A Baby is Born: the Impact of Childbirth on Italian Households

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Abstract

Childbirth engenders significant changes in labor market outcomes, household expenditures, and financial dynamics within a family. The arrival of a child reallocates parents' time between work and childcare, alters familial roles, and amplifies demand for child-specific goods. Meanwhile, parents face the challenge of adjusting discretionary spending when labor income remains constant or decreases. To investigate these dynamics, I use data from the Survey of Household Income and Wealth (SHIW) conducted by the Bank of Italy, and leverage the matching procedure of Kleven (2022) to build pseudo-panels of parents and households. Through this analysis, I explore the impact of childbirth on parents' labor market outcomes in Italy and examine how household consumption, savings, and assets adapt to this transformative event. The findings highlight disparities in labor market outcomes between mothers and fathers following childbirth and reveal potential inadequacies in financial preparedness, reflected by a decline in per-capita consumption post-childbirth.

1 Introduction

The event of childbirth engenders significant changes in labor market outcomes, household expenditures, and financial dynamics within a family. On one hand, the arrival of a child triggers alterations in parents' labor market outcomes, necessitating a redistribution of time between employment and childcare responsibilities, as well as adjustments in familial roles. On the other hand, the presence of a child amplifies household expenditures, stimulating the demand for child-specific goods. Consequently, given constant or diminished levels of income, parents are compelled to adapt their discretionary spending across various household items. This adjustment becomes particularly critical when parents fail to exhibit foresight in portfolio management (such as savings) or were unable to anticipate or insure against the array of shocks associated with childbirth.

The impact of childbirth on parents' labor market outcomes has been extensively studied, revealing an asymmetric effect between mothers and fathers. Women tend to reduce their labor supply and the intensity of hours worked following childbirth, while men's labor market trajectories remain relatively unaffected. This disparity in the parenthood effect has been named by the current literature 'child-penalty'[1] and, as education and human capital gender gaps have shown evidence of convergence over time, it is believed to account for the residual unexplained gender gap observed in the data (see Goldin (2014) for a discussion on these trends).

A natural consequence of the negative impact of childbirth on the labor market outcomes of mothers, and the null effect on those of fathers, is a reduction in total household labor income.

In this paper, I investigate two interconnected aspects within the Italian context. Firstly, I estimate the child penalty in the country by analyzing both the intensive margin (earnings) and extensive margin (employment) of labor supply, thereby assessing the magnitude of this effect. Secondly, I focus on the household-level implications of childbirth, specifically examining how household financial outcomes, including consumption, savings, and real and financial assets, respond to this special event. To accomplish this, I use repeated cross-section data from the comprehensive Survey of Household Income and Wealth (SHIW) provided by the Bank of Italy. Given the unavailability of administrative and panel data, I employ the innovative pseudo-panel methodology developed by Kleven (2022) to construct a

[1] Large child penalties have been found in Austria, Germany and the UK Kleven et al. (2019), Denmark Kleven et al. (2019), U.S. Kleven (2022), Sweden Angelov et al. (2016) and Norway Andresen and Nix (2022), among others.

pseudo-panel of mothers, fathers, and households to carry out the analysis.

I find that in Italy women experience an immediate and sizable decline in earnings and employment of approximately 28% and 23%, respectively, following childbirth, whereas men's labor market outcomes remain unaffected by this event. The initial drop in women's labor market outcomes is persistent and tends to amplify over time, reaching an estimated magnitude of 40%, possible due to the cumulative effect of additional children. Conducting a heterogeneity analysis, I identify variations in the child penalty across different subgroups. Specifically, self-employed women experience a more pronounced child penalty compared to their employee counterparts, while the child penalty is more substantial for women with lower educational attainment compared to those with higher levels of education. However, no statistically significant heterogeneity is observed based on the area of residence.

Regarding the dynamics of household finance outcomes surrounding childbirth, my analysis reveals several noteworthy patterns that had thus far not been examined with a reduced-form approach. Firstly, total consumption remains relatively stable both before and after the event. However, a closer examination indicates a decrease in durable consumption alongside an increase in non-durable and food expenditure. Secondly, in terms of portfolio behavior, households exhibit a tendency to draw on their financial assets through dissaving following childbirth. Additionally, there is evidence of a portfolio reallocation from riskier assets to safer ones. Nevertheless, from a welfare perspective, a reduction in per-capita consumption is observed, indicating that parents encounter challenges in maintaining the same standard of living before and after childbirth. These findings suggest that households may not have fully anticipated the income shock resulting from the child penalty or lacked foresight regarding the comprehensive range of changes associated with childbirth and their respective timing.

This paper contributes to the extensive literature on gender inequality in the labor market, with particular emphasis on the wage gap and the impact of motherhood (Waldfogel (1998); Anderson et al. (2002); Ejrnæs and Kunze (2013)).[2] This study is closely aligned with the recent child penalty literature, as evidenced by the works of Angelov et al. (2016), Kleven et al. (2019), and Kim and Moser (2021). Furthermore, it builds upon the methodology proposed by Kleven (2022) for constructing a pseudo-panel, which is employed for the first time in the context of the SHIW. The empirical strategy adopted in this study draws

[2]A comprehensive review of the literature on gender inequality in the labor market can be found in Olivetti and Petrongolo (2016), Bertrand (2020), and Goldin (2014).

inspiration from the event-study specification employed in the related literature. As a novel contribution, this paper is the first to provide evidence on the child penalty in Italy using repeated cross-sectional data from the SHIW.

Leveraging a matched employer-employee panel dataset spanning 1985-2018 and covering 7% of non-agricultural private sector workers in Italy, Casarico and Lattanzio (2023) provide valuable insights into the child penalty phenomenon. They estimate a child penalty of 52 log points, primarily driven by a decrease in weeks worked, and examine the role of firm sorting as an adjustment mechanism for mothers. However, their analysis is limited to employed women during pregnancy, using maternity leave as a proxy for childbirth, with non-mothers as the control group. In contrast, this study takes a broader approach by using the SHIW to estimate the child penalty for the entire working-age population, irrespective of employment status at childbirth. Additionally, by including fathers as the control group, a more comprehensive understanding of the child penalty in Italy is achieved. Furthermore, the unique SHIW dataset allows for the estimation of the child penalty for both employees and self-employed individuals, a dimension previously unexplored using the employer-employee dataset.

In the field of family economics, a significant body of literature (see Browning et al. (2011) for a comprehensive review) delves into the analysis of intra-household labor supply, consumption, and savings decisions in the context of fertility. Empirical studies have explored the economic behavior of households in response to the presence of children (Browning (1992); Souleles (2000); Browning and Ejrnaes (2009); Blundell et al. (2018)), as well as the ability of households to cope with wage shocks through labor supply adjustments and savings (Blundell et al. (2016)). Theoretical contributions, on the other hand, have developed life-cycle models to elucidate households' financial decision-making over time (Modigliani and Brumberg (1954); Friedman (1957); Nagatani (1972); Carroll (2001); Browning and Crossley (2001)). In the field of household finance literature, a branch of research has focused on disentangling anticipated from unanticipated income shocks by examining households' responses to changes in income (Pistaferri (2001); Kaufmann and Pistaferri (2009); Jappelli and Pistaferri (2010)), which, in the context of this study, correspond to the decrease in household labor income resulting from the child penalty.[3] This paper contributes to this literature by introducing an event-study analysis that examines

[3] Kuziemko et al. (2018) find evidence that mothers tend to underestimate the labor market costs associated with motherhood, suggesting that households may not fully anticipate the child penalty and may therefore be financially unprepared for the event of childbirth. This hypothesis will be explored in the empirical analysis of household finance outcomes presented in this study.

the effects of childbirth on household finance dynamics. To the best of my knowledge, this is the first application of the event-study approach to study the changes in household finance outcomes surrounding childbirth. This approach allows for a detailed examination of households' responses to the income and expenditure changes induced by childbirth, capturing the precise impact at each point in time. Additionally, I extend the methodology developed by Kleven (2022) to make it suitable for household-level data, demonstrating its validity through a comprehensive analysis of a combined pseudo-panel of mothers and fathers. The applicability of this methodology to survey data from other countries holds promising prospects for future research.

The paper is structured as follows. Section 2 provides descriptive facts on gender gaps, maternity leave, and childcare services in Italy. It also outlines the data and matching procedure for constructing pseudo-panels of mothers, fathers, and households. Section 3 examines the child penalty in labor market outcomes in Italy, employing an event-study framework. Section 4 investigates the dynamics of household finance outcomes before and after childbirth, presenting event-study results and relating them to existing literature. Robustness checks for household finance outcomes are discussed in Section 5. Finally, Section 6 concludes.

2 Institutional Background and Data

2.1 Institutional Background

Italy's labor market exhibits a persistent gender gap, aligning with the trends observed in many other OECD countries. However, Italy stands out with one of the highest gender gaps in Europe and a comparatively sluggish progress in gender convergence within the work domain.[4] Data sourced from the OECD Gender Data portal[5] allows to compare gender gaps in the labor market from 1990 to 2020 for Italy, Spain, and the U.S., among many. Notably, Italy's employment rate gap has narrowed from 33% in 1990 to 16.8% in 2021, demonstrating a lower reduction compared to Spain (36% to 10.5%) and a more significant decline compared to the U.S. (17.7 % to 10.7%) over the same period.

Similarly, Italy has witnessed a process of gender convergence in labor market participation rates and a declining trend in the gender earnings gap (refer to Figure B1 in the

[4]According to the Gender Equality Index computed by the European Institute for Gender Equality (2020), Italy scores 63.5 out of 100 (100=perfect gender equality). In the domain of work, Italy has the lowest score (63.3).

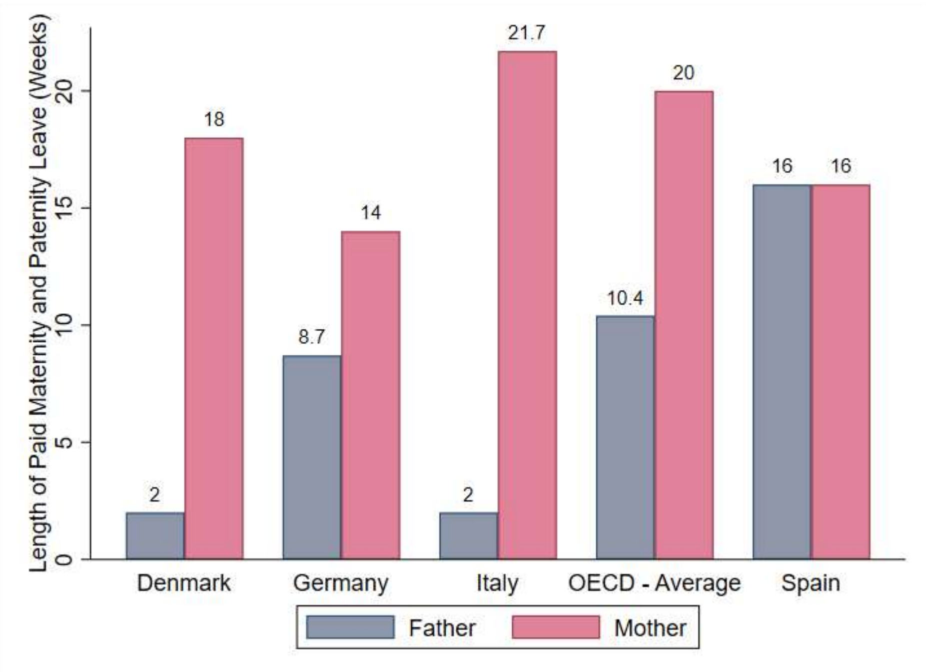
[5]OECD Gender Data Portal.

Appendix). As of 2021, the gender gap in labor force participation in Italy stood at 17.5%, while the gender earnings gap in 2020 was 7.8%. In comparison to the United States and Spain, Italy experienced a decrease of 13.6 percentage points in the labor force participation gap from 1990 to 2021, which is greater than the reduction observed in the United States (i.e. a decrease of 7.4 percentage points from 18.9 %. in 1990 to 11.5 % in 2021) and smaller than the decline in Spain (i.e. a decrease of 25.8 percentage points from 35.7 % in 1990 to 9.9 % in 2021).

In terms of parental leave policies, Italy stands out with a longer-than-average duration of maternity leave compared to OECD countries. However, there is a substantial disparity between the rates of paternity leave uptake ('daddy quotas') and maternity leave uptake, with the former being significantly lower (refer to Figure 1).

In terms of socio-educational services for early childhood day-care, Italy falls short of the necessary capacity to achieve universal childcare coverage. In 2019, the ratio of available childcare positions per 100 children aged 0-2 years old was 27.1, exhibiting regional variations across Italy: 32.8 in the North, 35.7 in the Centre, and 14.6 and 15.9 in the South and Islands, respectively[6].

Figure 1: Length of paid maternity/paternity leave, by gender and country



Notes: Elaboration using the *Length of maternity, parental and home care leave, and paid father-specific leave* dataset of the OECD Gender Data Portal.

[6]Data sourced from the Survey on early childhood education and care services conducted by ISTAT (2019).

2.2 Data

The dataset used in this study is the historical database of the Survey of Household Income and Wealth (SHIW) conducted by the Bank of Italy. The SHIW Historical Database (HD) encompasses data collected from 1977 to 2020. The survey is conducted bi-annually, and approximately 8,000 households are interviewed in each wave. The survey collects detailed information, including individual characteristics, occupational status, various sources of income (such as payroll and self-employment income, pensions, transfers, and property income) for all household members, household expenditure on durable and non-durable goods, properties owned or inhabited by the household, household financial assets and liabilities, sampling weights, and a deflator for monetary aggregates.[7]

2.3 Pseudo-Panel of Mothers and Fathers

To construct a pseudo-panel using repeated cross-sectional data, I employ the methodology developed by Kleven (2022). This approach involves assigning negative event-times to individuals without children in the cross-section through a matching procedure. In this context, event-time e refers to time indexed relative to first childbirth, so that $e = 0$ is assigned to all individuals in the cross-section interviewed in the year their first child was born, and $e = 3$ to those interviewed when their first child was 3 y.o. etc. For each household, I observe whether there are children and how old they are, and I am thus able to assign positive event-times $e \geq 0$. However, I do not observe whether non-parents in the cross-section will eventually become parents and, if so, when they will. To address this issue, I match individuals with event-time $e = 0$ to childless individuals in the cross-section, creating pseudo negative event-time observations. Namely, for each individual observed at event-time $e = 0$, I create n negative event-times by matching individual i of age a in year y with covariates X_i to childless individual(s) j observed in year(s) $y - n$, with corresponding age $a - n$ and time-invariant covariates $X_j = X_i$. The covariates X_i include gender, education[8], and region of residence. I only include in the donor pool individuals who identify themselves as either the head of the household or the spouse/partner of the head of the household. This avoids matching units with individuals who still live with their parents, which could lead to misinterpretation of the labor market/household finance outcomes over time. Whenever a unit is matched to multiple units, all units are retained,

[7]See SHIW Documentation for the microdata.

[8]Education is split into the categories: low (none, elementary, middle); medium (high school); and high (bachelor and postgrad).

and each one is weighted by the inverse of the cell size c (i.e. by $\frac{1}{c}$). Matching is done with replacement.

The rationale behind this approach is that by using covariates X_i, we can account for the factors influencing the selection into parenthood and assign negative event-times to childless individuals in the cross-section. This ensures that the matched individuals closely resemble the characteristics of those who will eventually become parents. Considering the prevalent bi-annual frequency of the surveys, I selected a range of n values between 1 and 6, allowing for matching up to 6 years preceding childbirth.

For positive event-times, I keep all parents whose total number of children range from 1 to at most 4. To ensure that the sample does not include very young parents, I restrict the selection to mothers in the age range $a \in [25; 45]$, and fathers in the age range $a \in [25; 50]$. Indeed, the median age at first childbirth is 30 for men and 27 for women[9], so that educational decisions are typically made and finalized by 6 years before childbirth. After completing the matching process, I retain only those individuals from the initial pool with an observation in negative event-time. In other words, I include individuals who have at least one match with a childless individual(s) in negative event-time.

In order to address the issue of small sample sizes in certain negative event-times, I employ a binning strategy where event-times are grouped into two-year bins. This approach serves to increase the statistical power of the analysis. Consequently, each event-time unit used in the empirical strategy represents a two-year bin (e.g. the first event-time after childbirth is denoted as $[0; 1]$, encompassing individuals observed in the year of first childbirth and the subsequent year; followed by event-time $[2; 3]$, which includes individuals with firstborns aged 2 and 3, and so forth). The choice to bin each event-time into two-calendar-year bins was also motivated by the alignment with the design of the SHIW survey which, as mentioned earlier in this section, is conducted once every two years, with some exceptions.[10]

2.4 Pseudo-Panel of Households

I expand upon the methodology proposed by Kleven (2022) and adapt it to household-level data. This enables the creation of a pseudo-panel consisting of household-year pairs, which serves as the basis for my analysis in Section 4, where I examine the impact of child-

[9]The median age at first childbirth is 30 for men and 27 for women in the SHIW sample, and 31 for men and 29 for women in the pseudo-panel sample (see Table 1 and 2).

[10]Notably, the survey was conducted annually during the period 1977-1984, as well as in the years 1986 and 1987.

birth on various household finance outcomes, including overall consumption, savings, and assets.

The household matching procedure follows a similar approach to that used for individuals. Specifically, for each household observed at event-time 0, I create n negative event-times by matching household h at year y when the wife/female partner is of age a with household(s) without children observed n years earlier, where the wife/female partner is exactly $a-n$ years old.[11] Furthermore, I ensure that the matched households have the same education levels for both the wife and husband as the mother and father at $e=0$, as well as the same region of residence. To maintain a focus on stable couple families and ensure comparability, the donor pool consists of households without children, namely couples without children, while the treated sample includes households with children, namely couples with children. In cases where a unit is matched to multiple units, I retain all the units and assign a weight of $\frac{1}{c}$ to each, where c represents the cell size. Matching is done with replacement.

As in the case of the pseudo-panel of mothers and fathers, I grouped the event-times into two-year bins. Lastly, I retained only those households observed at event $e=0$ that had at least one corresponding match in the negative event-time period.

3 Labor Market Outcomes

In this section, I address the first research question concerning the child penalty in labor market outcomes in Italy. The analysis begins by presenting descriptive statistics for both the raw data sourced from the SHIW HD and the constructed pseudo-panel. These statistics serve as a foundation for understanding the patterns and trends observed in the subsequent analysis. Successively, the empirical strategy utilized is outlined, followed by the presentation of the main findings derived from the analysis.

3.1 Descriptive Statistics

Table 1 provides the mean values for various demographic and labor market variables comparing mothers to non-mothers, and fathers to non-fathers in the SHIW (raw) sample, i.e. the sample taken from the SHIW HD and on which the matching procedure described in Section 2 will be applied. The descriptive statistics reveal several interesting patterns. Among women, those with children tend to be younger, have a higher prevalence in the

[11] Following Browning and Ejrnaes (2009), I match only on the age of the mother as it is the one most relevant for fertility decisions and their timing. For a robustness check, I tried the procedure by matching on the husband' age as well, but results were invariant.

southern regions of Italy, and exhibit a higher level of educational attainment compared to women without children. However, a relatively lower proportion of women with children possess a bachelor's degree or have achieved postgraduate education. In terms of labor market outcomes, the mean difference between the two groups for compensation for employees and net income from self-employment is statistically significant for the former and not statistically significant for the latter. Additionally, the differences in employment rate and total earnings are significant at the 5% level, with women with children being less likely to be employed and earning less than their childless counterparts. Turning to men, those with children are typically younger, more likely to reside in the southern regions of Italy, and have lower educational attainment compared to men without children. The labor market outcomes for fathers are consistently higher than those for non-fathers, with statistically significant differences observed across various indicators. As previous literature has highlighted, better labor market outcomes for fathers may be attributed to self-selection into parenthood rather than a causal effect of fatherhood on labor market outcomes, as in most countries the event-study approach has found no effect of parenthood on the labor market outcomes of men.[12] As expected, the data shows that both male and female parents have a higher likelihood of being married compared to non-parents.

Table 2 presents comparable statistics for men and women in the pseudo-panel. Among parents, mothers have a lower median age compared to fathers, and they tend to have their first child at a younger age as well. Furthermore, mothers generally exhibit a higher level of education compared to fathers. However, when considering labor market outcomes, mothers have a lower employment rate and earn less in comparison to fathers, conditional on working. It is worth noting that the fraction of married individuals is similar in both groups of parents.

In the Appendix, Tables A1 and A2 present the breakdown of educational attainment by gender for both the SHIW (raw) sample and the pseudo-panel, respectively. In both samples, men are over-represented across all levels of education compared to women, except for the categories of none and elementary education within the SHIW sample.

Finally, Table A3 and Table A4 present the distribution of workers by type of employment (self-employed and employee) in the SHIW (raw) sample and the pseudo-panel, respectively, disaggregated by gender. Conditional on employment, the distribution across types of employment is comparable between the two samples. Both for men and women, a larger proportion of workers are employees, while women exhibit a higher likelihood of

[12] See Kleven (2022).

being self-employed compared to men (e.g. 84% vs 75% in the SHIW sample, and 84% vs 76% in the pseudo-panel).

