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Andrea Albanese, Adrián Nieto, Konstantinos Tatsiramos

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Abstract

We study the effect of childbirth on local and non-local employment dynamics for both men and women using Belgian social security and geo-location data. Applying an event-study design that accounts for treatment effect heterogeneity, we show that 75 percent of the effect of the birth of a first child on the overall gender gap in employment is accounted for by gender disparities in non-local employment, with mothers being more likely to give up non-local employment compared to fathers. This gender specialisation is mostly driven by opposing job location responses of men and women to individual, household and regional factors. On the one hand, men do not give up non-local employment after childbirth when they are employed in a high-paid job, have a partner who is not participating in the labour market or experience adverse local labour market conditions, suggesting that fathers trade off better employment opportunities with longer commutes. On the other hand, women give up non-local jobs regardless of their earnings level, their partner's labour market status and local economic conditions, which is consistent with mothers specialising in childcare provision compared to fathers.

JEL-Codes: J130, J160, J610, C210, C230, J220, R230.

Keywords: gender gap, childbirth, job location, cross-border employment, specialisation.

Andrea Albanese
Luxembourg Institute of Socio-Economic Research (LISER)
Luxembourg / Luxembourg
andrea.albanese@liser.lu

Adrián Nieto
Luxembourg Institute of Socio-Economic Research (LISER), Luxembourg / Luxembourg
adrian.nietocastro@liser.lu

Konstantinos Tatsiramos
University of Luxembourg / Luxembourg
konstantinos.tatsiramos@uni.lu

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1 Introduction

Recent evidence has shown that the labour market trajectories of women and men diverge after the birth of their first child (Kleven et al., 2019a). While several mechanisms have been proposed to explain this gender gap, little is known about the role of job location. Access to better-paying job opportunities often requires working in distant jobs involving longer commutes (e.g. Manning, 2003). However, women have a lower preference for commuting compared to men (Meekes and Hassink, 2019; Petrongolo and Ronchi, 2020; Le Barbanchon et al., 2021). Therefore, the way parents adjust their job location decisions to the time constraints imposed by the birth of their first child might be an important determinant of the documented gender gap.

In this paper, we offer direct evidence on the importance of job location for the effect of childbirth on the gender gap in employment, as well as on the characteristics that drive gender specialisation in local or non-local jobs following childbirth. We use a novel administrative dataset from the Belgian Crossroad Bank of Social Security (CBSS) containing precise labour and fine-grained geo-location information on the universe of individuals living in Belgian regions bordering Luxembourg. Focusing on this specific border region is of relevance as it has one of the highest mobility and cross-border worker rates in the EU-27. On the one hand, non-local workers are subject to high mobility costs in terms of commuting. On the other hand, non-local jobs are often located in Luxembourg, which has the third highest GDP per capita in the world, and thus offer better working conditions than most local jobs. In this setting, the distance between home and the workplace creates a trade-off between mobility costs and higher earnings. To explore the dynamic effect of the birth of a first child on the employment decisions of mothers and fathers by job location, we use the difference-in-differences estimator proposed by Callaway and Sant'Anna (2021), which accounts for treatment effect heterogeneity over time and across groups.

We provide two main sets of results. First, we show that the birth of a first child generates important gender gaps in terms of overall, local and non-local employment. However, childbirth particularly reduces the probability of women (compared to men) to work in jobs located in non-local labour markets, which require longer commutes but offer better employment opportunities. The magnitude of this impact is substantial: we document that 75 percent of the effect of childbirth on the overall gender gap in employment is accounted for by a gender divergence in non-local employment. We also establish that the gender gap in non-local employment after childbirth is not due to changes in residential mobility (i.e., mothers moving closer to their workplace) but, rather, is a result of an adjustment of commuting decisions (i.e. mothers spending less time commuting).

Second, we examine several mechanisms through which this post-childbirth location-related gender specialisation occurs. We show that the gender gap in non-local employment emerging after childbirth is mostly driven by opposing job location responses of men and women to individual, household and regional factors. We find that men do not give up non-local employment when they work in high-paid jobs, which have an implicit higher opportunity cost of home production; when they have a partner who does not participate in the labour market, which relaxes their time constraints; and when they live in regions with adverse local labour market conditions. This suggests that fathers trade off better employment opportunities with longer commutes. In contrast, we show important drops in non-local employment for women that are independent of their earnings level, the labour market status of their partner and the local economic conditions of the region in which they live, which is consistent with mothers specialising in childcare provision compared to fathers.

The paper relates to two main literatures. First, it relates to the literature on the effect of children on gender inequality in the labour market. While the gender gaps in the labour market have narrowed considerably in recent years, sizable ones still exist and childbearing has gradually become their main driver (Kleven et al., 2019a). For example, prior literature has shown that after childbirth mothers participate less in the labour market relative to fathers (Rosenzweig and Wolpin, 1980; Angrist and Evans, 1998; Jacobsen et al., 1999; Kleven and Landais, 2017; Kleven et al., 2019a,b, 2020; Sieppi and Pehkonen, 2019; Fontenay et al., 2021; Kleven et al., 2021; Nieto, 2021), are less likely to be employed (Gutiérrez-Doménech, 2005; Narayan and Smyth, 2006; Cristia, 2008; Michaud and Tatsiramos, 2011; Fitzenberger et al., 2013; Kleven, 2022) and work fewer hours (Lundberg and Rose, 2000; Bridges and Mumford, 2001; Sasser, 2005; Paull, 2008; Miller, 2011; Fernández-Kranz et al., 2013; Lundborg et al., 2017; Kleven et al., 2019a, 2020; Fontenay et al., 2021; Kleven et al., 2021). Mothers are also less productive (Azmat and Ferrer, 2017; Krapf et al., 2017), less experienced (Klepinger et al., 1999; Fernández-Kranz et al., 2013), more likely to work in the public sector (Fernández-Kranz et al., 2013; Kleven et al., 2019a) and have lower labour responsibilities (Cools et al., 2017; Kleven et al., 2019a) following childbirth compared to fathers.

Second, this paper relates to the recent literature providing evidence on the existence of gender differences in preferences for commuting. Previous studies have shown that since women have higher domestic burdens than men, they dislike commuting more, which results in gender differences in earnings and employment (Meekes and Hassink, 2019; Petrongolo and Ronchi, 2020; Le Barbanchon et al., 2021). These gender differences are aggravated after the arrival of children, with mothers being less willing to commute compared to fathers, which leads to a greater monopsony power for the employers of mothers (Borghorst et al., 2021; Bütikofer et al., 2021).

We contribute to these two strands of the literature in three important ways. First, we provide direct causal evidence on the key role of job location in the effect of childbirth on the gender gap in employment, quantifying how much of the overall gender gap in employment is accounted for by gender divergences in local and non-local employment following childbirth. Second, we provide novel and extensive evidence on the plausible explanations that drive the location-related gender specialisation—i.e. mothers are more likely to give up non-local employment compared to fathers—focusing on individual, household and regional factors. Lastly, for the first time in the literature we provide evidence that is robust to treatment effect heterogeneity over time and across birth cohorts, studying the dynamic effect of childbirth on the labour market trajectories of mothers and fathers. Our estimates show that the classical two-way fixed effects estimator in an event-study model and estimators that account for treatment effect heterogeneity over time and across units lead to similar results, albeit the latter estimators show more clearly that the parallel trends assumption holds.

The remainder of the paper proceeds as follows. Section 2 provides some context on the evolution of gender equality and labour market integration over recent decades. Section 3 describes the data we use in the analysis and provides summary statistics of our sample. Section 4 explains our empirical strategy, and Section 5 presents our results on the effect of childbirth on the gender gap in local and non-local employment, as well as the mechanisms through which this impact takes place. Section 7 offers some concluding remarks.

2 Context

In recent decades, there has been a reduction in labour market gender gaps in most advanced economies, which is possibly explained by factors such as the introduction of anti-discrimination legislation, the increase in the educational level of women over time and the adoption of family-friendly policies. In the European context, and as shown in Figure 1, the gender gap in employment fell from 18.8 percent in 2002 to 11.3 percent in 2021 in EU-27 countries, on average, and from 25 percent to 9.1 percent in the Belgian regions bordering Luxembourg (Eurostat, 2022a), which is the area we focus on here. However, despite the progress made gender disparities in employment still exist today, making it important to understand the remaining barriers to gender equality in the labour market.

Together with these trends in the gender gap in employment, labour markets—especially in the European Union—have become more integrated over time. This has led to an increase in the proportion of the population working in non-local labour markets (i.e. in a different region or country than that of their residence). As shown in panel A of Figure 2, the share of individuals who work in a different region to the one in which they live has increased by 36 percent in the last fifteen years in the EU-27 and by 30 percent in the Belgian regions bordering Luxembourg. However, while the ongoing labour market integration has allowed individuals to access non-local and often better employment opportunities, gender differences in preferences towards commuting may introduce barriers that limit women's access to these job opportunities compared to men. Panels B and C of Figure 2 show that, indeed, this has been the case. While the proportion of men and women working in a region different to the one of residence (panel B) and as cross-border workers (panel C) has increased over time, the increases for men have been larger than for women. As a result, the gender gap in interregional commuting has increased by 25 percent, as shown in panel A of Figure 3, and that on cross-border commuting by 105 percent, as shown in panel B (Eurostat, 2022b). These facts motivate our study of the role of job location in the employment gender gap.

3 Data

We use a novel administrative dataset available from the Belgian Crossroad Bank of Social Security (CBSS), which is based on data from several social security institutions as well as the Belgian National Register. Our sample focuses on residents in the Belgian provinces bordering Luxembourg, and the uniqueness of the dataset lies in the provision of detailed geo-location longitudinal information on individuals' places of residence and work locations at the municipality and district level within Belgium and which specifies whether they are cross-border workers in Luxembourg. This allows us to construct detailed and very precise measures of the commuting behaviour and distance to work for workers, as well as to provide evidence on the effect of childbirth on parents' residential mobility and work location decisions.

Another important characteristic of our dataset is that it provides longitudinal information on the labour outcomes and socio-demographic characteristics of individuals. This allows us to explore the effect of childbirth on gender gaps in the labour market in detail, as well as plausible mechanisms. Regarding labour market characteristics, the dataset provides information on quarterly earnings, employment status, hours worked and wage level, among others. As for socio-demographic characteristics, the dataset contains individual information on gender, partnership status, age of the household members and the newborn's quarter of birth.

We use a large sample of 86,500 individuals who were born between 1972 and 1990 and lived in the Belgian provinces bordering Luxembourg at some point between 2007 and 2017 (74 percent of the target population). Figure 4 displays this region, which offers a very interesting setting to test the role of job location in gender inequality in the labour market. Due to language similarities and the absence of institutional barriers to international labour mobility, individuals living in this area can access the non-local labour market of Luxembourg, which offers much better employment opportunities than those available in Belgium. For example, the household disposable income in purchasing power parity is 30 percent higher in Luxembourg than in Belgium (Eurostat, 2022c).[1] This income difference may explain why 32 percent of workers commuted beyond the border in 2022 and why the region has one of the highest mobility rates in Europe (Eurostat, 2022b).[2] However, as about 50,000 individuals commute from Belgium to Luxembourg every day, which represents 11 percent of the Luxembourgish labour force (Statec, 2022), cross-border jobs impose strong time constraints in the form of

[1]Since this national statistic also includes the richer northern region of Belgium (Flanders), it is a lower bound of the economic difference between the Belgian region we use in the analysis and Luxembourg.
[2]Of the cross-border workers in our sample, 98 percent work in Luxembourg.

commuting due to traffic congestion.[3] For example, residents of the Belgian Province of Luxembourg take 47.5 minutes to commute when working in Luxembourg, on average, which is almost double the commuting time of working in Belgium (24.4 minutes—see Godefroy et al., 2021). These characteristics provide an ideal setting for our study, as individuals encounter a strong trade-off in terms of job location between better employment opportunities and higher commuting times.

During our period of analysis (i.e. 2007–2017), we follow individuals on a quarterly basis, which provides us with a panel of about 3.7 million individual-quarter observations.[4] As explained in Section 4, we account for time-invariant unobserved heterogeneity by implementing a difference-in-differences estimator. For this, we must drop treated units that are not observed in the baseline period (i.e. 5 quarters before the birth), that is, individuals who had their first child before the 3rd quarter of 2008. Following this selection, we remain with a panel of 53,494 individuals and about 2 million individual-quarter observations.[5] This sample thus provides substantial variation in our outcomes of interest, namely the probability of individuals working in 1) the district in which they live, 2) a different district to the one of residence and 3) a different country. All these characteristics make this hitherto unexploited database a unique source of information for the purposes of our analysis.

Column 1 of Table 1 presents summary statistics of the outcomes of interest, as well as of socio-demographic characteristics for the full sample.[6] Columns 2–5 present the same statistics separately for women, men, mothers and fathers, respectively. Comparing men and women allows exploring overall gender differences in the labour market, while comparing mothers and fathers provides descriptive evidence on whether these differences may be brought forth by childbirth. As shown below, while men are more likely to be employed than women, spend more time commuting and more often work in a district and country different to that of their residence, these gender gaps are modest. A possible explanation for the small gender differences is that this comparison includes individual-year observations before childbirth, when the gap may be narrow. In contrast, columns 4–5 show that the gender differences in the labour market widen after childbirth, with fathers being considerably more likely to be employed and to hold a non-local job compared to mothers, as well as to earn higher earnings. This descriptive evidence suggests that in the presence of children, mothers may specialise in childcare provision and fathers in market production.

[3] Almost half of the workforce of Luxembourg (46 percent) is composed of international commuters from the neighbouring regions of Belgium, France and Germany (Statec, 2022).

[4] This is the sample size we use for labour market outcomes, which we observe on a quarterly basis from the 2nd quarter of 2007. For other outcomes, such as job (residential) location, we have semester (year) information and thus use a sample of 1.9 (0.9) million individual-semester (year) observations.

[5] Of the 53,494 individuals, 20,619 experienced their first child's birth before the end of 2017, while 32,875 did not.

[6] Due to individuals immigrating (emigrating) to (from) Belgium, deceased individuals and unknown information, the sample is partially unbalanced. As shown in Section 5.3, however, our findings are robust to restricting the analysis to a balanced sample within five years.

4 Empirical method

Thanks to the longitudinal component of the data, we can observe individuals during multiple time periods before and after childbirth, with this event representing the treatment. Since childbirth occurs at different points in time for different treated individuals and the treatment is an absorbing state, we are in a staggered treatment framework. Recent evidence has shown that in this type of staggered setting, the standard two-way fixed effects estimator for event studies produces biased treatment effect estimates when these are heterogeneous across groups and time (Goodman-Bacon, 2021). To address these concerns, we implement the difference-in-differences estimator proposed by Callaway and Sant'Anna (2021).[7]

Callaway and Sant'Anna (2021) propose implementing many two-by-two difference-in-differences estimators to obtain average treatment effects for each treated group (i.e. birth cohorts who started the treatment at time d) and time period t, which are then aggregated in event-study dynamic effects over elapsed duration from the start of the treatment. The group-time specific difference-in-differences estimator compares the evolution of the outcomes of a treated group (D_d) to a control group of units who were never treated or not-yet treated by time t. The identifying assumption of the empirical strategy is the parallel trends of the potential outcome in the absence of treatment, which can be relaxed to hold only conditional on the covariates. As in the previous literature, we condition on a set of yearly age dummies to account for non-linearities of the outcome of interest over the life cycle.

Callaway and Sant'Anna (2021) propose three different estimation methods to implement the conditional differences-in-differences estimator, each of which models different parts of the data-generating process. First, the outcome regression approach (Heckman et al., 1997) requires correctly specifying the evolution of the counterfactual outcome in the absence of treatment given X. This approach predicts the change in the outcome from the reference period until t given the conditioning variables X and is accounted by the term $\widehat{m}_{d,t,\delta}(X) = E[Y_t - Y_{d-\delta-1}|X, C = 1]$. The model is estimated on the control group and then extrapolated to the treated group to represent the common time effect for all units. Second, the inverse-probability-weighting (IPW) difference-in-differences estimator (Abadie, 2005) reweights the control units by their propensity score of being treated at time d given their covariates $\widehat{p}_d(X)$). The IPW weights of the control units $\frac{\widehat{p}_d(X)C}{1-\widehat{p}_d(X)}$ are normalized by their expectations to improve their finite sample performance (Busso et al., 2014). The IPW method relies on the correct estimation of the propensity score of starting the treatment in time d and ensures that the reweighted control units have the same X characteristics as the treated units. Finally, the doubly robust estimator (Sant'Anna and Zhao, 2020) simultaneously relies on the two previous models but

[7]Other estimators attempting to solve the bias introduced by treatment effect heterogeneity in the staggered difference-in-differences setting have also been recently proposed, such as de Chaisemartin and D'Haultfœuille (2020), Sun and Abraham (2021) and Wooldridge (2021). In a sensitivity analysis, we rely on the extended two-way (Mundlak) fixed-effects approach recently proposed by Wooldridge (2021), which is also robust to treatment effect heterogeneity.

requires only one of their specifications to hold. In the empirical analysis, we implement this estimator to gain from these doubly robust properties to model misspecifications. Our model is given by the following expression:

$$\widehat{ATT}(d,t) = E\left[\left(\frac{D_d}{E\left[D_d\right]} - \frac{\frac{\widehat{p}_d(X)C}{1-\widehat{p}_d(X)}}{E\left[\frac{\widehat{p}_d(X)C}{1-\widehat{p}_d(X)}\right]}\right)\left(Y_t - Y_{d-\delta-1} - \widehat{m}_{d,t,\delta}(X)\right),\right] \tag{1}$$

where subscript t is calendar time, d is the time period when individuals receive treatment and δ is the number of time periods before the treatment where we may expect anticipation effects. To be consistent with the prior empirical literature focusing on childbirth, we set δ to 1 year (4 quarters, or 2 semesters) before childbirth.[8] We thus non-parametrically estimate a series of average treatment effects, $ATT(d,t)$, for each time period (t) and treated group (D_d). D_d is a binary variable equal to 1 if the individual belongs to the group that receives treatment at time d. C is a binary variable equal to 1 for the control group, which can consist of units that have not yet received treatment or units that are never treated, or both not-yet as well as never treated units. In the analysis, we retain all untreated individuals to gain precision but also show that our estimates are robust to the two alternative control groups. $\widehat{p}_d(X)$ is the estimated propensity score for being treated at time d given the covariates X. Y_t is the observed outcome at calendar time t. $Y_{d-\delta-1}$ is the outcome in the last unaffected pre-treatment period, which is used as the reference to study the evolution of the outcome (i.e. Y_t - $Y_{d-\delta-1}$).

