



UNIVERSITÀ POLITECNICA DELLE MARCHE
Dipartimento di Scienze Economiche e Sociali

IF NOT NOW, WHEN? THE TIMING OF
CHILDBIRTH AND LABOUR MARKET OUTCOMES

MATTEO PICCHIO, CLAUDIA PIGINI,
STEFANO STAFFOLANI, AND ALINA VERASHCHAGINA

QUADERNI DI RICERCA n. 425

ISSN: 2279-9575

February 2018

Comitato scientifico:

Marco Gallegati

Stefano Staffolani

Alessandro Sterlacchini

Giulia Bettin

Collana curata da:

Massimo Tamberi

Abstract

We study the effect of childbirth and its timing on female labour market outcomes in Italy. The impact on yearly labour earnings and participation is traced up to 21 years since school completion by estimating a factor analytic model with dynamic selection into treatments. We find that childbearing, especially the first delivery, negatively affects female labour supply. Women having their first child soon after school completion are able to catch up with childless women only after 12-15 years. The timing matters, with minimal negative consequences observed if the first child is delayed up to 7-9 years after exiting formal education

JEL Class.: C33, C35, J13, J22

Keywords: Female labour supply; fertility; discrete choice models; dynamic treatment effect; factor analytic model.

Indirizzo: Matteo Picchio, Corresponding author, *E-mail address:* m.picchio@univpm.it. Department of Economics and Social Sciences, Marche Polytechnic University, Italy; Sherppa, Ghent University, Belgium; IZA, Germany; GLO.
Claudia Pigni, Department of Economics and Social Sciences, Marche Polytechnic University, Italy; MoFiR, Italy.
Stefano Staffolani, Department of Economics and Social Sciences, Marche Polytechnic University, Italy
Alina Verashchagina, Department of Economics and Social Sciences, Marche Polytechnic University, Italy.

If not now, when? The timing of childbirth and labour market outcomes*

*Matteo Picchio, Claudia Pigni,
Stefano Staffolani, and Alina Verashchagina*

1 Introduction

When is the best time to have kids? This is a question that most women face at some point. Economic considerations play an important role, not only because children are an expensive endeavour, but also because the opportunity cost of career interruptions for women is often high. In the literature, the terms *motherhood penalty* and *motherhood pay gap* have been used to emphasise the monetary loss faced by women after giving birth, the amount of which may vary considerably across countries and groups of women, defined on the basis of education and race (Grimshaw and Rubery, 2015; Herr, 2016; Leung et al., 2016). To complicate matters, the opportunity cost of career interruptions may vary over the working life because, for example, the human capital may accumulate at a different pace over time and the employment protection and the consequent job stability typically increase with seniority. Postponed childbearing has thus been identified as a strategy to minimise losses after the childbirth (Miller, 2011; Troske and Voicu, 2013), which is coherent with an almost universally increasing age at first birth.¹ However, while the delay of childbirth may help to contain the adverse labour market outcomes, it might also explain the reduction in total fertility rates, as a result of the declining probability of conception with age (Bratti and Tatsiramos, 2012).

**We wish to thank the Ministry of Economics and Finance and the Giacomo Brodolini Foundation for providing us with the permission to use the dataset AD-SILC, Michele Raitano for his suggestions on the use of this dataset, and Massimiliano Bratti for his comments on a preliminary version of this paper. Any opinions expressed in this paper are those of the authors and not those of the Ministry of Economics and Finance, the European Commission, the Italian National Institute of Statistics (ISTAT), or the Italian National Social Insurance Agency (INPS).*

¹In OECD, the age at first birth passed from 26.2 years old in 1995 to 29.0 in 2015 (Family Database: <http://www.oecd.org/els/family/database.htm>, Chart SF2.3.B).

Our paper adds to the debate on the best time to give birth, in terms of labour market outcomes, by answering the following research questions:

1. What is the causal impact of childbirth on female labour earnings and the number of days worked in a year?
2. How does it change over the lifetime?
3. Does the timing of birth matter?