Table 1: Covariates Table, by parent status and gender - SHIW Sample

	Child	No Child	Difference	Standard Error
Panel A. Women				
Age (Median)	46	54	-	-
Year of birth (Median)	1958	1954	-	-
Year of birth (Median) with age first child =0	1969	-	-	-
Age First Child (Median)	27	-	-	-
Fraction South	0.35	0.26	0.09***	(0.00)
Education	3.18	3.15	0.03***	(0.01)
Fraction Bachelor's degree or higher'	0.08	0.11	-0.03***	(0.00)
Employment rate	0.42	0.45	-0.03***	0.00
Compensation for employees (YL)	13,003	13,787	-784***	(137)
Net income from self-employment (YM)	2,719	2,972	-254*	(135)
Earnings (YL + YM)	15,653	16,731	-1078***	(141)
Fraction married	0.59	0.46	0.13***	(0.00)
Panel B. Men				
Age (Median)	47	50	-	-
Year of birth (Median)	1957	1955	-	-
Year of birth (Median) with age first child=0	1966	-	-	-
Age First Child (Median)	30	-	-	
Fraction South	0.35	0.24	0.11***	(0.00)
Education	3.15	3.24	-0.09***	(0.01)
Fraction Bachelor's degree or higher'	0.09	0.11	-0.03***	(0.00)
Employment rate	0.86	0.73	0.13***	(0.00)
Compensation for employees (YL)	16,303	14,931	1,372***	(143)]
Net income from self-employment (YM)	6,754	6,025	729***	(192)
Earnings (YL + YM)	23,055	20,952	2,102***	(184)
Fraction married	0.63	0.43	0.20***	(0.01)

Notes: The table shows mean values and difference in means between mothers and non-mothers (Panel A) and fathers and non-fathers (Panel B) for the SHIW sample. I keep individuals with a total of children from 0 to 4, and in the working age range [15; 64]. Earnings are deflated at 2015€ and conditional on employment.

Table 2: Covariates Table, by gender - Pseudo-Panel

	Women	Men	Difference	Standard Error
Age (Median)	41	43	-	-
Year of birth (Median)	1956	1952	-	-
Year of birth (Median) with age first child =0	1967	1964	-	-
Age First Child (Median)	29	31	-	-
Fraction South	0.31	0.34	-0.03***	(0.00)
Education	3.56	3.30	0.26***	(0.01)
Fraction Bachelor's degree or higher'	0.14	0.11	0.03***	(0.00)
Employment rate	0.53	0.94	-0.41***	(0.00)
Compensation for employees (YL)	13,912	16,741	-2,829***	(136)
Net income from self-employment (YM)	2,639	6,366	-3,727***	(142)
Earnings (YL + YM)	16,505	23,105	-6,600***	(146)
Fraction married	0.61	0.61	-0.00	(0.00)

Notes: The table shows mean values and difference in means between women and men for the pseudo-panel sample. Earnings are deflated at 2015€ and conditional on employment.

3.2 Empirical Strategy

To identify the impact of childbirth on the labor market outcomes of interest, I follow the large literature in child penalty that employs event-studies (see Kleven et al. (2019)). Time indexed relative to first childbirth is defined as event-time, and I refer to it as e_i, where i stands for parent i. For example, given that I binned event-times, $e_i = [0, 1]$ encompasses parents observed in the cross-section during the year of or the year following the birth of their first child, and $e_i = [4, 5]$ all those parents observed in the year in which their first child is either 4 or 5 years old.

The main specification I use is the following:

$$Y_{ite}^{g} = \sum_{e \neq -1} \alpha_e^g \cdot \mathbb{1}(e_{it} = e) + \beta_{a(i)}^{g} + \gamma_t^g + \epsilon_{ite}^{g} \tag{1}$$

where g indicates that the parameters are gender-specific. Y_{ite} can be either earnings, employment, or hours worked of individual i observed in year t at event-time e. I include age $\beta_{a(i)}^{g}$ and time γ_t^g fixed-effects in order to control for life-cycle trends and business cycle trends, respectively. The event-time dummy $e_i = [-2; -1]$ is omitted, meaning that all the results are interpreted relative to the outcome one and two years prior to childbirth.

The identification assumption behind the empirical approach for labor market outcomes relies on a parallel trends assumption, which assumes that in the absence of childbirth, the labor market outcomes of both mothers and fathers would follow a parallel trajectory over time. Under the identification assumption, the coefficients $\{\alpha_e^g\}$ capture the causal impact of childbirth at event-time e and represent the main parameters of interest in our analysis.

To examine the heterogeneity of the childbirth event across different education levels and regions of residence, I will include interaction terms between the event-time dummies and each category, and allow for categorical year and time fixed effects. The modified specification is as follows:

$$Y_{ite}^g = \sum_{e \neq -1} \alpha_e^g \cdot \mathbb{1}(e_{it} = e) + \sum_{e \neq -1} \sum_{c} \theta_{ec} \cdot \mathbb{1}(e_{it} = e, C =_i c) + \beta_{ac(i)}^g + \gamma_{tc}^g + \epsilon_{ite}^g \tag{2}$$

where C is the categorical variable and c is the specific subcategory of interest. The fixed effects for time $\beta_{ac(i)}^g$ and year γ_{tc}^g are category-specific, allowing for the variation of each fixed-effect across the subcategories of interest.[13]

To interpret the results in percentage terms, I standardize the vector of $\{\alpha_e^g\}$ by dividing each estimated coefficient by the predicted outcome in the absence of childbirth, denoted as $\mathbf{E}[\tilde{Y}_{ite}^g|e]$ and computed by taking out the effect of the event-time dummies in regression (1). Specifically, the standardized coefficient P_e^g at each event-time e is computed as follows:

$$P_e^g = \frac{\hat{\alpha}_e^g}{\mathbf{E}[\tilde{Y}_{ite}^g|e]} \tag{3}$$

By applying this standardization, the coefficients can be interpreted as the percentage change in the outcome variable for gender g associated with childbirth at event-time e, with respect to the expected outcome in the absence of childbirth.

Finally, child penalties are calculated as a percentage of the counterfactual outcomes for women, following the approach of Kleven et al. (2019). Namely, the child penalty P_e at event-time e is defined as:

$$P_e = \frac{\hat{\alpha}_e^{\mathrm{m}} - \hat{\alpha}_e^{\mathrm{w}}}{\mathbf{E}[\tilde{Y}_{ite}^w|e]} \tag{4}$$

where m stands for men and w for women, and $\mathbf{E}[\tilde{Y}_{ite}^w|e]$ is the counterfactual outcome for women in the absence of childbirth. The resulting P_e value represents the differential

[13]Given that I allow for each fixed-effect to vary by subcategory of interest, specification (2) is equivalent to running separate regressions as in (1) for each subcategory.

impact of childbirth on women compared to men at event-time e, expressed as a percentage of women's counterfactual labor market outcome.

3.3 Main results

Figures 2a, 2b, 3, and 4 depict the estimated coefficients $\{P_e^g\}$ for men ($g = m$) and women ($g = w$) in relation to labor market outcomes, namely total earnings, employment, and hours worked.

Total earnings are derived by aggregating both wage income (YL) and self-employment income (YM) for all individuals. This aggregation is motivated by the presence of individuals in the sample who report both sources of income, despite identifying themselves as either employees or self-employed. Although the proportion of the sample affected by this situation is relatively small (as shown in Tables A3 and A4), I have chosen this measure of total earnings.[14]

For the employment variable, I use a measure that indicates whether the individual is employed or self-employed in the survey year, coded as 1 if employed and 0 otherwise.

In terms of hours worked, I rely on data from the payroll employment dataset (LDIP) and the self-employment datasets (LINB, LINC, LIND) in the SHIW HD.[15] However, it's important to note that not all individuals in the sample have corresponding matches in these datasets. Consequently, the event-study results for hours worked cannot be directly compared to those for earnings and employment due to differences in the sample composition.

I analyze two measures of hours worked: one specifically looks at changes in labor supply intensity after childbirth among those who remain employed, such as working fewer hours, part-time, or having longer work spells. The other measure considers both labor market exits and the intensity of hours worked among the employed.

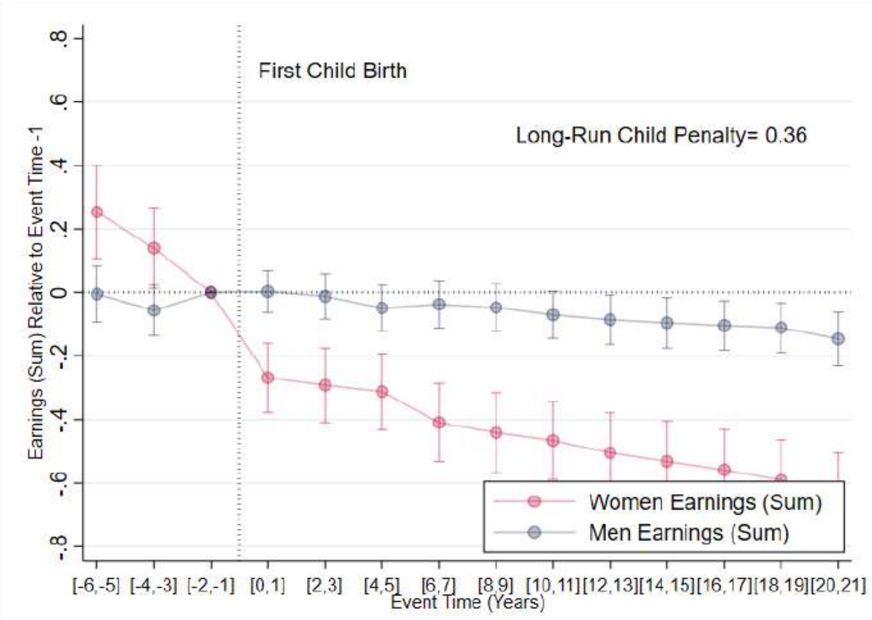
Examining the pre-childbirth trajectories of men and women allows us to assess the credibility of the parallel trends assumption. While a direct test of the assumption is not feasible, the available evidence indicates parallel pre-trends in earnings, employment, and hours worked. However, the employment rate exhibits a relatively weaker indication, as shown in Figure 2b. It is worth noting that for all the outcomes the post-event change in slope for women is both sharp and substantial compared to the pre-childbirth period, while

[14]Importantly, the results remain robust when considering only wage income for employees and self-employment income for self-employed individuals, as illustrated in Figure B2 in the Appendix.

[15]These datasets are included in the basic datasets of the SHIW HD. However, the English version of the documentation does not provide specific explanations for the acronyms used in these datasets.

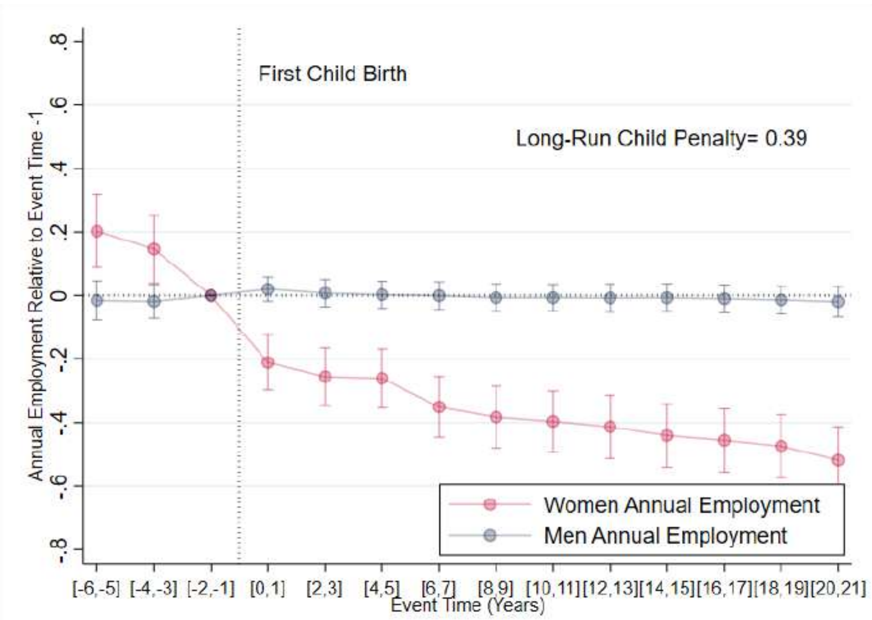
Figure 2: Event-studies of first childbirth for earnings and annual employment

(a) Event-study of first childbirth for earnings



Notes: The figure plots the estimated coefficients from regression (1) in percentage terms for men (blue) and women (pink) for earnings, defined as the sum of wage income (YL) and self-employment income (YM). The coefficients are standardised by their counterfactual outcome as in (3). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the id (individual) level. 'Long-Run Child Penalty' refers to the child-penalty at event-time $e = [10, 11]$ as defined in (4).

(b) Event-study of first childbirth for annual employment



Notes: The figure plots the estimated coefficients from regression (1) in percentage terms for men (blue) and women (pink) for annual employment. The coefficients are standardised by their counterfactual outcome as in (3). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the id (individual) level. 'Long-Run Child Penalty' refers to the child-penalty at event-time $e = [10, 11]$ as defined in (4).

any unobserved factors influencing these labor market outcomes should exhibit a smooth evolution over time. Additionally, the observed decline between event-time $e = [-4, -3]$ and $e = [-2, -1]$ for women can be attributed to capturing the impact of maternity leave in the reference period $e = [-2, -1]$. Furthermore, a small downward jump is observed in both earnings and employment around event-time $[4; 5]$ and $[6; 7]$. This phenomenon may be attributable to the influence of subsequent children, as women may have additional children later in the event-time. Consequently, these results reflect the cumulative effect of fertility and indicate a larger long-term penalty associated with multiple children. In the Appendix, I provide additional evidence that, by conditioning on total fertility of one child, the negative impact of childbirth on earnings and employment remains constant and persistent over time (refer to Figures B4a and B4b). Table A5 in the Appendix shows the distribution of children in the pseudo-panel sample, with a majority of parents having two children. The distribution is similar for men and women. Figure B3 in the Appendix displays the time lag between the first and second child, which is concentrated between 2 and 5 years. Given that labor market outcomes decline between intervals $[4, 5]$ and $[6, 7]$, this evidence suggests a potential "delayed" penalty for women with two children and a possible underestimation of the associated costs.

In addition, I performed a robustness check by calculating the average impact of childbirth on earnings and employment.[16] The results from this empirical approach can be found in Figures B5a and B5b in the Appendix.

Turning to the analysis, a significant decline is observed in all labor market outcomes for mothers following childbirth, while the effect on fathers is negligible. Examining the earnings figure, it is evident that women experience a persistent decrease in earnings, reaching 28% lower than their counterfactual earnings one to two years prior to childbirth. This can be rationalized within the framework of the household labor supply model of Cortés and Pan (2020)[17], where women may have a higher preference for the public good (children), or a lower hourly wage, or a combination of both factors. A similar magnitude of effect is observed for the employment rate, indicating an immediate drop of 23% and suggesting that the initial decrease in earnings is predominantly driven by a rise in unemployment, as earnings for the unemployed are recorded as zeros in the dataset. In light of the simplified

[16] Specifically, I employed specification (1) and assigned multiple event times to individuals based on all the children they had at the time of survey observation. For instance, if a woman is observed in year y with two children aged 2 and 4, she is assigned event times 2 and 4, respectively. This approach allows for the computation of an average childbirth effect, independent of the birth order of the children.

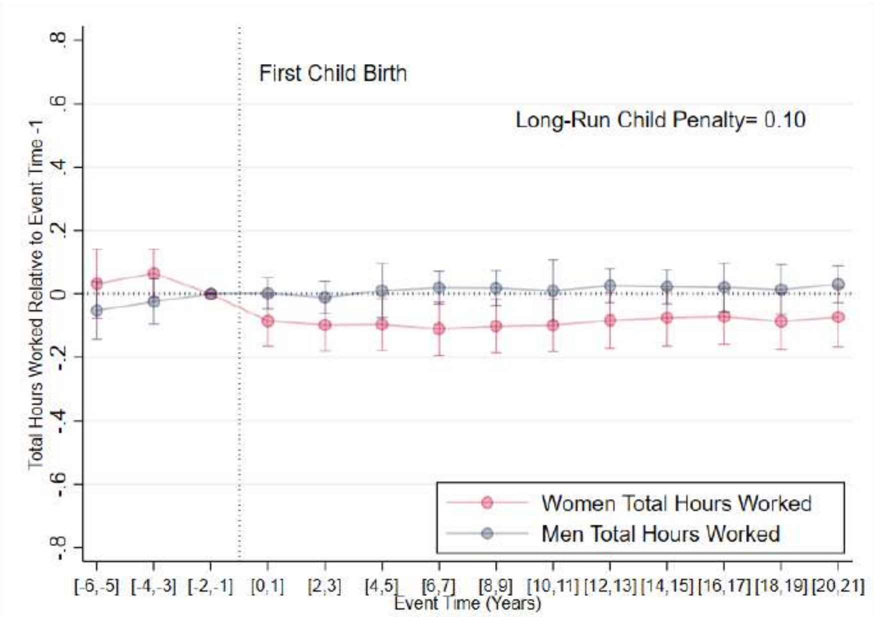
[17] Refer to the Appendix C for a concise illustration of the model and its predictions.

model, the exit of women from the labor market after childbirth can be interpreted as an advantage of mothers in terms of household work compared to market work. Furthermore, there is a decline of approximately 10% in hours worked conditional on employment.

Importantly, these gaps persist over the long term. Specifically, the child penalty at event-time $e = [10, 11]$ amounts to 36% for earnings, 39% for employment, and 10% for hours worked conditional on employment.

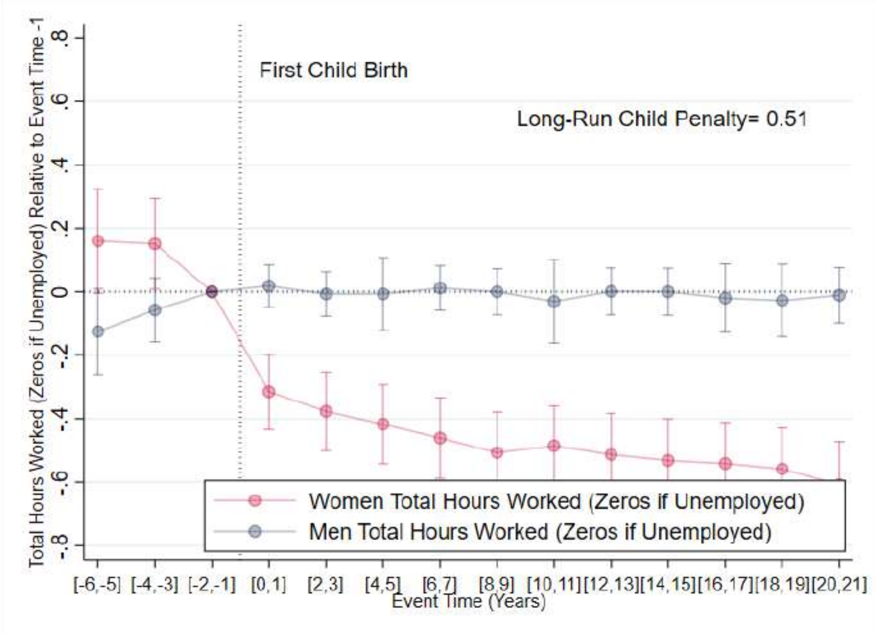
Considering hours worked unconditional on employment, Figure 4 accounts for the rising pre-trend in hours worked among men attributable to the extensive margin (increased employment rate), as well as the amplified penalty experienced by mothers following childbirth in terms of the extensive margin (reduced employment rate). Notably, the long-run child penalty for this outcome reaches 51%.

Figure 3: Event-study of first childbirth for hours worked, conditional on employment



Notes: The figure plots the estimated coefficients from regression (1) in percentage terms for men (blue) and women (pink) for hours worked, conditional on employment. The coefficients are standardised by their counterfactual outcome as in (3). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the id (individual) level. 'Long-Run Child Penalty' refers to the child-penalty at event-time $e = [10, 11]$ as defined in (4).

Figure 4: Event-study of first childbirth for hours worked (unconditional)



Notes: The figure plots the estimated coefficients from regression (1) in percentage terms for men (blue) and women (pink) for hours worked, unconditional of employment. The coefficients are standardised by their counterfactual outcome as in (3). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the id (individual) level. 'Long-Run Child Penalty' refers to the child-penalty at event-time $e = [10, 11]$ as defined in (4).

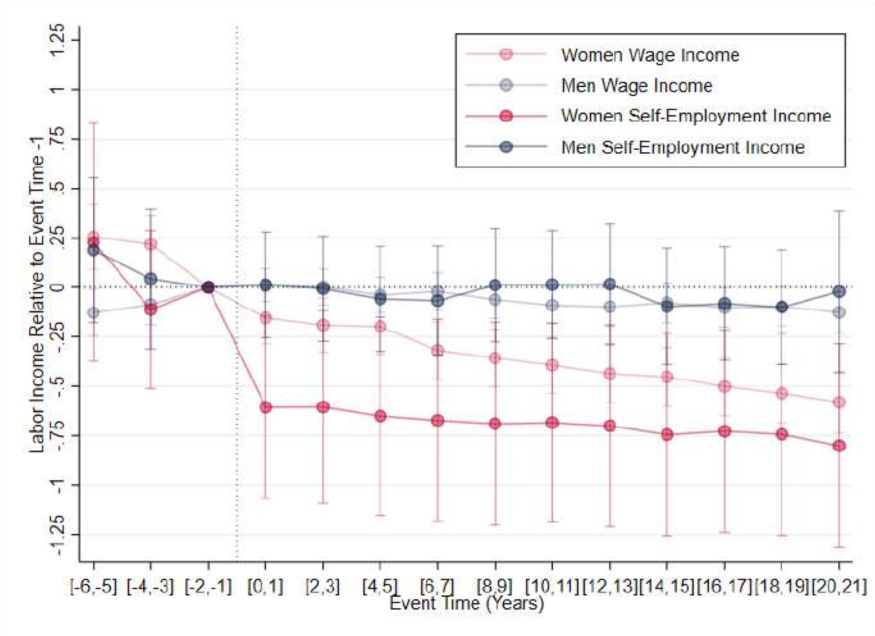
The SHIW dataset allows me to decompose earnings into wage income and income from self-employment, providing insights into the drivers of the child penalty in earnings. Figure 5 reveals that both wage income and self-employment income contribute to the decrease in earnings after childbirth, with self-employment income experiencing a larger drop (60% vs 15% for wage income).

