own earnings), region, along with individual and time fixed effects. We consider the age of the oldest sibling in the household (when there is more than one) at the time of childbirth. Column 1 shows the effect on employment when the older sibling belongs to 1–3 years age group. Column 2 reports the coefficients when the older sibling belongs to 4–8 years age group while Column 3 presents the coefficients when the older sibling belongs to 9–18 years age group. Heteroskedasticity robust standard errors, clustered at the individual level, are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6 Robustness

6.1 First Birth

Our main results include new childbirths - both first and higher-order - during the study period. Unlike prior literature ([Kleven et al., 2019](#); [Cortés and Pan, 2023](#); [Zhang et al., 2024](#); [Berniell et al., 2023a](#); [Abraham et al., 2021](#); [Gautham, 2022](#)) that has focused exclusively on first births, we were not able to perform the entire analysis restricted to the first birth due to the limited sample size and therefore we consider all births in our main specification. To ensure comparability of our findings with those in the existing literature, we conducted a sub-sample analysis and estimated equation (1) for mothers with first childbirth. These results are presented in Appendix II, [Figures A2](#) and [A3](#). [Figure A2](#) shows the results on earnings, LFP, employment, and work hours in urban regions and [Figure A3](#) report the corresponding coefficients in rural regions. An important point to note is that, although the pre-treatment coefficients are individually insignificant, they are jointly significant in this analysis. This raises concerns about the validity of the parallel trends assumption and complicates

the interpretation of the post-childbirth coefficients. Despite these concerns, the results may still offer suggestive evidence of no significant effect of first childbirth on mothers' labour market outcomes in both urban as well as rural regions. Even though we find a modest positive effect on mothers' earnings in urban regions, these coefficients are jointly insignificant at the 5% level of significance.

These results contrast with those observed in developed countries but are consistent with findings from several studies in developing countries, such as [Aaronson et al. \(2021\)](#), where the study finds small to negligible effects of childbirth on mothers' labour market outcomes. Our findings also align with those of [Abraham et al. \(2021\)](#), where they observed no significant impact up to four years after first childbirth, and only a modest increase in the likelihood of mothers' LFP in subsequent years. One possible explanation of these results is the constrained nature of labour market participation for women in India, where employment is often driven by economic necessity than by life events such as childbirth. Another possibility is that many mothers may be engaged in occupations that are more compatible with childcare responsibilities, enabling them to balance both roles, as suggested by [Kleven et al. \(2024\)](#) and [Aaronson et al. \(2021\)](#). It is also possible that women may transition into more informal or flexible types of work which keeps the overall employment and earnings unaffected. However, due to data limitations, particularly the lack of detailed occupational information for the whole study period, we are unable to uncover this mechanism.

6.2 Consistent Mother-Child Follow-up

We ensure that we have information on both the mother and the child after childbirth at the same point of time in order to mitigate concerns that the results may be confounded by child's intermittent movements or temporary absences such as emigration. The results are largely consistent with our main findings (Appendix II, [Figures A4](#) and [A5](#)).

6.3 Separate Analysis for Pre- and Post-Pandemic Periods

To ensure the robustness of the results to the pandemic period, we conduct separate analyses for the pre- (2016-2019) and post-COVID (2021-2023) periods along with restricting the age of the child up to one year in both periods. We restrict the age to avoid the potential confounding effects of child's age on mothers' labour market outcomes. The overall results align with our main findings where we do not observe significant effects on mothers' labour market outcomes compared to non-mothers' during the first year of childbirth (Appendix II, [Figures A6](#), [A7](#), [A8](#), and [A9](#)). It suggests that even before the pandemic period, childbirth had no discernible effect on mothers' labour market outcomes during the first year.²⁰ We are unable to estimate the effects on work hours in the pre-COVID (2016-2019) period since information on work hours is not available prior to 2019.

²⁰We do not consider child older than one year due to limited follow-up available in both periods.

6.4 Comparable Age Group

We replicate the analysis by restricting the sample to mothers and non-mothers who are aged 15–30 at the time they are first observed in the data, to ensure greater comparability between the treatment and control groups. While the individual coefficients for employment in urban and earnings in rural regions are not statistically significant, they are jointly significant. Overall, the results remain consistent with our main findings, albeit with slightly lower magnitudes (Appendix II, [Figures A10](#) and [A11](#)).

6.5 Weighted Regression

We do not use survey weights in our main specification since the [Callaway and Sant’Anna \(2021\)](#) estimator does not offer the flexibility to incorporate survey weights. However, as a robustness check, we estimate the TWFE model, incorporating survey weights provided by the CPHS, after adjusting for non-responses. These results are available in Appendix II, [Figures A12](#) and [A13](#). The overall results are similar with few exceptions, notably the larger effect of childbirth on earnings and a positive effect on employment which is now evident 12 waves (4 years) after childbirth in urban regions. In rural regions, the modest positive effects on LFP and employment which was evident 9 waves after childbirth, is no longer statistically significant.

7 Discussion and Conclusion

In contrast to the well established negative impact of childbirth on mothers’ labour market outcomes in developed countries, popularly known as the ‘motherhood penalty’, our results demonstrate that childbirth has a positive effect on mothers’ average earnings in urban and rural regions, after accounting for unobserved individual heterogeneity. These findings suggest the presence of a motherhood premium, rather than a penalty, in the Indian context, underscoring the importance of country-specific socio-economic conditions in shaping the relationship between childbirth and mothers’ labour market outcomes. This premium is likely driven by an increase in mothers’ likelihood of employment which could be attributed to the heightened responsibilities and financial burden of motherhood, which may compel mothers to enter the labour market. [Mukherjee and Sarkhel \(2025\)](#) also emphasized the need of mothers to take up full-time employment after having a child so that they are able to generate additional income, which can then be used to manage the increased financial demands associated with raising a child. Another possibility is that exiting the labour market is costly and re-entry is difficult, due to factors such as loss of human capital and discrimination by employers ([Mukhopadhyay, 2012](#)), who may be reluctant to hire women with a young child due to anticipated work interruptions ([Budig and England, 2001](#)), and thus mothers may want to avoid this adjustment cost associated with change in labour market status.

The heterogeneity analysis based on several household and individual characteristics, such as educational attainment, household income (excluding the individual’s own earnings), caste, and religion

reflects differential implications of childbirth across these characteristics. We do not observe significant effects on mothers' employment during pregnancy and first year of childbirth in urban as well as in rural regions. However, we find a positive effect on the likelihood of employment for mothers having primary education, belonging to poorer income quartile, lower caste, and Hindu religion in urban regions after first year of childbirth. In rural regions, the positive effect is driven by mothers belonging to the poorest income quartile. It likely reflects a complex interplay of economic necessity and constrained labour market choices. For these disadvantaged groups, the arrival of a child may reinforce the urgency of meeting basic consumption and childcare-related expenses, prompting women to enter the labour market. Prior studies suggest that women with lower levels of education often participate in the labour market primarily due to economic compulsion rather than choice (Klasen and Pieters, 2012; Chaudhary and Verick, 2014). In particular, Chatterjee et al. (2018) highlight that such women are more likely to be employed in the informal sector, engaging in manual labour, domestic work, or small household enterprises. The decision to (re)enter the labour market after childbirth is often driven by necessity - a point further reinforced by the positive effects observed among mothers from poorer households. This lends strong support to the interpretation that the observed motherhood premium is driven more by economic necessity than voluntary choice. It reflects the well-documented negative income effect (Goldin, 1994; Bertrand et al., 2010; Klasen and Pieters, 2015), wherein women from economically disadvantaged backgrounds step in as secondary earners or serve as a form of household insurance during periods of financial strain. This phenomenon is also popularly known as the "added-worker effect", as highlighted by Berniell et al. (2023b), which emphasizes the role of women as secondary workers in response to any unemployment shock or reduction in family income. The fact that women's labour market decisions are not only shaped by economic factors but also influenced by social, cultural, and religious norms is further backed by our findings of a positive effect for mothers belonging to the lower caste category and Hindu religion. This finding aligns with existing literature suggesting that social norms and stigma are less restrictive for women from lower castes than for their upper-caste counterparts (Sarkar et al., 2019; Mehrotra and Parida, 2017). Consequently, lower-caste women are more likely to participate in the labour market, whereas upper-caste women's labour market decisions are often constrained by prevailing societal expectations (Deshpande et al., 2018; Mehrotra and Parida, 2017; Sarkar et al., 2019; Das and Žumbyté, 2017). Moreover, women belonging to lower caste are generally disadvantaged and may be less concerned with occupational status or segregation, focusing instead on securing any available source of income. Similarly, religion also plays a crucial role where the positive effect is restricted to mothers belonging to Hindu religion, affirming the findings of Sarkar et al. (2019) and Das (2006) that norms related to working women are less stringent for Hindu women.