The answers to these questions are of utmost importance for designing policies effective in reducing the labour market penalties induced by childbearing without compromising the total fertility rate, especially in the absence of supportive family-friendly policies (Bratti, 2015). We empirically investigate these issues by using an Italian dataset (AD-SILC) obtained by merging survey data and administrative archives. Italy is quite an interesting case study, since it has one of the lowest levels of both female employment and fertility, and the highest age at first birth in Europe.²

The contribution of our study to the existing literature is threefold. The first one is methodological and involves the identification strategy of the effect of childbearing and its timing on labour market outcomes. We set-up a factor analytic dynamic model (Carneiro et al., 2003; Heckman and Navarro, 2007): i) with multiple dynamic treatments (one for each childbirth); ii) in which women giving birth at different times differ in unobserved determinants jointly affecting fertility choices and labour market outcomes (dynamic selection); iii) where the impact of each childbirth varies with its timing. Our model is close to those proposed by Carneiro et al. (2003) and by Fruehwirth et al. (2016), and extends them in two different directions: compared to the former, we allow the unobserved factor determining the dynamic treatments and the outcomes to be time-varying; with respect to the latter, we consider that units can receive multiple dynamic treatments (more than one child).³ In this respect, our framework is close to that considered by Troske and Voicu (2013), who however studied the effect of the timing of childbirths only on labour market participation and whose identification strategy was largely based on parametric assumptions.

²In 2015 the employment rate for women aged 20-64 stood at 50.6% in Italy versus 64.3% in the EU-28 area. In the same year, the fertility rate in Italy was as low as 1.35, coupled with the highest ever age at first birth reaching 30.8 years old (Eurostat online database: <http://ec.europa.eu/eurostat/data/database>).

³Carneiro et al. (2003) study the impact of different schooling levels on future returns, whereas Fruehwirth et al. (2016) estimate how retention affects subsequent school performance. Differently from our model and Carneiro et al. (2003), Fruehwirth et al. (2016) also incorporate essential heterogeneity, i.e. they allowed the treatment effect to vary with the time-varying unobserved determinants.

Nonparametric identification is achieved here by i) exploiting the loading factor structure of the unobserved determinants; ii) the longitudinal information in our data, which allows for the reconstruction of the complete fertility and working histories, thereby providing multiple observations over time of the endogenous variables; iii) measures of the latent factor which are free of selection into treatment (Carneiro et al., 2003), such as the employment experience before school completion and the number of siblings when the woman was 14 years old; and iv) treatment-specific overidentifying restrictions based on spacing between pregnancies and siblings-sex composition. In these respects, we improve upon the identification strategies so far adopted to quantify the effect of delaying child-births (see Bratti, 2015, for an extensive review): we combine a rich longitudinal structure, which allows for a flexible specification of time-varying unobserved heterogeneity, with the treatment-specific exogenous variation, commonly used in quasi-experimental settings,⁴ and with pre-sample information on the labour market status and composition of the family of origin, as additional overidentifying measurements *à la* Carneiro et al. (2003).

Second, we allow the effect of motherhood to vary over time and trace it for a longer period than what is typically done in the literature. Existing studies often stop at 5 years after childbirth (see e.g. Pacelli et al., 2013; Fitzenberger et al., 2013), and the motherhood penalty rarely disappears by that time. With our data, we are able to reconstruct working histories up to 21 years after school completion. We exploit this richness to identify not only the short and medium run effects, but also long run consequences of childbearing.

Third, the time profile of the impact of childbearing is allowed to vary according to its timing since school completion,⁵ which is taken as the starting point of fertility choices.⁶ In the empirical literature, an extra year of delay is typically assumed to affect linearly or log-linearly the labour market outcomes (see e.g. Miller, 2011; Bratti and Cavalli, 2014; Karimi, 2014; Herr, 2016). Instead, we assume that the impact of delaying childbirth could be non-linear over the time elapsed since school completion. This turns to be important for drawing policy implications.