After estimating the different $\widehat{ATT}(d,t)$, we aggregate them by the elapsed time since treatment exposure e to show treatment effect dynamics, in a similar way as in the event-study approach. To account for the relative size of the different treated groups D_d, each estimated $\widehat{ATT}(d, d+e)$ is reweighted by $P(D = d|d + e < T)$, where T represents the last available data point in the data (end of 2017).

$$\widehat{\theta}(e) = \sum_d 1(d + e < T)P(D = d|d + e < T)\widehat{ATT}(d, d + e) \tag{2}$$

To allow for greater comparability of the relative effect of childbirth between men and women, we follow Kleven et al. (2019a) and divide $\widehat{\theta}(e)$ by the predicted average counterfactual outcome in the absence of the treatment for the treated at elapsed time e. The last term is obtained by subtracting the estimated aggregated effect $\widehat{\theta}(e)$ from the average observed outcome $\widehat{Y}_e$ at elapsed time e.[9] Confidence intervals are obtained by a multiplier-type bootstrap

[8] This means that for outcomes with quarterly (semester) (yearly) measurement, the baseline period is 5 quarters (3 semesters) (2 years) before the birth.

[9] As the treated units enter the treatment at different t, while the end of the database T remains fixed, $\widehat{\theta}(e)$ is aggregated over different treated units across the elapsed treatment duration e. To ensure that the estimated treatment effect dynamics are not driven by the compositional changes in the treated, in a sensitivity analysis we retain only individuals who are fully observed from the baseline period until 4 years after the treatment and

procedure (see Callaway and Sant'Anna, 2021), which is clustered at the individual level to account for serial correlation.

5 Baseline results

5.1 Gender differences in employment

We first present evidence on the effect of the birth of a first child on the evolution of employment over time and by gender, using as our outcome variable the probability of being employed.[10] As shown in Figure 5, employment follows similar statistically insignificant trends in the years up to the birth of the first child for both men and women, supporting the parallel trends assumption for both genders. For women, employment starts declining in the year before the birth of a first child, probably due to the physical and health burden related to childbearing. One quarter after the birth of the child, the drop in employment for women is 10 percent. Employment for women continues to fall over time, reaching a drop of 20 percent after 7 years. For men, we observe a much smaller and gradual decline in employment, which starts immediately after the birth of a first child and continues, with a total drop of 7 percent after 7 years. This evidence shows a negative effect of children on the probability of employment that is larger for women relative to men, implying a gender gap in employment rates. These findings are consistent with those reported in prior studies (Kleven et al., 2019a,b).

The focus of this paper is to examine the role of job location in the effect of childbirth on employment, as well as plausible mechanisms. We thus focus on the effect of childbirth on overall, local and non-local employment. However, it is also important to examine whether the birth of a first child has an effect on earnings, hours of work and wages. We present these findings for mothers relative to fathers in Appendix A.2. The analysis of hours of work and wages is based on the sample of individuals working within Belgium as there is no such information available for cross-border workers. We find that mothers earn 30 percent less and work 15 percent fewer hours 7 years after the birth of their first child. In contrast, we find very modest negative effects of the birth of a first child on the earnings and working hours of fathers, indicating substantial gender gaps in these two labour outcomes. We also find a reduction of 1 percent in wages following childbirth for women, but no effect for males. These findings are in line with the results reported in the literature (Paull, 2008; Miller, 2011; Fernández-Kranz et al., 2013; Kleven et al., 2019a).

compare the estimates obtained on this balanced panel to the benchmark ones during these 5 years.

[10] Leave, such as maternal and parental leave, is considered as employment. In Appendix A.1, we show that when we exclude full-time leave from employment, we find a much more pronounced short-run negative effect for mothers.

5.2 Gender differences in employment by job location

The increase in parental time inputs to childcare and home production after the birth of a first child imposes a time constraint that might affect workers differently depending on the distance between their workplace and residence. Due to an increase in the opportunity costs of commuting time, we expect that the negative effect of the birth of a first child on employment may be larger for more distant jobs. To test this idea, we estimate the impact of childbirth on the unconditional probability of employment for men and women, distinguishing between local and non-local jobs. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to that of their residence.

Figure 6 shows the evolution of employment over time after the birth of a first child by job location. In panel A, we find a large gender gap in non-local employment after childbirth that is persistent over time. In the long-run, non-local employment for women drops by 30 percent, while for men it drops by 10 percent. In contrast, as shown in panel B, the gender gap in local employment is much smaller and mostly present in the first two years after childbirth. This evidence suggests that most of the gender difference in the impact of children on employment, reported in Figure 5, is due to a large drop in employment in distant jobs among women. Specifically, we find that 75 percent of the gender gap in employment after childbirth, in absolute terms, is accounted for by gender disparities in non-local employment.[11]

In our setting, almost half (45 percent) of non-local jobs are cross-border jobs in Luxembourg. Living in Belgium but working in Luxembourg generally offers more attractive opportunities in terms of wages and working conditions, but it also involves substantial commuting costs. In panel C of Figure 6, we show the effect of the birth of a first child on the probability of being a cross-border worker. Similar to the findings in panel B for overall non-local employment, the probability of being a cross-border worker for women drops by 30 percent after childbirth, leading to a gender gap in cross-border employment.[12]

The sharp fall in non-local employment rates, especially among women, may reflect either an adjustment of residential location so that workers live closer to their workplace or a job change that requires shorter commuting. To distinguish between these two possible margins of adjustment, we first estimate the effect of the birth of a first child on residential mobility at the district level. In panel A of Figure 7, we show that the probability of moving to a different district drops by more than 60 percent after the birth of a first child for both men and women. This suggests that the post-childbirth employment decline in non-local jobs is not due to parents moving closer to their workplace. If anything, the birth of a first child seems to act as a

[11] As shown in Appendix A.3, this result can be obtained by dividing the absolute gender gap induced by childbirth for non-local employment in percentage points (9 p.p.) by the gender gap for total employment (12 p.p.).

[12] In Appendix A.4, we show the child penalty on women relative to men at event time t as defined in Kleven et al. (2019a). This is calculated by subtracting the absolute effect at time t for men from that of women, which is then divided by the counterfactual outcome of women at the same time.

barrier to residential mobility, possibly due to the increased costs associated with such residential moves. Moreover, since the magnitude of the drop in residential mobility after childbirth is similar for both men and women, it cannot explain the gender differences in child penalties shown earlier.

In contrast, in panel B of Figure 7 we show that, conditional on employment, there is a drop in commuting time after the birth of a first child for women, while men commute more.[13] This gender disparity in commuting time increases over the years following childbirth and, in combination with the reduction in residential mobility, provides additional evidence that the gender gap in employment is mostly driven by women being more likely to give up distant jobs relative to men. In Section 6, we explore plausible explanations behind this location-related form of gender specialisation.

5.3 Robustness

We implement several sensitivity checks that provide further evidence of the validity of our empirical strategy and test the robustness of the baseline results. First, Appendix A.6 presents the estimates of two specifications similar to the baseline model in which we use as a control group individuals who are never treated and not-yet treated, respectively. Second, Appendix A.7 explores whether our findings are robust to the use of a balanced sample. We examine this possibility by focusing on the time window that covers the period from one year before to four years after childbirth, providing estimates using a balanced and unbalanced sample to allow for comparability. Third, Appendix A.8 shows the results when we control for age with a simpler quadratic specification. While this test controls less precisely for non-linearities of employment over the life cycle, it is useful to examine whether the baseline results are robust to a simpler functional form approach and are thus not driven by the way in which we account for age. Fourth, in Appendix A.9 we re-estimate the baseline model after controlling for other pre-treatment covariates such as the district of residence, labour characteristics of the prior job such as whether it was a white- or blue-collar job, whether it was public or private, as well as the salary and working hours.[14] The additional controls allow us to further relax the parallel trends assumption but also increase the complexity of our specification. Fifth, Appendix A.10 examines whether the results are robust to the implementation of alternative estimators that account for treatment effect heterogeneity over time and across cohorts, using the extended

[13]Commuting time is approximated by the time needed to reach the municipality where the job is located from that of residence in minutes by car during rush hour (Tom-Tom data, date of reference 28/05/2020, leaving at 08:00 AM). Individuals working in Luxembourg are assumed to work in Luxembourg City. In Appendix A.5, we change this to the distance to the closest border-access point (a lower bound of the actual commuting time) or a midpoint between the border and Luxembourg City. We find similar estimates to the baseline results on commuting.

[14]We can retrieve information on the last job up to 2003.

two-way (Mundlak) fixed effects estimator proposed by Wooldridge (2021).[15] It is reassuring to find that the estimates of all sensitivity analyses are very similar to the benchmark results.

Lastly, Appendix A.11 examines the extent to which the estimates change when we do not account for treatment effect heterogeneity, by presenting the baseline results when using a standard two-way fixed effects estimator for event-study models. These estimates do not change much relative to our baseline results, but accounting for treatment effect heterogeneity over time and across units shows more clearly that the parallel trends assumption holds.

6 Plausible explanations

The evidence presented so far shows that women experience a larger drop in non-local employment after childbirth relative to men, which accounts for 75 percent of the overall gender gap in employment. However, what are the underlying mechanisms that can explain this finding? In the remainder of the paper, we explore several potential explanations behind the location-related form of gender specialisation we find in the baseline results. We study potential drivers at the individual, household and regional level to provide a full picture of plausible mechanisms.

6.1 The role of individual opportunity costs of home production

One possible mechanism is related to women taking on a greater share of the childcare burden, meaning they face a higher increase in the opportunity costs of commuting compared to men after childbirth and thus have to exit the non-local labour market more frequently. However, some women may be less willing to give up employment after having children—especially those in high-paid and career-oriented jobs—such that the opportunity costs of home production may also play an important role. As a result, location-related gender specialisation may occur, with women, and especially high-paid ones, switching to local employment, which allows them to balance work and family life, while men (especially high-paid ones) retain spatial flexibility, which allows them to consider better employment opportunities in distant locations. We investigate these mechanisms by estimating the effect of the birth of a first child on higher- and lower-paid employment by job location.[16] We define a job as high(low)-paid if the daily wage is above (below) the gender-specific median 5 quarters before the birth (109.6 and 114.4 euros for women and men in 2014 prices).

[15] This is a two-way fixed effects estimator in which all the independent variables are interacted while the covariates are demeaned. To simplify the model, we only control for age with a quadratic specification and do not include event dummies for the pre-treatment periods. The average effect over treatment duration is retrieved by calculating the linear combinations of the time-cohort-specific treatment effect dummies.

[16] Since we do not have information on the wage rates of cross-border workers, in this analysis non-local jobs do not include cross-border jobs (i.e. the outcome is equal to zero). However, due to wage differences between Belgium and Luxembourg, many of these workers are likely to be categorized into higher-paying jobs. As shown in Appendix A.12, categorizing cross-border jobs as non-local high-paid jobs only enhances the precision of the estimates.

Panels A and B of Figure 8 show that the gender gap in non-local employment that emerges after the birth of a first child is mostly driven by the divergence in the employment trajectories of men and women working in high-paid jobs. In panel A, the non-local employment of high-paid women drops by 10 percent in the short-run, reaching almost a 30 percent drop 7 years after the birth of a first child. Instead, the non-local employment of high-paid men remains unchanged during the same time window. In panel B, we show that low-paid non-local employment drops by 30 percent for both men and women 7 years after childbirth.

These findings provide evidence of location-driven specialisation after childbirth. Among high-paid workers, women value working closer to home while men trade off higher wages with longer commutes. For low-paid workers, instead, the opportunity costs of commuting dominate for both men and women, so they experience similar drops in non-local employment.

Women who give up non-local jobs after childbirth may consider employment in local jobs or drop out completely from the labour market. To the extent that employment opportunities of similar quality may be more limited in local labour markets, especially for more qualified high-paid women, we may expect women previously employed in non-local jobs to transition either to lower-paid local jobs or to exit the labour market. As shown in panel C of Figure 8, childbirth leads to a gender gap in high-paid local employment, which is nevertheless much smaller than the gender gap in high-paid non-local employment we found in panel A. This is mainly driven by differences in women's local and non-local employment trajectories, as the drop in local employment for high-paid women 7 years after childbirth is 10 percent, compared to 30 percent for non-local employment, while the effect for men is similar for local and non-local high-paid jobs. In panel D, we find that childbirth generates a gender gap in low-paid local employment in the short-term, which, however, reverts over time, driven by the gradual convergence of women's employment to pre-childbirth levels. The fact that childbirth leads to drops in local and non-local employment for women implies that a fraction of mothers become jobless. However, we also show that an important share of mothers who lose their non-local job are likely to switch to low-paid local jobs.

The findings of this section suggest that the increase in gender inequality in employment after childbirth is mostly driven by an increase in gender inequality in high-paid employment, and especially in employment based in workplaces requiring a longer commute, which women may give up due to childcare considerations and be unable to fully replace with similar jobs in local labour markets.

6.2 The importance of the partner's labour market status

The decision of whether to work and the location of the workplace after childbirth may also depend on the partner's labour market status. Having a partner who participates in the labour market increases household income but also the need to share childcare and home production more equally among household members. As a result, individuals with a partner who is active in the labour market may be more likely to give up and less likely to take up non-local jobs, which offer better labour opportunities but also impose tighter time constraints in terms of commuting. In contrast, those with an inactive partner may be more likely to look for better employment opportunities and wages, undertaking longer commutes due to of intra-household specialisation. However, as women are more likely to be the primary providers of childcare and home production, they may also be more likely to avoid non-local employment after childbirth, irrespective of the labour market status of their partner. Instead, men may be more likely to avoid non-local employment when they have an active partner in the labour market, so that they can contribute more to childcare provision and home production.

In Figure 9, we report the estimates of the impact of the birth of a first child on local and non-local employment by partner's labour market status for both men and women.[17] We obtain heterogeneous estimates by splitting the sample of men and women into two groups according to the partner's labour status the year before the birth.[18] In panel A, we find a large gender gap in non-local employment following childbirth for parents whose partner is inactive, which is driven by a decline in the probability of women working in distant jobs, while the non-local employment trajectory of men remains essentially unchanged. Instead, as shown in panel B, we find that the gender gap in non-local employment after childbirth is smaller for parents who have an active partner. This is because while women experience a similar drop in employment in distant jobs regardless of the labour market status of their partner, the non-local employment of men only declines when they have an active partner, who may not be able to take full responsibility for childcare provision.

Unlike employment in distant jobs, in panel C we find no gender gap in local employment following childbirth for parents whose partner is inactive; the employment decline is similar and rather small—less than 10 percent—for both men and women. Finally, in panel D we find a small gender gap in local employment after childbirth for parents with an active partner. The magnitude of this gap is similar to that for distant jobs in the first year after childbirth, but it closes over time as local employment gradually returns to pre-childbirth levels for both men and women. Overall, men's local employment seems more resilient when the partner is active, which might be due to the need to work nearby when the mother is also working. In contrast, as for non-local jobs, the drop in local employment for mothers is irresponsive to the activity status of their partner.[19]

These findings provide evidence that the gender gap in employment following child-

[17]In Appendix A.13, we also investigate the effect of childbirth on total employment by partner's labour market status for both men and women.

[18]We measure belonging to these groups during the baseline pre-treated period to avoid issues of endogeneity (and it is randomized for never-treated units). However, since the labour status of the partner is actually time-variant, the division is less sharp for the longer-run estimates.

[19]Since the employment location of women is not affected by their partner's labour status while the more positive response regarding non-local jobs for men when the partner is inactive is compensated by a more negative effect on local jobs, we do not observe differences in the gender gap on overall employment by activity status of the partner (see Figure 9).

birth is mostly the result of a location-related form of specialisation within the household, with women working less frequently in distant jobs, irrespective of their partner's labour status, while men's non-local employment is essentially unchanged, especially when they have a partner who is not working.

6.3 The role of the local labour market conditions

The previous evidence shows that earnings and the labour status of one's partner are important determinants of the effect of the birth of a first child on local and non-local employment. In addition to individual and household characteristics, local labour market conditions may also affect job location decisions. For example, high local unemployment increases the difficulty of finding a local job and may thus push parents to search for non-local vacancies. In contrast, low local unemployment increases local employment opportunities, allowing parents to combine work and family life after childbirth. The local labour market conditions may also affect men and women differently depending on the degree of household specialisation and the division of labour between parents. To the extent that fathers shoulder a lower share of the childcare burden and thus enjoy higher spatial flexibility, their employment location may be more responsive to local labour market conditions compared to mothers. When the local labour market conditions are adverse, mothers may have to decide between holding a local job or fully dropping out of the labour market.

We investigate the sensitivity of local and non-local employment decisions after childbirth to local labour market conditions by gender, comparing the heterogeneous impact of the birth of a first child for individuals living in high- or low-unemployment districts during the baseline pre-treated period.[20] We define as high-unemployment districts (respectively, low-unemployment districts) those with a share of long-term unemployed above (below) the third (first) quartile.[21]

The evidence shown in Figure 10 suggests that the gender gap in employment is mostly driven by a divergence in non-local employment trajectories between men and women, especially for those living in high-unemployment areas. As shown in panel A, we find that when local unemployment is high the non-local employment of men remains unchanged after childbirth. Instead, for women non-local employment declines sharply even though the poor local labour market conditions may prevent them from finding a local job. In panel B, we can see that when local unemployment is low men eventually reduce their employment in distant jobs

[20] Data are retrieved from the online statistics of BCSS. See `https://dwh-live.bcss.fgov.be/fr/dwh/dwh_page/content/websites/datawarehouse/menu/application-web-chiffres-locaux.html`. Since in this data source cross-border workers are registered as inactive individuals, the unemployment rate is considerably upwardly biased in areas with a high incidence of cross-border employment. To address this concern, we split the sample based on the share of long-term unemployed (out of total unemployed) to define a low- or high-unemployment district.

[21] Similar conclusions are reached if we rely instead on the median value, as shown in Appendix A.14.

as they face better local economic conditions. For women, non-local employment also falls considerably when local economic conditions are favourable and follows a similar trajectory to that of women employed in distant jobs when facing high local unemployment.

Therefore, we find that women give up distant jobs irrespective of the local economic conditions, possibly because they are not able to combine their work and family life while holding a job that requires long commutes. In contrast, men are more likely to specialise in market work given their lower share of the childcare burden, thus adapting their employment location decisions to the local economic conditions. More specifically, when men face adverse local labour market conditions, which reduce the likelihood of finding jobs locally, they do not give up distant jobs even if they are more costly in terms of commuting. When local employment opportunities are more favourable, men tend to somewhat reduce employment in distant jobs to better reconcile their work and family life and, possibly, share home production and childcare more equally with their partner.

In panel C of Figure 10, we show that when local unemployment is high the birth of a first child reduces the probability of mothers and fathers holding a local job, thus only leading to a short-term gender gap in local employment that gradually closes over time and vanishes in the medium and long term. In panel D, we instead observe that local employment remains at pre-birth levels for both men and women when the local labour market is in good condition, leading to a child penalty of almost zero in local employment.