Interestingly, unlike urban regions, where we observe considerable variation in the post-childbirth employment effect across different socio-economic groups, such heterogeneity is largely absent in rural regions. The positive effect in rural areas is evident only among mothers from the poorest income quartile, suggesting that economic necessity remains the primary driving force behind mothers' employment. A plausible explanation is that women from disadvantaged backgrounds in rural regions are

already engaged in subsistence activities such as working on family farms or casual agricultural labour. As a result, factors like caste, religion, education or birth order may not play as significant a role as they do in urban regions. The observed positive effects for higher order births in urban regions is consistent with prior studies suggesting that the effect of childbirth on mothers' employment can vary significantly between first and subsequent births. One possible mechanism through which childbirth leads to an increase in mothers' likelihood of employment is the presence of older siblings, particularly those aged between 9 and 18 years, who may contribute to childcare responsibilities or assist with household chores. This intra-household support can alleviate some of the caregiving burden which is typically borne by mothers, thereby freeing up their time and enabling them to engage in paid work.

Thus, the observed motherhood premium is, in reality, a motherhood penalty. It does not necessarily signal improved economic opportunities for women but may instead reflect economic compulsion. For these women, childbirth heightens the need to supplement household income, compelling them to overcome barriers that might otherwise limit their labour market participation. This pattern likely reflects economic vulnerability, where LFP serves as a coping mechanism in response to financial distress rather than as evidence of enhanced labour market outcomes. While the data does not allow us to observe the precise nature or quality of the jobs taken up, it is plausible that such employment is concentrated in low-paying or less secure segments of the labour market, given the limited education and social disadvantage of these women.

One of the potential concerns associated with the CPHS is under-representation of poorer households, women, and rural populations (Somanchi, 2021; Abraham and Shrivastava, 2022). This concern largely stems from its sampling design, which tends to begin from the main street in villages and census enumeration blocks, thereby potentially excluding households located in the interior regions. Furthermore, some discrepancies exist in women's labour force participation and employment rates when comparing CPHS with other nationally representative datasets, such as the Periodic Labour Force Survey (PLFS). For instance, the estimates from CPHS tend to be lower from those reported by PLFS. Nonetheless, as noted by Afridi et al. (2022), the overall trends in women's employment across urban and rural regions remain broadly consistent- lower in urban and higher in rural regions. Despite these limitations, the unique structure of the CPHS, with data collected since 2014 every four months, makes it well-suited for studying short- and longer-term effects of childbirth. Moreover, the issue of sample representativeness is less of a concern in our context, as we are more interested in comparing the cohorts over time. Given its high frequency and longitudinal nature, CPHS has become increasingly popular in recent research on labour market dynamics (Deshpande and Singh, 2021; Kumari et al., 2025; Abraham et al., 2022; Abraham and Kesar, 2025). The other concern relates to the potential endogeneity of childbirth, which we are unable to explicitly account for. However, the sharp changes in mothers' labour market outcomes, observed only after childbirth, suggest that these outcomes are responding to the event of childbirth rather than to broader changes in labour market conditions (or their unobserved determinants), thereby mitigating the extent of potential bias. Additionally, the estimated effects on work hours may capture some selection effect into employment,

which we are unable to formally address due to the limited sample size.

On the policy front, our findings highlight the need for a more holistic and comprehensive approach to maternity and parental leave policies. This includes enhanced maternity leave provisions, affordable and subsidized childcare services, and targeted skill development programs that can reduce the burden on disadvantaged women and foster a labour market that enables genuine choice and well-being for all women. Many women from disadvantaged backgrounds are compelled to enter the labour market under precarious conditions due to limited childcare options, inadequate workplace support, and economic pressures. Although India's 2017 amendment to the Maternity Benefit Act extended paid maternity leave from 12 to 26 weeks, the policy largely benefits women in the formal sector, excluding a substantial share of the female workforce. Moreover, prior studies ([Banerjee et al., 2022](#); [Bose and Chatterjee, 2024](#)) suggest that even among those covered, the Act has may have had unintended adverse effects on women's labour market outcomes. These findings underscore the urgent need to move beyond the current framework and design policy interventions that promote equitable and inclusive employment opportunities for all women.

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A Appendix I

A1. Identification of mothers and non-mothers

CPHS does not provide information regarding birth history of any individual. Thus, we rely on the approach by [Deshpande and Singh \(2021\)](#) to identify new child birth and corresponding mothers. New childbirth is defined as the presence of a child who is 12 months old or younger and has the relationship of either son or daughter to the HOH. However, the reported age in the survey does not show an increase of four months after each wave. Therefore, we use the age when an individual has been observed for the first time in the data and add the exact interval of months found between the two corresponding surveys. This is because there are instances when the survey interval is either shorter or longer than four months. After identifying new childbirth, we identify the corresponding mothers only in cases when they are either HOH or spouse of the HOH with reported gender as female throughout the study period. We define non-mothers as those women who have never had children during the study period.

Moreover, CPHS provides information on employment and income in two separate files, namely, People of India and Income Pyramids. Employment data is available for each wave (four-month interval) but income is available monthly because individuals have been asked about their income of the preceding four months in each wave. To have both data at the same frequency, we use the information available for the month in which the interview took place and merge both files based on the month of the interview. This suggests that the combined file includes both an individual's employment details and their income for a particular month.

Table A1: Sample Construction

	Observation	%
Females	5,654,413	100%
Mothers and non-mothers	320,101	5.66%
Inconsistency in gender and merging with income data	177,415	3.13%
Non-responses (Missing employment data)	143,807	2.54%
Restricting the age of mothers' and non-mothers' to 15-35	95,205	1.68%
Restricting to 3 years before and 7 years after childbirth	88,530	1.56%
Final Sample Size	88,530	

Notes: This table presents the sample construction process, showing how we arrive at the final sample size.