⁴Instrumental variables strategies using sibling-sex composition or biological fertility shocks for the timing of birth have been adopted by Angrist and Evans (1998), Miller (2011), and Karimi (2014). Fertility shocks include the occurrence of miscarriage, undesired pregnancies while using contraception, and longer time elapsed from first conception attempt to first birth. They have however been criticised for not being reliable enough. Wilde et al. (2010) suggest that background characteristics could be more appropriate for this purpose.

⁵Our definition of the timing of birth with respect to the moment of school completion is similar to the definition with respect to the labour market entry analysed by Herr (2016) and used by Karimi (2014).

⁶Only 195 women in our sample had a kid before school completion. We removed them from the sample.

Our findings suggest that childbearing, especially the first delivery, negatively affects female labour supply and that the effect is amplified if the birth occurs soon after school completion. It takes about 12-15 years for the gap in earnings between mothers and childless women to close. The adverse effects on yearly earnings and on the number of days at work in a year are minimised if the first child is delayed up to 7-9 years after exiting formal education.

The structure of the paper is as follows. Section 2 provides the literature review. Section 3 describes the data at hand and the sample of women used for the analysis. Section 4 explains the econometric model. Section 5 presents and comments on the estimation results. Section 6 concludes. A downloadable [Online Appendix](#) contains additional descriptive statistics, details on the estimation strategy, and the full set of estimation results.

2 Literature Review

There is a long tradition of studies on female labour supply and fertility.⁷ The two processes are often jointly modelled, in recognition of the fact that motherhood matters for female career choices and viceversa ([Browning, 1992](#); [Iacovou, 2001](#)). Within this strand of literature, we are mainly interested in two specific blocks, focusing on the *motherhood penalty* and on the *timing of birth*.

From a theoretical standpoint, the impact of childbearing on earnings may have an unclear sign. On the one hand, motherhood can positively affect labour supply and earnings, if new mothers are willing to work more in order to face the extra costs entailed by raising children. On the other hand, women's reservation wages may increase, especially if free childcare services are not available or limited, and, at the same time, both their degree of labour market attachment and human capital accumulation may decrease. Depressing effects on labour market performance can therefore be expected.⁸

Empirical research suggests that the reasons behind losses in labour market outcomes include career break and downward occupational mobility ([Bratti et al., 2005](#); [Fitzenberger et al., 2013](#); [Waldfogel, 1997](#); [Herr, 2016](#)), hazard reduction and transition to flexible work schedules ([Felfe, 2012](#)), as well as family-oriented career choices made both before and after becoming a mother ([Adda et al., 2017](#)). A non-negligible loss in wages/earnings and a reduction in the hours worked after childbirth were reported to be at place in many countries ([Harkness and Waldfogel, 2003](#)). The empirical evidence is

⁷See, among others, [Killingsworth and Heckman \(1986\)](#), and [Blundell and MaCurdy \(1999\)](#).

⁸See [Ermisch \(1990\)](#) for a review of the theoretical models.

vast for the US (Taniguchi, 1999; Miller, 2011; Herr, 2016), where the motherhood wage gap for women with a high-school diploma or a college degree was found to be about 10% per child (Anderson et al., 2002). More recently, Wilde et al. (2010) reported at least twice that loss. By using longitudinal data and individual fixed effects models to account for time-invariant unobserved heterogeneity, the estimated wage losses for the first child are reported to be of about 6% in the US and 9% in the UK (Waldfogel, 1998) and Spain (Fernández-Kranz et al., 2013).⁹ Evidence for Italy comes from Pacelli et al. (2013), who showed that three years after childbirth the wages of mothers who work full-time are still significantly lower than those of childless women by about 3%.