These findings suggest that when the local labour market conditions are favourable, both mothers and fathers prefer holding jobs that allow them to reconcile their work and family life. Instead, when the local labour market conditions are poor, fathers specialise in non-local labour opportunities that require longer commutes while women may be forced to drop out of employment as they are prevented from working locally and non-locally. We next study whether this is the case by looking at heterogeneity in the effect of childbirth on men and women's total employment rates according to local labour market conditions. As shown in Appendix A.15, the overall employment of women is more negatively affected by childbirth when they live in areas of high unemployment, suggesting that reduced access to non-local labour markets due to childbirth makes women more vulnerable to the poor labour market conditions and makes them fully drop out of the labour force. In contrast, for men overall employment is affected by childbirth equally, regardless of the local unemployment rate, given that part of the decline in local employment following childbirth is compensated by increases in employment in more distant jobs. All this leads to a larger gender gap in employment when the local economic conditions are adverse.[22]

[22]We also investigated heterogeneous effects depending on other local conditions such as childcare availability (source: Iweps, 2022) or the quality of public transportation (accessibility index retrieved from SPF mobilité et transports, 2019). We found that poorer provision of public transportation and a lower availability of childcare services in the local area leads to a marginally higher gender gap in non-local employment. However, these local conditions seem to be less relevant for the gender gap in non-local employment than the local labour market conditions we explored in this section. These results are available in Appendix A.16.

7 Conclusions

This paper examines the role of job location decisions in the effect of the birth of a first child on the gender gap in employment. We use Belgian social security and geo-location data with an event-study design that accounts for treatment effect heterogeneity over time and across groups. Despite men and women's employment levels following a parallel and similar trend prior to the birth of a first child, we find that their trajectories diverge following childbirth, with mothers suffering from a considerably higher drop in employment. We show that 75 percent of this gender gap in employment is accounted for by a divergence in non-local employment. Moreover, we provide evidence that the disparity in non-local employment does not originate from changes in residential mobility—as both mothers and fathers are equally less likely to move to a different region following childbirth—but from work location decisions, as childbirth reduces the time spent commuting more for mothers than for fathers.

We also examine plausible explanations for why job location decisions play such an important role in the gender gap in employment following childbirth, with mothers being more likely to give up non-local employment compared to fathers. We do so by exploring potential drivers at the individual, household and regional level, finding opposing job location responses between men and women, which suggests gender specialisation following childbirth. First, we show that regardless of pay, women stop working in non-local jobs while men are willing to accept longer commutes for better employment opportunities, as they do not give up high-paid non-local jobs. Second, we show drops in non-local employment for women independent of the labour status of their partner, while men continue working in non-local jobs when they have an inactive partner. Lastly, we show that women experience falls in non-local employment regardless of the unemployment rate in their region of residence, while men adapt to the regional economic conditions and more frequently work in non-local jobs when they live in regions with a high unemployment rate. Reduced access to non-local labour markets thus makes women more vulnerable to poorer local labour market conditions.

Our findings are also relevant from a methodological point of view. We reach similar conclusions both with the classical two-way fixed effects estimator and with estimators that account for treatment effect heterogeneity. The analysis thus confirms that the estimates provided by the previous literature on the impact of childbirth on gender inequality in the labour market are reliable. Our novel findings regarding the role of job location suggest that policymakers should consider job location decisions in the design of labour market policies aiming to address gender gaps in the labour market, as well as the individual, household and regional characteristics that force mothers out of non-local employment following childbirth.

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Tables

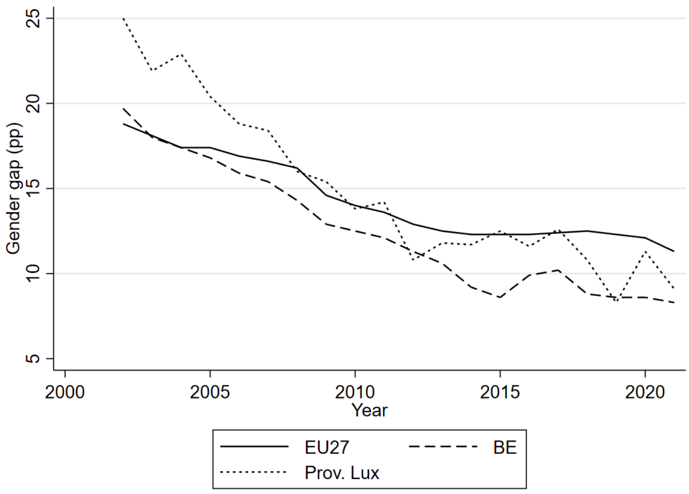
Table 1: Descriptive statistics

	All (1)	Women (2)	Men (3)	Women after birth (4)	Men after birth (5)
Woman	0.45	1.00	0.00	1.00	0.00
	(0.50)	(0.00)	(0.00)	(0.00)	(0.00)
Age	28.58	28.10	28.97	31.41	33.12
	(5.61)	(5.48)	(5.69)	(4.30)	(4.28)
Employment rate	0.67	0.66	0.68	0.79	0.88
	(0.47)	(0.47)	(0.47)	(0.41)	(0.33)
Local employment rate	0.26	0.28	0.25	0.35	0.30
	(0.44)	(0.45)	(0.44)	(0.48)	(0.46)
Non-local employment rate	0.36	0.33	0.38	0.40	0.55
(including cross-border)	(0.48)	(0.47)	(0.49)	(0.49)	(0.50)
Cross-border employment rate	0.14	0.12	0.16	0.14	0.25
	(0.35)	(0.32)	(0.37)	(0.35)	(0.43)
Low-paid local employment rate	0.16	0.16	0.16	0.17	0.13
	(0.37)	(0.37)	(0.36)	(0.38)	(0.34)
High-paid local employment rate	0.10	0.11	0.10	0.17	0.17
	(0.30)	(0.31)	(0.29)	(0.38)	(0.37)
Low-paid non-local employment rate	0.10	0.10	0.10	0.09	0.09
	(0.30)	(0.30)	(0.31)	(0.29)	(0.29)
High-paid non-local employment rate	0.09	0.10	0.09	0.13	0.16
	(0.29)	(0.29)	(0.29)	(0.34)	(0.37)
Change place of residence (NUTS-3)	0.10	0.10	0.10	0.05	0.04
	(0.30)	(0.29)	(0.30)	(0.21)	(0.20)
Commuting time by car (minutes)	36.26	34.08	38.03	31.08	39.29
	(31.82)	(30.93)	(32.41)	(27.69)	(30.04)
Full-time equivalent (full-time=100)	44.96	44.19	45.58	48.03	51.61
	(47.04)	(44.91)	(48.69)	(42.16)	(48.88)
Quarterly gross remuneration (euros)	2883.87	2829.50	2928.04	3209.40	3939.96
	(3638.96)	(3500.66)	(3746.97)	(3599.95)	(4421.51)
N	1,948,707	879,885	1,068,822	211,863	176,894

Column 1 of the table presents summary statistics (means and standard deviations in parentheses) of the outcomes of interest, as well as of socio-demographic characteristics for the full sample. Columns 2–5 present the same statistics separately for women, men, mothers and fathers, respectively. Comparing men and women allows us to explore overall gender differences in the labour market, while comparing mothers and fathers provides descriptive evidence on whether these differences may be brought forth by childbirth. The low-paid and high-paid non-local employment rates do not include cross-border workers, as there is no information on their wages in the dataset.

Figures

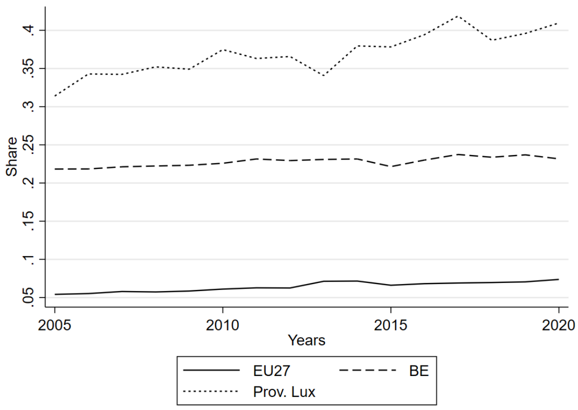
Figure 1: Employment rate gender gap



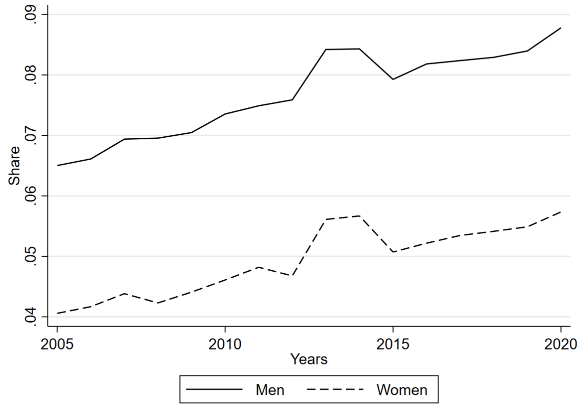
Source: Own elaboration on Eurostat (2022a) data. The figure shows the gender gap in the employment rates of the EU-27, Belgium and the Belgian Province of Luxembourg. We define as employment rate the number of employed individuals aged 25–64 divided by the working-age population (25–64 years of age). We define the gender gap in employment for each region and period as the difference in the employment rate between men and women.

Figure 2: Share of non-local jobs out of total jobs

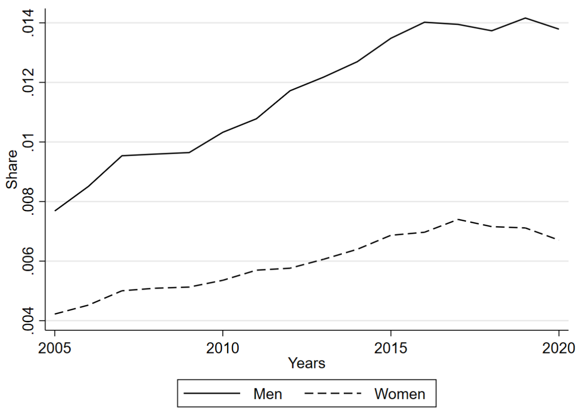
(a) Evolution of non-local jobs across regions



(b) Evolution of non-local jobs in the EU-27 by gender



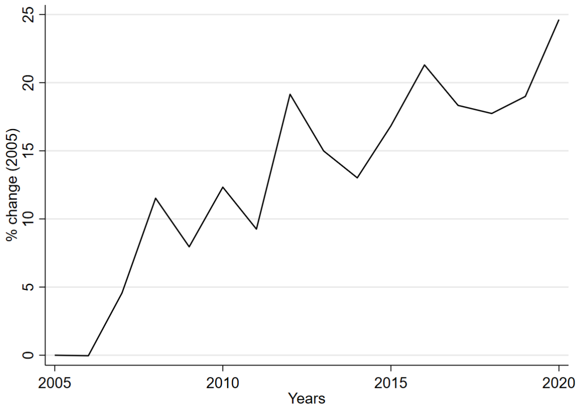
(c) Evolution of cross-border jobs in the EU-27 by gender



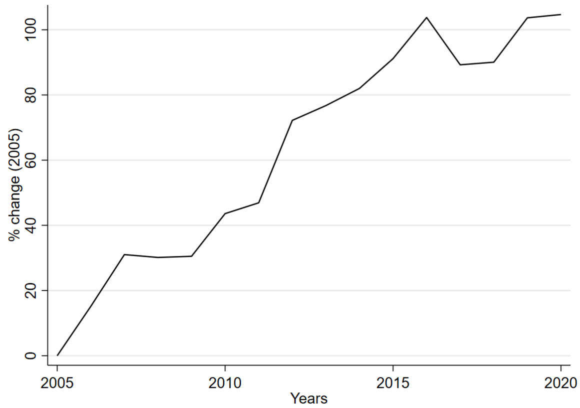
Source: Own elaboration on Eurostat (2022b) data. Panel A shows the share of non-local jobs out of total jobs in the EU-27, Belgium and the Belgian Province of Luxembourg. Panel B shows the share of non-local jobs out of total jobs in the EU-27 by gender. Panel C displays the share of cross-border jobs out of total jobs in the EU-27 by gender. We calculate these shares based on the population of employed individuals aged 20–64.

Figure 3: Gender gaps in non-local and cross-border employment

(a) Gender gap in non-local employment EU-27

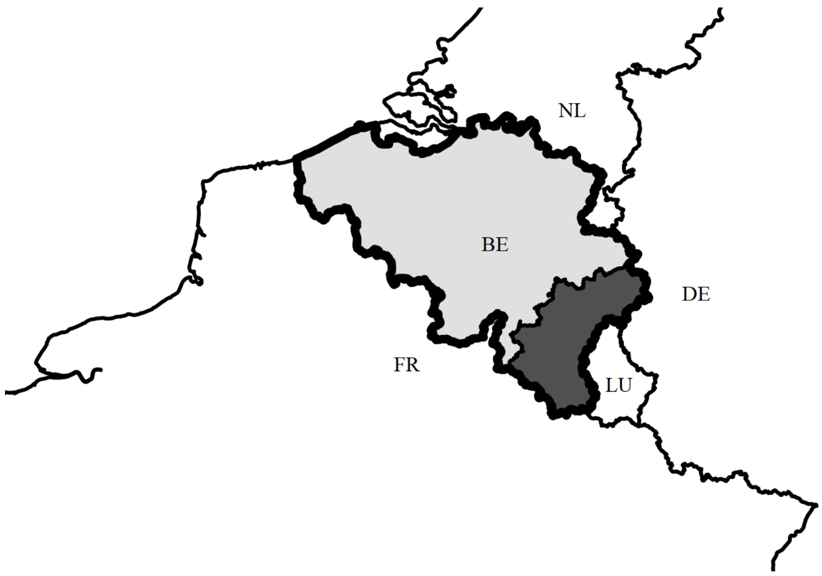


(b) Gender gap in cross-border employment EU-27



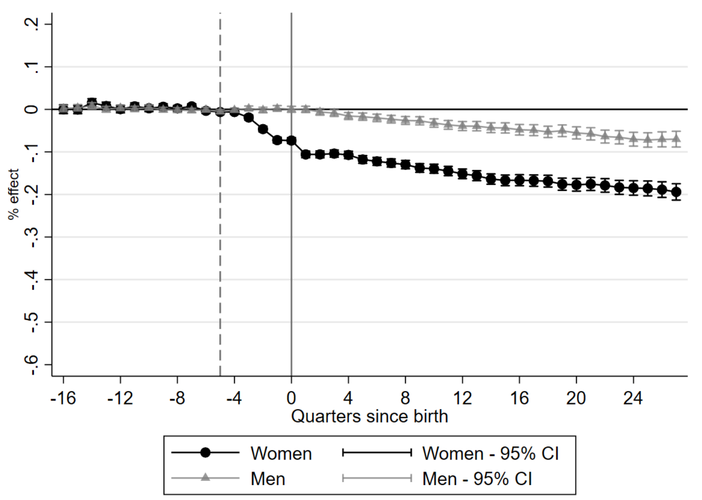
Source: Own elaboration on Eurostat (2022b) data. Panels A and B show the deviation in the gender gap in non-local and cross-border employment, respectively, in the EU-27 relative to year 2005. We calculate the gender gap in non-local and cross-border employment as the difference in the non-local and cross-border employment rate between men and women in a specific year. We calculate the deviation in the gender gap in non-local and cross-border employment relative to year 2005 as the ratio between the gender gap in each of these outcomes in a specific year divided by the existing gender gap for each of these outcomes in 2005. We calculate these deviations based on the population of individuals aged 20–64.

Figure 4: Sampling area



The figure shows the Belgian Provinces bordering Luxembourg in dark grey, which is the region in Belgium in which individuals in our sample lived at some point between 2007 and 2017. The area offers a very interesting setting to test the role of job location in gender inequality in the labour market, as individuals living in this area encounter a strong trade-off regarding job location between better employment opportunities and higher commuting time. FR stands for France, BE for Belgium, LU for Luxembourg, NL for the Netherlands and DE for Germany.

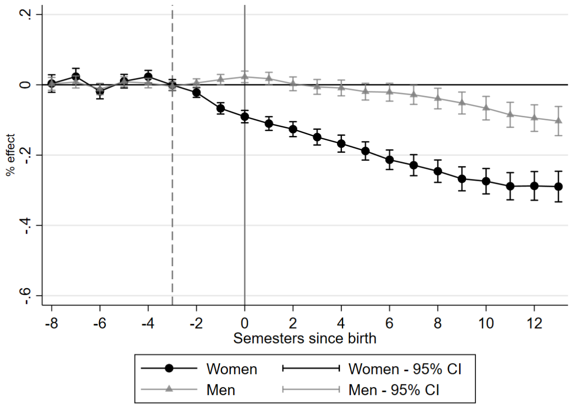
Figure 5: Employment rate



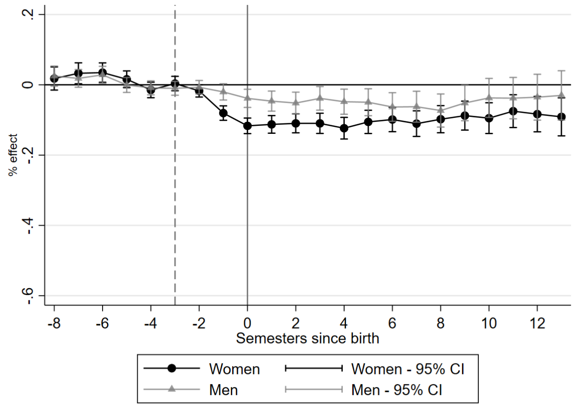
The figure shows event-study dynamic relative effects (in percentages) on employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and 0 otherwise. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure 6: Employment rate - local and non-local

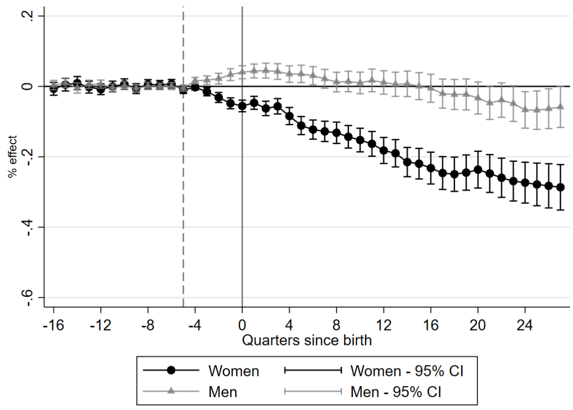
(a) Non-local employment



(b) Local employment



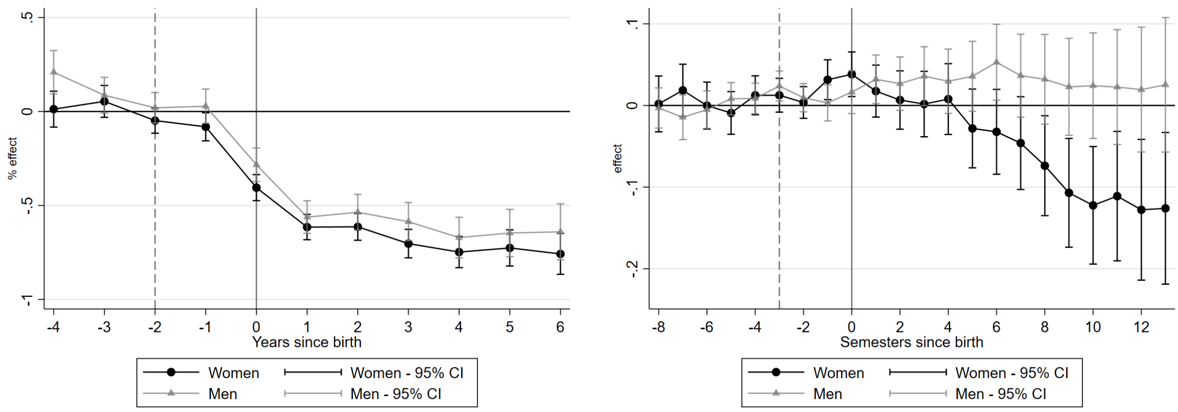
(c) Cross-border employment



The figure shows event-study dynamic relative effects (in percentages) on local, non-local and cross-border employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. In panels A–C, we use as dependent variable a dummy that takes a value of 1 if the individual holds a local, non-local and cross-border job, respectively, and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure 7: Residential and commuting patterns