a. Estimation Results using Tobit model

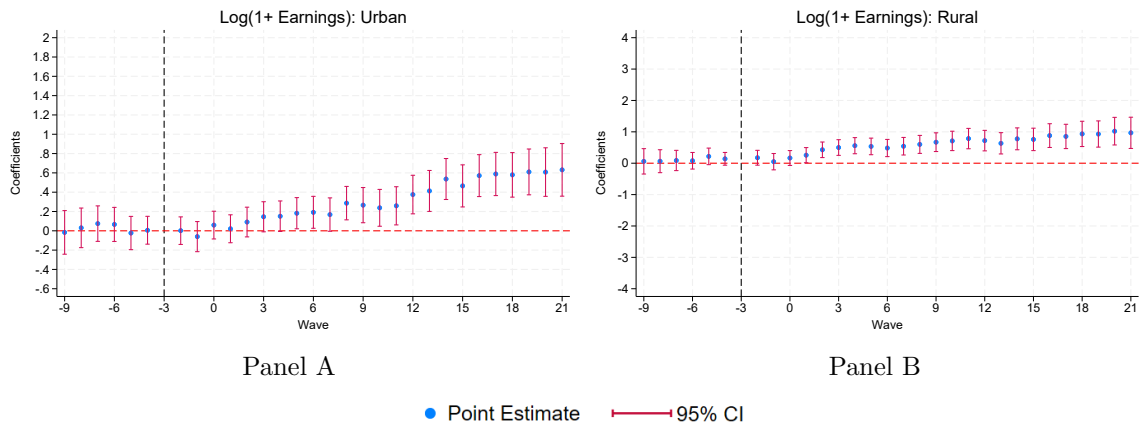


Figure A1. Effect of childbirth on Earnings

Notes: The figure shows the event-time coefficients estimated using equation (2) for mothers' unconditional earnings, separately for urban and rural regions. The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The line at -3 wave indicates the omitted base (reference) period. The coefficients are reported for 9 waves (3 years) before and 21 waves (7 years) after childbirth. Each coefficient shows the effect of childbirth on mothers' average earnings compared to non-mothers', relative to three waves (one year) before childbirth. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

B Appendix II

a. First Birth: Urban regions

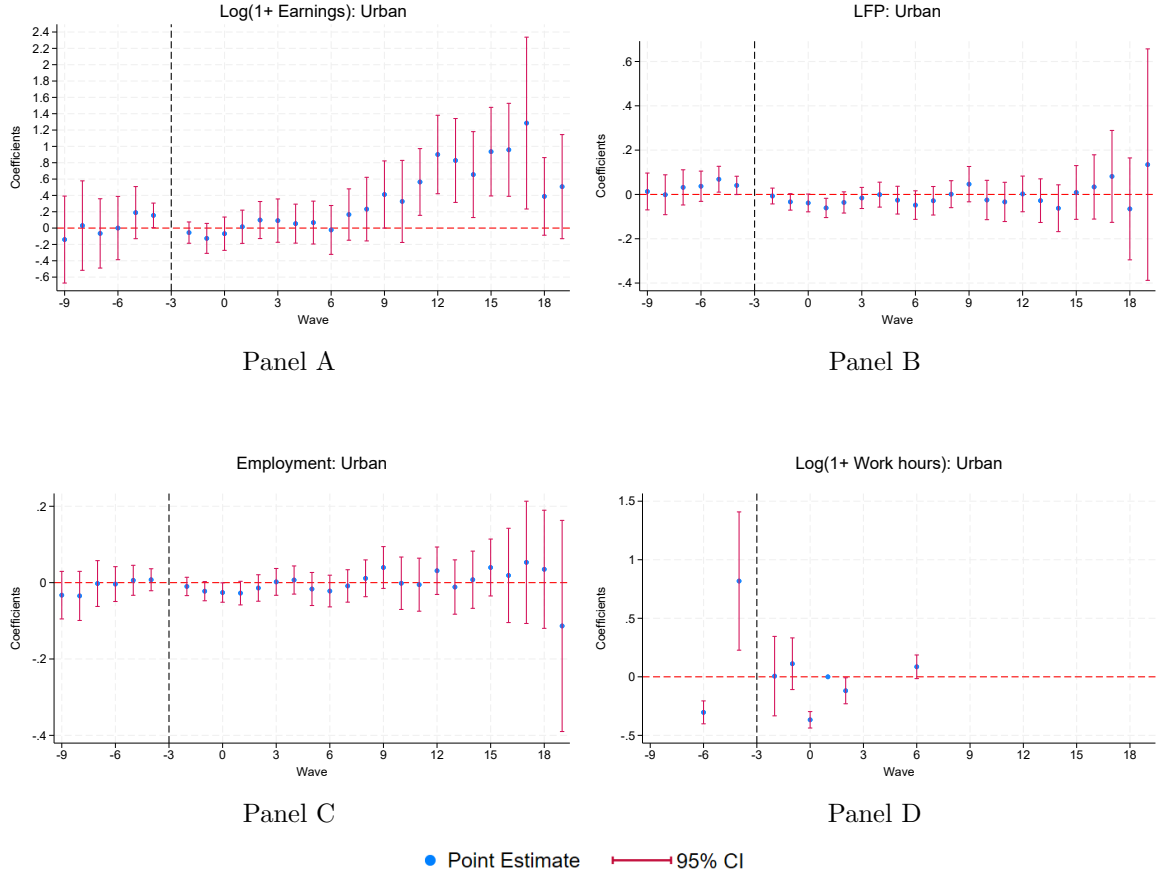


Figure A2. Effect of first childbirth on labour market outcomes: Urban regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for various labour market outcomes, restricting the sample to mothers with first birth in urban regions. We define a first birth as a case where no other household member is identified as an older sibling of the child. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), employment (Panel C), and work hours (Panel D). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=245$). The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

b. First Birth: Rural regions

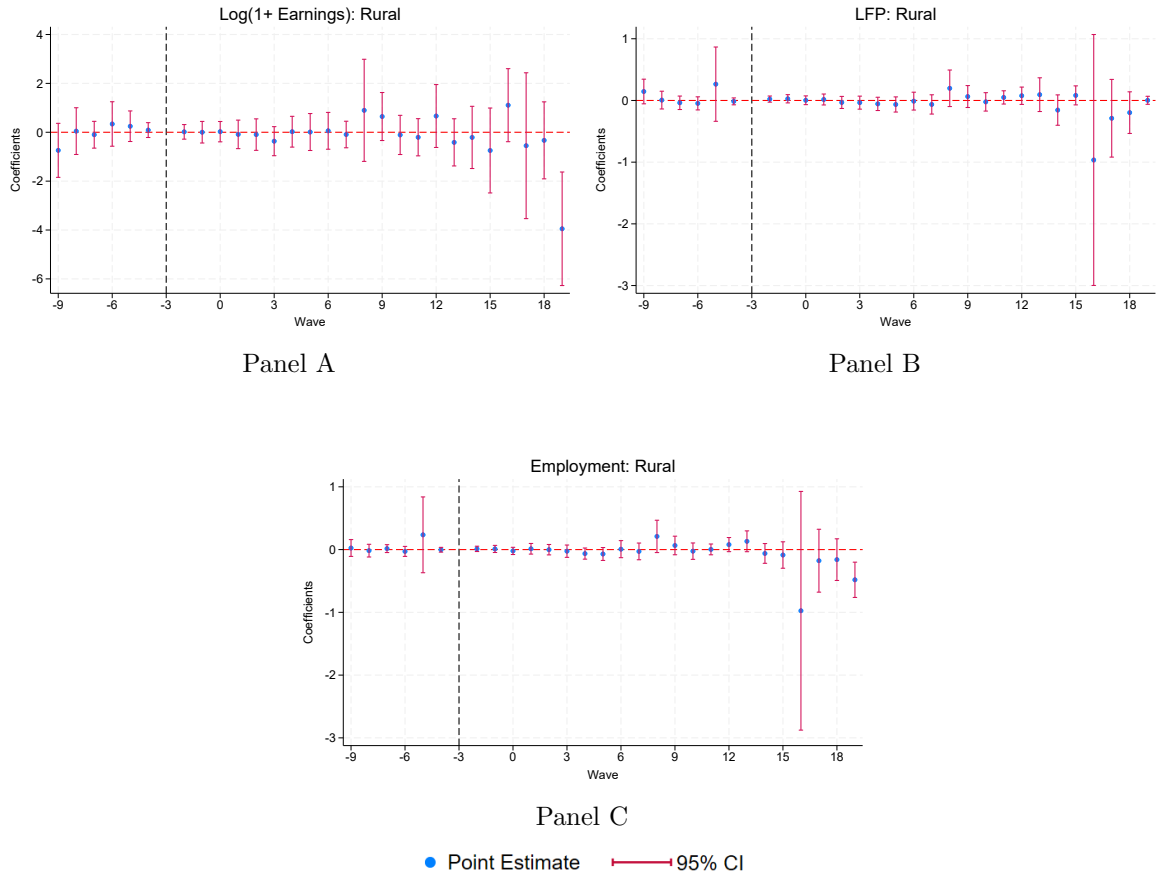


Figure A3. Effect of first childbirth on labour market outcomes: Rural regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for various labour market outcomes, restricting the sample to mothers with first birth in rural regions. We define a first birth as a case where no other household member is identified as an older sibling of the child. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), and employment (Panel C). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=0$) and thus we are unable to estimate the effect on work hours. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