A further relevant policy question is: how long does the motherhood penalty last? Earlier studies argued that the wage losses are persistent (Waldfogel, 1997) while, more recently, they were found to be temporary. Still, it may take almost a decade for the wage gap between mothers and childless women to close (Datta Gupta and Smith, 2002; Lalive and Zweimüller, 2009; Fernández-Kranz et al., 2013). For Italy, Pacelli et al. (2013) conclude that there is no sign of the wage gap closing five years after childbirth. On the contrary, Rondinelli and Zizza (2011) argue that the effect of motherhood on female participation tends to be non-persistent once it is instrumented with infertility shocks data. This latter finding was supported by Michaud and Tatsiramos (2011) who, focusing on 7 European countries, showed that Italy and Spain exhibit relatively low direct birth effects on female employment. This was explained by reliance on family ties.

The theoretical research on fertility decisions has also focused on the timing of pregnancies.¹⁰ Life cycle models emphasise that an early childbirth increases the parents' utility due to the longer life spent with the child. Having a child earlier can however generate higher costs or lower expected earnings: with an imperfect capital market, the opportunity costs of the time spent caring for children and the net direct expenditures may not be affordable at the beginning of the career (Hotz et al., 1997). Even in the case of a perfect capital market, motherhood generates costs for the time spent out of the labour market and for the loss of human capital, with both of these costs varying over the

⁹The above results seem to be less robust for studies focusing only on college-educated women. Amuedo-Dorantes and Kimmel (2005) finds that college-educated mothers might even experience wage boost as compared to college-educated childless women, mainly because of better job matches with more female-friendly firms.

¹⁰The growing amount of sociological literature also seeks to understand which factors drive an almost universal trend of postponed motherhood in developed countries. Mills et al. (2011) argue that the key reasons are: the rise of effective contraception methods, increases in female education and labour market participation, value changes, gender equity, partnership changes, housing conditions, economic uncertainty and the absence of supportive family policies.

woman's working life.

Theoretical models generate somehow ambiguous conclusions, depending on the variables that are assumed to be the main determinants of the optimal time for motherhood (see e.g. [Cigno, 1983](#); [Tomes, 1985](#); [Cigno and Ermisch, 1989](#); [Walker, 1995](#); [Gustafsson, 2001](#)). Among them, the female human capital before childbirth, the decay of job skills, the rate of return to human capital, and the length of the time spent out of the labour force play a major role. According to [Gustafsson \(2001\)](#), all these variables are positively linked with the postponement of pregnancy. Nevertheless, other factors can play an important role ([Herr, 2016](#)). The employment profile of inexperienced workers is typically intermittent, especially right after school completion, and the rate of human capital accumulation may be slow at the beginning of the career. If, instead, the accumulation of human capital is most intense at the initial stage of the career and employment protection increases with seniority, then a career interruption at the very beginning might turn out to be critical.

From an empirical perspective, an increasing number of studies is investigating how the timing of birth determines the amount of loss in future earnings and the way motherhood penalty changes over the lifetime. Dynamic life-cycle models ([Adda et al., 2017](#)) and the dynamic treatment approach by ([Fitzenberger et al., 2013](#)) confirm a strong and quite persistent negative effect of childbirth on earnings, but cannot define a clear-cut effect of the timing of birth. On the one hand, the delay makes it possible to reach a higher-wage career track. On the other hand, it may increase the probability of exiting the labour force ([Frühwirth-Schnatter et al., 2016](#)). [Miller \(2011\)](#) reports a substantial improvement in labour market outcomes if motherhood is delayed in the US: an increase in earnings by 9% per year of delay, in wages by 3%, and in working hours by 6%. Focusing on highly educated women in Sweden, [Karimi \(2014\)](#) finds instead that motherhood delay produces adverse career consequences: postponing motherhood has a significantly negative effect on both career earnings and the average career wage (15% and 5% loss, respectively). Apart from the fact that Swedish context is very different from the American one, the explanation offered to this contrasting finding is that spacing between several births gets more stringent with every delay. Looking only at the first birth, typically done by most of existing studies, might therefore not be enough. In order to understand how the effect of the first birth evolves over time one should consider the possibility of overlapping effects from subsequent births.