The self-employed have greater flexibility in adjusting their labor supply on both the intensive and extensive margins compared to employees. However, self-employed women face unique challenges as they balance running their own businesses and caring for their children. Limited access to parental leave policies and lack of job protection may explain the larger child penalty for this group. Additionally, in Italy, a significant portion of self-employment jobs are family-run small and medium enterprises (SMEs).[18] These family dynamics may involve intra-household bargaining, where the father continues to manage the business while the mother focuses on household work. This suggests that mothers may internalize prevailing gender norms or comply with them, which leads them to put a relatively lower weight on their career with respect to their partner's one, a factor which in

[18]In Italy, SMEs account for 99.9% of Italian firms (Financing SMEs and Entrepreneurs 2022). The Cerved SMEs Report (2019) shows that family-run SMEs make up more than 50% of total SMEs in all sectors (agriculture, building, industry, services, and utility). See Cerved SMEs Report - 2018, page 119.

Cortés and Pan (2020)'s model is incorporated by the parameter δ_m.

Figure 5: Event-study by type of labor income



Notes: The figure shows the event-study of first child birth by type of labor income (*i.e.* wage income in blue and self-employment in red). Estimates are obtained by running equation (1) separately for the sample of non-zero wage income earners and non-zero self-employment income earners, respectively. The coefficients are standardised by their counterfactual outcome as in (3). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the id (individual) level.

3.4 Heterogeneity

In this subsection, I examine the heterogeneity effects of childbirth by area of residence and education level on the outcomes of earnings and employment. Since childbirth is a non-event for men in the data, I retain the baseline estimates of specification (1) for the sample of men. For women, I divide the sample into subgroups based on the categories of interest and estimate separate coefficients for each category.[19]

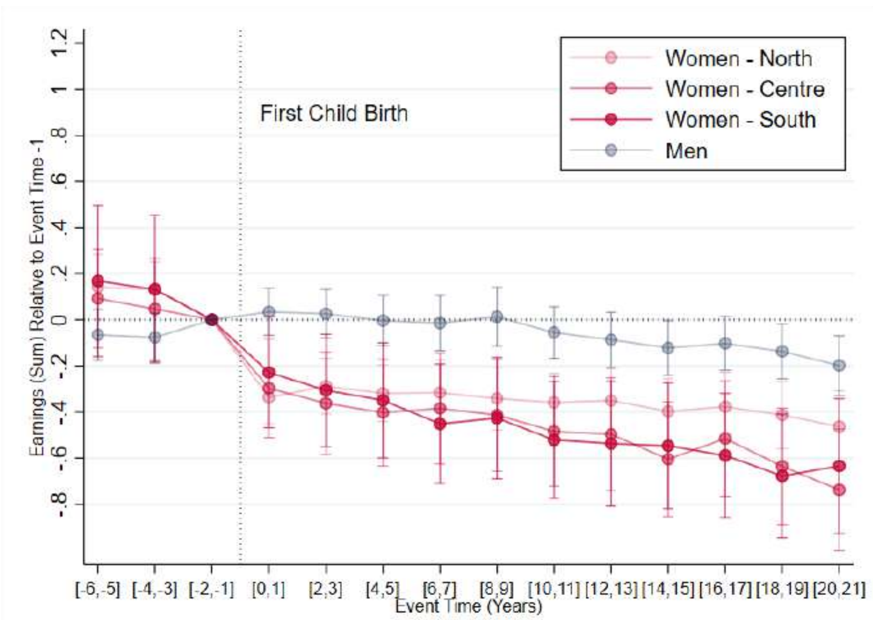
Figures 6a and 6b illustrate the coefficients estimated by area of residence. The coefficients are obtained by employing specification (2) and categorizing the residence into North, Centre, and South and Islands.

Regarding earnings, the three sub-samples initially exhibit similar effects in the first few years after childbirth. However, starting from event-time $e = [6, 7]$, there is a relatively smaller earnings gap observed in the North compared to the Centre and South of Italy, although the difference in coefficients is not statistically significant. In terms of employment, there is a clearer disparity in the gap between the North and the Centre/South. Mothers

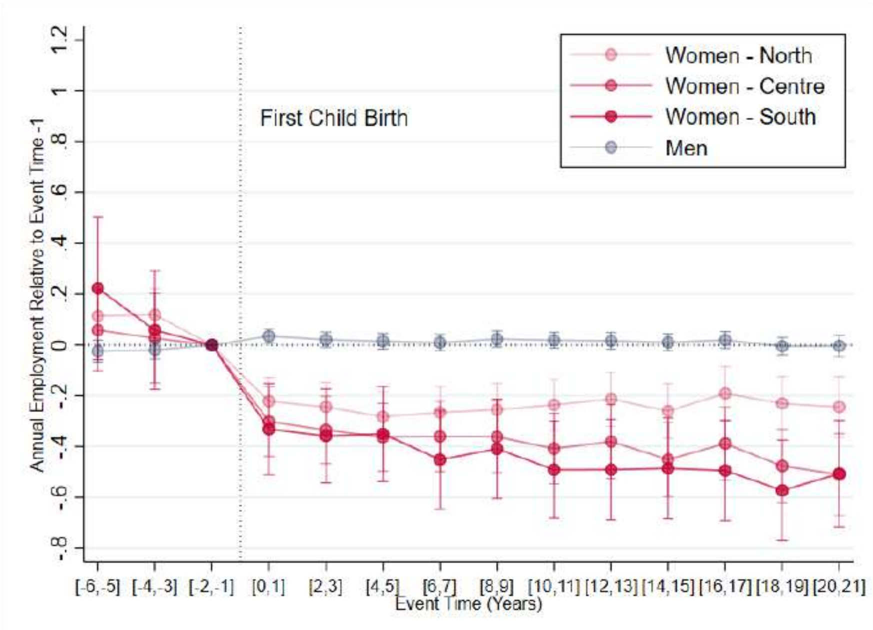
[19] I also conducted the analysis for men, but found no significant heterogeneity effects. This is consistent with a null effect of childbirth on men's outcomes.

Figure 6: Heterogeneity Analysis by Area of Residence

(a) Event-study of first childbirth for earnings, by Area of Residence



(b) Event-study of first childbirth for annual employment, by Area of Residence



Notes: The figures plot the estimated coefficients from regression (1) in percentage terms for men (blue) and women (pink) for earnings and annual employment. The sample of women is further split into sub-samples by area of residence, running specification (1) separately for each sub-sample and plotting the coefficients in the same graph. The coefficients are standardised by their counterfactual outcome as in (3). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the id (individual) level. Areas of residence are defined according to the ISTAT classification.

in the North experience an initial and persistent drop of around 20%, while mothers in the Centre and South face a larger drop of 40%. The variation in the child penalty across different areas of residence in Italy, similarly to the heterogeneity observed between self-employed individuals and employees, may stem from differences in how mothers prioritize their career relative to their partners', which is captured by the parameter δ_m in Cortés and Pan (2020)'s model. The North, being the most economically developed region with more favorable cultural norms towards working women, might have higher values of δ_m, whereas the Centre and South, being less economically developed regions with more prevalent patriarchal gender norms, may have lower values of δ_m.[20] These are just a few potential explanations for such heterogeneity, and other factors such as differences in childcare services and infrastructure availability between areas should also be considered (as discussed in Section 2). However, the differences in coefficients for these factors are not statistically significant.

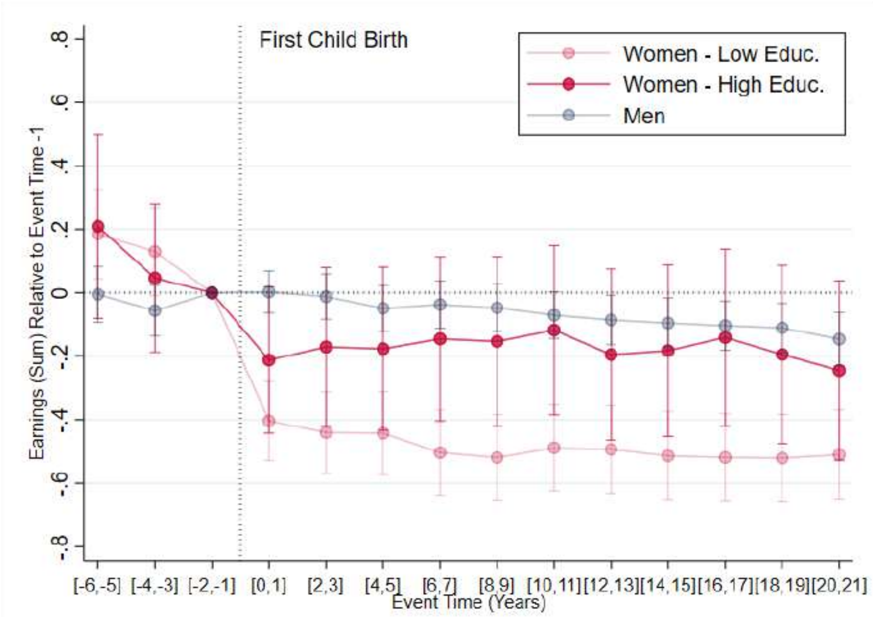
Figures 7a and 7b present the estimated coefficients by level of education. Low-educated women are defined as those with none, elementary, middle, or high school education, while highly-educated women have a bachelor's degree or post-graduate education.

In terms of earnings, I find that low-educated women experience a larger child penalty compared to their highly-educated counterparts, although I cannot reject the null hypothesis of an equal effect between the two groups. According to Cortés and Pan (2020)'s model, this smaller gap may be partially attributed to a comparative advantage within the household, where highly-educated mothers specialize in labor market work. However, it is important to note that there must be other factors influencing the earnings gap, as I still observe a persistent and modest (around 20%) gap for highly-educated women. Similarly, when considering employment rate, highly-educated women face a lower child penalty compared to their low-educated counterparts, and the coefficients for these groups are statistically distinct from each other.

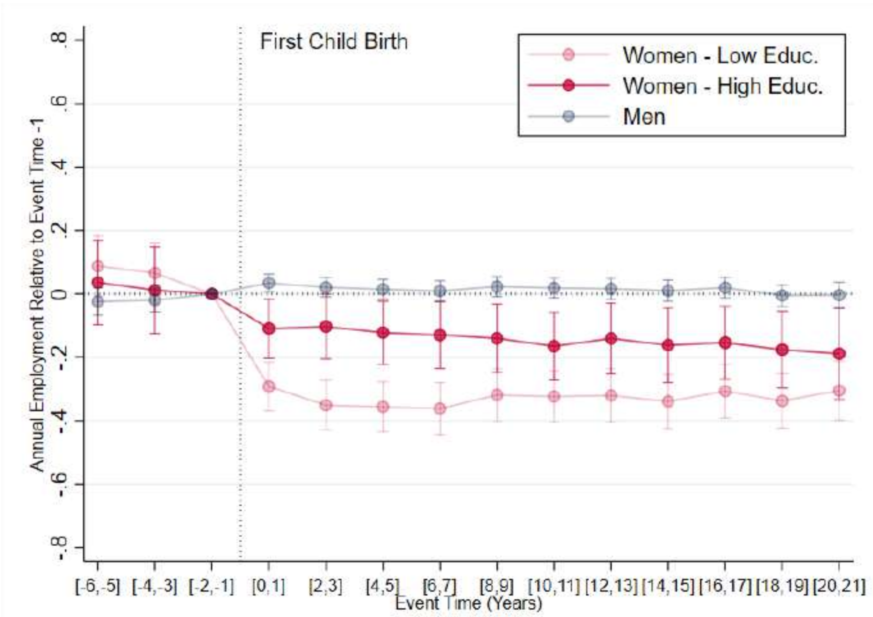
[20]As a proxy for the heterogeneity of gender norms across Italian areas, I computed an index using the European Values Survey (2017) I used questions v72, v73, v74 and v75 which asked whether the respondent agrees with the statements 'When a mother works for pay, the children suffers', 'A job is alright but what most women really want is a home and children', 'All in all, family life suffers when the woman has a full-time job', 'A man's job is to earn money; a woman's job is to look after the home and family', respectively. Answers were coded from 1 to 4, with higher values implying stronger disagreement with the statement (i.e. more pro working mother attitudes). The index was computed by averaging the answers to the 4 questions by group (area of residence) using survey calibration weights. The index is 2.51 in the North, 2.50 in the Centre, and 2.30 in the South and the Islands. A t-test for difference in means finds statistically significant differences for the pairs North-South and Centre-South.

Figure 7: Heterogeneity Analysis by Education Level

(a) Event-study of first childbirth for earnings, by Education Level



(b) Event-study of first childbirth for annual employment, by Education Level



Notes: The figure plots the estimated coefficients from regression (1) in percentage terms for men (blue) and women (pink) for earnings and annual employment. The sample of women is further split into sub-samples by level of education, running specification (1) separately for each sub-sample and plotting the coefficients in the same graph. The coefficients are standardised by their counterfactual outcome as in (3). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the id (individual) level. Low educated women are defined as those with none, elementary, middle and high school education, whereas highly-educated women are those with a bachelor's degree or post-grad education.

4 Household Finance Outcomes

In this section, I analyze the dynamics of household financial outcomes in Italy surrounding the arrival of a newborn. Using a pseudo-panel dataset created by matching households based on their characteristics (Section 2.4), I examine descriptive statistics for both the raw data from the SHIW HD and the constructed pseudo-panel, gaining insights into the observed patterns. I provide an overview of life-cycle and household decision-making models, serving as a conceptual framework for interpreting the event-study analysis findings. Finally, I outline the empirical strategy and present the main results derived from the analysis.

4.1 Descriptive Statistics

Before proceeding with the event-study analysis, I present a covariate balance table for household finance outcomes by the presence of children in the household. The table offers a first insight on variations in household finance variables and their association with the presence of children in the household. The outcomes I examine are shown in Table A6 in the Appendix.

Table 3 presents the main differences in household outcomes based on the presence of babies. The category "with babies" refers to households that have a child aged one year or younger. On the other hand, the category "no babies" includes couples without children, where the wife's age falls between 24 and 33 years old. This age range aligns with the demographic profile of mothers with a child aged one year or younger in the SHIW dataset.

Households with babies exhibit several distinct characteristics compared to households without babies. They tend to have lower labor income, consumption, net income, and savings. In terms of consumption patterns, households with babies have higher consumption of non-durable goods but lower consumption of durables. Additionally, they allocate a higher proportion of their budget towards food expenditure and receive more economic support. Notably, households with babies tend to have higher net wealth, primarily driven by greater holdings of real assets. Moreover, they tend to accumulate more debt related to the purchase or restructuring of buildings. When considering per-capita measures of consumption and expenditure, households with babies generally have lower values across various categories, except for food expenditure. Table A8 in the Appendix presents a similar analysis using the pseudo-panel of households.

Table 4 shows the breakdown of consumption into durables and non-durables across the different datasets employed. The analysis reveals that the majority of consumption is attributed to non-durables, accounting for 94% of total consumption. Within the category of durable goods, the largest share is taken by "other durables", which encompass durable goods excluding transport equipment (refer to Table A6 for details). Moreover, Table 5 focuses on the differences in the decomposition of consumption between households with and without babies. The findings align with the initial results presented in Table 3, indicating a higher consumption of non-durable goods and a lower consumption of durable goods for households with babies compared to those without.

Table 3: Household Covariates Table, by Babies presence - SHIW

	With Babies	No Babies	Difference	Standard Error
Panel A. Total				
Labour Income	28,430	30,396	-1,966***	(644)
Household Net Income	34,876	36,645	-1,769**	(850)
Savings	7,027	8,098	-1,071	(697)
Savings Ratio	0.28	0.31	-0.03**	0.01
Consumption	27,245	27,951	-707	(555)
Consumption of Durables	3,101	4,641	-1,540***	(356)
Consumption of Transport	1,724	2,061	-337	(225)
Consumption of Other Durables	1,331	2,470***	-1,139	(280)
Consumption of Non-Durables	24,441	23,491**	949	(436)
Net Wealth	158,980	129,830	29,150***	(10,089)
Financial Assets	21,852	20,893	+959	(2,117)
Share of Risky Assets	0.07	0.09	-0.02**	(0.01)
Financial Liabilities	23,468	17,750	5,718**	(2,308)
Debt used for the purchase/restructuring of buildings	14,419	10,378	4,041**	(1,585)
Real Assets	138,281	115,000	23,281***	(7,637)
Expenditure on food	7,101	6,087	1,014***	(124)
Amount of Economic Support	1,712	738	974**	(404)
Panel B. Per Capita				
Consumption	16,039	17,012	-973***	(332)
Consumption of Durables	1,831	2,834	-1,003***	(214)
Consumption of Transport	1,014	1,259	-245*	(136)
Consumption of Other Durables	793	1,511	-718***	(171)
Consumption of Non-Durables	14,391	14,295	96	(261)
Expenditure on food	4,180	3,706	474***	(74)

Notes: The table shows mean values and differences in means between households with and without babies for the SHIW sample. Households with babies are those with a child aged less than/equal to 1 years old. I keep only household consisting of couples and with the wife aged between 24 and 33 years old. All values are deflated at 2015€. Per-capita values are computed assigning consumption weights as in Browning and Ejrnaes (2009) (see A7 in the Appendix).

Table 4: Consumption Decomposition, by Dataset

	(1) SHIW Sample	(2) Pseudo-panel (Pooled)	(3) Pseudo-panel (Matching)
CD/C	0.06	0.07	0.06
CD1/C	0.33	0.35	0.34
CD2/C	0.67	0.65	0.66
CN/C	0.94	0.93	0.94

Notes: The table shows total consumption decomposition by dataset used. Column (1) uses the SHIW sample keeping only households consisting of couples with a number of children from 0 to 4 per household; column (2) uses the pseudo-panel obtained by pooling the pseudo-panel of mothers and fathers together (see Section 5); and column (3) uses the pseudo-panel obtained by matching at the household level.

Table 5: Consumption Decomposition, by Babies Presence

	With Babies	No Babies	Difference	Standard Error
CD/C	0.09	0.12	-0.03***	(0.01)
CD1/C	0.39	0.36	0.03	(0.05)
CD2/C	0.65	0.66	-0.02	(0.03)
CN/C	0.91	0.88	0.03***	(0.01)

Notes: The table shows total consumption decomposition between households with and without babies for the SHIW sample. Households with babies are those with a child aged less than/equal to 1 years old. I keep only household consisting of couples and with the wife aged between 24 and 33 years old.

4.2 Conceptual Framework

A substantial body of literature in household finance focuses on the development of models that explain how households make financial decisions throughout their life cycle. In this section, I provide a concise overview of the conceptual framework underlying these models, which serves as a guide for interpreting the empirical findings.

At the core of this field are the influential life-cycle models of Modigliani and Brumberg (1954) and Friedman (1957). These models posit that individuals make sequential decisions regarding consumption, saving, and labor supply in order to maximize their life-time utility, using the available information to the best of their ability. A key implication of these models is that households employ savings to smooth income fluctuations, exhibiting minimal response to anticipated income changes but adjusting consumption one-to-one in the face of unanticipated (permanent) income shocks. Similarly, in terms of portfolio behavior, households save proportionally in response to transitory income shocks, while permanent shocks have no impact on their savings decisions.

These models offer a framework for investigating whether the decline in household labor income resulting from the child penalty represents an anticipated income shock. However, empirical challenges arise when the observed data deviate from the theoretical model. Consumption may not fully respond to permanent shocks, and savings may react to permanent shocks, indicating a departure from the anticipated versus unanticipated income shock framework. Factors such as uncertainty and precautionary savings motives (Nagatani (1972); Carroll (2001); Heathcote et al. (2009)), non-separability between consumption and leisure, liquidity constraints in credit markets, myopic behavior, lack of self-control, and alternative forms of insurance (e.g., government transfers, family networks) can contribute to the violation of the basic life-income hypothesis.[21] Moreover, people may adjust their consumption of specific goods based on their income levels in order to buffer against income shocks, serving as an additional channel to smooth utility.[22]

The inclusion of a demographics motive in these life-cycle models is highly relevant for my analysis. Household size and the presence of children can introduce preference shifts in the household utility function, affecting consumption behavior. Previous studies have shown that controlling for the presence of children eliminates the correlation between income changes and consumption sensitivity.[23] For instance, Browning and Ejrnaes (2009) demonstrate that consumption closely follows income only when the effects of children and household size are not considered, as their model incorporates resource reallocation across periods with and without children.[24] Additionally, they find that the impact of children on consumption varies across different age groups. Similarly, Pistaferri (2001) finds a positive effect of household size and a negative effect of children on savings and consumption. However, accurately predicting the timing of fertility can be challenging for households, resulting in sub-optimal behavior in the data.

[21] Refer to Browning and Crossley (2001) for a comprehensive overview of life-cycle models.