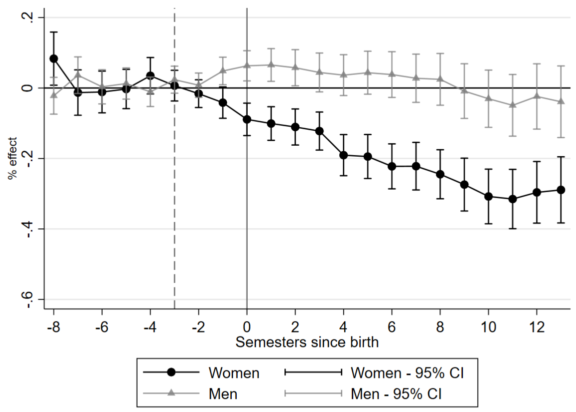
(a) Changing place of residence (NUTS-3) (b) Commuting time



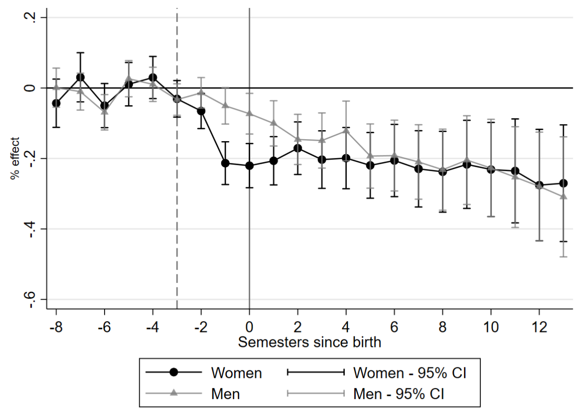
The figure shows event-study dynamic relative effects (in percentages) on residential mobility and commuting time over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. In panels A and B, we use as dependent variable the probability of individuals moving to a different NUTS-3 region and the logarithm of the time that individuals spend commuting, respectively. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure 8: Employment by wage and place of work

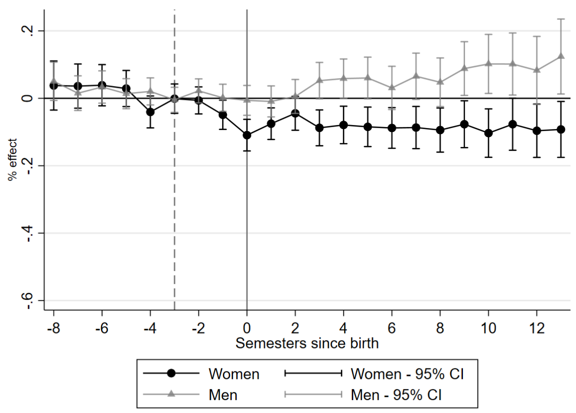
(a) High-paid non-local jobs



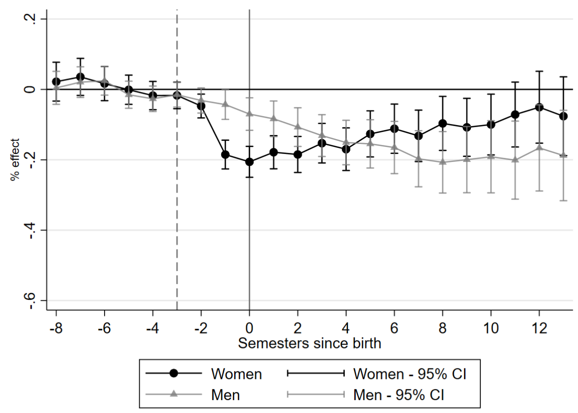
(b) Low-paid non-local jobs



(c) High-paid local jobs



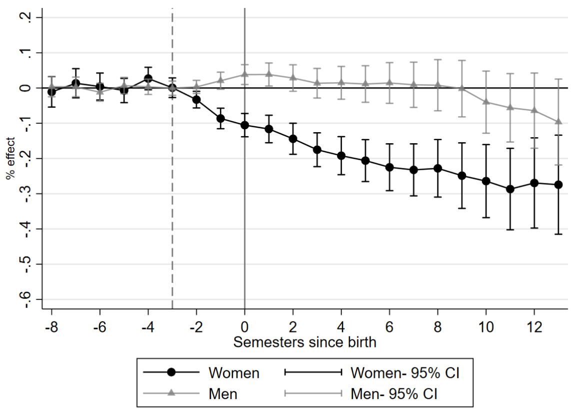
(d) Low-paid local jobs



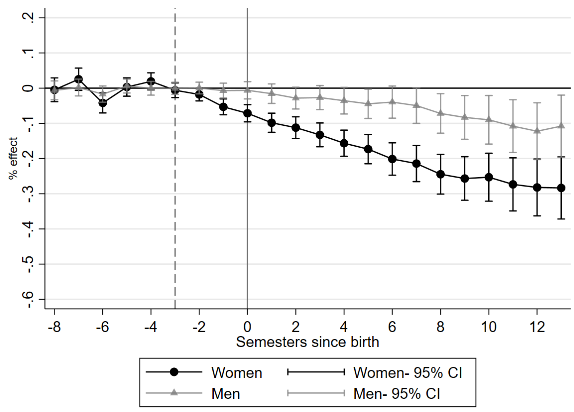
The figure shows event-study dynamic relative effects (in percentages) on low-paid and high-paid local and non-local employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. In panels A–D, we use as dependent variable a dummy that takes a value of 1 if the individual holds a low-paid local, low-paid non-local, high-paid local and high-paid non-local job, respectively, and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We define a job as high (low)-paid if the daily wage is above (below) the gender-specific median 5 quarters before the birth (109.6 and 114.4 euros for women and men, respectively, in 2014 prices). Cross-border jobs do not contribute to any employment due to missing information regarding their salaries. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure 9: Partner's labour status

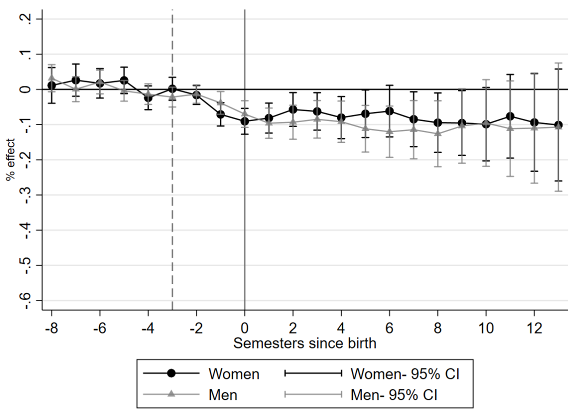
(a) Non-local employment: Inactive partner



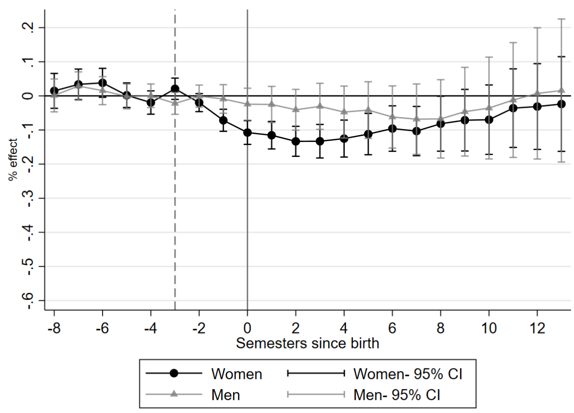
(b) Non-local employment: Active partner



(c) Local employment: Inactive partner



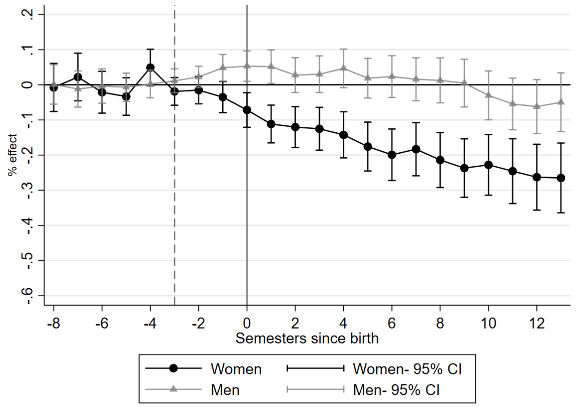
(d) Local employment: Active Partner



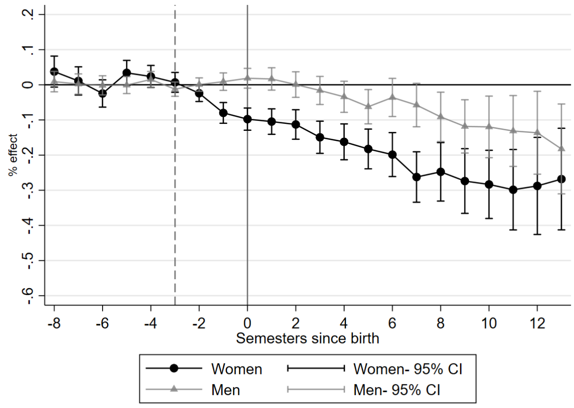
The figure shows event-study dynamic relative effects (in percentages) on local and non-local employment over elapsed duration from the birth of a first child, separately for women and men. We also split the sample of men and women into two groups according to the partner's labour status during the baseline treated period. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. In panels A and B (C and D), we use as dependent variable a dummy that takes a value of 1 if the individual holds a local (non-local) job and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure 10: Local labour market conditions

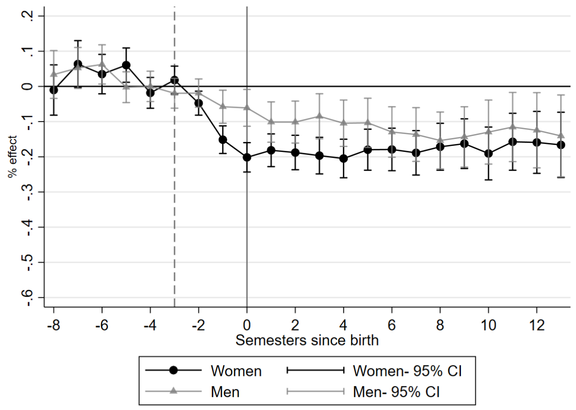
(a) Non-local employment: High unemployment



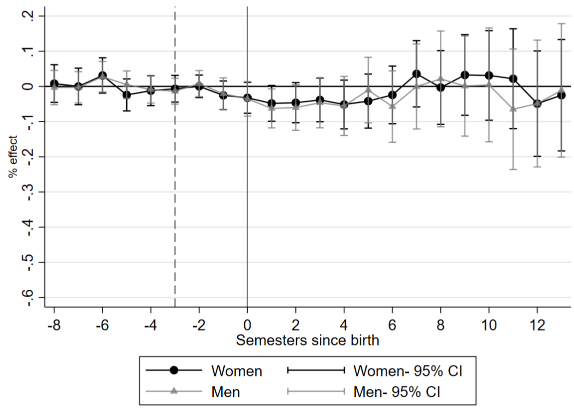
(b) Non-local employment: Low unemployment



(c) Local employment: High unemployment



(d) Local employment: Low unemployment

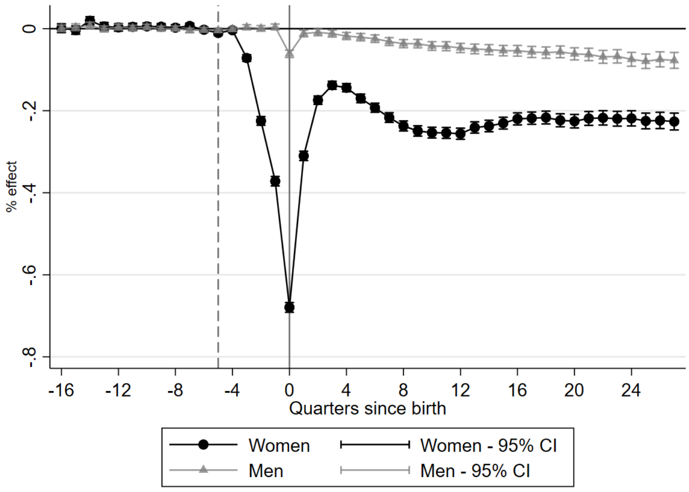


The figure shows event-study dynamic relative effects (in percentages) on local and non-local employment over elapsed duration from the birth of a first child, separately for women and men. We also split the sample of men and women into two groups according to whether they lived in high- or low-unemployment districts during the baseline pre-treated period. We define as high-unemployment districts (respectively, low-unemployment districts) those with a share of long-term unemployed above (below) the third (first) quartile. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. In panels A and B (C and D), we use as dependent variable a dummy that takes a value of 1 if the individual holds a local (non-local) job and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Appendices

A.1 Alternative definition of employment

Figure A.1: Active employment excluding full-time leave

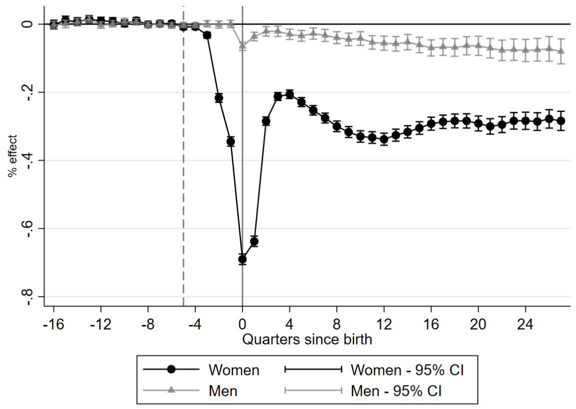


The figure shows event-study dynamic relative effects (in percentages) on employment, separately for women and men over elapsed duration from the birth of a first child. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and not taking full-time leave and 0 otherwise. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

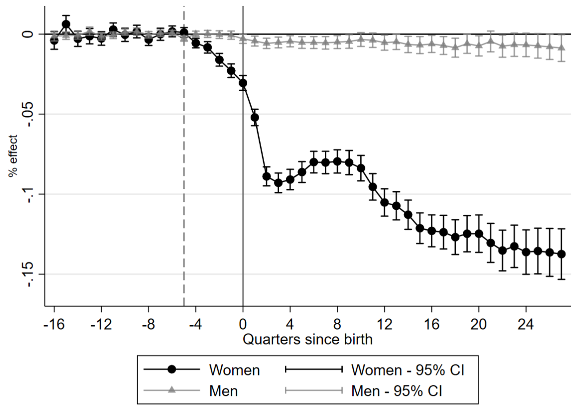
A.2 Other outcomes

Figure A.2: Type of employment (in Belgium)

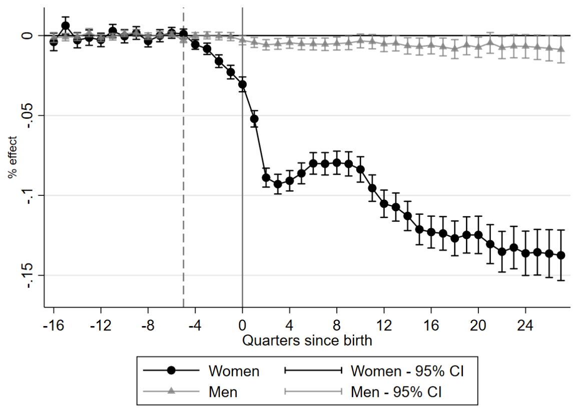
(a) Gross quarterly labour income



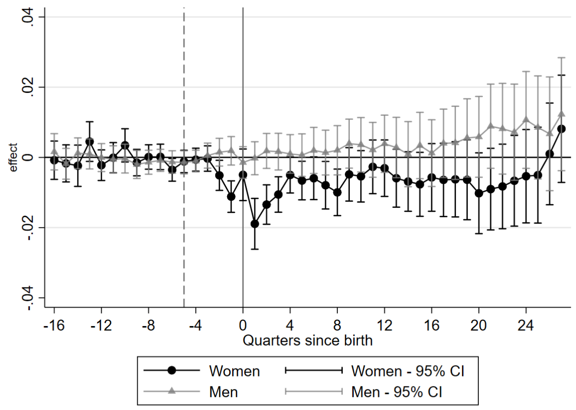
(b) Total hours of work (unconditional)



(c) Hours of work (conditional on working)



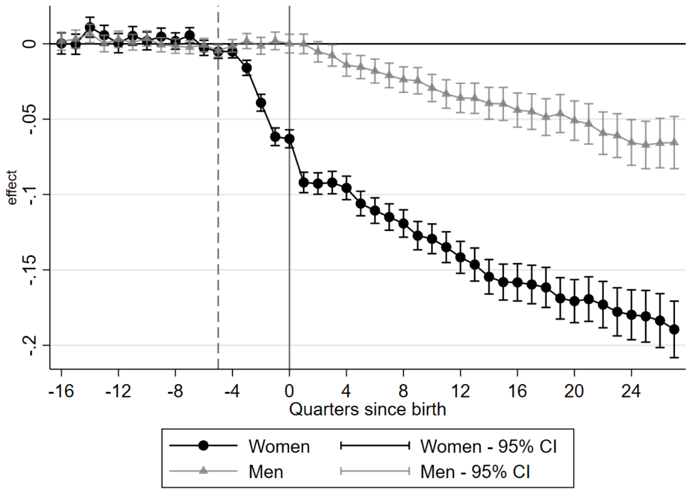
(d) Daily wage (conditional on working)



The figure shows event-study dynamic relative effects (in percentages) on several labour outcomes over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. In panels A–D, we use as dependent variable the gross quarterly labour income, the unconditional number of working hours, the number of hours of work conditional on being employed, and the logarithm of individuals' daily wages, respectively. Cross-border jobs are not considered due to missing information, i.e. the outcome is set to zero (missing) for unconditional (conditional) outcomes. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