c. Consistent Mother-Child Follow-up: Urban regions

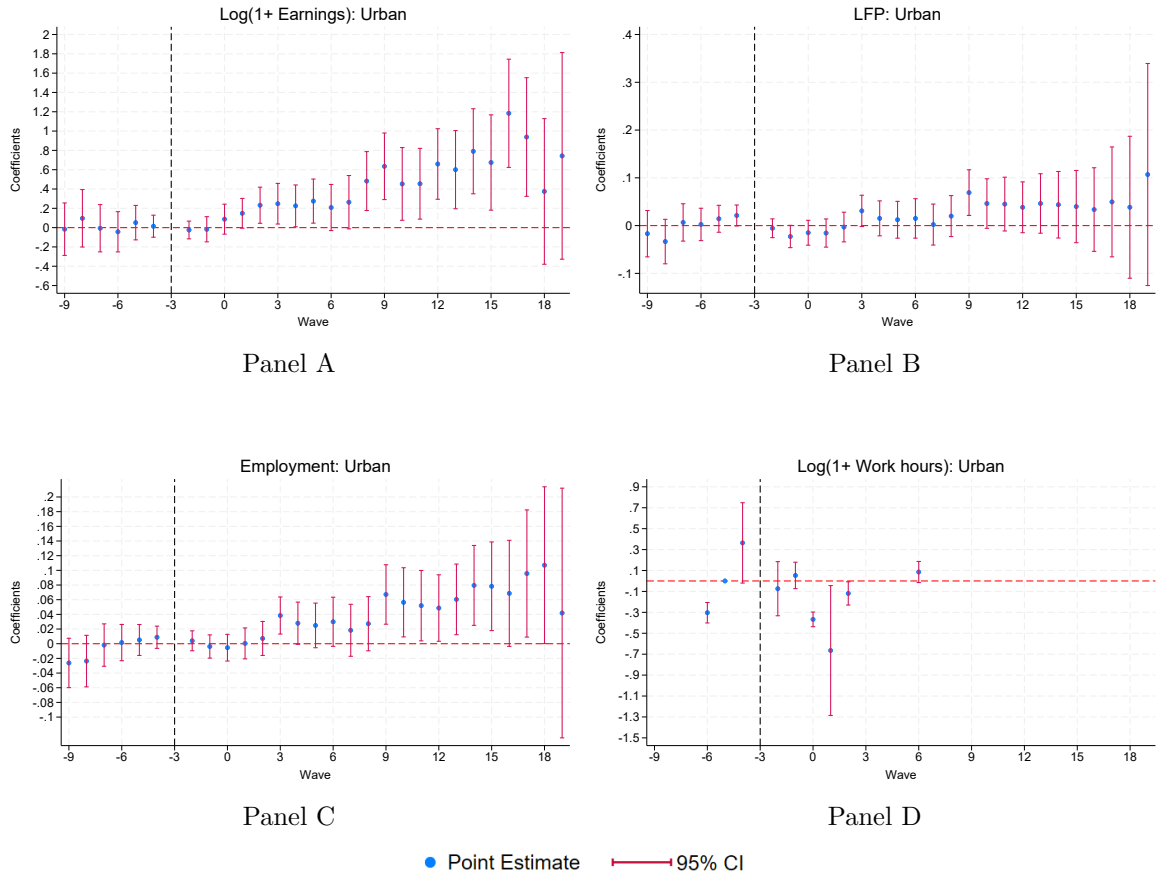


Figure A4. Effect of childbirth on labour market outcomes: Urban regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for various labour market outcomes in urban regions, restricting the sample where we have information on both the mother and the child at the same point of time. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), employment (Panel C), and work hours (Panel D). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=330$). The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

d. Consistent Mother-Child Follow-up: Rural regions

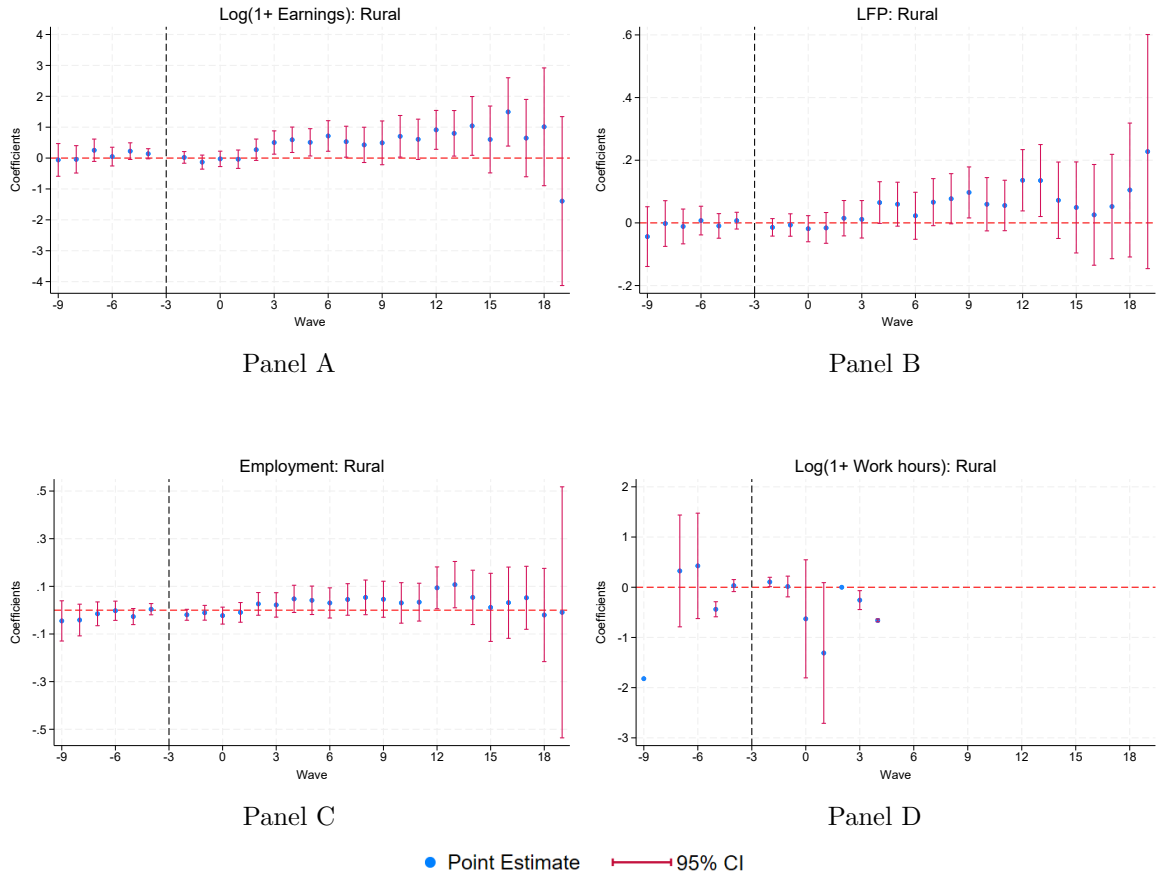


Figure A5. Effect of childbirth on labour market outcomes: Rural regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for various labour market outcomes in rural regions, restricting the sample where we have information on both the mother and the child at the same point of time. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), employment (Panel C), and work hours (Panel D). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=441$). The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