[22] For instance, in a study by Browning et al. (1999), it is observed that spending on small durable goods is considerably more responsive to changes in income compared to expenditures on food. This consumption pattern can be explained by the fact that significant fluctuations in durable goods spending do not necessarily result in significant changes in the service flows derived from durables, and it might optimal for individuals to postpone their purchase during periods of low income and instead prioritize them during times of higher income. This evidence highlights the ability of individuals to effectively manage their utility flow over time, even in situations where total expenditures, particularly on durable goods, exhibit considerable volatility.

[23] Thurow (1969) was the first to notice that both income and consumption had a similar inverted U-shape in U.S. cross-sectional data.

[24] There is consensus now that the empirical fact of consumption tracking income in the data can be explained by a combination of a precautionary savings motive and the presence of children over the life-cycle (Attanasio et al. (1999); Browning (1992)).

4.3 Empirical Strategy

The specification I use to carry out the household-level is the following:

$$Y_{hte} = \sum_{e \neq -1} \alpha_e \cdot \mathbb{1}(E_{ht} = e) + \beta_{a^{hh}(h)} + \gamma_t + \epsilon_{hte} \tag{5}$$

where Y_{hte} is any household finance outcome attached to household h observed in year t at event-time e. I incorporate age of the head-of-household[25] $\beta_{a^{hh}(h)}$ and time fixed-effects γ_t to control for life-cycle and business-cycle trends which may influence household financial decisions. I exclude the event-time dummy $e_i = [-2; -1]$, so all results are relative to the outcome one and two years before childbirth. Standard errors are clustered at the household level to address potential correlation within households, especially in cases where a household unit was matched to multiple households in the negative event-time period.

In the household analysis, my focus will be on examining the evolution of α_e over event-time, which captures the changes in household finance outcomes before and after the event of childbirth. It is worth noting that I do not impose a no anticipation assumption, as it is plausible that households make plans in advance for the arrival of a child and make adjustments to their household finance outcomes accordingly. Therefore, observing any pre-trend is an integral part of the analysis, as it will aid in interpreting the changes and adjustments in household finance that may not have been anticipated by households beforehand, if any.

Similarly to the analysis on labor market outcomes, I aim to interpret the household finance results in percentage terms relative to the counterfactual outcomes of a household without children. This is achieved by standardizing the vector of $\{\alpha_e^g\}$ using the following formula:

$$P_e^h = \frac{\hat{\alpha}_e^h}{\mathbf{E}[\tilde{Y}_{hte}^h | e]} \tag{6}$$

where $\mathbf{E}[\tilde{Y}_{hte}^h | e]$ represents the counterfactual outcome for household h that would have occurred if childbirth had not taken place (i.e. estimating regression (5) while removing the effect of event-time dummies). The resulting standardized values, denoted as P_e^h, allow for a meaningful comparison of the actual outcomes of households with children to the hypothetical outcomes in the absence of childbirth.

In Section 5, I compare the event-study findings obtained using this sample and empiri-

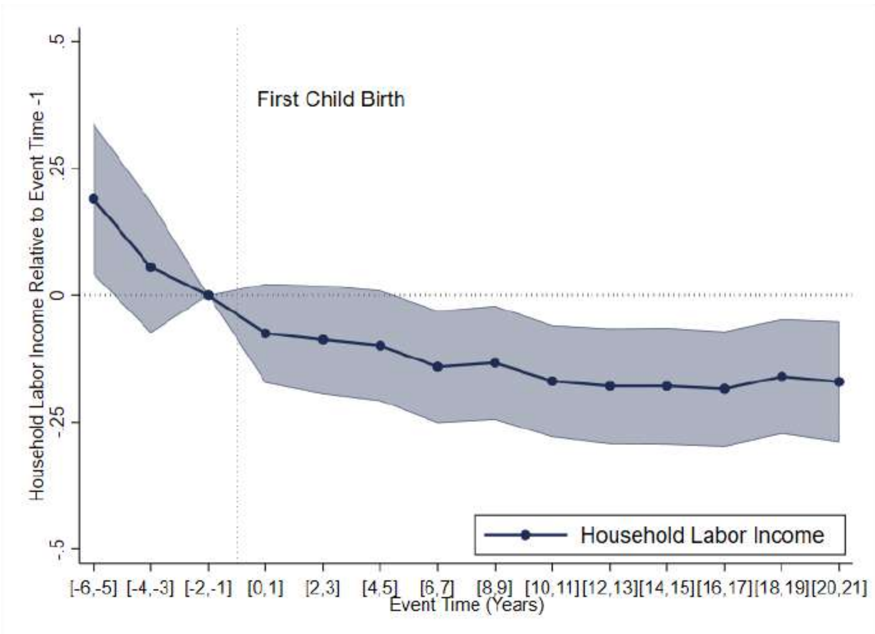
[25] The use of the age of the head-of-household fixed effect is motivated by household finance literature and the finding of a strong correlation between the age of the household head and household financial outcomes (see Campbell (2006), and Love (2010)). The results are robust to controlling for both the age of the head of household and the age of the spouse/partner.

cal specification, with a pooled pseudo-panel of mothers and fathers (as outlined in Section 5.1). The analysis reveals that the results remain consistent and do not exhibit variations when considering different samples and specifications.

4.4 Main Results

As demonstrated in the previous section, a notable consequence of childbirth is the decline in women's earnings and employment rate, which consequently leads to a decrease in household labor income (see Figure 8). The initial impact shows an approximate 8% decrease, which further increases in magnitude over time, eventually stabilizing at around 17%. It is worth noting that in the raw SHIW dataset, women's contribution to household labor income is about 25%. However, when we specifically consider mothers, this share decreases slightly to 22%, providing an explanation for the smaller decrease observed in the percentage of household labor income compared to the decline in women's earnings discussed in Section 3. On the other hand, total consumption levels exhibit no significant

Figure 8: Event-study of first childbirth for Labor Income



Notes: The figure plots the estimated coefficients from regression (5) for labor income, defined as the sum of payroll income and net self-employment income (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

variation before and after childbirth, as illustrated in Figure 9a. However, when examining per-capita consumption, a decline becomes apparent starting from the fourth year after childbirth, while no decrease is observed in the first three years. This pattern aligns with the literature's findings that household size positively affects total consumption, while the presence of children of any age has a negative impact Browning and Ejrnaes (2009). Consequently, in terms of overall welfare, the stable level of total consumption around childbirth implies a decrease in per-capita consumption to accommodate the increased consumption needs resulting from a larger household size.

The presence of children can influence the composition of household consumption, leading to changes in discretionary spending on household items and a shift in consumption towards child-related goods. While the SHIW data does not provide detailed information on specific components of the consumption basket, I can examine the consumption patterns in terms of durables, non-durables, and food expenditure. The findings in Figure 10 reveal a persistent increase of approximately 10% in non-durable consumption, including food and clothing, following childbirth, along with a decrease in durable consumption by an average of 35%. This decrease in durable consumption aligns with the findings of Browning et al. (1999), who highlight the propensity to postpone the purchase of durable goods during periods of low income.[26] Similar trends are observed in per-capita values, except for a decrease in per-capita non-durable consumption after event-time $[6, 7]$ (see Figure B8 in the Appendix). When examining food expenditure specifically (refer to Figure 11), there is a notable increase of 20% following childbirth, peaking around event-time $[14, 15]$ and stabilizing at approximately 35%. However, this increase in food allocation diminishes and eventually disappears as the child reaches 18 years old, as observed in per-capita values. The decline in per-capita food expenditure from event-time $[18, 19]$ onwards could be influenced by the fact that children start using their own income to cover their food-related expenses, which may not be reported by the household respondent (i.e. the head of the household).

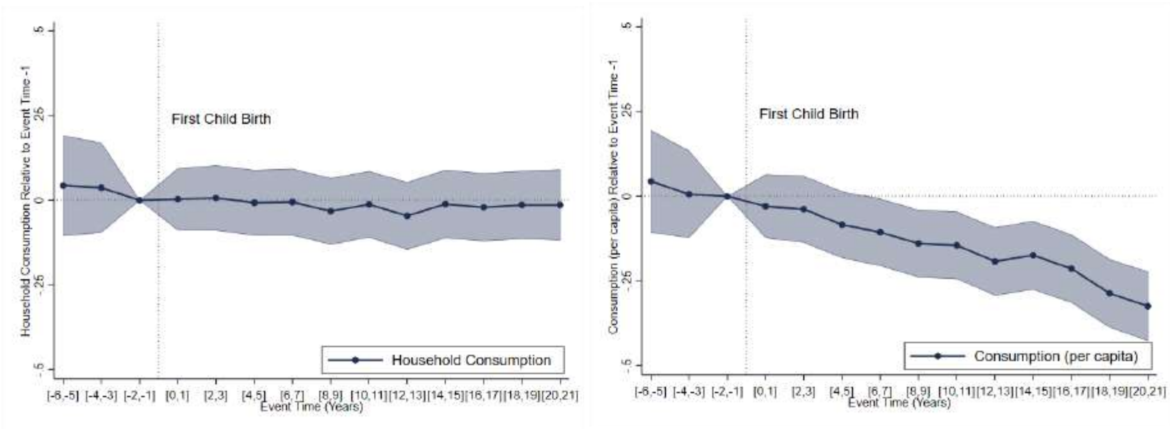
I observe evidence indicating an increase in government-provided insurance for households following childbirth.[27] Drawing on the framework introduced by Blundell et al. (2016), this government-provided insurance can play a significant role in mitigating the financial challenges faced by households during this period. Namely, the rise in consumption expenditures associated with having children, as well as the decline in labor income resulting from the child penalty.

[26] Similarly, according to Parker (1999), individuals facing temporary constraints are more likely to reduce their consumption of goods with high inter-temporal substitution.

[27] In the data, economic support transfers include disabled person carers' allowance, maintenance, guaranteed minimum income, food allowance, and other forms of assistance from government agencies or private welfare organizations.

Figure 9: Event-study of first childbirth for Consumption and Consumption per capita

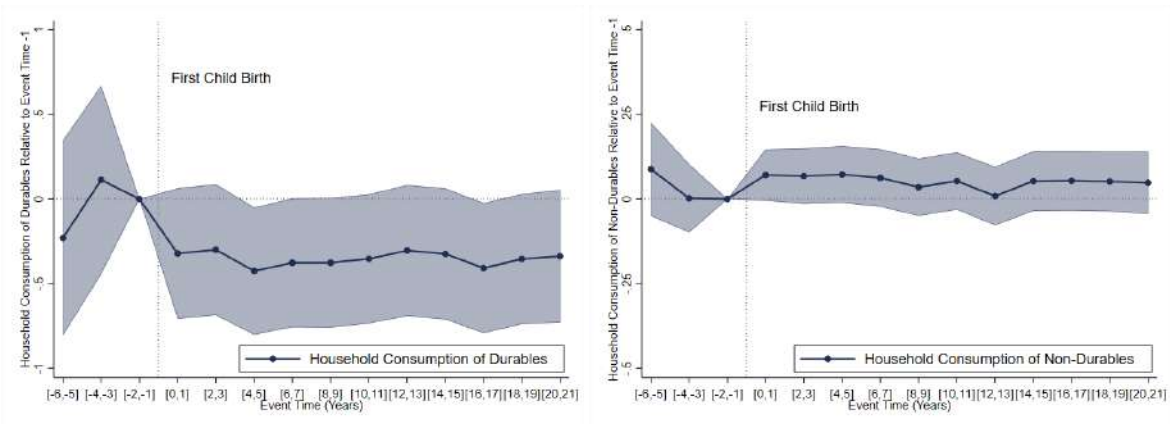
(a) Event-study of first childbirth for Consumption **(b)** Event-study of first childbirth for Consumption per-capita



Notes: The figure plots the estimated coefficients from regression (5) for consumption (9a) and consumption per-capita (9b), defined as the sum of consumption per-capita of durables and non-durables (see Table A6). Per-capita values are computed using consumption weights as in Browning and Ejrnaes (2009) (see A7 in the Appendix). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

Figure 10: Event-studies of first childbirth for Consumption, Durables vs Non-Durables

(a) Event-study of first childbirth for Consumption of Durables **(b)** Event-study of first childbirth for Consumption of Non-Durables

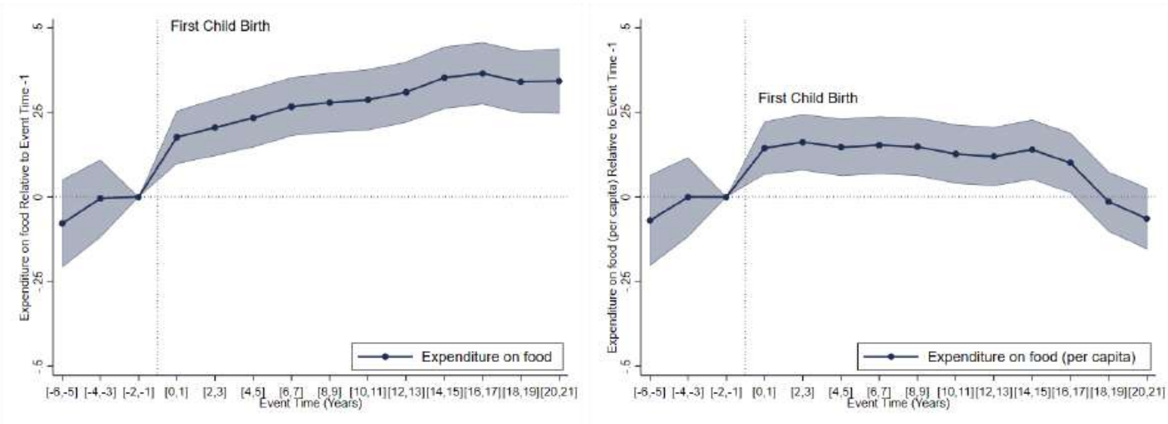


Notes: The figure plots the estimated coefficients from regression (5) for total consumption of durables (10a), and total consumption of non-durables (10b) (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

Figure 11: Event-studies of first childbirth for Expenditure on Food

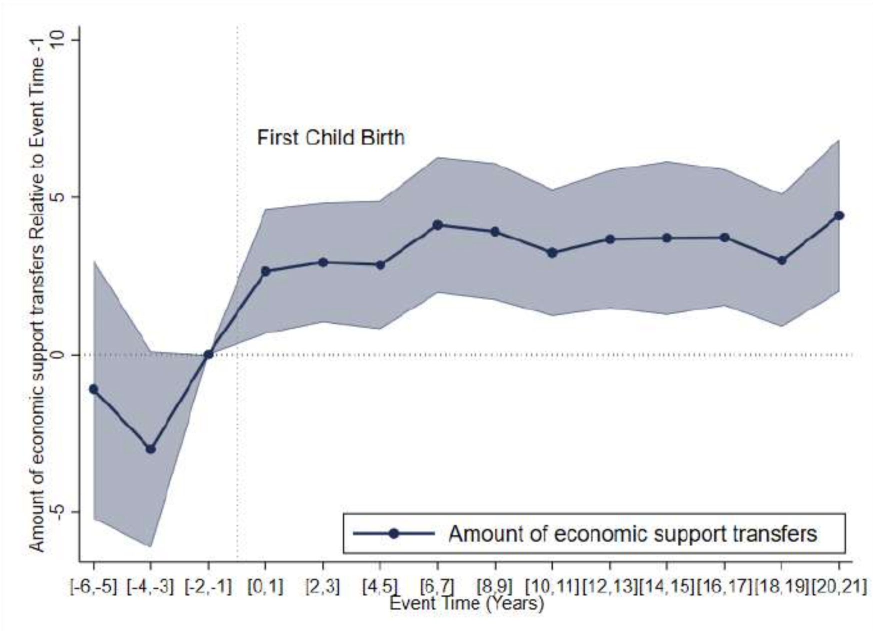
(a) Event-study of first childbirth for Expenditure on Food

(b) Event-study of first childbirth for Expenditure on Food (per-capita)



Notes: The figure plots the estimated coefficients from regression (5) for total expenditure on food (11a) and total expenditure on food per-capita (11b) (see Table A6). Per-capita values are computed using consumption weights as in Browning and Ejrnaes (2009) (see A7 in the Appendix). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

Figure 12: Event-study of first childbirth for Amount of Economic Support Transfers

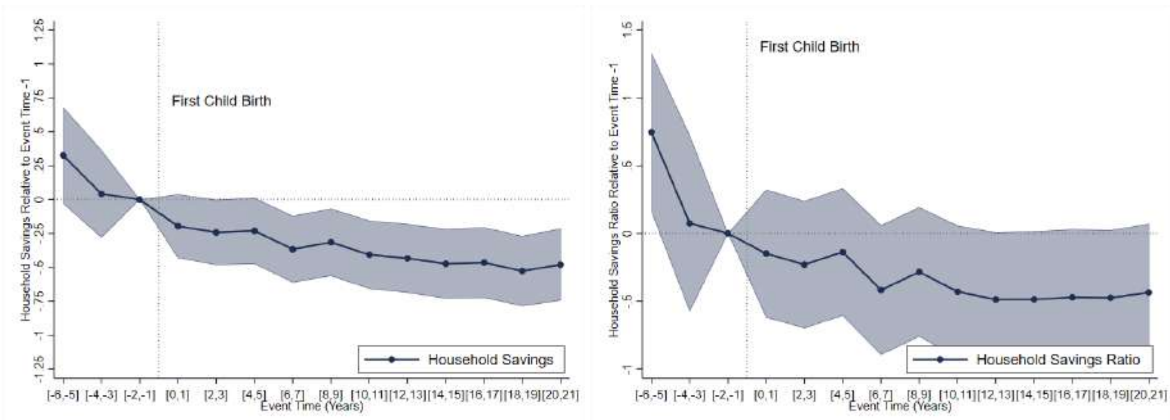


Notes: The figure plots the estimated coefficients from regression (5) for the amount of economic support transfers. (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

If parents anticipate a decrease in income following childbirth, one might expect them to accumulate savings beforehand to mitigate the anticipated decline in the mother's earnings. However, this behavior is also consistent with the inter-temporal resource allocation observed in previous studies, where parents reallocate their resources from periods without children to periods with children (Browning (1992)). In the dataset, savings are a flow calculated as the difference between net household income (Y) and household consumption (C).[28] Therefore, I cannot directly observe whether the absolute amount of savings increased or decreased after childbirth, but rather whether households started saving more or less following the event. Figure 13a illustrates a decreasing trend in savings after childbirth, with the magnitude of the decrease growing as the child ages. This implies a reduction in the savings accumulated by households at each event-time. This decline in savings is driven by the mechanical effect of the decrease in labor income and total net household income (see Figure B10a in the Appendix) resulting from the child penalty, while total consumption remains stable. Another way to examine changes in savings is by looking at the savings rate in Figure 13b, which shows a significant drop between event-times $[-6, -5]$ and $[-4, -3]$. This decline aligns with the increased consumption of durables observed at event-time $[-4, -3]$ in Figure 10a. The rise in durable goods expenditure, including furniture and furnishings, may indicate household preparations to accommodate additional members in the house in the future.

Figure 13: Event-study of first childbirth for Savings and Savings Ratio

(a) Event-study of first childbirth for Savings **(b)** Event-study of first childbirth for Savings Ratio



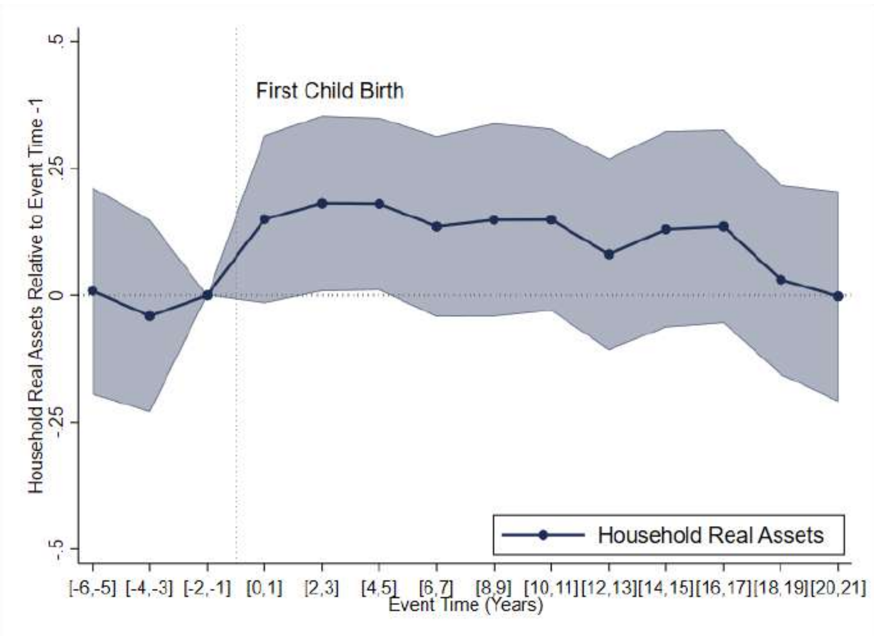
Notes: The figure plots the estimated coefficients from regression (5) for savings (13a), and savings ratio (13b) (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

[28]Pistaferri (2001) uses a different savings definition, considering the difference between household income Y (including income from financial assets) and consumption of non-durables. In this alternative definition, durables are considered a form of capital that generates a service flow. Consequently, the service flow should be included in asset income and added to consumption, nullifying its effect on savings. In the Appendix, I conduct a robustness check using this alternative savings measure, and the results are consistent with the definition employed in this section (see Figure B9).