A.3 Absolute effects

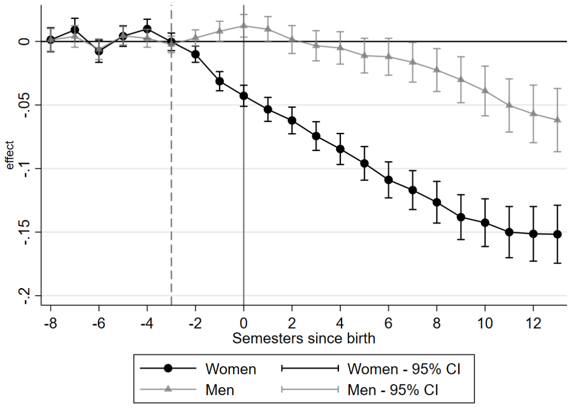
Figure A.3: Employment rate



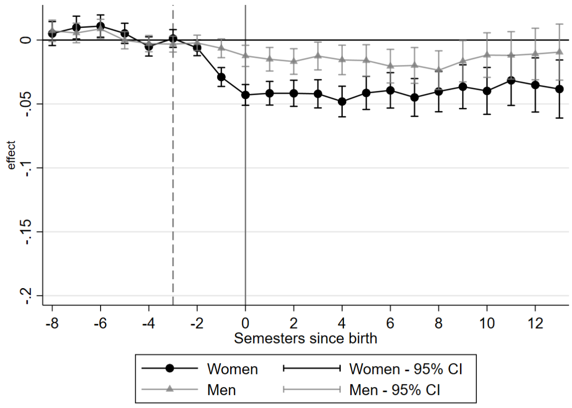
The figure shows event-study dynamic absolute effects (in percentage points) on employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and 0 otherwise. Contrary to the baseline results, we do not present relative effects but absolute ones. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.4: Employment rate - local and non-local

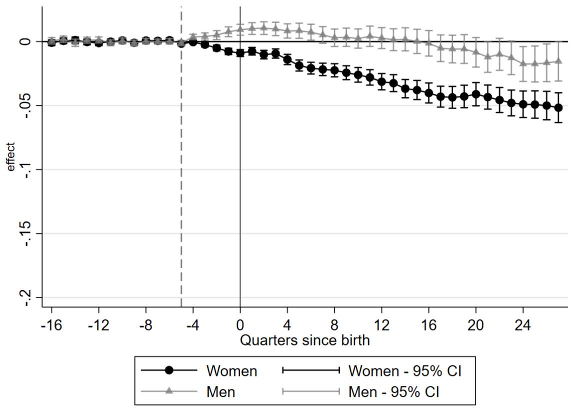
(a) Non-local employment



(b) Local employment

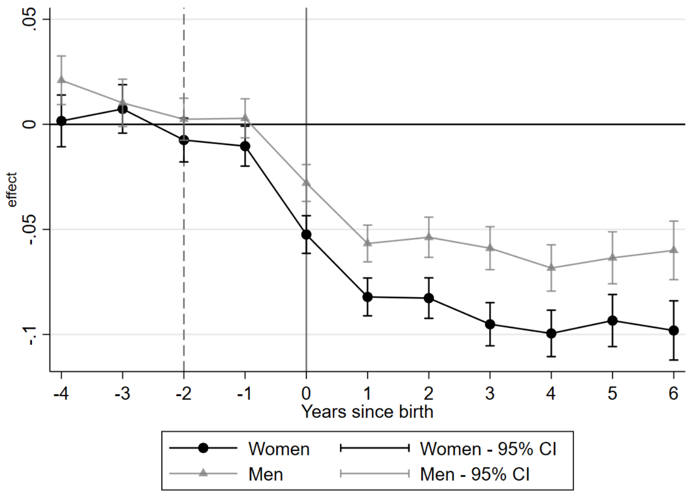


(c) Cross-border employment



The figure shows event-study dynamic absolute effects (in percentage points) on local, non-local and cross-border employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. In panels A–C, we use as dependent variable a dummy that takes a value of 1 if the individual holds a local, non-local and cross-border job, respectively, and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

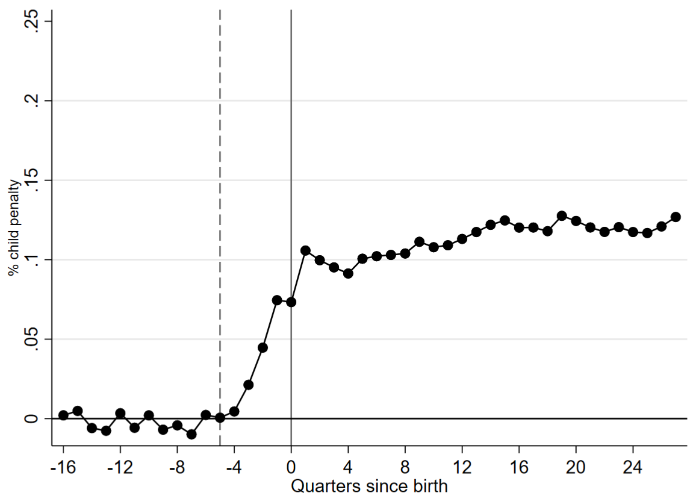
Figure A.5: Changing place of residence (NUTS-3)



The figure shows event-study dynamic absolute effects (in percentage points) on residential mobility over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We use as dependent variable the probability of individuals moving to a different NUTS-3 region. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

A.4 Child penalty

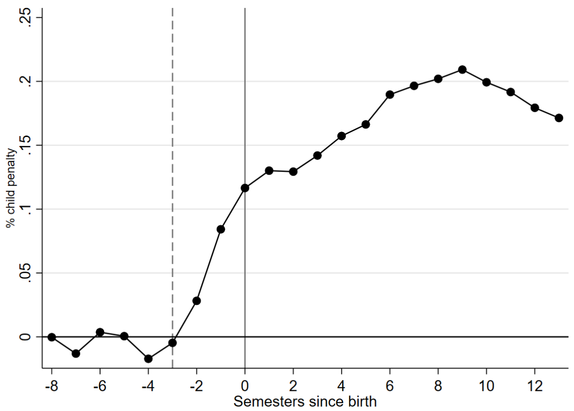
Figure A.6: Employment rate



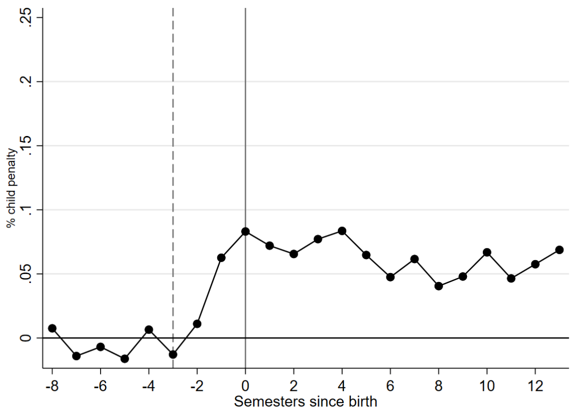
The figure shows event-study dynamic effects on the child penalty in employment for women relative to men over elapsed duration from the birth of a first child. We follow Kleven et al. (2019a) and define the child penalty in employment as the difference in the estimate of the effect between women and men divided by the predicted average counterfactual outcome for treated women in the absence of the treatment. The estimates for men and women are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.7: Employment rate - local and non-local

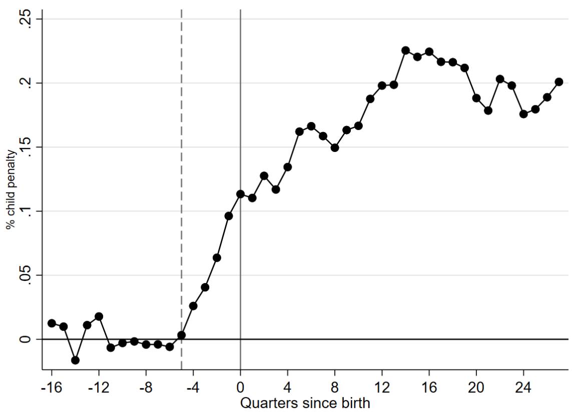
(a) Non-local employment



(b) Local employment



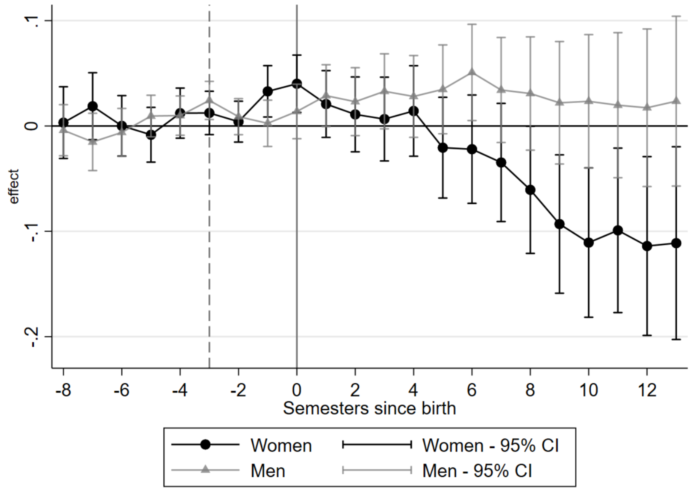
(c) Cross-border employment



The figure shows event-study dynamic effects on the child penalty in local, non-local and cross-border employment (respectively) for women relative to men over elapsed duration from the birth of a first child. We follow Kleven et al. (2019a) and define the child penalty in employment as the difference in the estimate of the effect between women and men divided by the predicted average counterfactual outcome for treated women in the absence of the treatment. The estimates for men and women are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

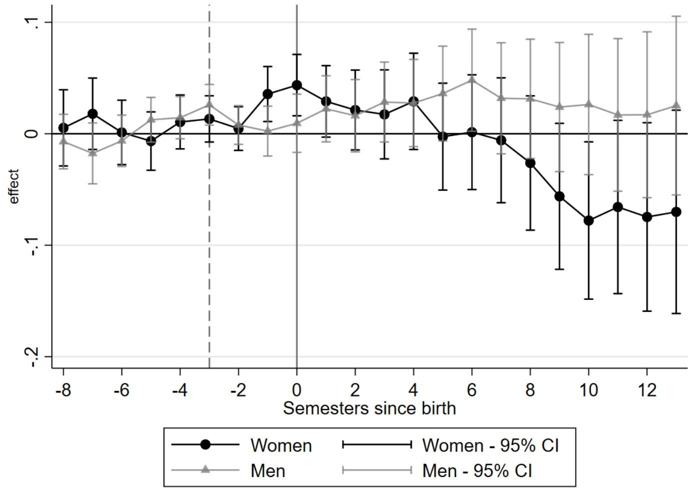
A.5 Alternative definition of commuting

Figure A.8: Alternative definition of commuting to Luxembourg: Midpoint between border and Lux. City



The figure shows event-study dynamic relative effects (in percentages) on commuting time over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We use as dependent variable the logarithm of the time that individuals spend commuting. For cross-border workers, we calculate commuting time from their neighbourhood of residence to a midpoint between the border and Luxembourg city. For cross-border workers, we calculate commuting time from their neighbourhood of residence to the closest border-access point (a lower bound of the actual commuting time). We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.9: Alternative definition commuting to Luxembourg: Border

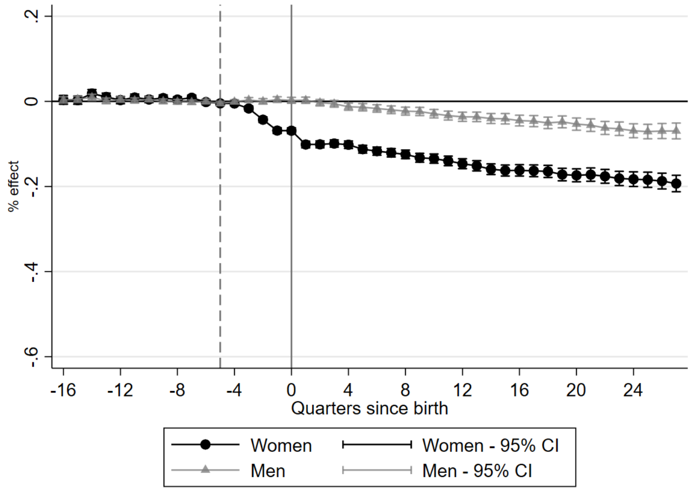


The figure shows event-study dynamic relative effects (in percentages) on commuting time over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We use as dependent variable the logarithm of the time that individuals spend commuting. For cross-border workers, we calculate commuting time from their neighbourhood of residence to the closest border-access point (a lower bound of the actual commuting time). We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

A.6 Alternative control group

Never treated only

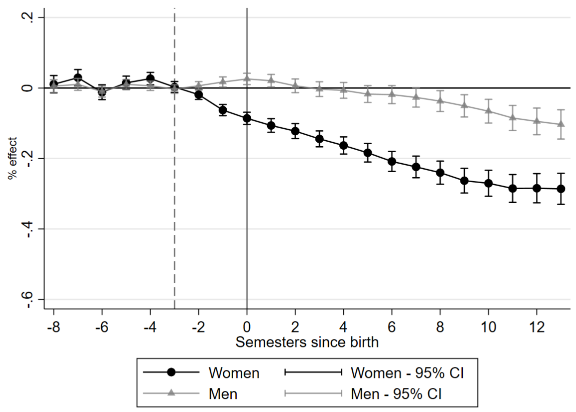
Figure A.10: Employment rate



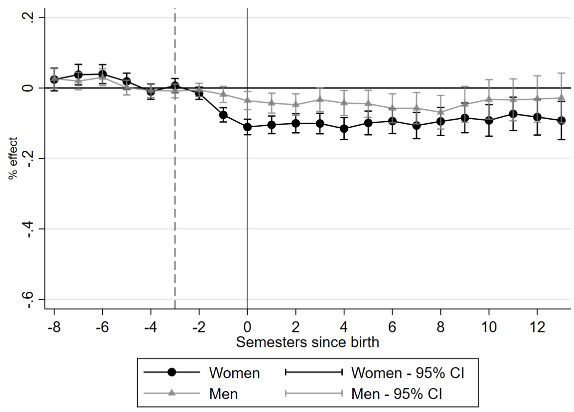
The figure shows event-study dynamic relative effects (in percentages) on employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but using as the control group only individuals that are never treated. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and 0 otherwise. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.11: Employment rate - local and non-local

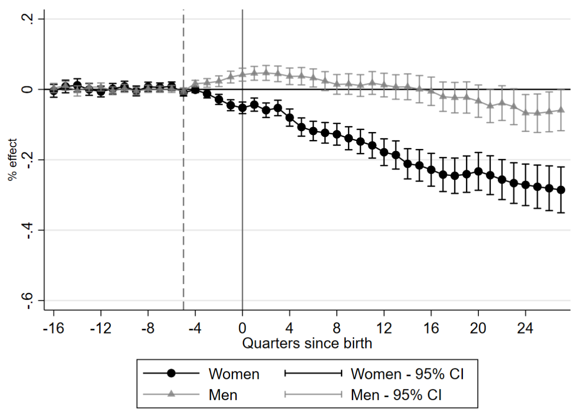
(a) Non-local employment



(b) Local employment



(c) Cross-border employment

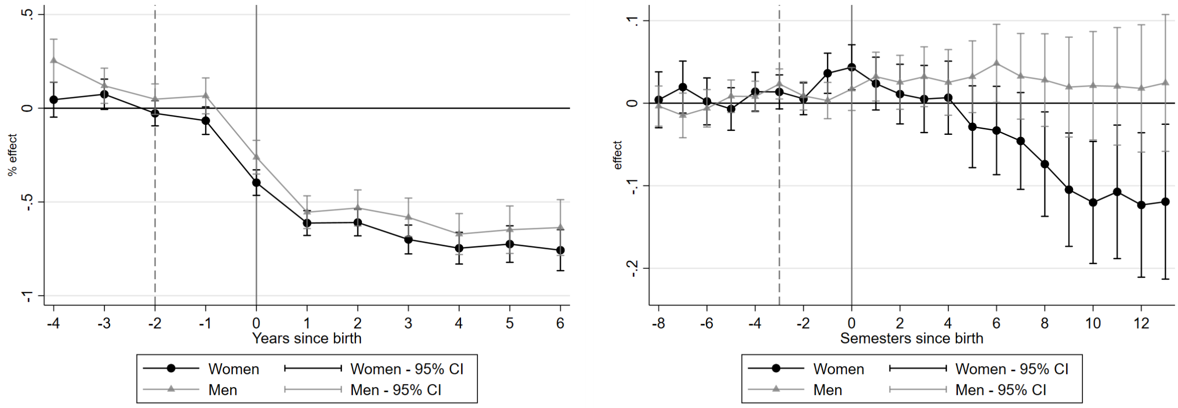


The figure shows event-study dynamic relative effects (in percentages) on local, non-local and cross-border employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but using as the control group only individuals that are never treated. In panels A–C, we use as dependent variable a dummy that takes a value of 1 if the individual holds a local, non-local and cross-border job, respectively, and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.12: Residential and commuting decisions

(a) Changing place of residence (NUTS-3)

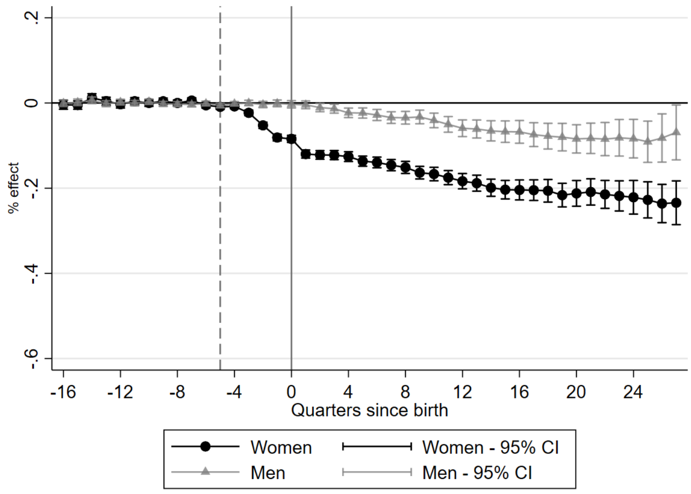
(b) Commuting time



The figure shows event-study dynamic relative effects (in percentages) on residential mobility and commuting time over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but using as the control group only individuals that are never treated. In panels A and B, we use as dependent variable the probability of individuals moving to a different NUTS-3 region and the logarithm of the time that individuals spend commuting, respectively. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Not-yet treated only

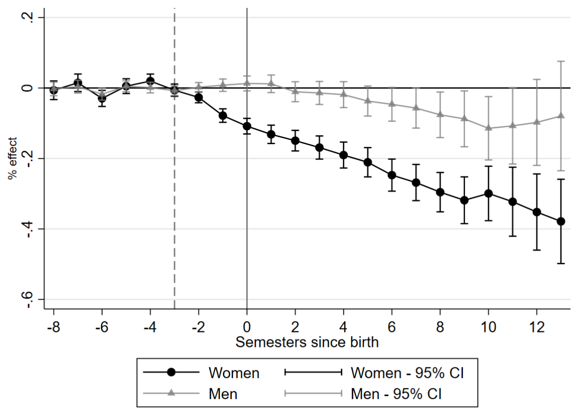
Figure A.13: Employment rate



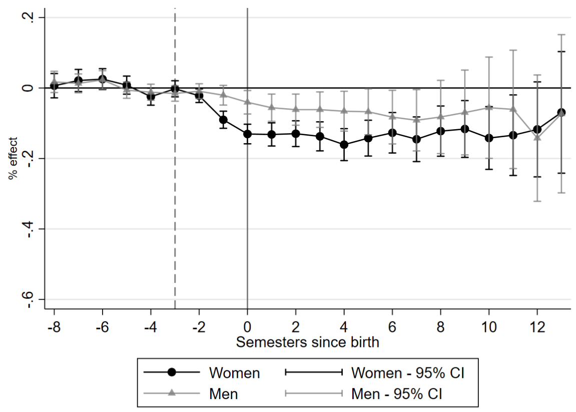
The figure shows event-study dynamic relative effects (in percentages) on employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but using as the control group only individuals that are not yet treated. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and 0 otherwise. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.14: Employment rate – local and non-local