e. Pre-COVID Analysis (2016-2019): Urban regions

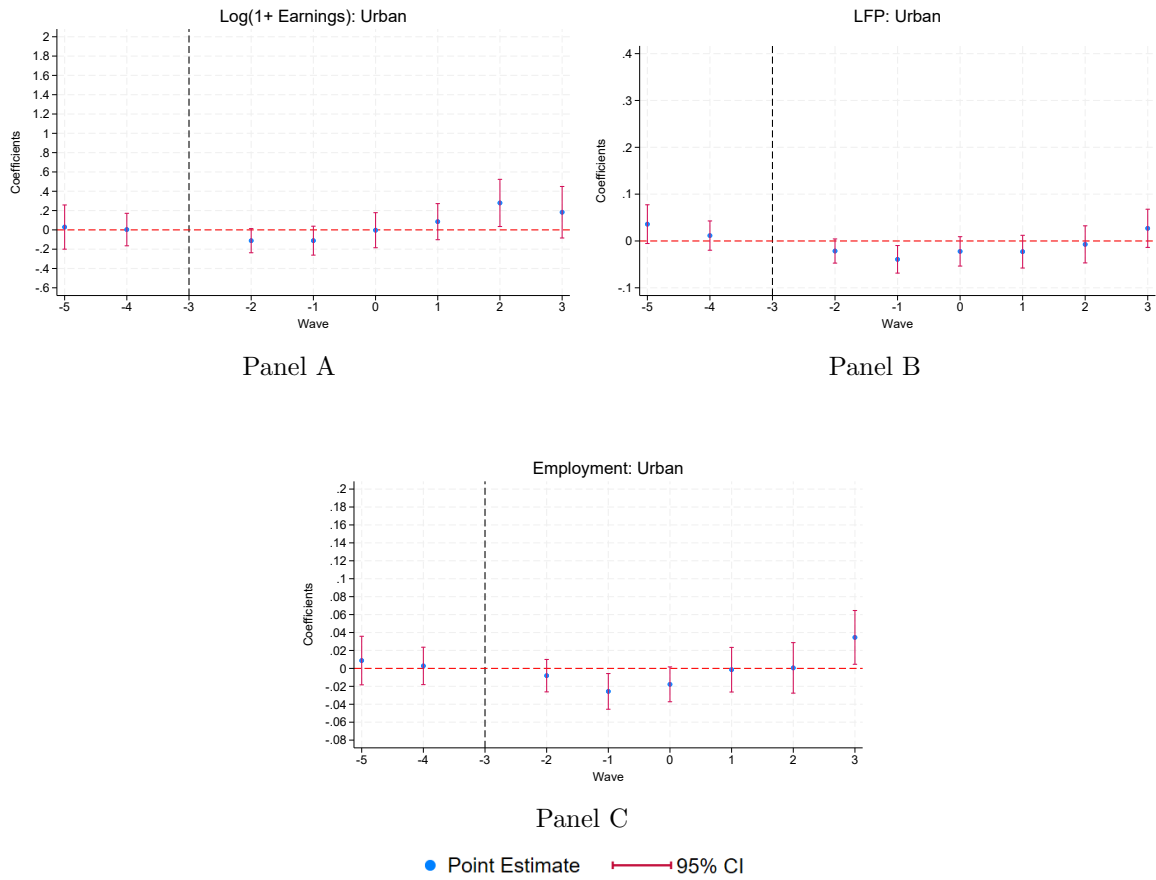


Figure A6. Effect of childbirth on labour market outcomes: Urban regions

Notes: The figure shows the event-time coefficients estimated using equation (1) after restricting the study period to 2016-2019 (pre-COVID) along with restricting the age of the child up to one year in urban regions. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), and employment (Panel C). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed. Thus, we are unable to estimate the effect on work hours. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

f. Pre-COVID Analysis (2016-2019): Rural regions

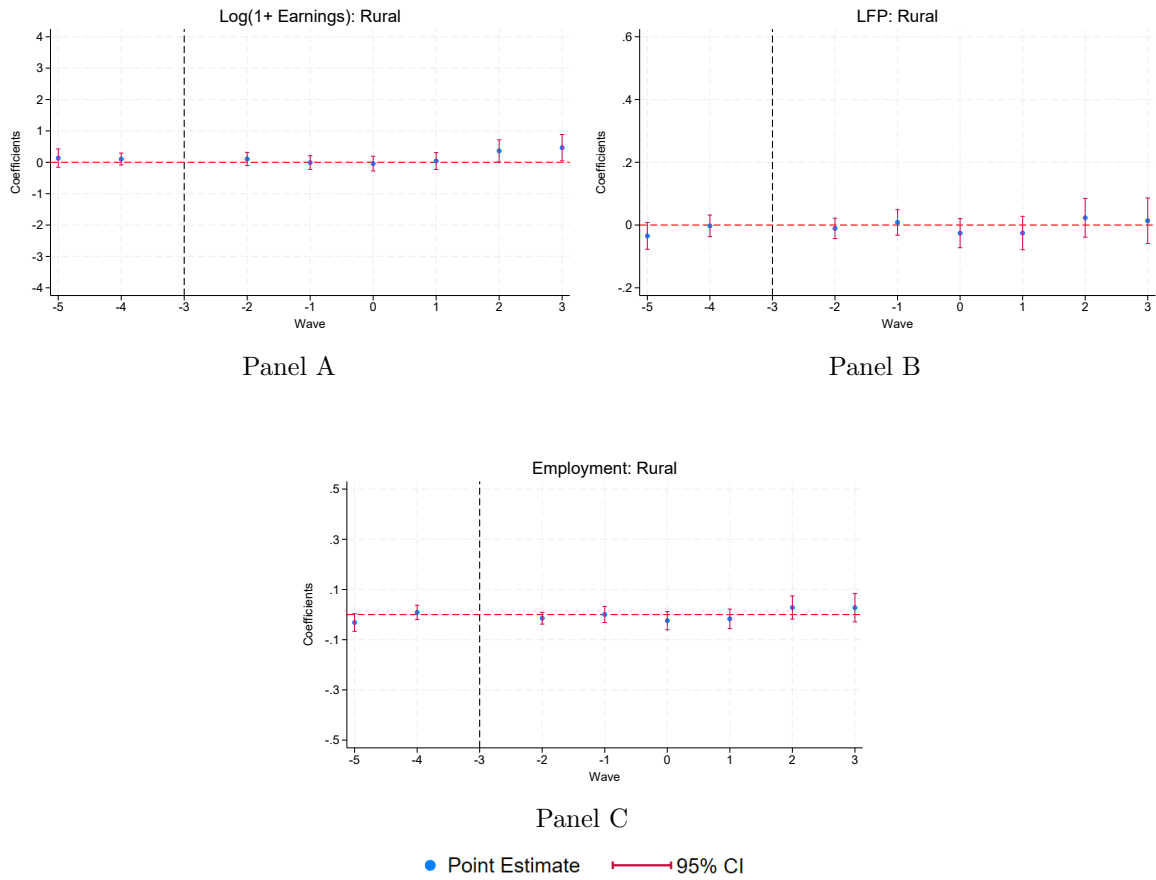


Figure A7. Effect of childbirth on labour market outcomes: Rural regions

Notes: The figure shows the event-time coefficients estimated using equation (1) after restricting the study period to 2016-2019 (pre-COVID) along with restricting the age of the child up to one year in rural regions. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), and employment (Panel C). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed. Thus, we are unable to estimate the effect on work hours. The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