For Italy, [Bratti and Cavalli \(2014\)](#) found that delaying the first birth by one year increases labour market participation by 1.2 percentage points and working time by about

half an hour per week. At the same time, they find no evidence that late motherhood prevents a worsening of new mothers' job conditions.

3 Data and Sample

3.1 Sample Selection Criteria

The empirical analysis is based on the AD-SILC, which is obtained by matching two data sources: i) the IT-SILC database gathered from the Italian National Institute of Statistics (ISTAT); ii) the administrative data on labour market contracts from the National Social Insurance Agency (INPS). Since INPS manages social security, the database contains gross earnings and the number of working days for each working episode in each year for all the salaried employees. Furthermore, we matched the AD-SILC with the regional time series of unemployment, employment, and fertility rates from ISTAT, used as time-varying controls in our empirical analysis.

We mainly exploit the IT-SILC to rebuild fertility histories. We extract data on Italian women aged between 26 and 45 and interviewed in the 2005 and 2011 surveys.¹¹ These two waves are the only ones with the *ad hoc* module on intergenerational transmission of poverty and disadvantages, and it provides information on the family situation when the respondents were 14 years old. We will exploit this predetermined information to model fertility decisions after school-leaving. We did not include in the analysis women younger than 26, because the module on intergenerational transmission was submitted only to individuals older than 25. We exclude from our sample women older than 45 in order to reduce the risk of errors in rebuilding mothers' childbearing history: the older the woman, the higher the risk of not assigning a child to her, simply because the child might have already left home.¹² In order to have at least 3 years of labour market data between school departure and the IT-SILC interview, we further selected women who obtained their highest educational diploma before 2003 if interviewed in 2005, and before 2009 if interviewed in 2011.¹³ Since the regional time series of unemployment, employment,

¹¹This implies that we removed from the 2005 (2011) dataset women born after 1980 (1986) and before 1960 (1966).

¹²The imputation to each woman younger than 46 of her complete fertility history is likely to be measurement error free, because: i) the IT-SILC regards children of the household being educated away from home as household members and therefore interviews them; ii) in Italy children typically leave home very late, on average when older than 26 (Leopold, 2012); iii) according to Eurostat, Italy has the highest mean age of women at birth of first child (29 years in 1997 and 31 years in 2015).

¹³For the 141 women interviewed both in 2005 and 2011, we only kept the 2011 data, since more recent

and fertility rates gathered from ISTAT and used as time-varying controls are available from 1977, we further limit the sample to those women who exited formal education after 1976. From the starting female sample of 50,673 units, these selection criteria¹⁴ reduced the sample size to 9,387 women for whom, thanks to the INPS administrative data, we rebuilt all their past labour market histories up to the moment in which they were interviewed for the IT-SILC. Table A.1 of the [Online Appendix](#) reports in detail the impact of each selection criterion on the sample size. It shows that 85% of the removed observations is due to the age being lower than 26 or higher than 45 at the moment of the IT-SILC interview.

3.2 Descriptive Statistics

The construction of the sample is such that only women who completed school more than 3 years before the IT-SILC interview were kept; we can therefore observe, for all the 9,387 women, their labour market outcomes at least up to 3 years after school completion. The number of women for whom we observe longer labour market histories is decreasing with the size of the time window after school completion. In our empirical analysis, we look at the effect of childbearing on labour market outcomes until at most 21 years after school completion. The number of women for whom we can observe 21 years of labour market experience between school completion and the IT-SILC interview amounts to 3,596. Table 1 shows in detail the number of observations from 3 to 21 years after school completion grouped by periods of three years, together with some descriptive statistics concerning the main time invariant characteristics. Women that are observed for a longer period necessarily belong to older cohorts, are less educated on average, have a larger number of siblings, and are less likely to have been at work in the year before school completion. The sample observed 3 years after school completion has an average

and therefore richer in the construction of the fertility history.