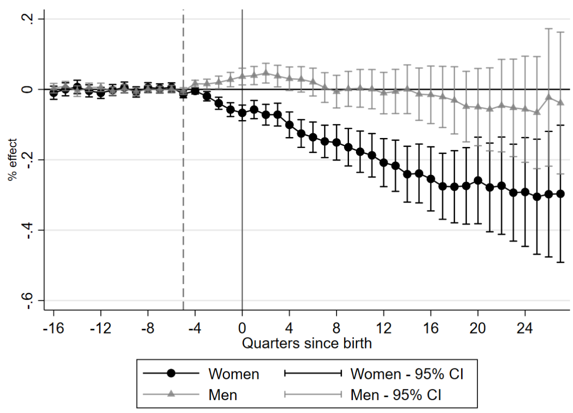
(a) Non-local employment



(b) Local employment



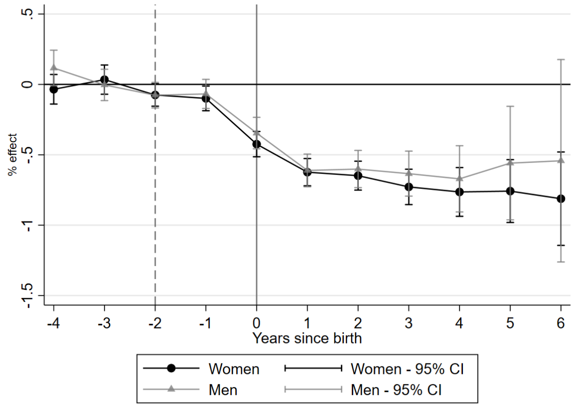
(c) Cross-border employment



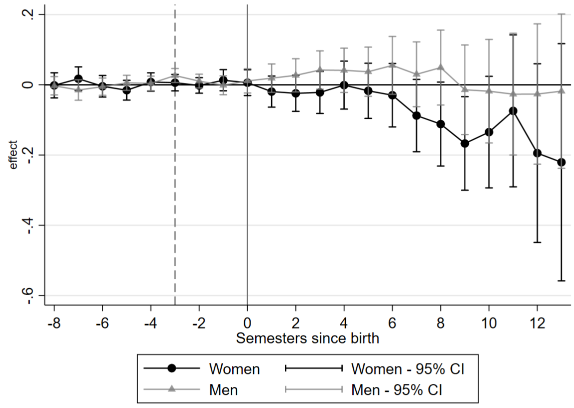
The figure shows event-study dynamic relative effects (in percentages) on local, non-local and cross-border employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but using as the control group only individuals that are not yet treated. In panels A–C, we use as dependent variable a dummy that takes a value of 1 if the individual holds a local, non-local and cross-border job, respectively, and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.15: Residential and commuting decisions

(a) Changing place of residence (NUTS3)



(b) Commuting time

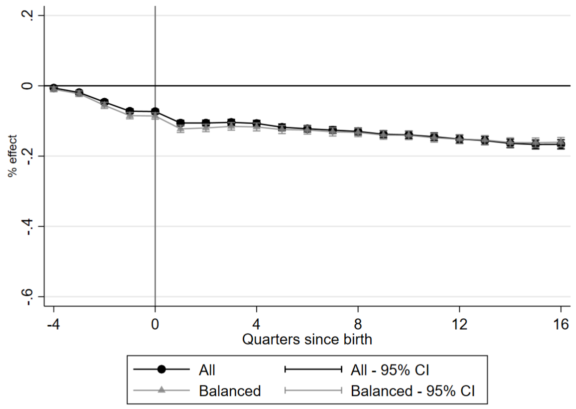


The figure shows event-study dynamic relative effects (in percentages) on residential mobility and commuting time over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but using as the control group only individuals that are not yet treated. In panels A and B, we use as dependent variable the probability of individuals moving to a different NUTS-3 region and the logarithm of the time that individuals spend commuting, respectively. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

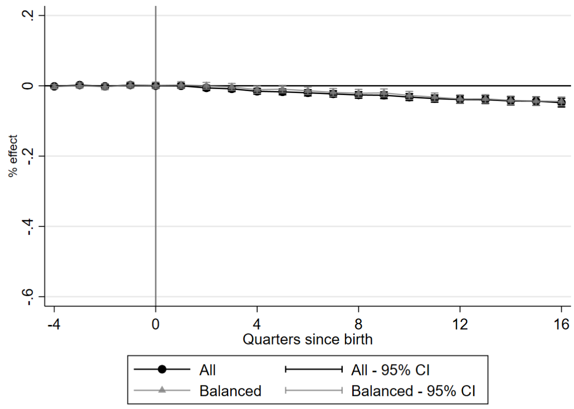
A.7 Balanced vs unbalanced sample

Figure A.16: Employment rate

(a) Women



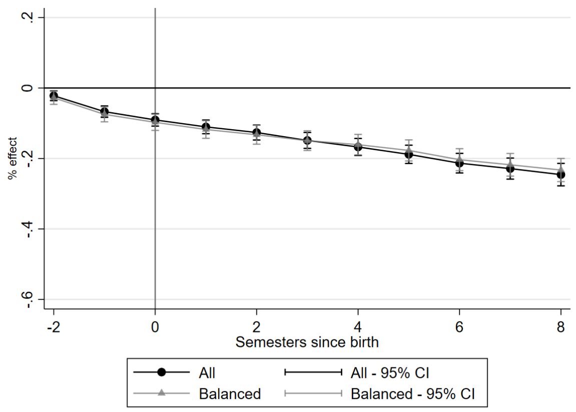
(b) Men



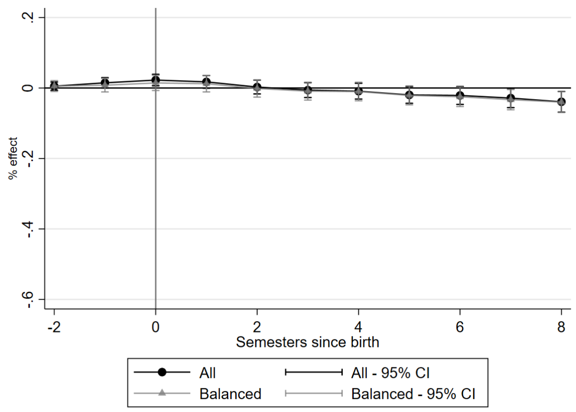
Panel A shows event-study dynamic relative effects on women's employment over elapsed duration from the birth of a first child, using the full sample or restricted to a balanced sample within the period covering one year before the occurrence of childbirth and four years after. Panel B is similar to panel A but for men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and 0 otherwise. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.17: Employment rate – local and non-local

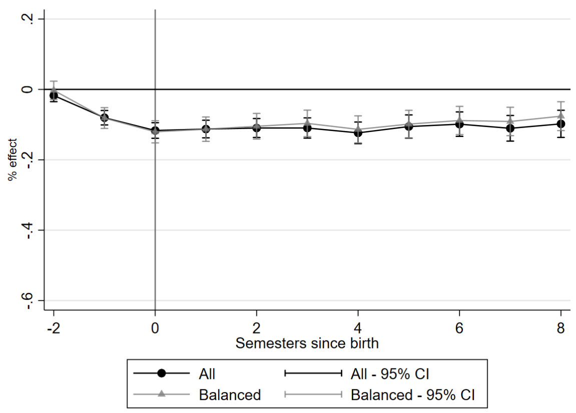
(a) Women: Non-local employment



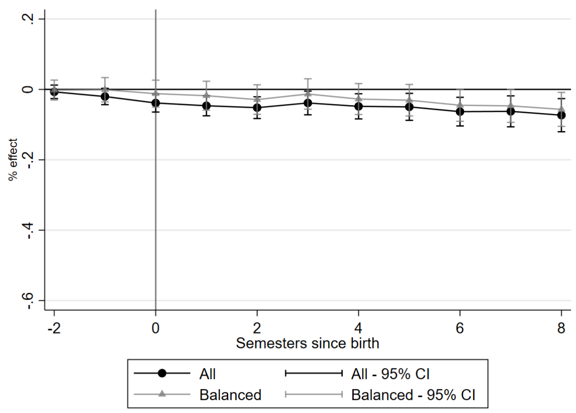
(b) Men: Non-local employment



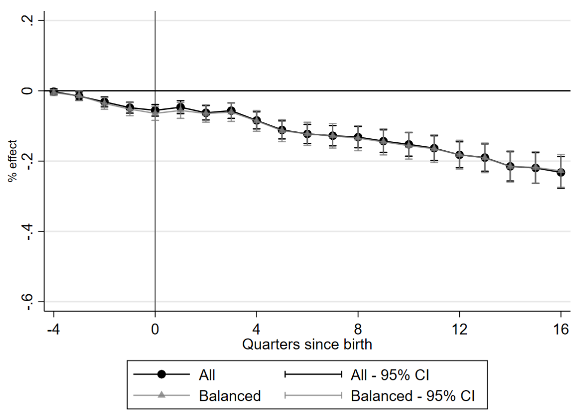
(c) Women: Local employment



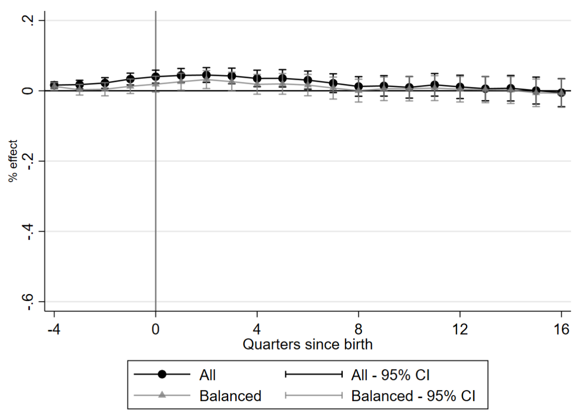
(d) Men: Local employment



(e) Women: Cross-border employment



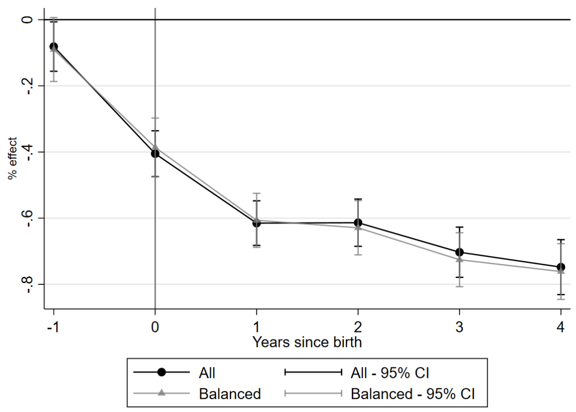
(f) Men: Cross-border employment



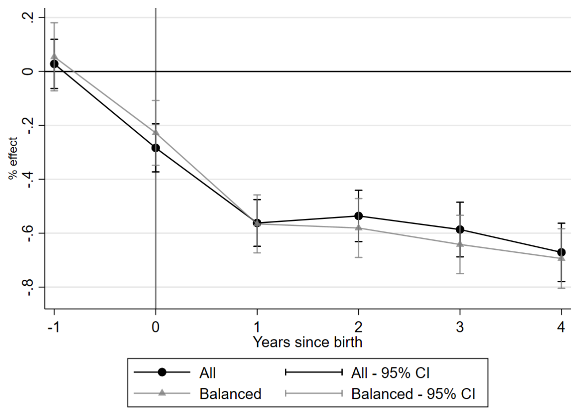
Panels A, C and E show event-study dynamic relative effects on women's local, non-local and cross-border employment, respectively, over elapsed duration from the birth of a first child, using the full sample or restricted to a balanced sample within the period covering one year before the occurrence of childbirth and four years after. Panels B, D and F are similar to panels A, C and E but for men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. Depending on the panel, we use as dependent variable a dummy that takes a value of 1 if the individual holds a local, non-local or cross-border job and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.18: Residential and commuting decisions

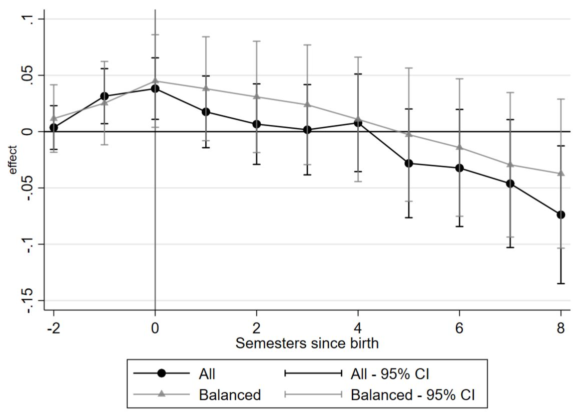
(a) Women: Changing place of residence (NUTS-3)



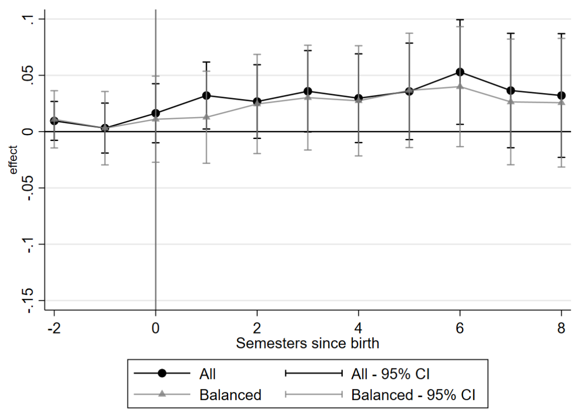
(b) Men: Changing place of residence (NUTS-3)



(c) Women: Commuting time



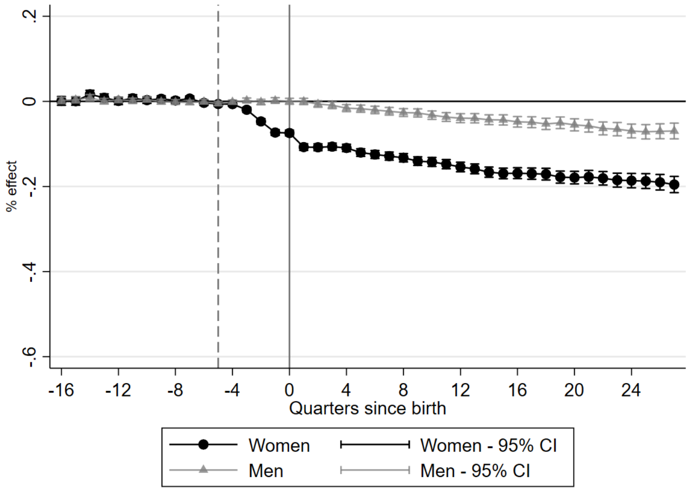
(d) Men: Commuting time



Panels A and C show event-study dynamic relative effects on women's residential mobility and commuting time, respectively, over elapsed duration from the birth of a first child, using the full sample or restricted to a balanced sample within the period covering one year before the occurrence of childbirth and four years after. Panels B and D are similar to panels A and C but for men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. Depending on the panel, we use as dependent variable the probability of individuals moving to a different NUTS-3 region or the logarithm of the time that individuals spend commuting. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

A.8 Controlling for quadratic age

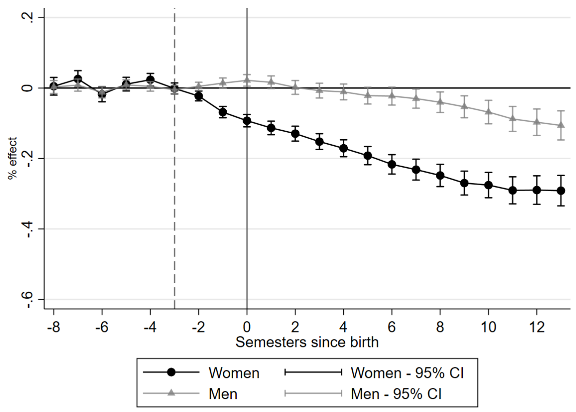
Figure A.19: Employment rate



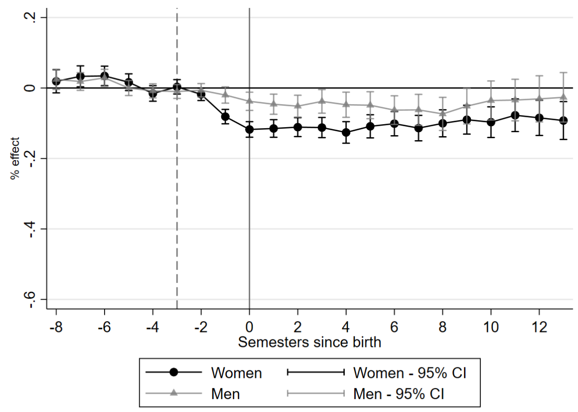
The figure shows event-study dynamic relative effects (in percentages) on employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but controlling for age with a simpler quadratic specification. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and 0 otherwise. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.20: Employment rate – local and non-local

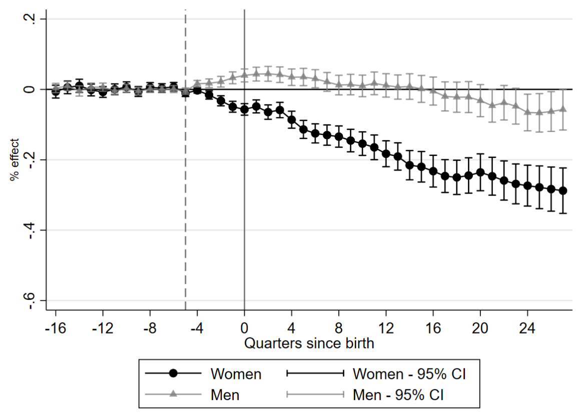
(a) Non-local employment



(b) Local employment



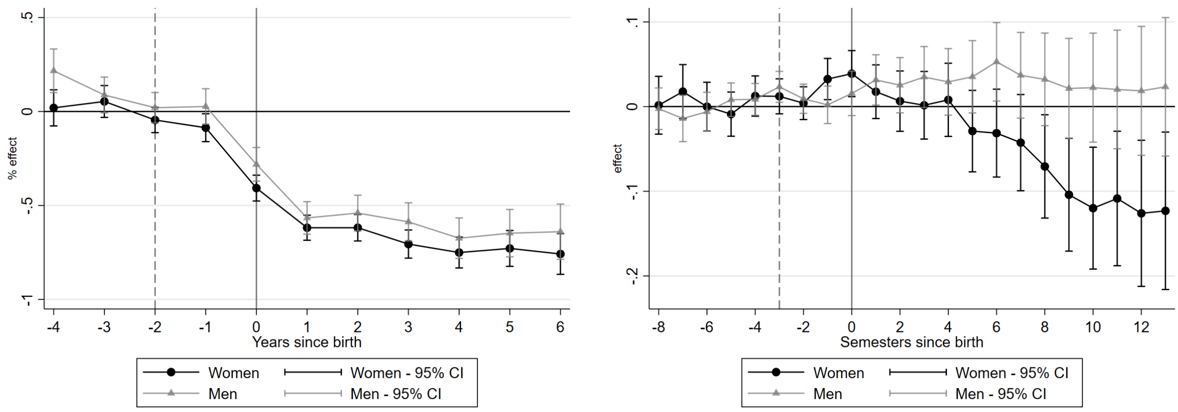
(c) Cross-border employment



The figure shows event-study dynamic relative effects (in percentages) on local, non-local and cross-border employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but controlling for age with a simpler quadratic specification. In panels A–C, we use as dependent variable a dummy that takes a value of 1 if the individual holds a local, non-local and cross-border job, respectively, and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.21: Residential and commuting decisions