g. Post-COVID Analysis (2021-2023): Urban regions

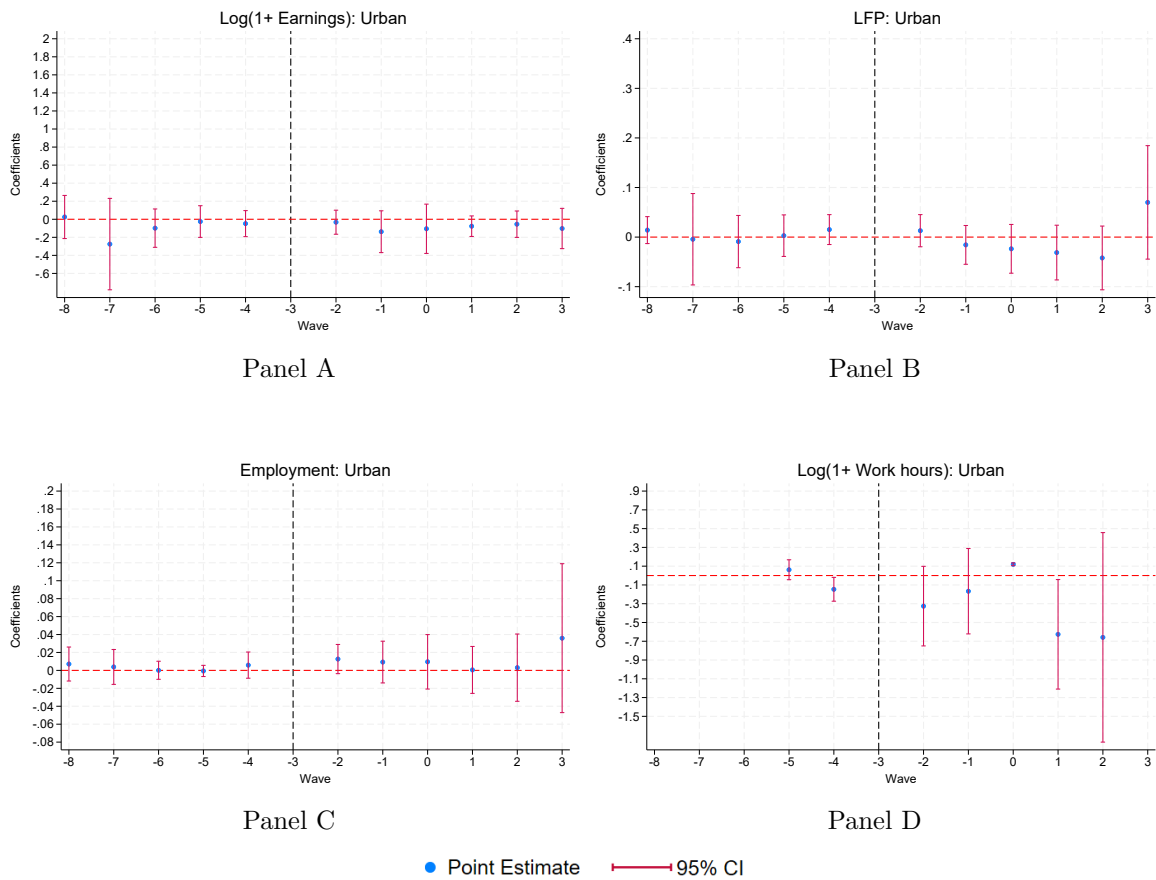


Figure A8. Effect of childbirth on labour market outcomes: Urban regions

Notes: The figure shows the event-time coefficients estimated using equation (1) after restricting the study period to 2021-2023 (post-COVID) along with restricting the age of the child up to one year in urban regions. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), employment (Panel C), and work hours (Panel D). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=158$). The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

h. Post-COVID Analysis (2021-2023): Rural regions

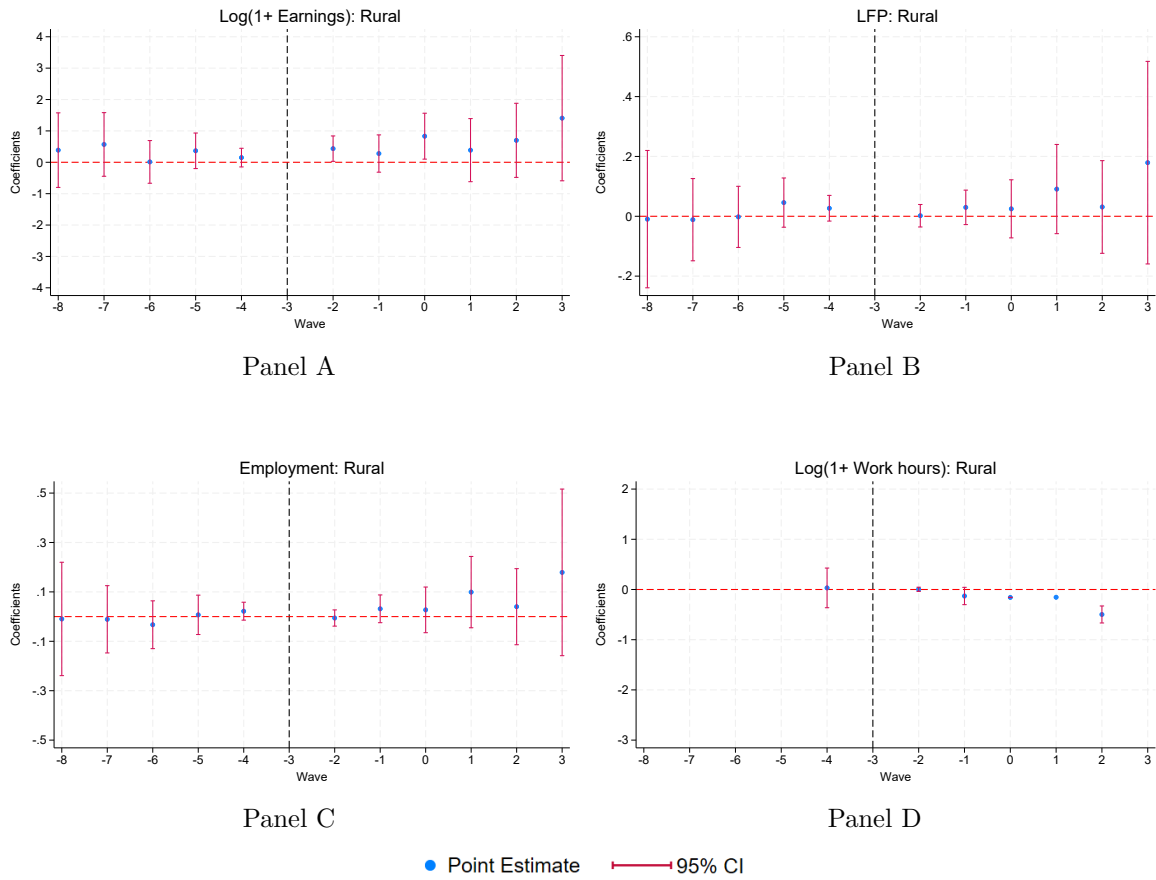


Figure A9. Effect of childbirth on labour market outcomes: Rural regions

Notes: The figure shows the event-time coefficients estimated using equation (1) after restricting the study period to 2021-2023 (post-COVID) along with restricting the age of the child up to one year in rural regions. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), employment (Panel C), and work hours (Panel D). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=127$). The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