¹⁴ For the sake of having a homogeneous sample and removing strange observations in terms of timing of education, we removed women younger than 13 or older than 32 at the time of their highest diploma (399 observations). We also removed women with more than 3 children at the time of the IT-SILC interview (96 units) or women who had children before completing education (195 women). In 67 cases, relevant data on parents and siblings were missing and observations were therefore removed. This IT-SILC sample was then merged with the INPS database. There were 628 women who were among the respondents of the IT-SILC survey, but they did not appear in the INPS database. This happens for example when a woman has never had a payroll employment position up to the moment of the IT-SILC interview. We deleted these 628 observations from the sample. 37 women were excluded from the database because they died during the period and 30 because of missing or inconsistent information, such starting date of the working period prior to the ending date, or daily earnings higher than €400.

age at diploma of 18.8 years. Graph (a) of Figure A.2 in the [Online Appendix](#) provide more information on the distribution of age at diploma: 71.7% of the sample completed the school when 19 years old or younger, 90.5% when 25 or younger.

Table 1: Sample composition at 3, 6, 9, 12, 15, 18, 21 years after school completion: Year of birth, age at diploma, education, number of siblings at 14, and employment 1 year before school completion

Years after school completion	Number of women	Year of birth	Age at diploma	Primary education	Secondary education	Tertiary education	Number of siblings at 14	Employment 1 year before school exit
3 years	9,387	1971.3	18.78	0.29	0.45	0.26	1.39	0.101
6 years	9,008	1971.0	18.48	0.29	0.47	0.24	1.41	0.093
9 years	8,228	1970.4	18.06	0.33	0.47	0.20	1.44	0.081
12 years	7,296	1969.7	17.64	0.36	0.47	0.17	1.48	0.075
15 years	6,148	1968.7	17.24	0.40	0.46	0.14	1.51	0.066
18 years	4,895	1967.8	16.77	0.44	0.45	0.11	1.54	0.056
21 years	3,596	1966.9	16.28	0.50	0.42	0.08	1.58	0.046

[Herr \(2016\)](#) showed that an appropriate measure to determine the impact of the timing of childbearing on a labour market outcome is based on the “career timing”, rather than on the biological age: the most important factor in explaining how the timing of childbearing affects female wage profiles is indeed the level of work experience at the moment of the first birth. Hence, we define the timing as the time elapsed since school completion. The yearly labour earnings measure gross earned income from the labour market as a salaried employee, excluding maternal/parental leave benefits, as well as other types of transfers.

Table 2 shows summary statistics of the labour market outcomes and fertility variables from 3 to 21 years after school completion. The average number of kids per woman reaches the unity between 15 and 18 years after school completion. The labour earnings increase during the firsts 9 years and then remain stable.

Table 3 reports the mean gross labour earnings and the mean fraction of days spent in employment in a year by the number of kids from 3 to 21 years from school completion. The number of children is negatively correlated both to earnings and to the fraction of days in employment, almost in each year after school completion. The earnings and labour force participation penalties seem however to be slowly declining over time. While 6 years after school completion, women with one child earn 23% less and work 15% less than childless women, 21 years after school completion these figures decline to 20% and 10%, respectively. Further descriptive statistics are displayed in Section A of the [Online Appendix](#).

Table 2: Number of kids, yearly gross labour earnings, and fraction of days worked in a year evaluated at 3, 6, 9, 12, 15, 18, 21 years after school completion

Years after school completion	Observations	Number of childbearings [†]		Yearly labour earnings (€) [§]		Fraction of days at work in a year	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
3 years	9,387	0.075	0.287	7,612.42	9,742.48	0.441	0.461
6 years	9,008	0.229	0.505	10,525.25	10,889.79	0.568	0.462
9 years	8,228	0.454	0.696	11,941.37	11,740.24	0.619	0.457
12 years	7,296	0.739	0.828	12,154.15	12,296.94	0.627	0.458
15 years	6,148	0.998	0.903	12,070.04	12,438.80	0.626	0.458
18 years	4,895	1.193	0.918	12,047.93	12,689.56	0.626	0.462
21 years	3,596	1.332	0.926	12,012.06	12,565.84	0.626	0.465

[§] Yearly labour earnings are in 2014 prices and deflated by the ISTAT consumer price index.