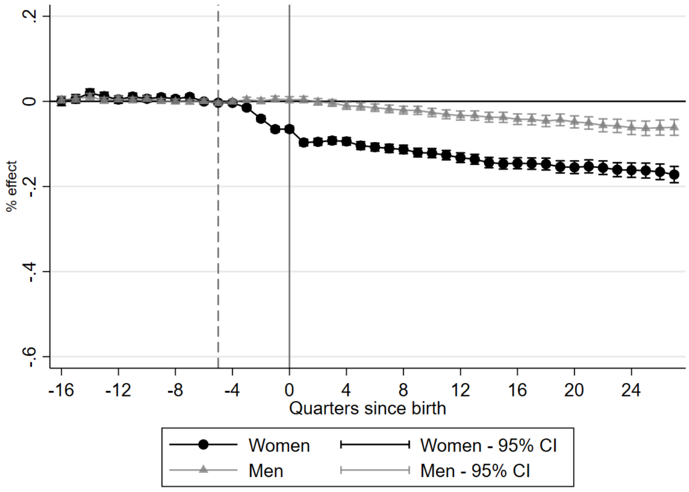
(a) Changing place of residence (NUTS3) (b) Commuting time



The figure shows event-study dynamic relative effects (in percentages) on residential mobility and commuting time over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but controlling for age with a simpler quadratic specification. In panels A and B, we use as dependent variable the probability of individuals moving to a different NUTS-3 region and the logarithm of the time that individuals spend commuting, respectively. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

A.9 Controlling for previous job characteristics

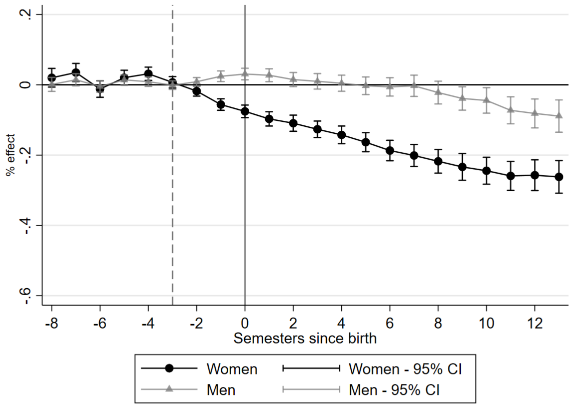
Figure A.22: Employment rate



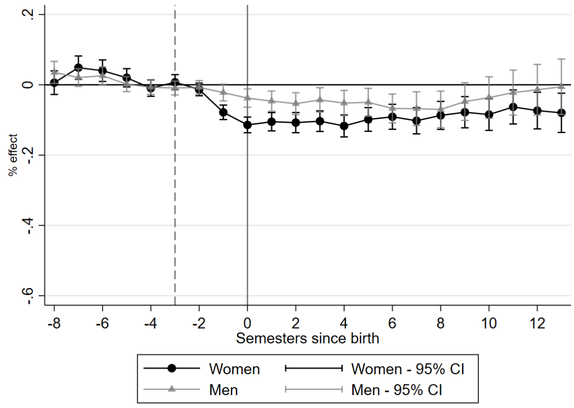
The figure shows event-study dynamic relative effects (in percentages) on employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but also controlling for other pre-treatment covariates such as the district of residence, labour characteristics of the previous job such as whether it was a white- or blue-collar job, whether it was public or private, as well as the salary and working hours. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and 0 otherwise. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.23: Employment rate - local and non-local

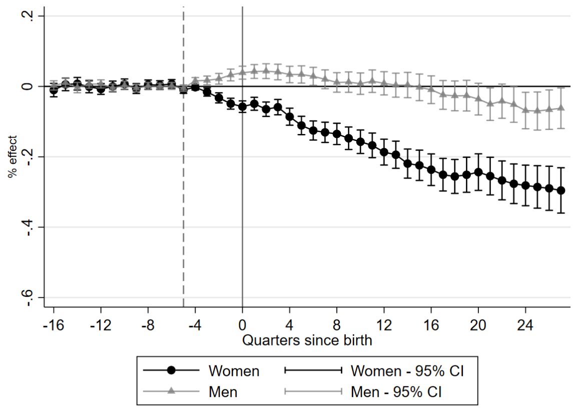
(a) Non-local employment



(b) Local employment



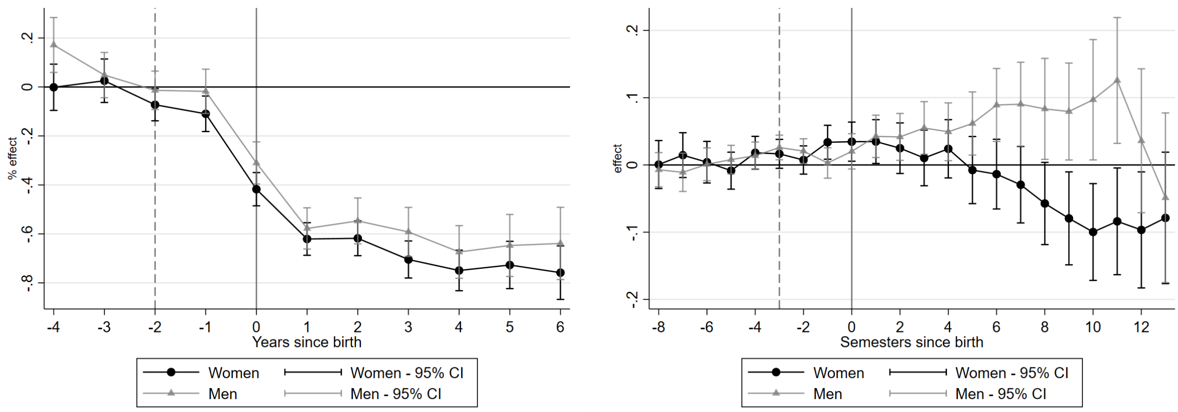
(c) Cross-border employment



The figure shows event-study dynamic relative effects (in percentages) on local, non-local and cross-border employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but also controlling for other pre-treatment covariates such as the district of residence, labour characteristics of the previous job such as whether it was a white- or blue-collar job, whether it was public or private, as well as the salary and working hours. In panels A–C, we use as dependent variable a dummy that takes a value of 1 if the individual holds a local, non-local and cross-border job, respectively, and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.24: Residential and commuting decisions

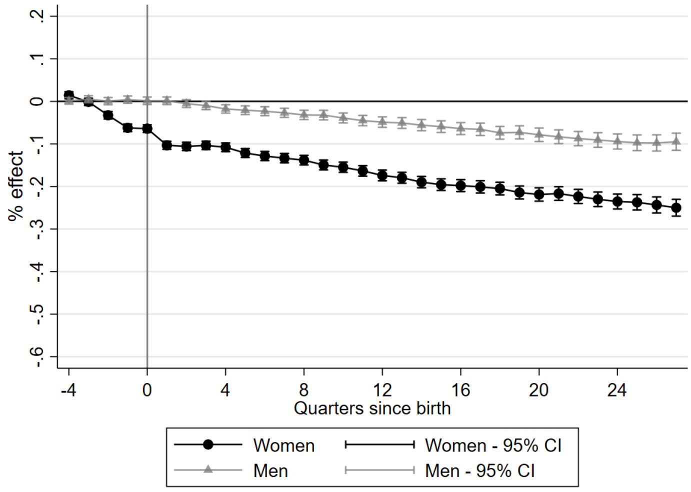
(a) Changing place of residence (NUTS3) (b) Commuting time



The figure shows event-study dynamic relative effects (in percentages) on residential mobility and commuting time over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4, but also controlling for other pre-treatment covariates such as the district of residence, labour characteristics of the previous job such as whether it was a white- or blue-collar job, whether it was public or private, as well as the salary and working hours. In panels A and B, we use as dependent variable the probability of individuals moving to a different NUTS-3 region and the logarithm of the time that individuals spend commuting, respectively. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

A.10 Extended two-way fixed effects event study

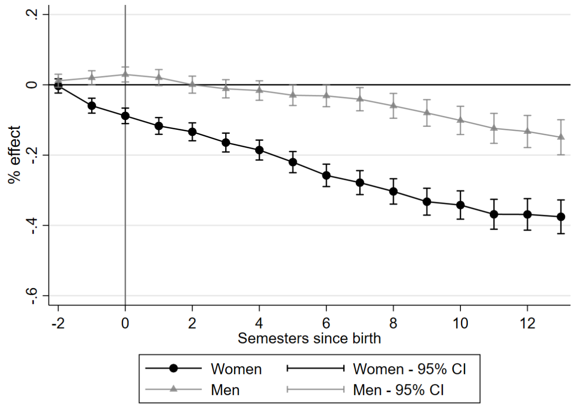
Figure A.25: Employment rate



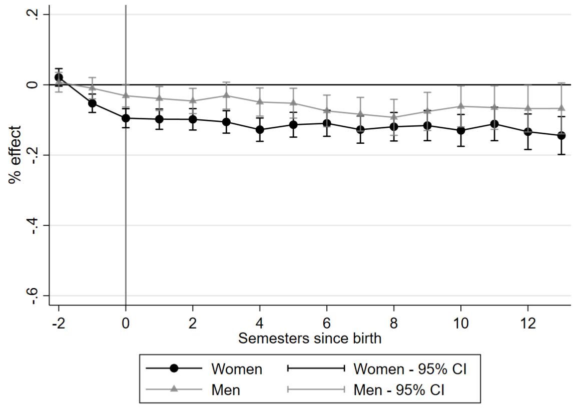
The figure shows event-study dynamic relative effects (in percentages) on employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the extended two-way (Mundlak) fixed effects approach recently proposed by Wooldridge (2021), which is also robust to treatment effect heterogeneity. The entire pre-treatment period is used as a baseline to simplify the interactive model and enhance precision. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and 0 otherwise. We present 95% confidence intervals, which are clustered at the individual level.

Figure A.26: Employment rate — local vs non-local

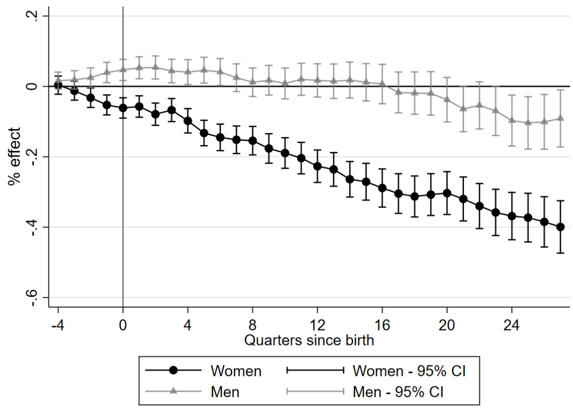
(a) Non-local employment



(b) Local employment



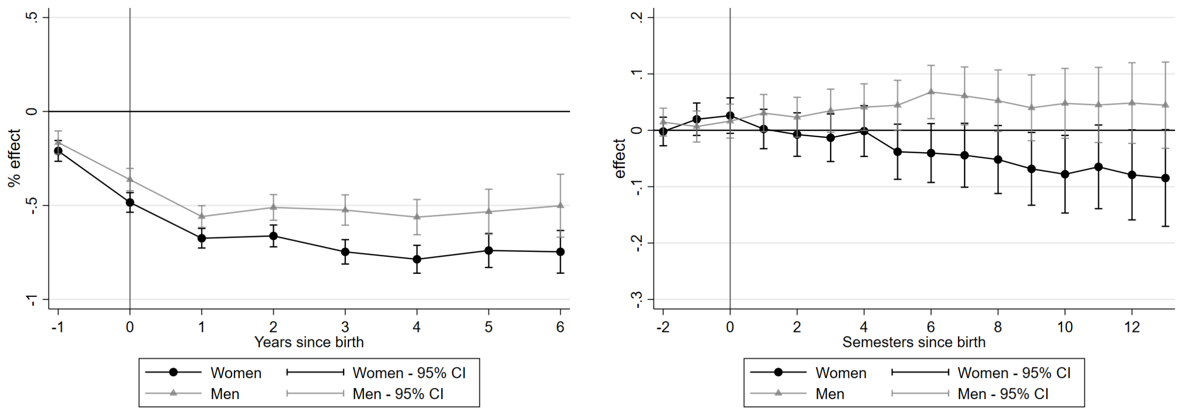
(c) Cross-border employment



The figure shows event-study dynamic relative effects (in percentages) on local, non-local and cross-border employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the extended two-way (Mundlak) fixed effects approach recently proposed by Wooldridge (2021), which is also robust to treatment effect heterogeneity. The entire pre-treatment period is used as a baseline to simplify the interactive model and enhance precision. In panels A—C, we use as dependent variable a dummy that takes a value of 1 if the individual holds a local, non-local and cross-border job, respectively, and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which are clustered at the individual level.

Figure A.27: Mobility

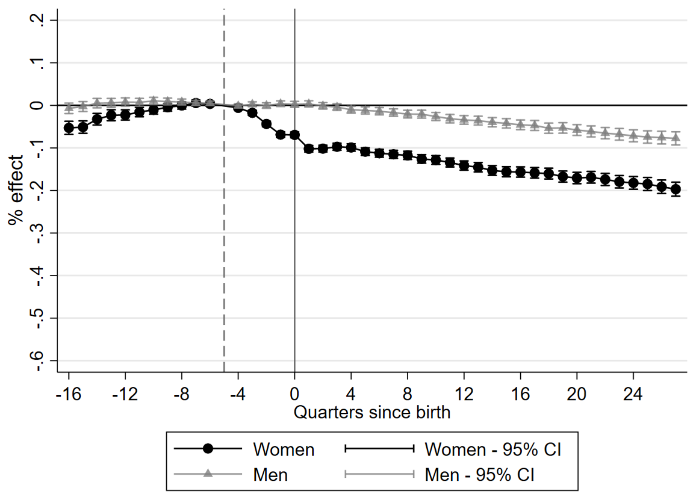
(a) Changing place of residence (NUTS-3) (b) Commuting time



The figure shows event-study dynamic relative effects (in percentages) on residential mobility and commuting time over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the extended two-way (Mundlak) fixed effects approach recently proposed by Wooldridge (2021), which is also robust to treatment effect heterogeneity. The entire pre-treatment period is used as a baseline to simplify the interactive model and enhance precision. In panels A and B, we use as dependent variable the probability of individuals moving to a different NUTS-3 region and the logarithm of the time that individuals spend commuting, respectively. We present 95% confidence intervals, which are clustered at the individual level.

A.11 Standard two-way fixed effects event study

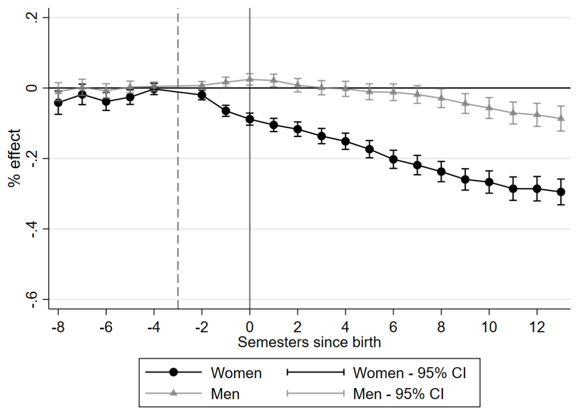
Figure A.28: Employment rate



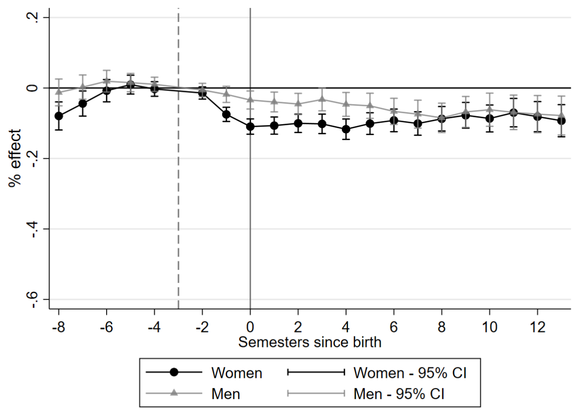
The figure shows event-study dynamic relative effects (in percentages) on employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the classical event-study estimator after accounting for age and calendar-quarter dummies as well as individual fixed effects. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and 0 otherwise. We present 95% confidence intervals, which are clustered at the individual level.

Figure A.29: Employment rate - local vs non-local

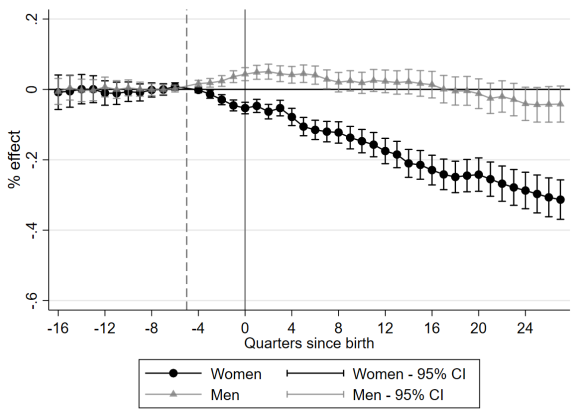
(a) Non-local employment



(b) Local employment



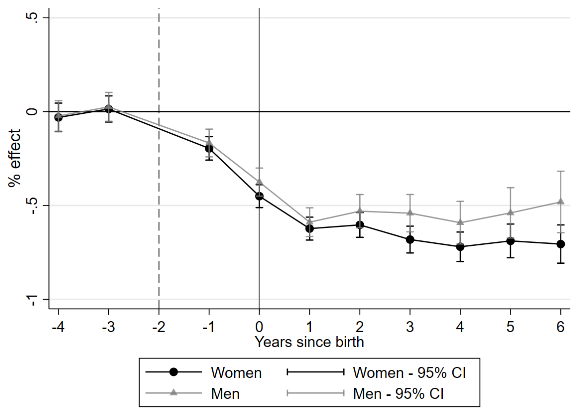
(c) Cross-border employment



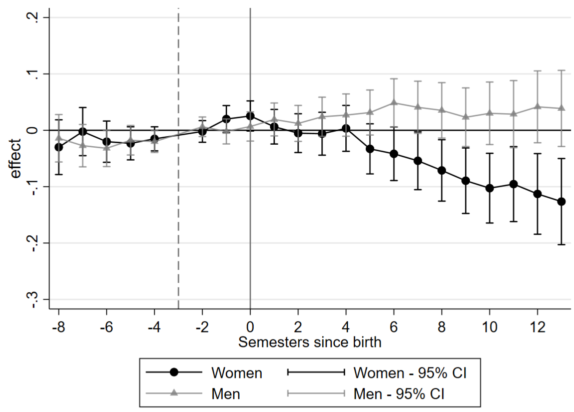
The figure shows event-study dynamic relative effects (in percentages) on local, non-local and cross-border employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the classical event-study estimator after accounting for age and calendar-quarter dummies as well as individual fixed effects. In panels A–C, we use as dependent variable a dummy that takes a value of 1 if the individual holds a local, non-local and cross-border job, respectively, and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which are clustered at the individual level.