Upon analysing real assets, which encompass real estate, businesses, and valuables, I observe a notable increase ranging from 10% to 15% after the event of childbirth (Figure 14). This increase persists over time, indicating a sustained effect that aligns with the acquisition of property following the birth of a child. However, a closer examination of the individual components, such as real estate (AR1), businesses (AR2), and valuables (AR3) in Figure B7 in the Appendix, reveals an unexpected trend: the rise in real assets seems primarily driven by a significant increase in owned businesses. This unexpected finding raises interesting questions which are left for future research.

Figure 15d illustrates the changes in debt owed to banks and financial companies for the purchase or restructuring of buildings following childbirth. The graph shows a peak in the first year after childbirth, followed by a decreasing trend as households begin to repay the debt incurred for housing-related expenses. Although the coefficient for the peak is not statistically significant, and the overall figure is very noisy, the analysis using the pooled pseudo-panel of mothers and fathers in Section 5 reveals a clear and statistically significant peak, which closely resembles the pattern observed in household financial liabilities (refer to Figures B16c and B16d).

Figure 14: Event-study of first childbirth for Real Assets



Notes: The figure plots the estimated coefficients from regression (5) for real assets, defined as the sum of real estate, businesses, and valuables (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

In terms of financial assets, the data reveals a decrease in financial assets (Figure 15a) following childbirth, indicating a pattern of dissaving. This reduction becomes more pronounced as the child grows older, potentially reflecting the need to cover expenses related to education, such as school-related costs.[29] Furthermore, the event of childbirth appears to influence households' risk attitudes and preferences. Figure 15b illustrates that the share of risky assets held by households exhibits an upward trend initially. However, starting from event-time $[-2,-1]$, there is a noticeable decline of approximately 25%, which continues until event-time $[8,9]$. Subsequently, the decline stabilizes at a level 50% lower than the counterfactual share of risky assets that households would have held without the occurrence of childbirth. This suggests a shift in risk-taking behavior and a potential reassessment of risk preferences following the birth of a child. The shift in household portfolio composition becomes evident when examining Figure B6 in the Appendix. The event-study results for the share of the different asset categories in the household financial portfolio, presented in both percentage terms and using the raw coefficients $\{\alpha_e\}$, reveal notable changes. After childbirth, there is a significant increase in the share of safe assets within the household portfolio, while the allocation towards riskier assets such as government securities, bonds, and equity decreases.

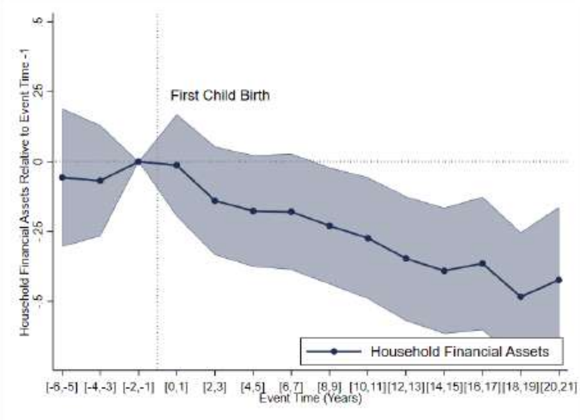
On the other hand, financial liabilities appear to be more prominent during the early years of a child's life, gradually decreasing in later years, similar to the pattern observed for debt related to the purchase or restructuring of buildings (Figure 15c). However, the coefficients for these outcomes are not statistically significant, and the figure itself exhibits considerable noise.

Consistently with the patterns observed for real assets, financial assets, and financial liabilities, net wealth demonstrates a slight hump-shaped pattern following childbirth (refer to Figure B10b in the Appendix).

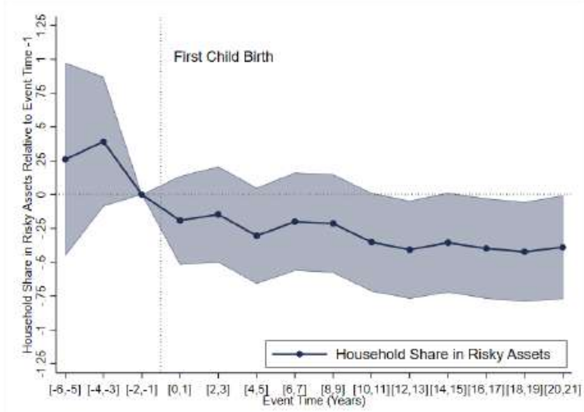
[29]Regarding this aspect, a study by Souleles (2000) reveals that households in the United States demonstrate effective consumption smoothing when it comes to financing college education expenses.

Figure 15: Event-studies of first childbirth for Financial Assets and Financial Liabilities

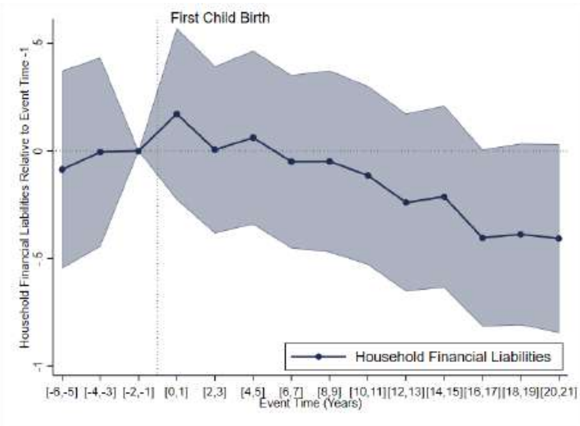
(a) Event-study of first childbirth for Financial Assets



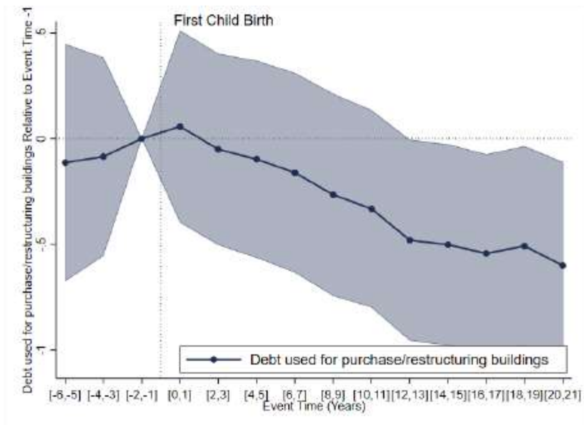
(b) Event-study of first childbirth for Share of Risky Assets



(c) Event-study of first childbirth for Financial Liabilities

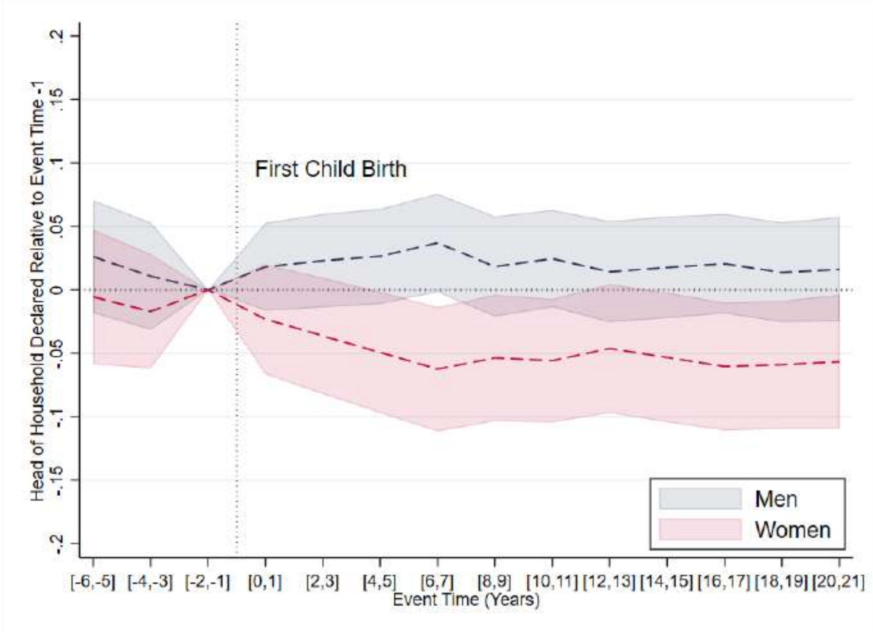


(d) Event-study of first childbirth for Debt for Purchase/Restructuring Buildings



Notes: The figure plots the estimated coefficients from regression (5) for financial assets (15a), share of risky assets (15b), financial liabilities (15c), and debt for the purchase/restructuring of buildings (15d) (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

Figure 16: Event-study of first childbirth for Probability of Household Headship



Notes: The figure plots the estimated coefficients from regression (1) for the probability of being declared head of household, defined as the person in charge of household economic and financial management, for men and women. The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the individual level.

The dynamics of household finance management following childbirth provide insights into the intra-household bargaining dynamics and the differential impact of parenthood on men and women. To investigate this aspect, I analyze the variable *cfdic* in the survey, which indicates whether the individual is declared as the head of the household, i.e. the person in charge of or more informed on the household economic and financial management. Figure 16 displays the event-study results for this outcome for both men and women. Prior to childbirth, the probability of being the head of household for both genders followed a similar trend. However, following childbirth, there is a clear 5% decrease in the probability for mothers to hold the position of head of household, accompanied by a corresponding 5% increase for fathers. The disparity in headship probability between men and women may be attributed to comparative advantage factors and the positive relationship between labor force participation and household financial management. The withdrawal of women from the labor market after childbirth could make them less suited for the role of financial headship. However, this hypothesis alone cannot account for the change on impact observed in this outcome. An alternative explanation posits that childbirth introduces an 'attention shock' for mothers, leading to a reallocation of tasks related to financial management to fathers due to the time-intensive nature of these responsibilities.[30] This reallocation

[30]This is consistent with Bertocchi et al. (2014)'s finding on a positive relationship between headship and time

process may be influenced by gender norms, with regions characterized by more equal gender norms experiencing a smoother transition. Considering the potential inefficiencies and sub-optimal outcomes associated with decisions influenced by gender norms (Guiso and Zaccaria (2023)), investigating this issue further will be a key focus of my future research.

5 Robustness Checks

In this section, I introduce an alternative sample that I use to validate the robustness of the findings regarding household finance outcomes presented in Section 4. This sample is constructed by combining the pseudo-panels of mothers and fathers, which were created using the methodology outlined in Kleven et al. (2019) and employed in Section 3. Detailed figures illustrating the event-study results obtained using this alternative sample can be found in the Appendix. Table A9 provides descriptive statistics for this sample.

5.1 Pooled Pseudo-Panel of Mothers and Fathers

To validate the household finance outcomes obtained in Section 4, I employ a pooled pseudo-panel of mothers and fathers. This approach involves combining the pseudo-panel of mothers and fathers created in Section 2, and considering their respective household identifiers to construct a pseudo-panel of household-year pairs.[31] To account for within-household correlation, I cluster the standard errors at the household level in the regression analysis. This adjustment is particularly relevant for households where both the mother and father are observed in the data during negative event-time but were matched to different households.

Ideally, I would like to focus on stable married or cohabiting couples and examine how they adjust their household finance outcomes before and after the occurrence of childbirth. To achieve this, I narrow down the scope of my analysis to couples who do not have children prior to event-time $[0, 1]$, as well as couples who have children at or after event-time $[0, 1]$. Similar to the previous subsection, I select from the initial pool of household units at event-time $e = 0$ those that have at least one observation in negative event-time. This ensures that I include couples with children who have at least one matching observation to a couple without children in the negative event-time period.

availability.

[31] It is important to note that I retain only one observation per household, and in cases where multiple observations exist due to different matchings within a household, I assign a weight of $1/n$ to each observation, where n represents the number of distinct matchings for the same household-year pair.

The rationale for employing this sample as a robustness check to validate the findings from Section 4 is based on the assumption that, if the matching methodology used in Kleven et al. (2019) effectively addresses selection bias at the individual level for becoming a parent, it should also be capable of predicting households that will experience parenthood in the future. Since each individual in the cross-section is part of a household, the matching procedure is expected to accurately identify households that will eventually have children.

5.2 Main Results

Overall, the findings obtained using this alternative sample are consistent with the results reported in Section 4.

The analysis reveals a significant decline in household labor income, ranging from 10% to 25%, as depicted in Figure B11a. Consistent with the earlier results in Section 4, the results demonstrate a relatively smooth trajectory in consumption patterns, accompanied by a decrease in consumption per capita, as evidenced in Figure B12a and B13a. However, it should be noted that for total consumption, there is an observed decreasing trend, although not statistically significant, after event-time $e = [12, 13]$. The peak in durable goods consumption between event-times $[-6, -5]$ and $[-4, -3]$, followed by a persistent drop after childbirth, is consistent with the patterns observed in Section 4 (see Figure B12c). Additionally, the modest and slightly statistically non-significant increase in non-durables consumption observed after childbirth in Figure B12d aligns with the earlier results. The results on per-capita outcomes in Figure B13 confirm the results of the previous Section. Moreover, there is a notable increase in both total and per-capita expenditure on food, as depicted in Figures 11a and 11b. The dynamics of economic support transfers align with the findings presented in Figure 12, further confirming the results obtained in the previous section. Additionally, the results on savings, savings ratio, and net income also demonstrate a decreasing trend after childbirth, as depicted in Figures B14a, B14b, and B11c, respectively. Although there are slight differences in the point estimate values, the overall patterns remain consistent with the previous section. Furthermore, the results for real assets, financial assets, share of risky assets, financial liabilities, debt used for purchase/restructuring buildings, and net wealth, as illustrated in Figures B15, B16a, B16b, B16c, B16d, and B11d, respectively, confirm the findings from Section 4, with the exception of real assets.

It is noteworthy to observe the similarity between Figure B16c, which represents financial liabilities, and Figure B16d, which shows debt taken for the purchase/restructuring of buildings. Although the peak at event-time $[0, 1]$ is more pronounced for financial liabilities, the overall patterns of these two outcomes are nearly identical. This suggests that a significant portion of financial liabilities incurred by households after childbirth is primarily allocated towards the acquisition or renovation of residential properties.

6 Conclusions

In this paper, I examine two interconnected aspects related to the event of childbirth within the Italian context.

Firstly, I investigate the differential impact of childbirth on the labor market outcomes of women and men in Italy. Using the SHIW data from the Bank of Italy and employing the matching procedure in Kleven (2022) to construct a pseudo-panel, I find that women experience a significant decline in earnings and employment rate after childbirth, with drops of 28% and 23%, respectively, relative to their pre-childbirth levels and compared to their counterfactual outcomes in the absence of childbirth. This negative effect on labor market outcomes for women persists in the long run and is more pronounced for self-employed women and those with lower levels of education. However, I find no evidence of heterogeneous effects based on the area of residence. In contrast, men's labor market outcomes remain unaffected by childbirth. My findings contribute to the existing literature in Italy by focusing on the overall working-age population in fertility age, regardless of their employment status at the time of childbirth, and by considering income sources from both wages and self-employment.

Secondly, I examine the dynamics of household finances around and after childbirth for Italian households. Overall, I find that Italian households demonstrate a relatively effective ability to smooth total consumption during this period. They rely on various resources such as financial assets, government transfers, and adjustments in their financial portfolio to mitigate the income shock associated with childbirth. Additionally, households reallocate their consumption towards non-durable goods and increase expenditures on food-related items. However, per-capita consumption declines compared to pre-childbirth levels and the counterfactual scenario without childbirth, indicating that parents face challenges in maintaining their pre-childbirth standard of living despite their efforts to adjust discretionary spending and reduce financial assets. This suggests that parents may not fully anticipate the income shock resulting from the child penalty after childbirth or may be unable to foresee all the changes associated with childbirth, including shifts in the consumption utility function due to the presence of a new household member and the timing of the event. Furthermore, I find that after childbirth, women are less likely to be in charge of the economic and financial management of the household, while men are more likely to assume this role. This finding is consistent with theories of comparative advantage or prevailing gender norms and warrants further investigation.

Overall, this paper sheds light on the inequalities that arise within households between mothers and fathers following childbirth in Italy. It also documents how households' financial decisions change and adapt to this significant life event. While I cannot disentangle the labor income shock from other preference changes occurring at the time of childbirth, the observed decrease in per-capita consumption suggests that the child penalty, at least partially, represents an unanticipated income shock for the household.

The use of household survey data expands the range of outcomes that can be examined in an event-study framework centered around the time of first childbirth, and this analysis could be extended to other countries. Future research should delve into the life-cycle models that best explain the patterns observed in the data.

References

Anderson, D. J., M. Binder, and K. Krause (2002). The motherhood wage penalty: Which mothers pay it and why? *American economic review 92*(2), 354–358.

Andresen, M. E. and E. Nix (2022). What causes the child penalty? evidence from adopting and same-sex couples. *Journal of labor economics 40*(4), 971–1004.

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

Attanasio, O. P., J. Banks, C. Meghir, and G. Weber (1999). Humps and bumps in lifetime consumption. *Journal of Business & Economic Statistics 17*(1), 22–35.

Bertocchi, G., M. Brunetti, and C. Torricelli (2014). Who holds the purse strings within the household? the determinants of intra-family decision making. *Journal of Economic Behavior & Organization 101*, 65–86.

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

Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2016). Consumption inequality and family labor supply. *American Economic Review 106*(2), 387–435.

Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2018). Children, time allocation, and consumption insurance. *Journal of Political Economy 126*(S1), S73–S115.

Browning, M. (1992). Children and household economic behavior. *Journal of Economic Literature 30*(3), 1434–1475.

Browning, M., P.-A. Chiappori, and Y. Weiss (2011). Family economics.

Browning, M., T. Crossley, et al. (1999). *Shocks, stocks and socks: consumption smoothing and the replacement of durables during an unemployment spell*. The Australian National University.

Browning, M. and T. F. Crossley (2001). The life-cycle model of consumption and saving. *Journal of Economic Perspectives 15*(3), 3–22.

Browning, M. and M. Ejrnaes (2009). Consumption and children. *The Review of Economics and Statistics 91*(1), 93–111.

Campbell, J. Y. (2006). Household finance. *The journal of finance 61*(4), 1553–1604.

Carroll, C. D. (2001). Precautionary saving and the marginal propensity to consume out of permanent income.

Casarico, A. and S. Lattanzio (2023). Behind the child penalty: understanding what contributes to the labour market costs of motherhood. *Journal of Population Economics 36*, 1–23.

Cortés, P. and J. Pan (2020). Children and the remaining gender gaps in the labor market. Technical report, National Bureau of Economic Research.

Ejrnæs, M. and A. Kunze (2013). Work and wage dynamics around childbirth. *The Scandinavian Journal of Economics 115*(3), 856–877.

Fernández, R., A. Fogli, and C. Olivetti (2004). Mothers and sons: Preference formation and female labor force dynamics. *The Quarterly Journal of Economics 119*(4), 1249–1299.

Friedman, M. (1957). The permanent income hypothesis. In *A theory of the consumption function*, pp. 20–37. Princeton University Press.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review 104*(4), 1091–1119.

Guiso, L. and L. Zaccaria (2023). From patriarchy to partnership: Gender equality and household finance. *Journal of Financial Economics 147*(3), 573–595.

Heathcote, J., K. Storesletten, and G. L. Violante (2009). Quantitative macroeconomics with heterogeneous households. *Annu. Rev. Econ. 1*(1), 319–354.

Jappelli, T. and L. Pistaferri (2010). The response of consumption to income changes. *Annual Review of Economics 2*(1), 479–506.

Kaufmann, K. and L. Pistaferri (2009). Disentangling insurance and information in intertemporal consumption choices. *American Economic Review 99*(2), 387–392.

Kim, S. D. and P. Moser (2021). Women in science. lessons from the baby boom. Technical report, National Bureau of Economic Research.

Kleven, H. (2022). *The Geography of child penalties and gender norms: evidence from the United States*. NBER Working Paper 30176.

Kleven, H., C. Landais, J. Posch, A. Steinhauer, and J. Zweimüller (2019). Child penalties across countries: Evidence and explanations. In *AEA Papers and Proceedings*, Volume 109, pp. 122–126. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Kleven, H., C. Landais, and J. E. Søgaard (2019). Children and gender inequality: Evidence from denmark. *American Economic Journal: Applied Economics 11*(4), 181–209.

Kuziemko, I., J. Pan, J. Shen, and E. Washington (2018). The mommy effect: Do women anticipate the employment effects of motherhood? Technical report, National Bureau of Economic Research.

Love, D. A. (2010). The effects of marital status and children on savings and portfolio choice. *The Review of Financial Studies 23*(1), 385–432.

Modigliani, F. and R. Brumberg (1954). Utility analysis and the consumption function: An interpretation of cross-section data. *Franco Modigliani 1*(1), 388–436.

Nagatani, K. (1972). Life cycle saving: theory and fact. *The American Economic Review 62*(3), 344–353.

Olivetti, C. and B. Petrongolo (2016). The evolution of gender gaps in industrialized countries. *Annual review of Economics 8*, 405–434.

Parker, J. A. (1999). The reaction of household consumption to predictable changes in social security taxes. *American Economic Review 89*(4), 959–973.

Pistaferri, L. (2001). Superior information, income shocks, and the permanent income hypothesis. *Review of Economics and Statistics 83*(3), 465–476.

Souleles, N. S. (2000). College tuition and household savings and consumption. *Journal of Public Economics 77*(2), 185–207.

Thurow, L. C. (1969). The optimum lifetime distribution of consumption expenditures. *The American Economic Review 59*(3), 324–330.

Waldfogel, J. (1998). Understanding the 'family gap'in pay for women with children. *Journal of economic Perspectives 12*(1), 137–156.