i. Age-group (15-30): Urban regions

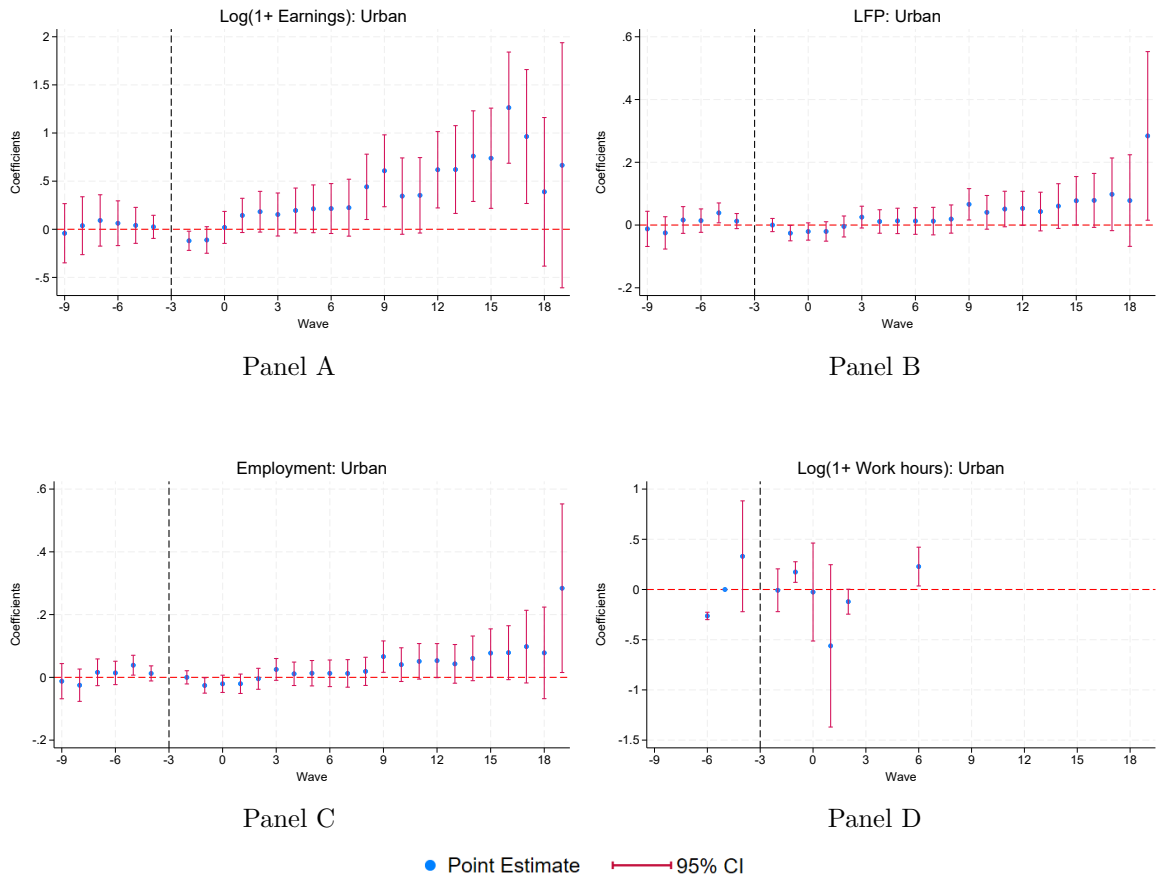


Figure A10. Effect of childbirth on labour market outcomes: Urban regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for various labour market outcomes, restricting the mothers' age to 15-30 when they are observed for the first time in the data in urban regions. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), employment (Panel C), and work hours (Panel D). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=283$). The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

j. Age-group (15-30): Rural regions

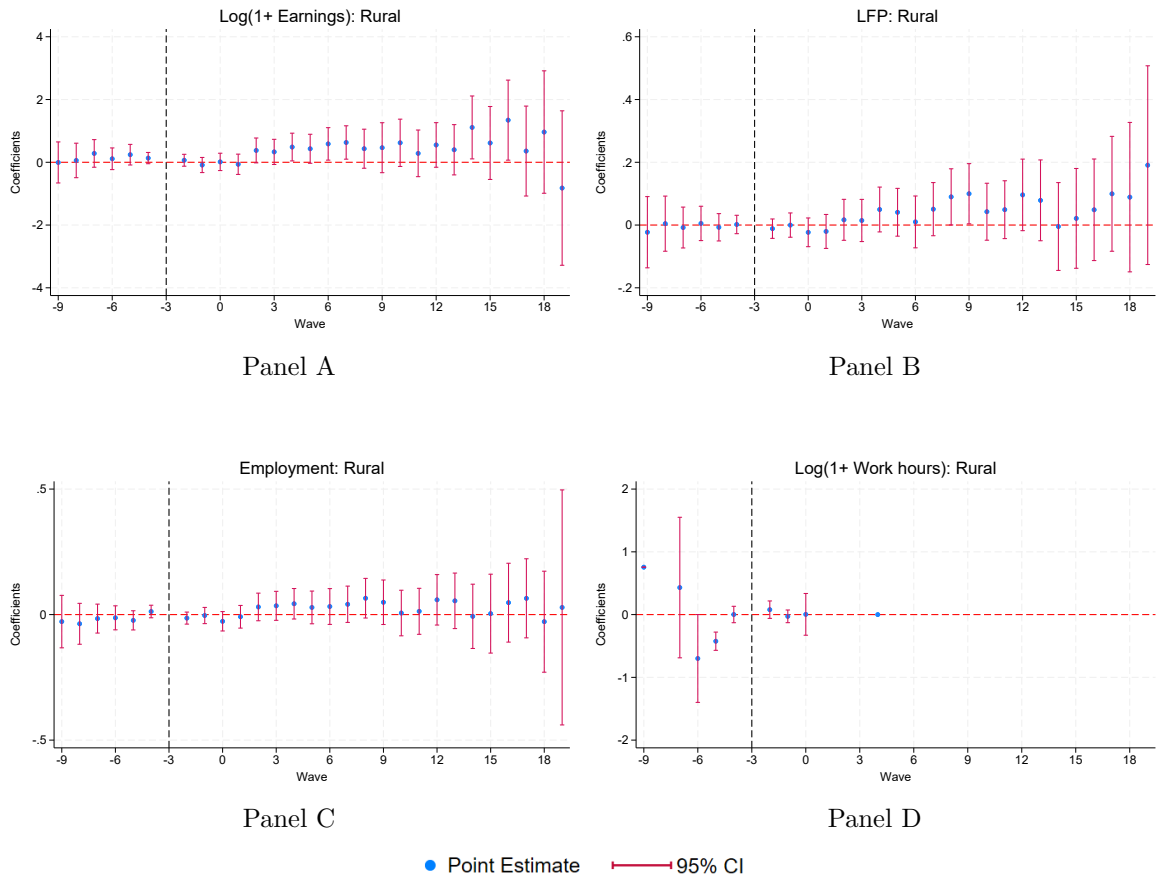


Figure A11. Effect of childbirth on labour market outcomes: Rural regions

Notes: The figure shows the event-time coefficients estimated using equation (1) for various labour market outcomes, restricting the mothers' age to 15-30 when they are observed for the first time in the data in rural regions. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), employment (Panel C), and work hours (Panel D). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at $l=-3$ wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=338$). The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