Figure A.30: Mobility

(a) Changing place of residence (NUTS3)



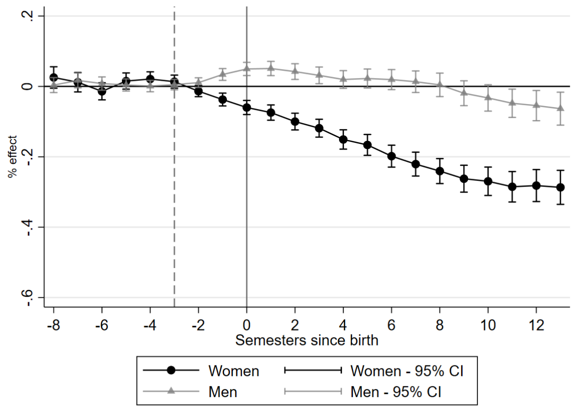
(b) Commuting time



The figure shows event-study dynamic relative effects (in percentages) on residential mobility and commuting time over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the classical event-study estimator after accounting for age and calendar-quarter dummies as well as individual fixed effects. In panels A and B, we use as dependent variable the probability of individuals moving to a different NUTS-3 region and the logarithm of the time that individuals spend commuting, respectively. We present 95% confidence intervals, which are clustered at the individual level.

A.12 Alternative definition of non-local employment

Figure A.31: Cross-border jobs as non-local high-paid jobs



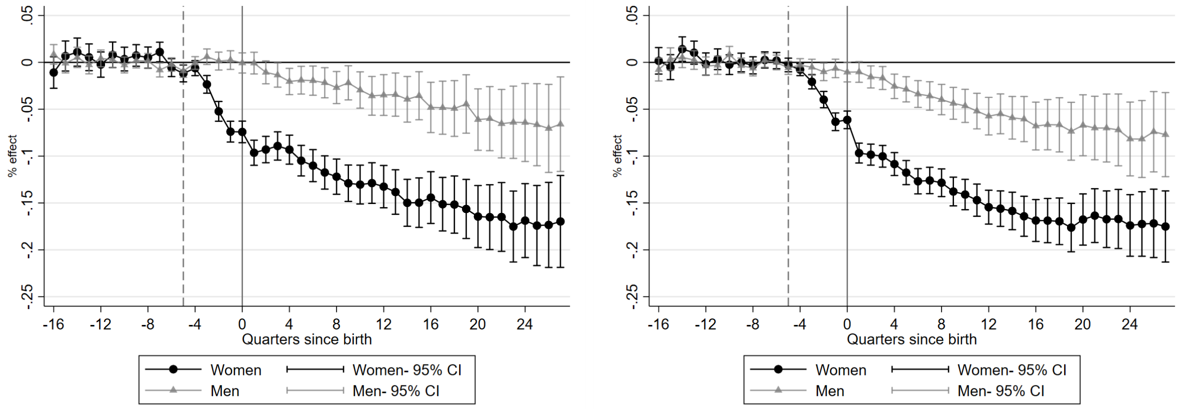
The figure shows event-study dynamic relative effects (in percentages) on non-local high-paid employment over elapsed duration from the birth of a first child, separately for women and men. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We use as dependent variable a dummy that takes a value of 1 if the individual holds a non-local high-paid job and 0 otherwise. We define jobs as non-local when individuals work in a different NUTS-3 region (i.e. district) than the one of residence. We define a job as high-paid if an individual's daily wage is above the gender-specific median 5 quarters before the birth (109.6 and 114.4 euros for women and men, respectively, in 2014 prices). Contrary to the baseline results, we assume that cross-border workers are high-paid non-local workers. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

A.13 Partner's labour status

Figure A.32: Employment rate

(a) Non-active

(b) Active

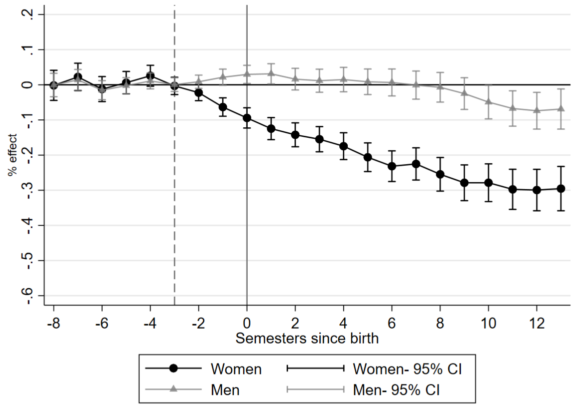


The figure shows event-study dynamic relative effects (in percentages) on total employment over elapsed duration from the birth of a first child, separately for women and men. We also split the sample of men and women into two groups according to the partner's labour status during the baseline treated period. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and 0 otherwise. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

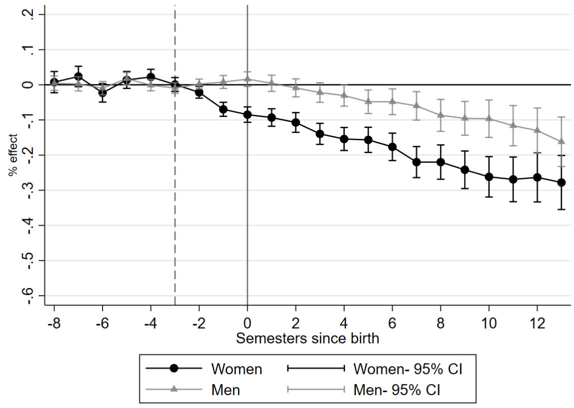
A.14 Local labour market conditions - sensitivity

Figure A.33: Local labour market conditions - median

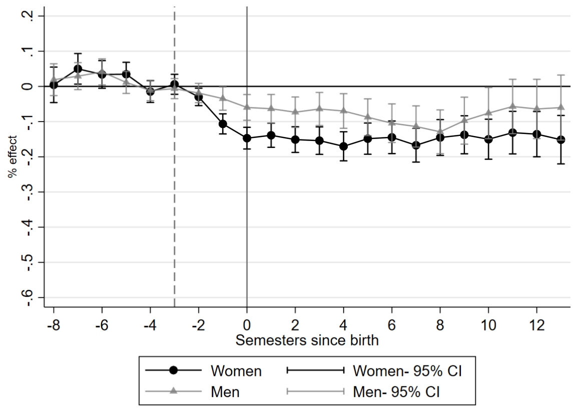
(a) Non-local employment: High unemployment



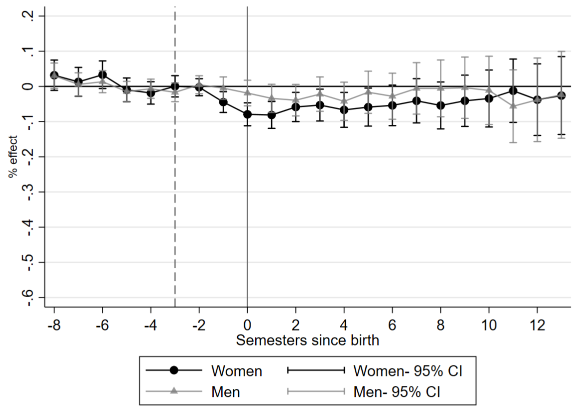
(b) Non-local employment: Low unemployment



(c) Local employment: High unemployment



(d) Local employment: Low unemployment

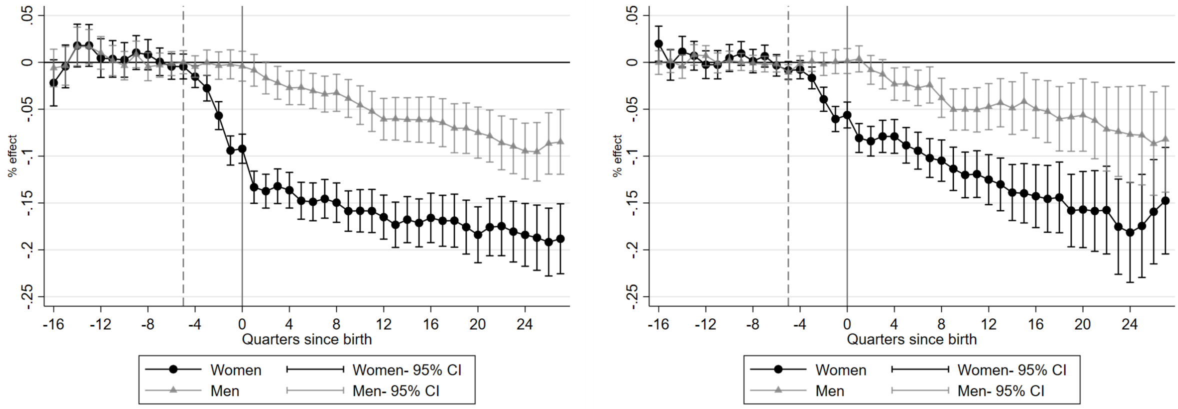


The figure shows event-study dynamic relative effects (in percentages) on local and non-local employment over elapsed duration from the birth of a first child, separately for women and men. We also split the sample of men and women into two groups according to whether they lived in high- or low-unemployment districts during the baseline pre-treated period. We define as high-unemployment districts (respectively, low-unemployment districts) those with a share of long-term unemployed above (below) the median. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. In panels A and B (C and D), we use as dependent variable a dummy that takes a value of 1 if the individual holds a local (non-local) job and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

A.15 Local labour market conditions

Figure A.34: Employment rate

(a) High unemployment (b) Low unemployment

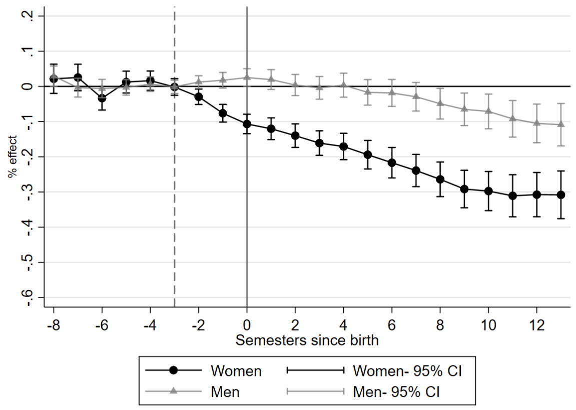


The figure shows event-study dynamic relative effects (in percentages) over elapsed duration from the birth of a first child on total employment, separately for women and men. We also split the sample of men and women into two groups according to whether they lived in high- or low-unemployment districts during the baseline pre-treated period. We define as high-unemployment districts (respectively, low-unemployment districts) those with a share of long-term unemployed above (below) the third (first) quartile. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. We use as dependent variable a dummy that takes a value of 1 if the individual is employed and 0 otherwise. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

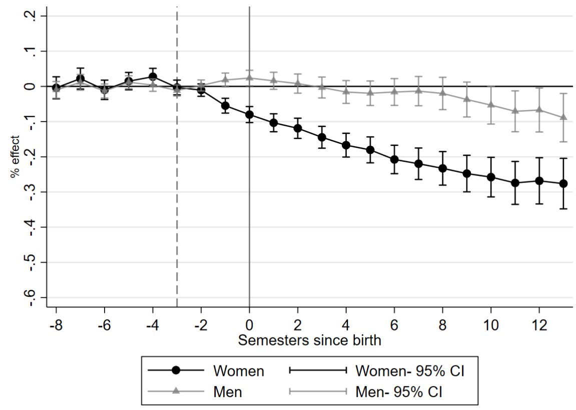
A.16 Childcare and public transport availability

Figure A.35: Local childcare availability

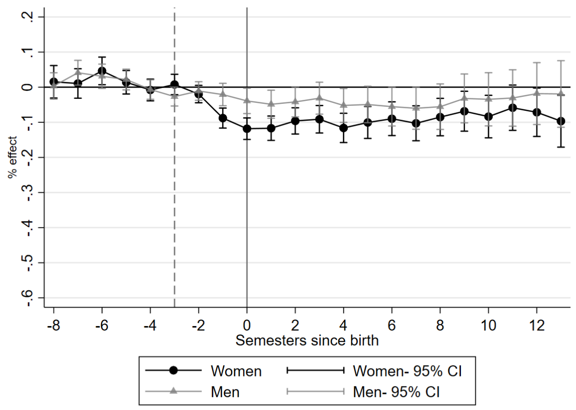
(a) Non-local employment: Low availability of childcare



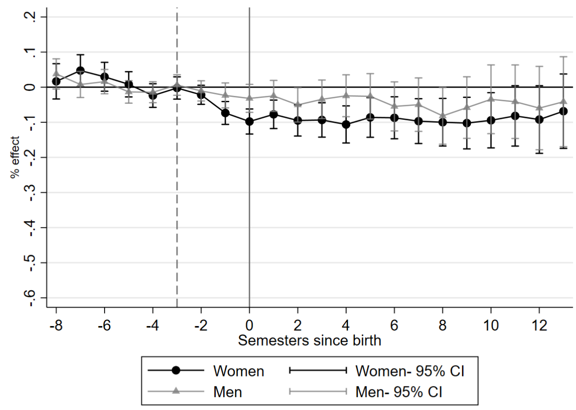
(b) Non-local employment: High availability of childcare



(c) Local employment: Low availability of childcare



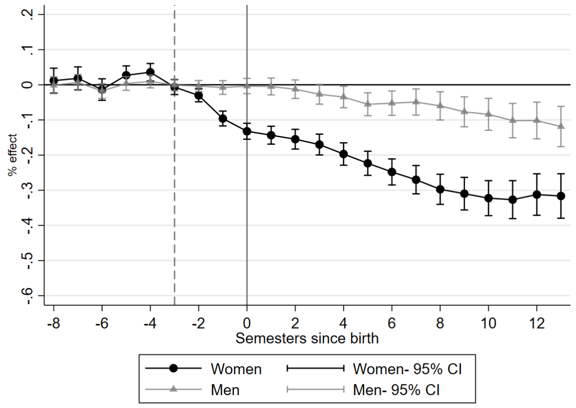
(d) Local employment: High availability of childcare



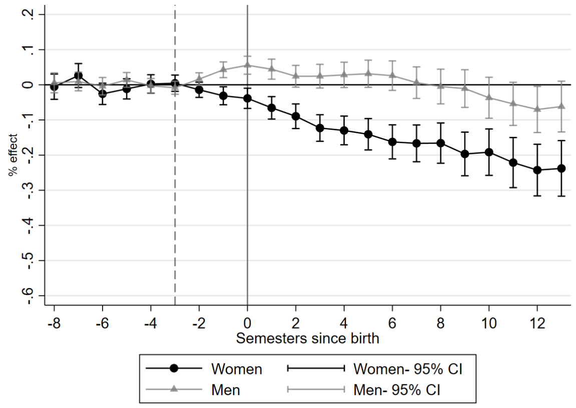
The figure shows event-study dynamic relative effects (in percentages) on local and non-local employment over elapsed duration from the birth of a first child, separately for women and men. We also split the sample of men and women into two groups according to whether they lived in districts with high or low childcare availability during the baseline pre-treated period. We define childcare availability in a district as the number of childcare places available for children between 0 and 2.5 years old divided by the number of children of the same age living in the area (Iweps, 2022). We classify districts into high and low childcare availability districts depending on whether childcare availability is above or below the median. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. In panels A and B (C and D), we use as dependent variable a dummy that takes a value of 1 if the individual holds a local (non-local) job and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.

Figure A.36: Public transport availability

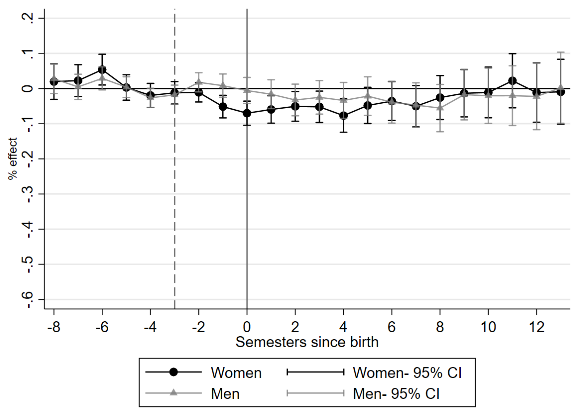
(a) Non-local employment: Low availability of pub. transport



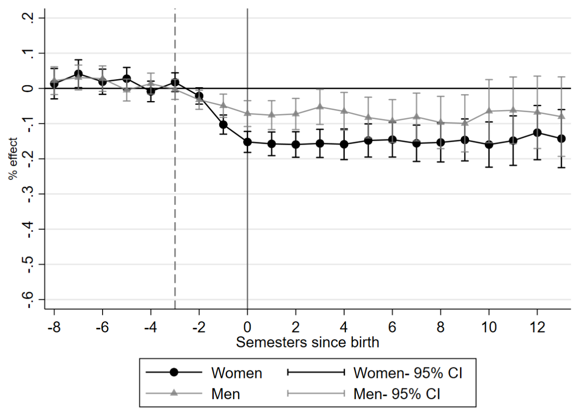
(b) Non-local employment: High availability of pub. transport



(c) Local employment: Low availability of pub. transport



(d) Local employment: High availability of pub. transport



The figure shows event-study dynamic relative effects (in percentages) on local and non-local employment over elapsed duration from the birth of a first child, separately for women and men. We also split the sample of men and women into two groups according to whether they lived in districts with high or low public transport availability during the baseline pre-treated period. We define public transport availability in a district as an index from 1 to 5 according to how easy it is for individuals living in an area to use public transport (SPF mobilité et transports, 2019). We classify districts as high and low public transport availability districts depending on whether public transport availability is above or below the median. The estimates are obtained by implementing the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), as explained in Section 4. In panels A and B (C and D), we use as dependent variable a dummy that takes a value of 1 if the individual holds a local (non-local) job and 0 otherwise. We define jobs as local when individuals work and live in the same district (i.e. NUTS-3 region) and as non-local when they work in a district different to the one of residence. We present 95% confidence intervals, which we obtain using a multiplier-type bootstrap procedure clustered at the individual level.