Appendix

A Tables

Table A1: Percentage of Educational Attainment, by gender - SHIW Sample

	None	Elementary	Middle	High	Bachelor's	Postgrad
Men	5.85	12.04	17.09	12.15	3.88	0.22
Women	7.13	13.05	13.67	11.15	3.64	0.13
Total	12.98	25.09	30.75	23.30	7.52	0.35

Notes: The table shows a cross tabulation of educational attainment and gender in the SHIW sample.

Table A2: Percentage of Educational Attainment, by gender - Pseudo-Panel

	None	Elementary	Middle	High	Bachelor's	Postgrad
Men	1.18	11.43	22.73	18.52	6.75	0.46
Women	0.65	5.02	12.11	14.43	6.43	0.29
Total	1.83	16.45	34.83	32.95	13.19	0.75

Notes: The table shows a cross tabulation of educational attainment and gender in the pseudo-panel sample.

Table A3: Share of Type of Employment, by gender - SHIW Sample

	Men	Women	All
Share of Self-Employed	12%	4%	8%
Conditional on Being Employed	25%	16%	22%
Share of Employees	35%	21%	28 %
Conditional on Being Employed	75%	84%	78%
Double Income Declared (Share)	1.15%	0.29%	0.7%
Conditional on Being Employed	2.4%	1.1%	2%

Notes: The table shows the share of type of employment (*i.e.* self-employed vs employee) by gender for the SHIW sample.

Table A4: Share of Type of Employment, by gender - Pseudo-Panel

	Men	Women	All
Share of Self-Employed	23%	8%	16%
Conditional on Being Employed	24%	16%	22%
Share of Employees	71%	44%	59 %
Conditional on Being Employed	76%	84%	78%
Double Income Declared (Share)	2.82%	0.66%	1.9%
Conditional on Being Employed	3%	1.25%	2.5%

Notes: The table shows the share of type of employment (*i.e.* self-employed vs employee) by gender for the pseudo-panel sample.

Table A5: Total Children, by gender - Pseudo-Panel

	Men		Women		All	
Total Children	Count	Percentage	Count	Percentage	Count	Percentage
1	16,902	41.94	14,708	46.94	31,610	44.13
2	18,110	44.94	13,257	42.31	31,367	43.79
3	4,402	10.92	2,815	8.98	7,217	10.08
4	887	2.20	551	1.76	1,438	2.01
Total	40,301	100.00	31,331	100.004	71,632	100.00

Notes: The table shows the total number of children per household in the pseudo-panel sample of mothers and fathers.

Table A6: Household Covariates and Definition - SHIW

	Label	Definition
Variable Name		
Labor Income	YL + YM	Payroll Income + Net Self-Employment Income
Net Disposable Income	Y	Labor income + Pensions & Net transfers (YT) + Property income (YC)
Savings	S	Computed as a residual from Y=C+S
Savings Ratio	-	Computed as S/Y
Consumption	C	CD +CN
Consumption of Durables	CD	CD1 + CD2
Consumption of Transport	CD1	Transport equipment (cars, motorcycles, bicycles)
Consumption of Other Durables	CD2	Furniture, furnishing, household appliances
Consumption of Non-Durables	CN	Food, fuel, clothing, cosmetics etc.
Expenditure on Food	CONSAL	-
Amount of economic support	ASSIS	E.g. Assistance for disabled persons, maintenance, guaranteed minimum income, food allowance etc.)
Net Wealth	W	AR + AF - PF
Financial Assets	AF	Deposits + Govt & other securities + Trade credit
Share of Risky Assets	AF3**/AF	-
Real Assets	AR	Real estate + Business equity + Valuables*
Financial Liabilities	PF	Liabilities to banks + Trade debt + Liabilities to other households
Debt Incurred for the Purchase/ Restructuring of Buildings	DEB12A	-

Notes: The table shows the household finance variables from the SHIW historical database used in the event-study analysis in the current section. For more detailed information, see SHIW Documentation for the microdata.
**Valuables = jewelley, ancient or gold coins, works of art, antiques including furniture.
**AF3 = bonds,mutual funds,equity,shares in private limited companies and partnerships, foreign securities, loans to cooperatives.

Computation of per-capita Values

Following Browning and Ejrnaes (2009), I compute per-capita values of consumption by dividing total consumption measured by the household equivalent size. The household equivalent size is computed by assigning to each adult inside the household a unity weight, whereas children under the age of 18 are assigned weights on the basis of their age band as in Table A7.

Finally, individual weights are summed up at the household level and raised to the power of 0.7 to capture scale effects:

$$W^{\text{HH}} = \left(\sum_{m=1}^{N} w_m \right)^{0.7}$$

where N = max. # household members.

Age	Weight
$[0-2]$	0.1
$[3-4]$	0.15
$[5-10]$	0.25
$[11-16]$	0.35
$[17-18]$	0.65

Table A7: Individual weights according to age-band for children under age of 18 in the household (Browning and Ejrnaes (2009))

Table A8: Household Covariates Table - Pseudo-Panel (Matching)

	Mean	Standard Deviation	Count
Panel A. Total			
Labour Income	30,632	18,229	28,024
Household Net Income	40,714	23,508	19,834
Savings	9,616	15,661	19,834
Consumption	30,042	14,820	25,905
Consumption of Durables	2,651	5,855	24,366
Consumption of Transport	1,779	5,212	19,834
Consumption of Other Durables	831	2,125	19,834
Consumption of Non-Durables	27,590	12,542	24,366
Net Wealth	241,494	307,653	16,952
Financial Assets	28,599	58,151	19,834
Share of Risky Assets	0.11	0.25	17,842
Financial Liabilities	19,285	44,841	16,952
Debt used for the purchase/restructuring of buildings	9,520	30,297	27,997
Real Assets	197.522	257,093	28,024
Expenditure on food	8,473	3,510	18,468
Amount of Economic Support	1,617	3,105	905
Panel B. Per Capita			
Consumption	8,396	4,451	25,905
Consumption of Durables	752	1,700	24,366
Consumption of Transport	511	1,517	19,834
Consumption of Other Durables	238	625	19,834
Consumption of Non-Durables	7,706	3,737	24,366
Expenditure on food	2,378	991	18,468
Observations	28,024		

Notes: The table shows mean values and standard deviations of household units in the pseudo-panel obtained through matching. All values are deflated at 2015€. Per-capita values are computed using consumption weights as in Browning and Ejrnaes (2009) (see A7 in the Appendix).

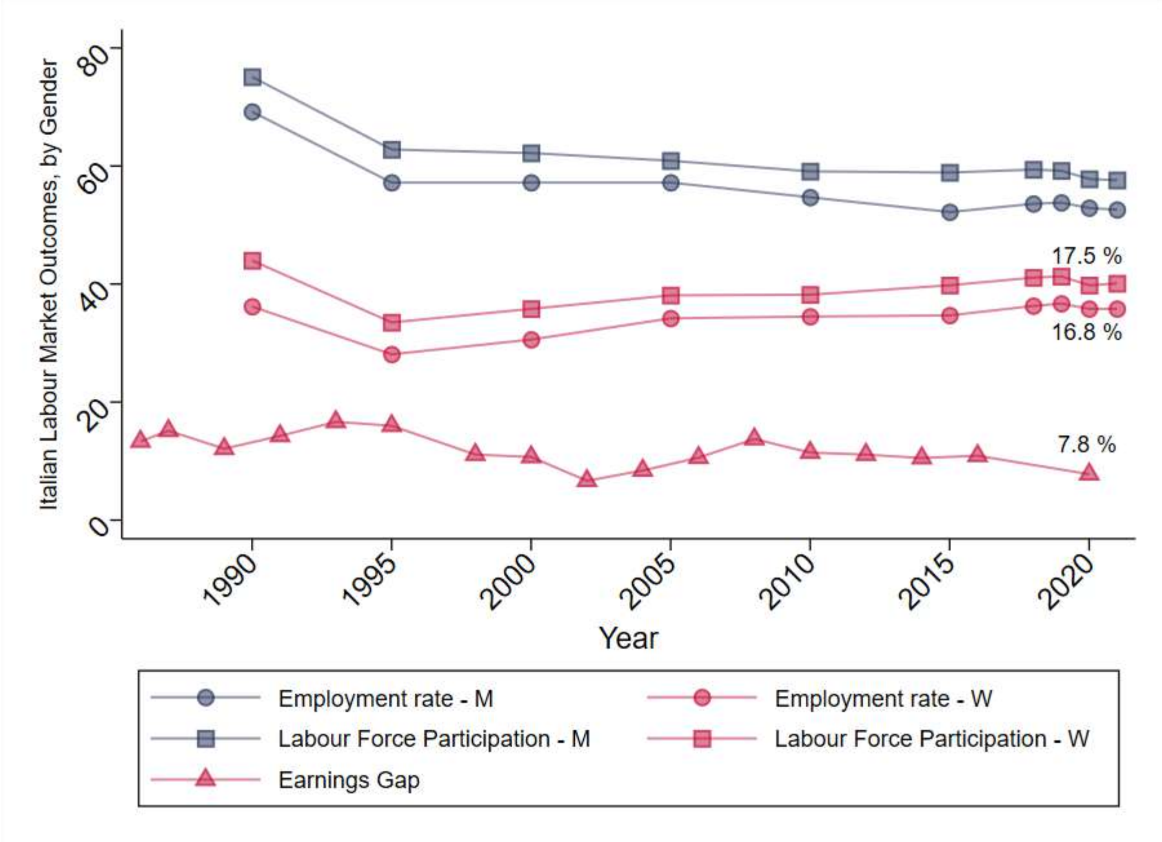
Table A9: Household Covariates Table - Pseudo-Panel (Pooled)

	Mean	Standard Deviation	Count
Panel A. Total			
Labour Income	29,267	17,385	40,845
Household Net Income	38,334	22,494	28,369
Savings	8,469	14,886	28,369
Savings Ratio	0.28	0.17	39,157
Consumption	28,888	14,365	37,828
Consumption of Durables	2,593	5,753	35,124
Consumption of Transport	1,711	5,011	28,369
Consumption of Other Durables	814	2,150	28,369
Consumption of Non-Durables	26,519	12,104	35,124
Net Wealth	219,314	288,861	23,268
Financial Assets	25,704	52,911	28,369
Share of Risky Assets	.09	.23	25,082
Financial Liabilities	17,712	41,172	23,268
Debt used for the purchase/restructuring of buildings	8,351	27,557	40,802
Real Assets	177,888	238,173	40,845
Expenditure on food	8,386	3,499	25,908
Amount of Economic Support	2,164	3,322	2,301
Panel B. Per Capita			
Consumption	14,848	7,473	37,828
Consumption of Durables	1,348	3,025	35,124
Consumption of Transport	893	2,636	28,369
Consumption of Other Durables	430	1,153	28,369
Consumption of Non-Durables	13,628	6,253	35,124
Expenditure on food (per capita)	4,326	1,749	25,908
Observations	40,845		

Notes: The table shows summary statistics of household units for the pooled pseudo-panel of mothers and fathers. To ensure consistency with the pseudo-panel obtained through matching at the household level, I keep just households consisting of couples (with no children before childbirth and with children after childbirth). All values are deflated at 2015€. Per-capita values are computed as in Browning and Ejrnaes (2009) (see A7).

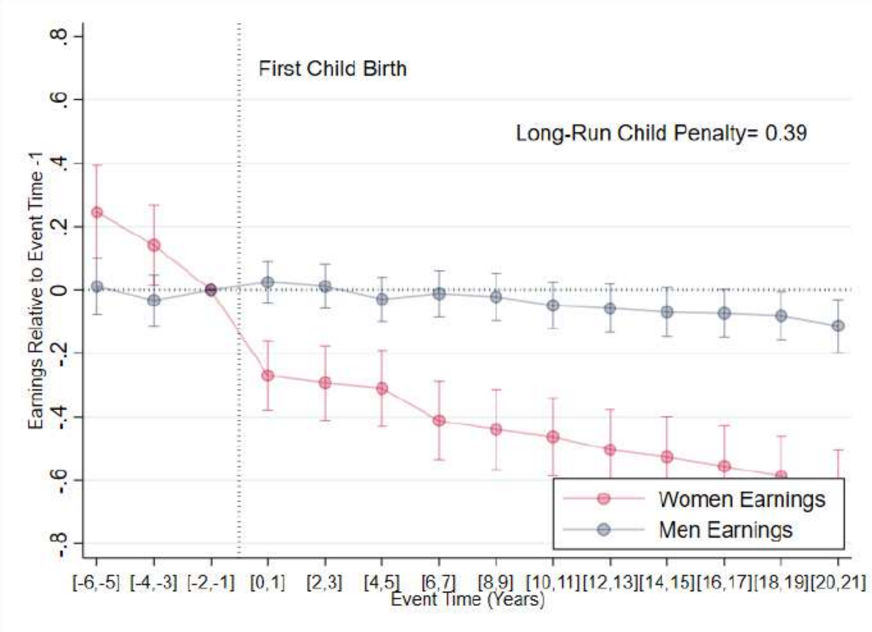
B Figures

Figure B1: Gender Gap in Labor Market Outcomes, Italy



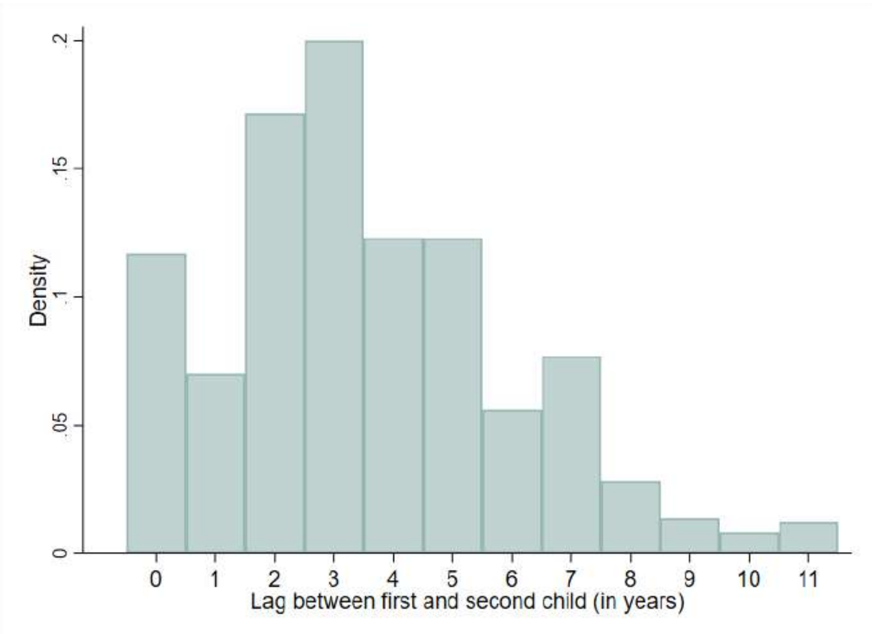
Notes: Elaboration using the *Employment/population ratio, by sex and age group* and the *Labor force participation rate, by sex and age group* datasets of the OECD Gender Data Portal. The earnings gap was computed using SHIW data from the Bank of Italy. It is the difference between median earnings of men and women relative to median earnings of men for full-time employees of working age (15-64 y.o.). Values are deflated at 2015 price levels.

Figure B2: Event-study of first childbirth for earnings



Notes: The figure plots the estimated coefficients from regression (1) in percentage terms for men (blue) and women (pink) for earnings, defined as wage income (YL) for individuals that declared themselves as employees ($qualp3 == 1$), self-employment income (YM) for those that declared themselves as self-employed ($qualp3 == 2$), and zero for the declared unemployed ($qualp3 == 3$). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the id (individual) level. 'Long-Run Child Penalty' refers to the child-penalty at event-time $e = [10, 11]$ as defined in (4).

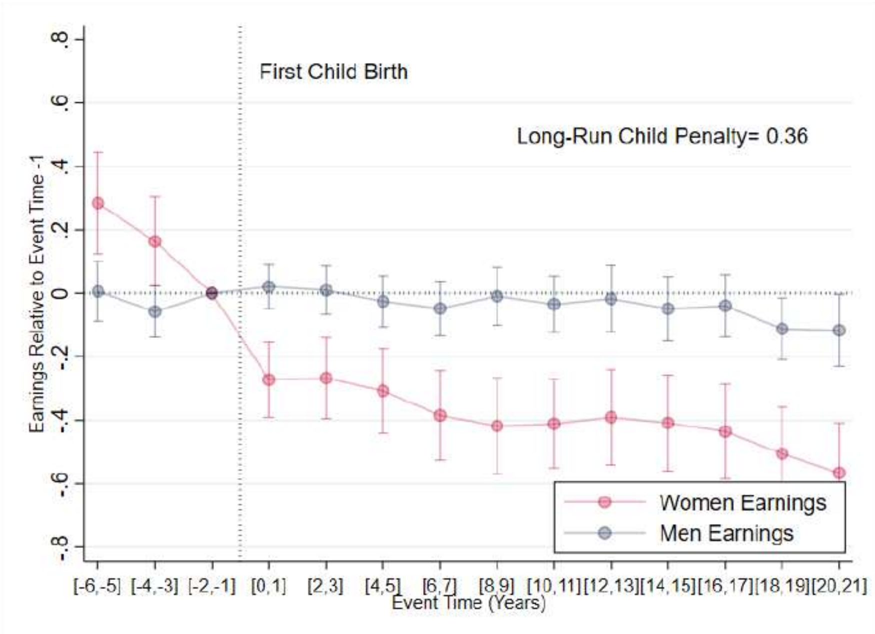
Figure B3: Distribution of the lag between the first and second child (in years)



Notes: The histogram shows the distribution of the lag between the first and second child for the pooled pseudo-panel of mothers and fathers.

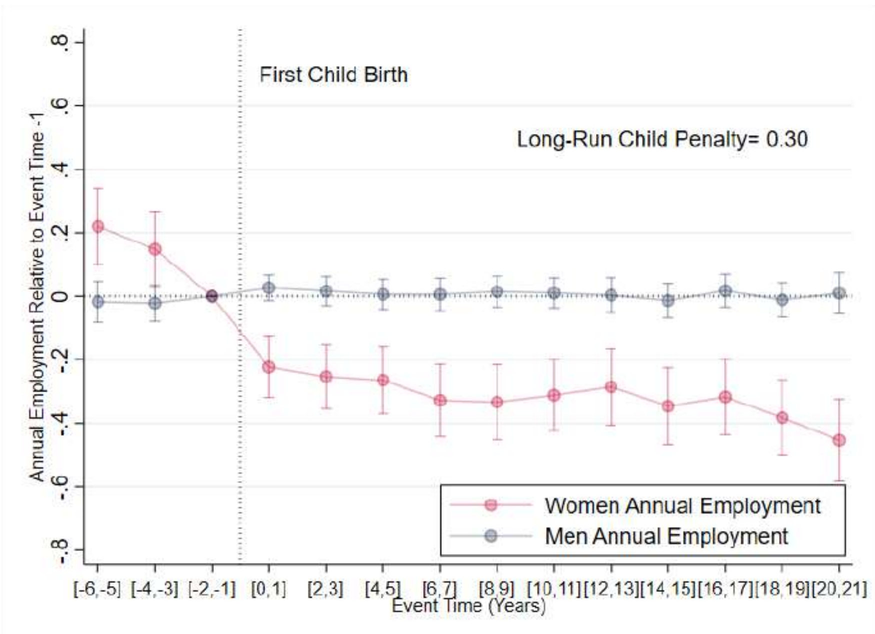
Figure B4: Event-studies of first childbirth for earnings and annual employment, conditional on total fertility of one child

(a) Event-study of first childbirth for earnings, conditional on total fertility of one child



Notes: The figure plots the estimated coefficients from regression (1) in percentage terms for men (blue) and women (pink) for earnings. I condition on a total fertility of one child by keeping only the units with a total of one child observed in the pseudo-panel. The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the id (individual) level. 'Long-Run Child Penalty' refers to the child-penalty at event-time $e = [10, 11]$ as defined in (4).