k. Weighted Regression: Urban regions

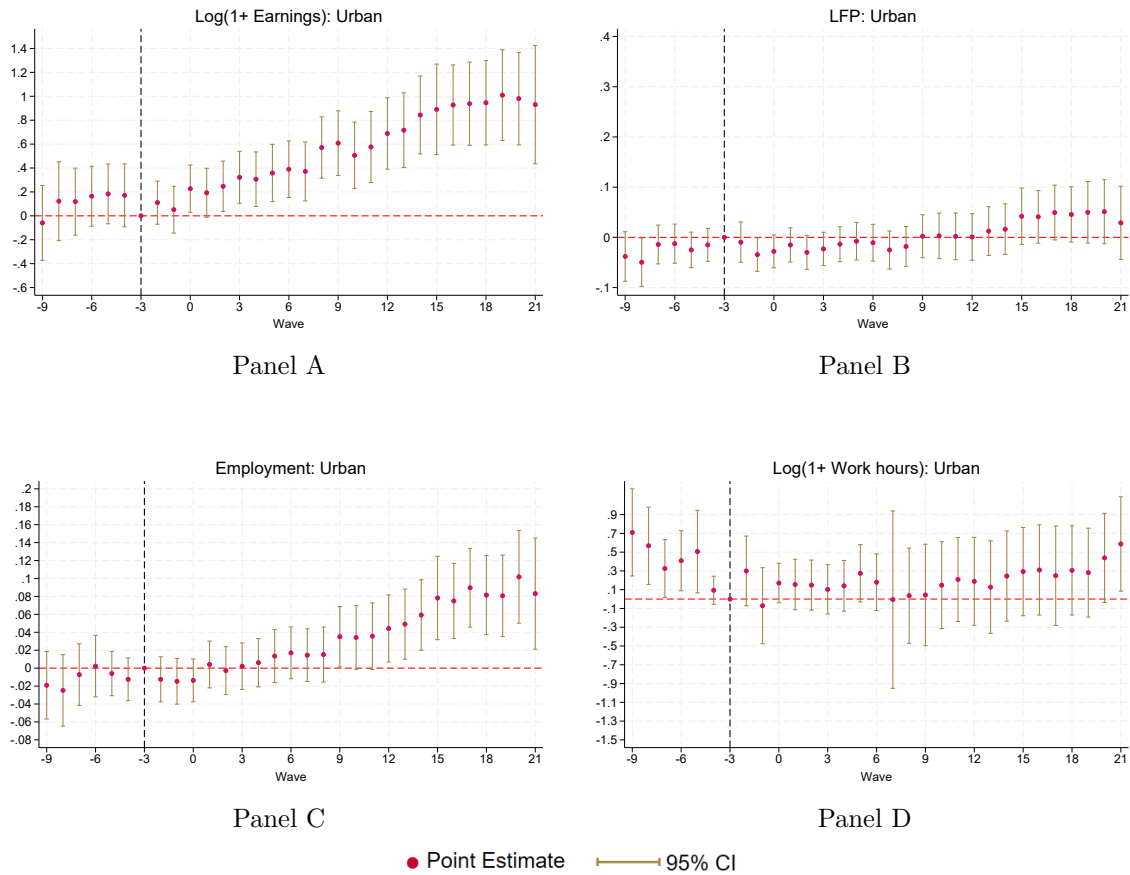


Figure A12. Effect of childbirth on labour market outcomes: Urban regions

Notes: The figure shows the event-time coefficients estimated using TWFE estimator for various labour market outcomes after incorporating survey weights in urban regions. We use survey weights provided by CPHS for individuals above 15 years of age, after adjusting for non-responses. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), employment (Panel C), and work hours (Panel D). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=1,308$). The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.

1. Weighted Regression: Rural regions

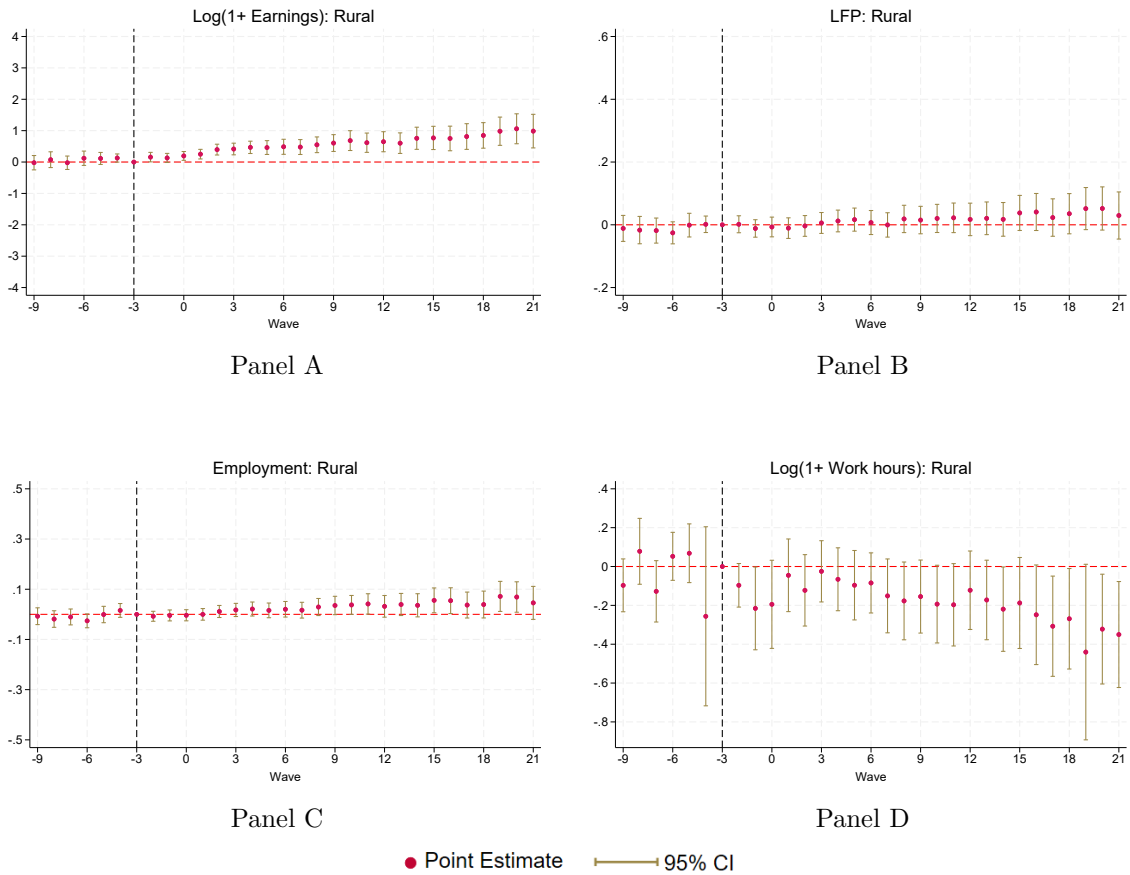


Figure A13. Effect of childbirth on labour market outcomes: Rural regions

Notes: The figure shows the event-time coefficients estimated using TWFE estimator for various labour market outcomes after incorporating survey weights in rural regions. We use survey weights provided by CPHS for individuals above 15 years of age, after adjusting for non-responses. The outcome variables are unconditional earnings (Panel A), LFP (Panel B), employment (Panel C), and work hours (Panel D). The control variables include age, quadratic term of age, and household income (excluding the individual's own earnings). The event time $l=0$ denotes the wave when the child is observed for the first time in the data. The dashed line at -3 wave indicates the omitted (reference) base period. Each coefficient shows the effect of childbirth on mothers' labour market outcome compared to non-mothers', relative to three waves (one year) before childbirth. Information on work hours is available only from 2019 (wave 18) and for those who are employed, resulting in a smaller sample size ($N=1,601$). The bars indicate 95% confidence intervals obtained from heteroskedasticity robust standard errors, clustered at the individual level.