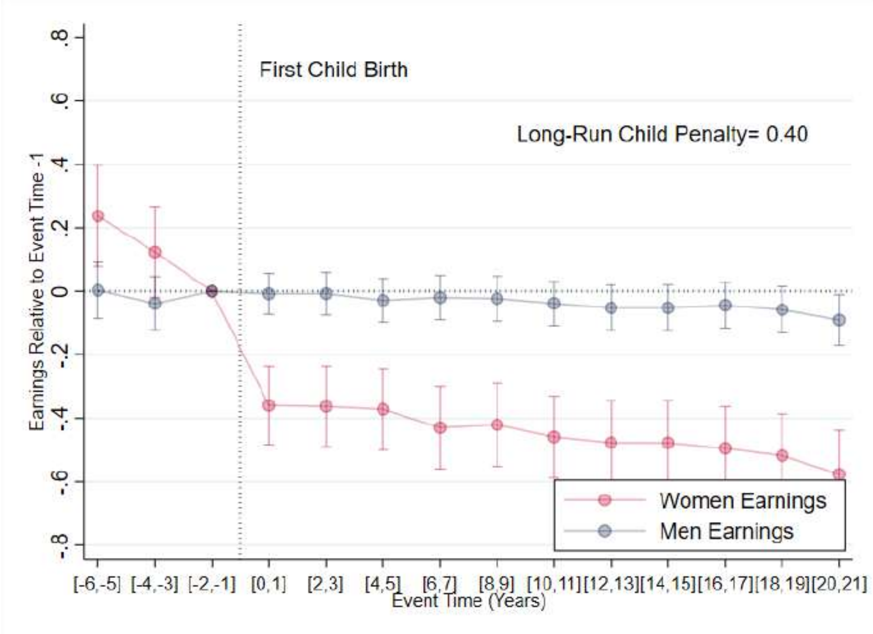
(b) Event-study of first childbirth for annual employment, conditional on total fertility of one child



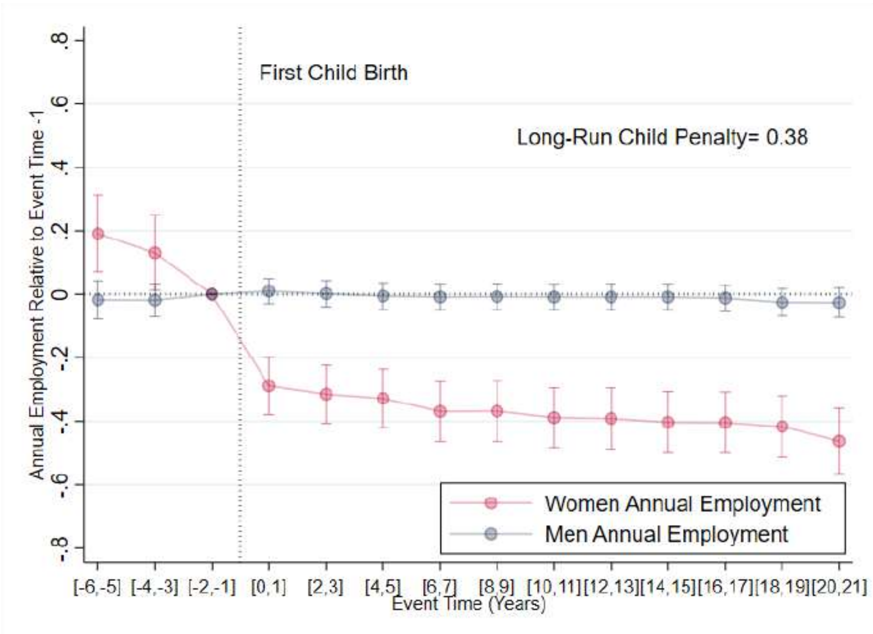
Notes: The figure plots the estimated coefficients from regression (1) in percentage terms for men (blue) and women (pink) for employment. I condition on a total fertility of one child by keeping only the units with a total of one child observed in the pseudo-panel. The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the id (individual) level. 'Long-Run Child Penalty' refers to the child-penalty at event-time $e = [10, 11]$ as defined in (4).

Figure B5: Event-studies of (average) childbirth for earnings and annual employment

(a) Event-study of (average) childbirth for earnings



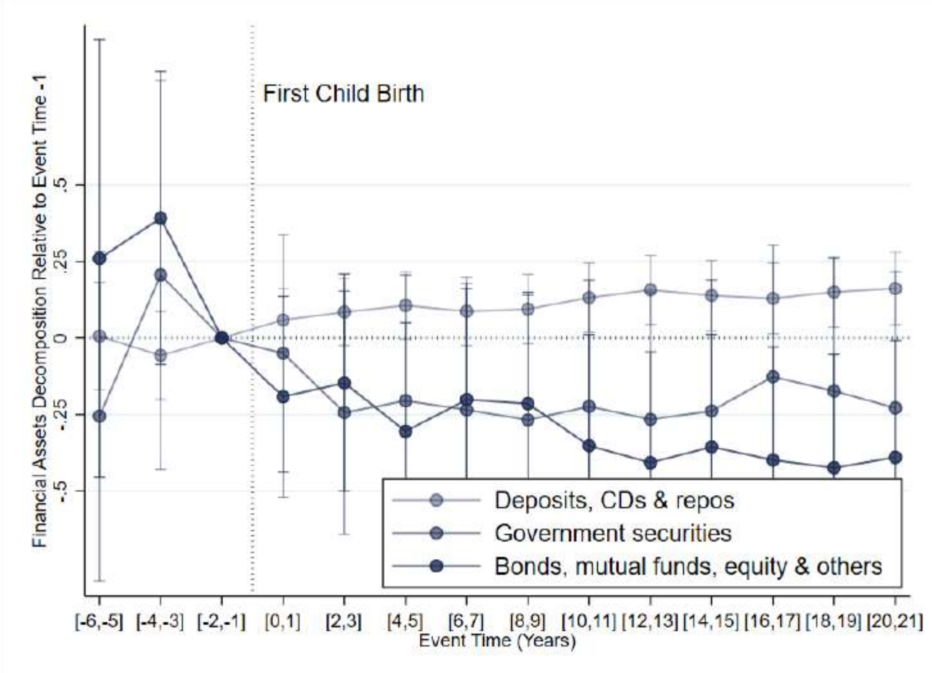
(b) Event-study of (average) childbirth for annual employment



Notes: The figure plots the estimated coefficients from regression (1) in percentage terms for men (blue) and women (pink) for earnings (B5a) and annual employment (B5b). To estimate the average effect of childbirth, event-time is indexed with time respect to the childbirth of every child observed in the household at the time of the survey. For example, a woman observed in year 2000 with two children of 2 and 4 years old, is attributed both event-time 2 and 4. The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the id (individual) level. 'Long-Run Child Penalty' refers to the child-penalty at event-time $e = [10, 11]$ as defined in (4).

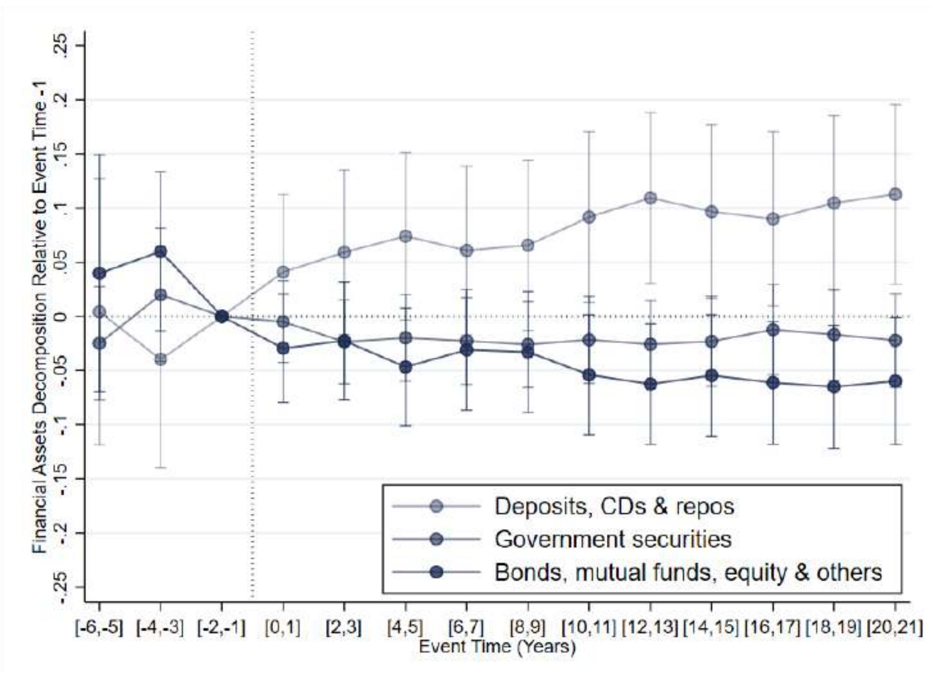
Figure B6: Event-study of first childbirth for Financial Assets (Decomposition)

(a) Event-study of first childbirth for Financial Assets (Decomposition)



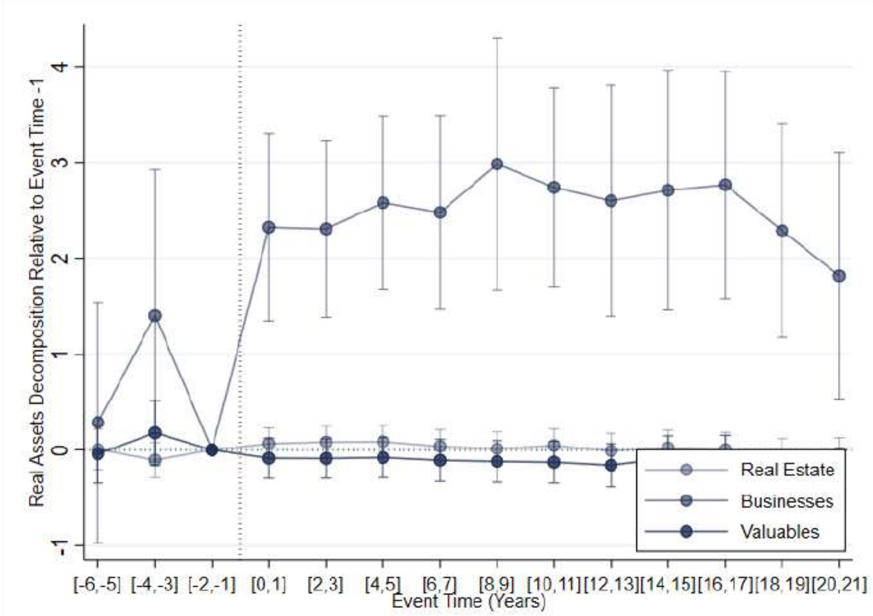
Notes: The figure plots the estimated coefficients from regression (5) separately for the main financial assets categories (Deposits, CDs and repos (AF1), Government securities (AF2), and Bonds, mutual funds, equity and others (AF3). I use as dependent variables the share of each category over all household financial assets. The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

(b) Event-study of first childbirth for Financial Assets (Decomposition) - Raw coefficients



Notes: The figure plots the estimated coefficients from regression (5) separately for the main financial assets categories (Deposits, CDs and repos (AF1), Government securities (AF2), and Bonds, mutual funds, equity and others (AF3). I use as dependent variables the share of each category over all household financial assets. The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

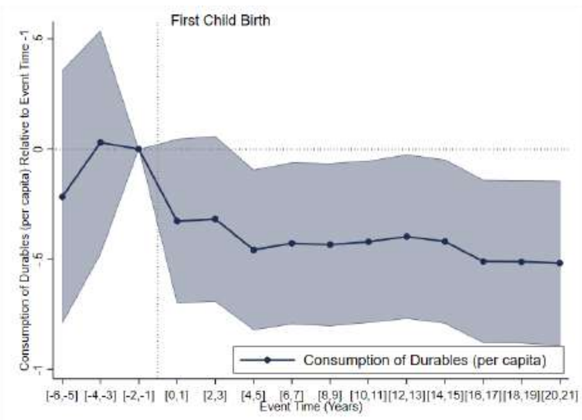
Figure B7: Event-study of first childbirth for Real Assets (Decomposition)



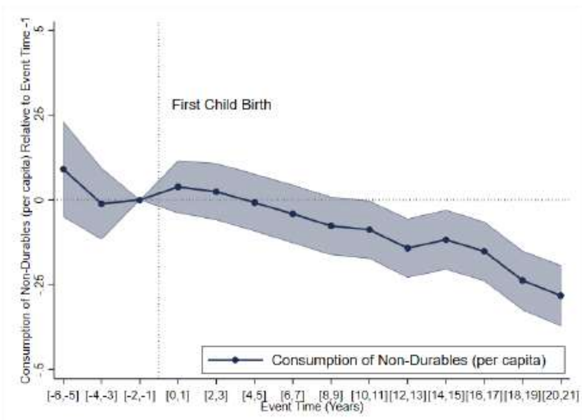
Notes: The figure plots the estimated coefficients from regression (5) separately for the main real assets categories (Real estate (AR1), Businesses (AR2), and Valuables (AR3)). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

Figure B8: Event-study of first childbirth for Consumption of Durables and Non-Durables (per-capita)

(a) Event-study of first childbirth for Consumption of Durables (per-capita)



(b) Event-study of first childbirth for Consumption of Non-Durables (per-capita)

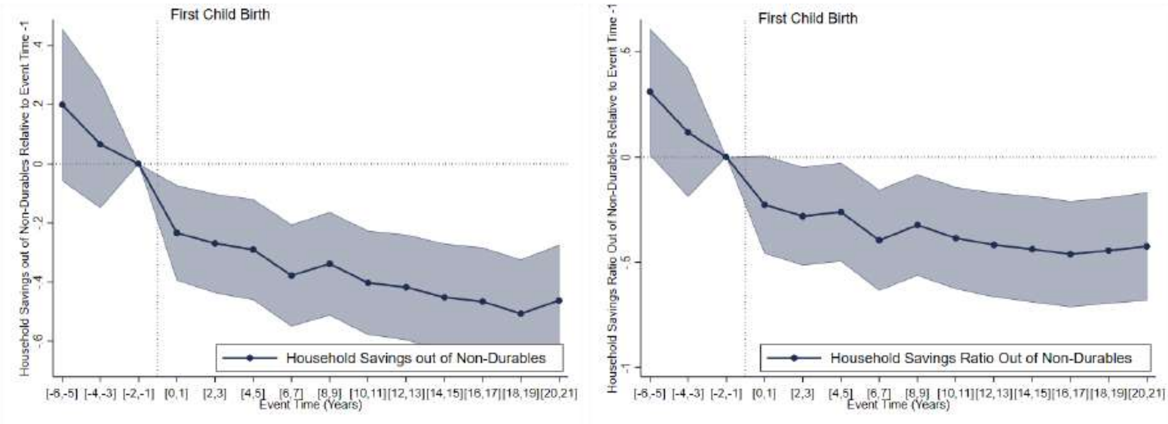


Notes: The figure plots the estimated coefficients from regression (5) for consumption of durables (B8a) and consumption of non-durables (B8b) per-capita (see Table A6). Per-capita values are computed using consumption weights as in Browning and Ejrnaes (2009). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

Figure B9: Event-study of first childbirth for Savings and Savings Ratio (Out of Non-Durables)

(a) Event-study of first childbirth for Savings (Out of Non-Durables)

(b) Event-study of first childbirth for Savings Ratio (Out of Non-Durables)

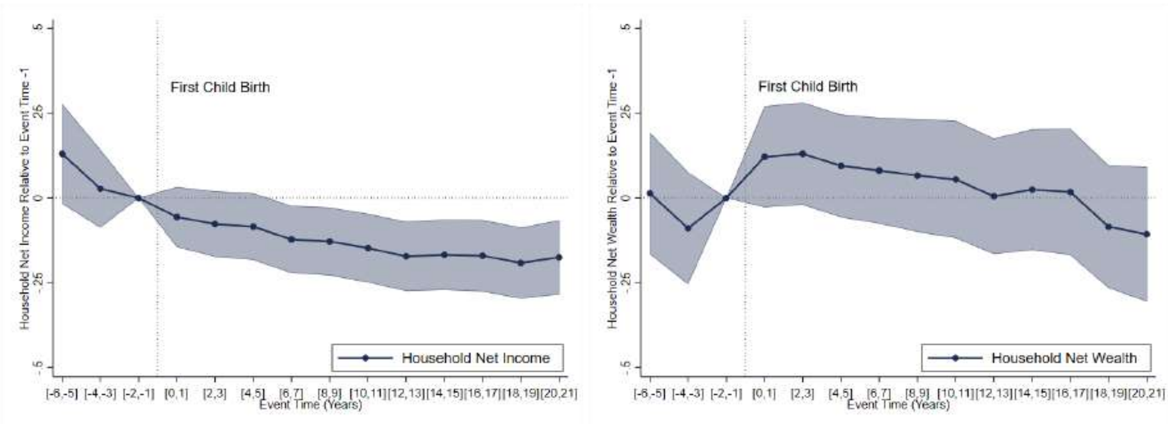


Notes: The figure plots the estimated coefficients from regression (5) for savings (B9a) and savings ratio (B9b) out of non-durables, defined as the ratio between savings out of non-durables and household net income (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

Figure B10: Event-study of first childbirth for Net Income and Net Wealth

(a) Event-study of first childbirth for Net Income

(b) Event-study of first childbirth for Net Wealth



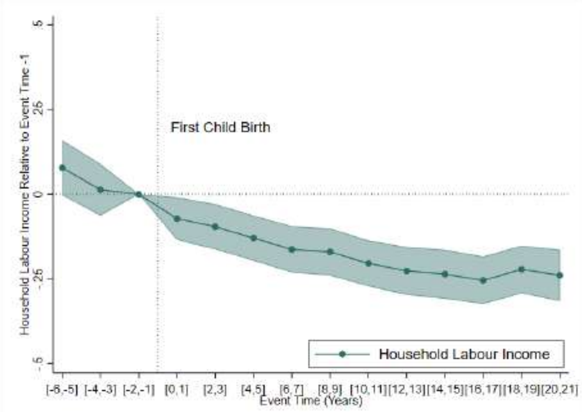
Notes: The figure plots the estimated coefficients from regression (5) for net income (B10a) and net wealth (B10b) (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

Household Finance Outcomes - Robustness Checks

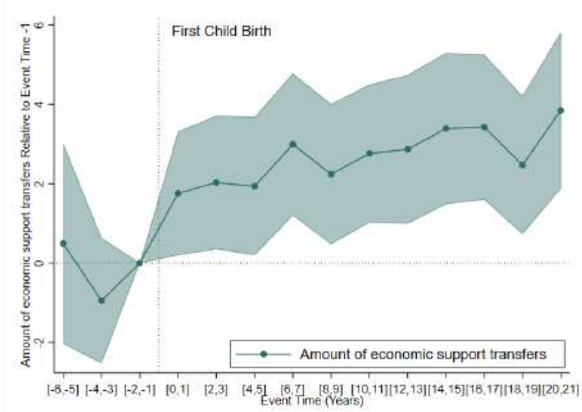
In this subsection, I show the robustness checks discussed in Section 5. Details about the dataset used and the regression specification implemented can be found in Section 2 and 5, respectively.

Figure B11: Event-study of first childbirth for Labor Income, Amount of Economic Transfers, Net Income, and Net Wealth

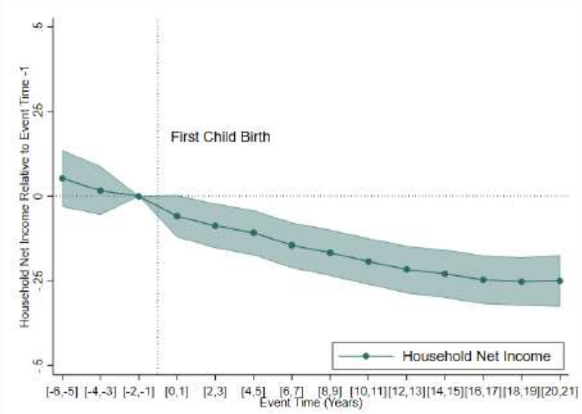
(a) Event-study of first childbirth for Labor Income



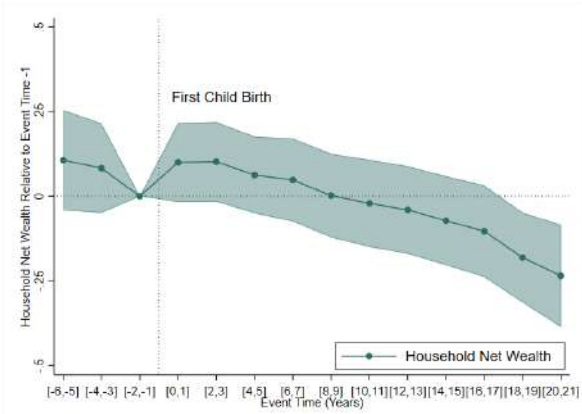
(b) Event-study of first childbirth for Amount of Economic Support Transfer



(c) Event-study of first childbirth for Net Income

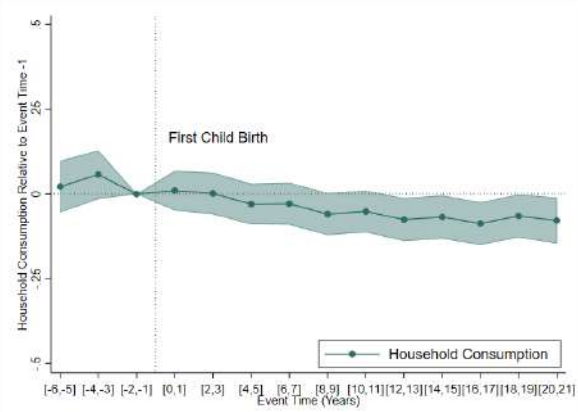


(d) Event-study of first childbirth for Net Wealth

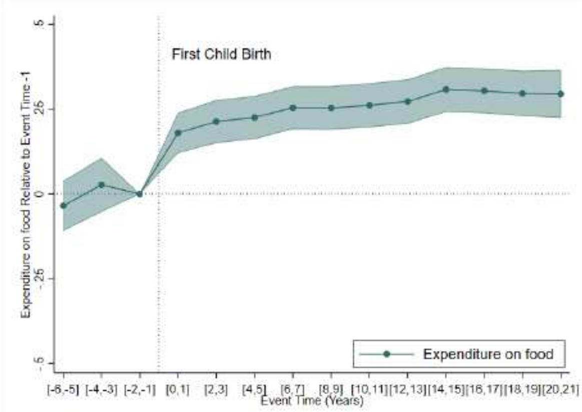


Notes: The figure plots the estimated coefficients from regression (5) for labor income (B11a), amount of economic support transfers (B11b), net income (B11c), and net wealth (B11d) (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

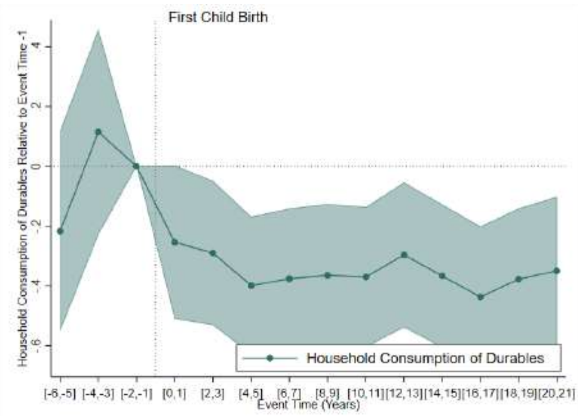
Figure B12: Event-study of first childbirth for Consumption (Total, Durables, and Non-Durables) and Expenditure on Food



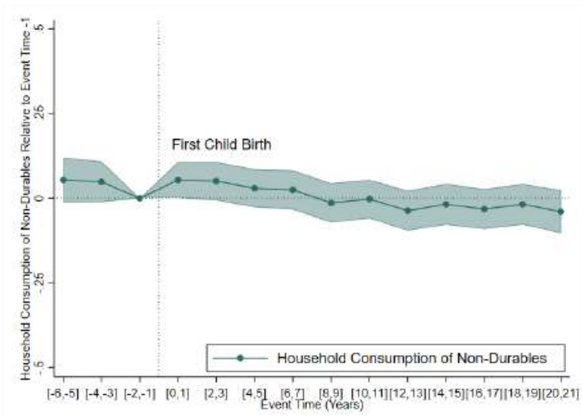
(a) Event-study of first childbirth for Consumption



(b) Event-study of first childbirth for Expenditure on Food



(c) Event-study of first childbirth for Consumption of Durables

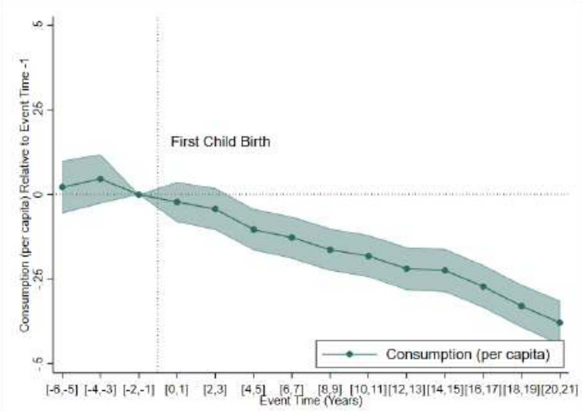


(d) Event-study of first childbirth for Consumption of Non-Durables

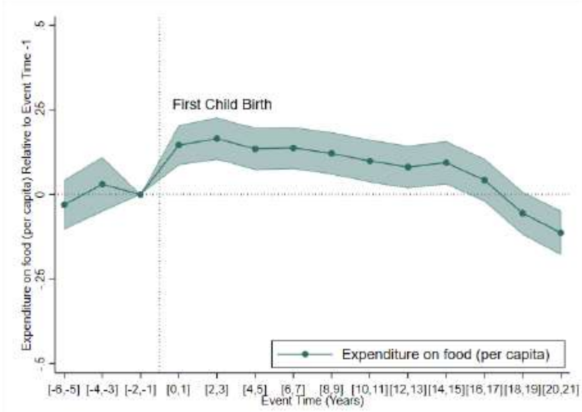
Notes: The figure plots the estimated coefficients from regression (5) for consumption (B12a), expenditure on food (B12b), consumption of durables (B12c), and consumption of non-durables (B12d) (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

Figure B13: Event-study of first childbirth for Consumption (Total, Durables, and Non-Durables) and Expenditure on Food in per-capita terms

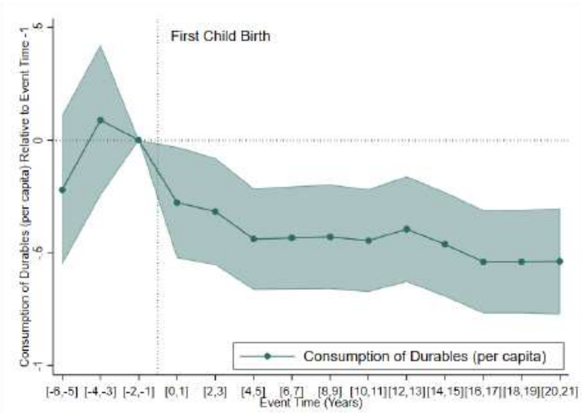
(a) Event-study of first childbirth for Consumption per-capita



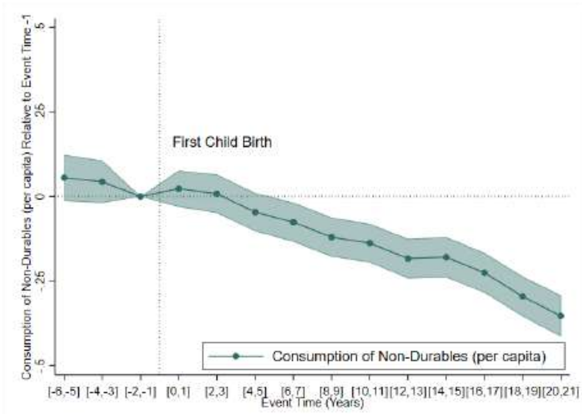
(b) Event-study of first childbirth for Expenditure on Food (per-capita)



(c) Event-study of first childbirth for Consumption of Durables (per-capita)



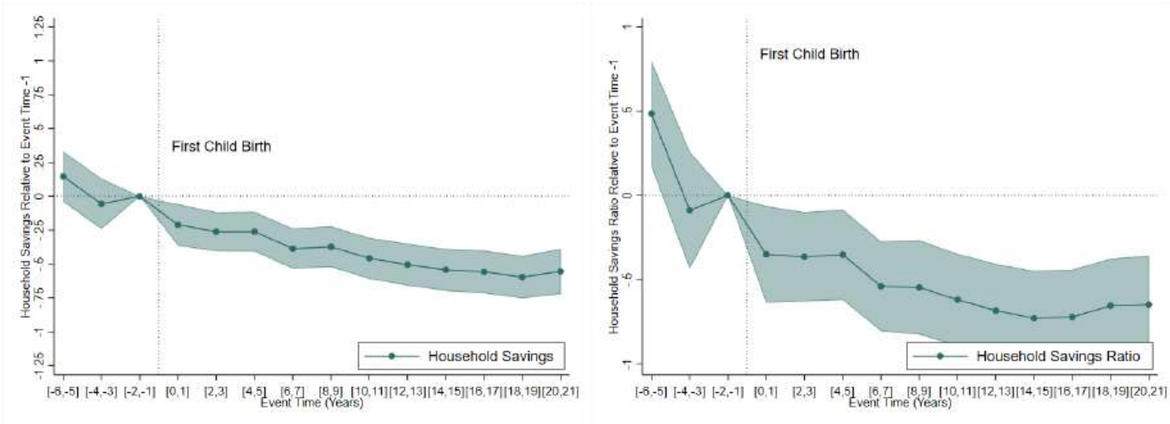
(d) Event-study of first childbirth for Consumption of Non-Durables (per-capita)



Notes: The figure plots the estimated coefficients from regression (5) for consumption (B13a), expenditure on food (B13b), consumption of durables (B8a), and consumption on non-durables (B8b) in per-capita terms (see Table A6). Per-capita values are computed using consumption weights as in Browning and Ejrnaes (2009). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

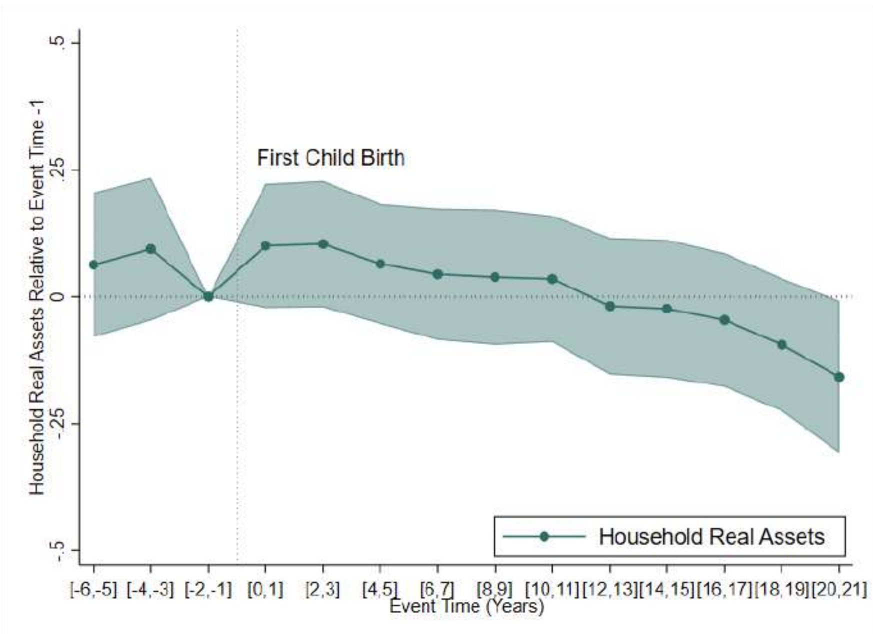
Figure B14: Event-study of first childbirth for Savings and Savings Ratio

(a) Event-study of first childbirth for Savings **(b)** Event-study of first childbirth for Savings Ratio



Notes: The figure plots the estimated coefficients from regression (5) for savings (B14a) and savings ratio (B14b) (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

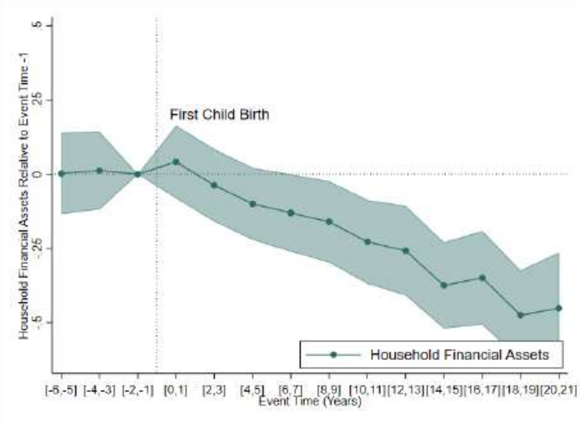
Figure B15: Event-study of first childbirth for Real Assets



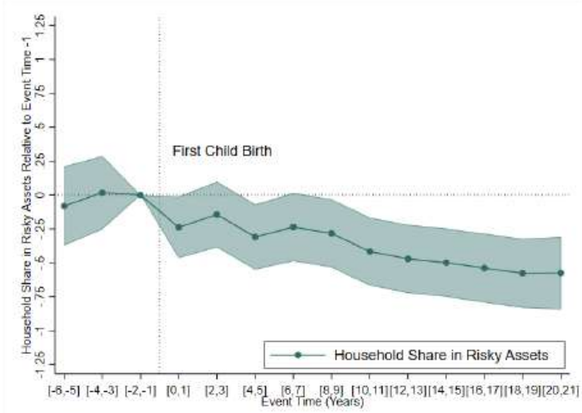
Notes: The figure plots the estimated coefficients from regression (5) for real assets, defined as the sum of real estate, businesses, and valuables (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

Figure B16: Event-studies of first childbirth for Financial Assets, Share of Risky Assets, Financial Liabilities, and Debt for Purchase/Restructuring Buildings

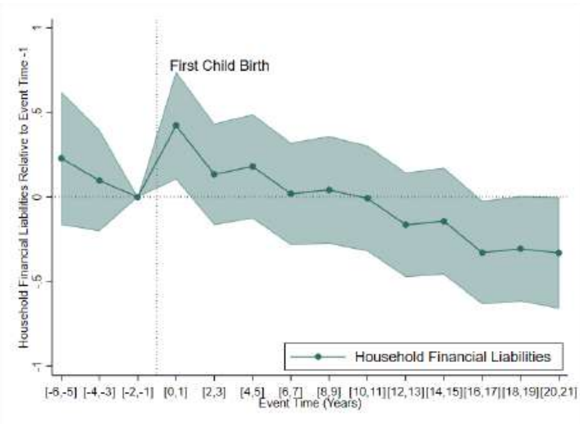
(a) Event-study of first childbirth for Financial Assets



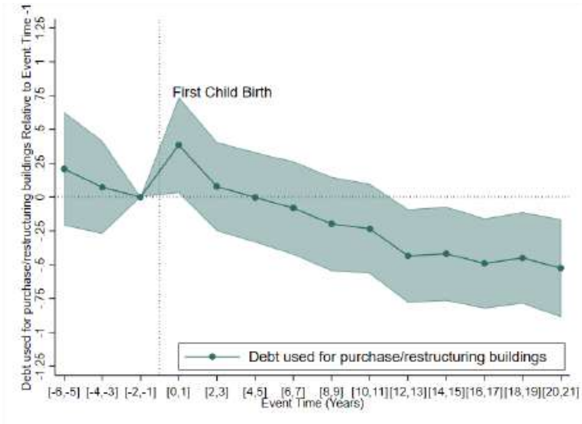
(b) Event-study of first childbirth for Share of Risky Assets



(c) Event-study of first childbirth for Financial Liabilities



(d) Event-study of first childbirth for Debt for Purchase/Restructuring Buildings



Notes: The figure plots the estimated coefficients from regression (5) for financial assets (B16a), share of risky assets (B16b), financial liabilities (B16c), and debt owed for the purchase/restructuring of buildings (B16d) (see Table A6). The coefficients are standardised by their counterfactual outcome as in (6). The excluded event-time is $e = [-2, -1]$. Standard errors are cluster at the household id level.

C Models

A model of household labor supply (Cortés and Pan (2020))

I will rely on the household labor supply model proposed by Cortés and Pan (2020)[32] as a framework for interpreting the empirical results. In what follows, I provide a concise overview of the model and discuss its implications.

The model assumes that partners maximize their utility by making decisions regarding their time allocation between labor market work and household work. The utility of each partner is determined by their own consumption, their partner's consumption, and the consumption of a public good, which in this context represents the presence of children in the household. Specifically, each partner can choose how much time to allocate to work in the labor market, denoted as h_i, and/or to household work $(1 - h_i)$. The wage rate in the labor market is given by w_i. Household work, which involves caring for and spending time with children, is captured by a child-rearing function denoted as $f(\cdot)$.

Each partner $i \in \{m, f\}$ (m represents the mother, f the father) maximizes the following utility function:

$$U_i(w_i, w_j) = \max_{0 \leq h_i \leq 1} \delta_i w_i h_i + w_j h_j + \beta_i f(1 - h_i, 1 - h_j)n$$

where n is the number of (exogenous) children. The utility function captures the trade-off between labor market work and household work, particularly the time spent with children. Each individual takes as given the partner's labor supply h_j. δ_i is a preference parameter that reflects the relative weight placed by each individual on their partner's career, and β_i represents the relative importance an individual assigns to their time spent with children compared to their labor market work. The public good production function assumed is logarithmic and linear in hours worked: $f(1 - h_i, 1 - h_j) = ln(\alpha_i(1 - h_i) + \alpha_j(1 - h_j))$, where α_i represents household productivity of individual i.

Model Predictions

The model generates the following predictions, which differ depending on whether a unitary model or a non-cooperative model of household decision-making is considered[33].

In the unitary version of the model (where $\beta_i = \beta$ for all individuals and $\delta_i = 1$ for all individuals), assuming $w_f > w_m$ and $w_f > \beta$, and assuming homogeneity in household

[32]Similar models of can be found in Fernández et al. (2004), and Andresen and Nix (2022), among others.

[33]For a comprehensive review of unitary, non-cooperative, and cooperative models of household decision-making, see Browning et al. (2011).

productivity with $\alpha_f = \alpha_m = \alpha$, the model predicts the following labor supply decisions:

$$\begin{aligned}
&h_f^* = 1; && \\
&h_m^* = 0 && \text{if } w_m < \beta; \\
&h_m^* = 1 - \frac{\beta}{w_m} && \text{if } w_m > \beta;
\end{aligned}$$

Therefore, in a model with no heterogeneity in preference parameters and household productivity, the higher wage of the father explains his full allocation of time to market work. On the other hand, the mother's labor supply decision depends on the relative productivity of household work and labor market work ($\frac{\beta}{w_m}$), and her intensive margin of hours worked is negatively related to the former and positively related to the latter.

If heterogeneity in household productivity is introduced (i.e. $\alpha_f \neq \alpha_m$), the model predicts that if $\alpha_m > \alpha_f$ and $\frac{w_m}{\alpha_m} \leq \frac{w_f}{\alpha_f}$, the partner with a comparative advantage in the labor market will specialize in market work, while the other partner will specialize in household work. This implies that in such a scenario, it is possible to observe mothers choosing to stay at home even when their wage is higher than that of the father, indicating that they have a comparative advantage in household production.

In the non-cooperative version of the model, where there is heterogeneity in both β_i and δ_i, the following predictions are made:

$$\begin{aligned}
&h_i^* = 0 && \text{if } \ w_i < \frac{\beta_i}{\delta_i}; \\
&h_i^* = 1 - \frac{\beta_i}{\delta_i} w_i && \text{if } \ w_i > \frac{\beta_i}{\delta_i};
\end{aligned}$$

Compared to the unitary model, the non-cooperative model introduces the factor δ_i, representing the relative importance each individual places on their own career compared to their partner's. The extensive margin of labor supply now depends positively on δ_i, reflecting the individual's preference for their own career. The intensive margin still depends negatively on β_i and positively on the labor market wage w_i, which are now specific to each individual. Additionally, the intensive margin also has a positive dependence on δ_i, reflecting the individual's preference for their own career relative to their partner's.

Life-Cycle Model and Permanent Income Hypothesis (Modigliani and Brumberg (1954); Friedman (1957))

In this model, the individual aims to maximize their utility, subject to a budget constraint and a final wealth condition:

$$\max \mathbf{E}_t \sum_{s=0}^{\infty} \left(\frac{1}{1+\delta} \right)^t u_{t+s}(C_{t+s})$$

$$\text{s.t.} \quad a_{t+1} = (1 + r_t)(a_t + e_t - c_t)$$

where a_s define assets at time s, e_t denotes the endowment or earnings at time t, and c_t represents consumption at time t. δ is the inter-temporal discount rate, and r_t is the real interest rate at time t.

Under quadratic preferences, and assuming a constant interest rate equal to the discount rate, the Euler equation for consumption can be expressed as:

$$c_t = c_{t-1} + \epsilon \tag{7}$$

where $\epsilon = c_t - \mathbf{E}_{t-1}c_t$ is an innovation to consumption at time t. In this model, consumption behaves as a martingale, and the current consumption level serves as the best predictor of the next period's consumption. This principle guides the determination of the optimal consumption path[34]. Consequently, in this model, changes in consumption are solely driven by innovations:

$$\Delta c_{it} = \epsilon_t \tag{8}$$

Notably, for working-age households, the primary source of uncertainty is labor income, which can be incorporated into Equation (8) as follows:

$$\Delta c_t = \frac{r}{1+r} \sum_{s=0}^{\infty} (1+r)^{-s} (\mathbf{E}_t - \mathbf{E}_{t-1}) y_{t+s} \tag{9}$$

Equation (9) implies that the optimal consumption trajectory is adjusted only when new information regarding future income becomes available, prompting the household to revise their income expectations between periods $t-1$ and t. A common characterisation of the income process is:

$$y_t = P_t + \nu_t \tag{10}$$

where

$$P_t = P_{t-1} + u_t.$$

P_t represents the permanent component of income and follows a martingale process, while ν_t represents the transitory component of income and is independently and identically distributed (i.i.d.). The permanent component P_t evolves over time as a cumulative sum of shock terms, denoted by u_t. A shock to the permanent component u_t has a lasting impact on how labor income expectations are formed, while a transitory shock affects only the current income outcome at time t. Under the income process described by Equation (10), the consumption change equation (8) can be rewritten as:

$$\Delta c_t = \frac{r}{1+r} \nu_t + u_t \tag{11}$$

[34]It is important to note that consumption smoothing, as emphasized by Browning and Crossley (2001), does not imply keeping consumption constant. Rather, the original Euler equation underlying (7) (before assuming any specific form of utility function) states that $\mathbf{E}_{t-1}[u'(c_t)] = u'(c_{t-1})$, indicating that smoothing involves individuals' attempts to maintain the marginal utility of consumption relatively constant over time, which may lead to varying consumption levels and expenditures.

This equation indicates that consumption responds only slightly to transitory shocks, with a sensitivity of $\frac{r}{1+r}$ (i.e. $\frac{\partial \Delta C_t}{\partial \nu_t} = \frac{r}{1+r}$). On the other hand, consumption responds fully to permanent shocks, with a sensitivity of 1 (i.e.$\frac{\partial \Delta C_t}{\partial u_t} = 1$). In other words, permanent shocks have a one-to-one effect on consumption, while transitory shocks have a much smaller impact.

The savings function corresponding to (9) can be expressed as follows:

$$s_t = -\sum_{j=1}^{\infty} \frac{\mathbf{E}_t \Delta y_{t+j}}{(1+r)^j} \tag{12}$$

This equation reveals that individuals save when they anticipate a decline in their income and borrow when they anticipate an increase. This pattern of portfolio behavior forms the foundation of life-cycle and permanent income models, where individuals use savings is to smooth income fluctuations, and they are expected to have minimal or no response to anticipated income shocks.

In the case of the income process described by equation (10), the savings function can be expressed as follows:

$$s_t = \frac{1}{1+r}\nu_t \tag{13}$$

This equation demonstrates that savings are highly responsive, almost one-to-one, to transitory shocks (i.e., $\frac{\partial s_t}{\partial \nu} = 1$), while they are relatively unaffected by permanent shocks. This model is often referred to as 'saving for a rainy day', as it suggests that individuals save more in anticipation of temporary income fluctuations.