[†] The timing of childbearing is equal to the timing of childbirths minus 9 months, in order to take into account in the econometric analysis that women could start reacting, and therefore being “treated”, before the delivery.

Table 3: Yearly labour earnings and the fraction of days worked in a year evaluated at 3, 6, 9, 12, 15, 18, 21 years after school completion by number of kids

Years after school completion	Number of childbearings [†]	Frequency		Yearly labour earnings (€) [§]	Fraction of days at work in a year
		Absolute	Relative		
3 years	0	8,748	0.932	7,662.64	0.445
	1	576	0.061	7,114.01	0.404
	2	63	0.007	5,196.04	0.404
6 years	0	7,286	0.809	11,058.95	0.588
	1	1,404	0.156	8,500.37	0.499
	2 or 3	318	0.035	7,237.10	0.417
9 years	0	5,401	0.656	13,148.26	0.666
	1	1,986	0.242	9,856.94	0.550
	2 or 3	841	0.102	9,112.88	0.472
12 years	0	3,559	0.488	14,372.73	0.706
	1	2,226	0.305	10,564.46	0.595
	2 or 3	1,511	0.207	9,270.44	0.486
15 years	0	2,266	0.369	14,824.28	0.726
	1	1,875	0.305	11,422.04	0.618
	2 or 3	2,007	0.326	9,5657.69	0.521
18 years	0	1,396	0.285	15,037.97	0.729
	1	1,446	0.295	12,272.72	0.657
	2 or 3	2,053	0.419	9,856.43	0.534
21 years	0	855	0.238	15,653.52	0.734
	1	977	0.272	12,511.80	0.662
	2 or 3	1,764	0.490	9,970.28	0.556

[§] Yearly labour earnings are in 2014 prices and deflated by the ISTAT consumer price index.

[†] The timing of childbearing is equal to the timing of childbirths minus 9 months, in order to take into account in the econometric analysis that women could start reacting, and therefore being “treated”, before the delivery.

4 Econometric Model

4.1 General Framework

In order to evaluate the effect of childbearing on labour market outcomes, we consider a model with multiple treatments (one for each delivery), multiple time periods, and in which treatment effects are allowed to be heterogeneous according to the time in which a childbearing occurs since school completion. In this respect, our set-up is close to the models proposed by [Carneiro et al. \(2003\)](#) and employed by [Fruehwirth et al. \(2016\)](#).

Let $i = 1, \dots, n$ index a woman and $t = 1, \dots, T_i$ index the time elapsed since school completion. The observable time elapsed since school completion (T_i) differs across women, and depends on the time between the IT-SILC interview and the year of school completion. We denote by R_i^k the random variable indicating the duration between school completion and the time period in which the k -th childbearing occurs, with $R_i^k \in \{1, \dots, R, \infty\}$, and $k = 1, \dots, K$. In our dataset, we observe the year and quarter of each childbirth. We define the time of childbearing as the time of childbirth minus 9 months. We observe childbearing k in our time window if $R_i^k \leq T_i \quad \forall k$. We let $R_i^k = \infty$ for women who do not give birth for the k -th time before the end of the observed time window. Finally, since we retained in our sample only women who had at most three kids, K is equal to 3.

Let our labour market outcomes of interest be denoted as Y_{it}^j , $j = 1, \dots, J$ and let us define a dummy variable D_{it}^k , which is equal to 1 if woman i is pregnant for the k -th time at time r ,¹⁵ with $r = 1, \dots, R$, and 0 if $R_i^k = \infty$. To clarify the notation, consider the evaluation of the effect of a second childbearing occurring 6 years after school completion on labour earnings, denoted by $j = 1$, fifteen years after school completion: then the treatment dummy will be denoted as D_{it}^2 and the outcome Y_{it}^1 , with r and t indexing the years after school completion.

We assume no anticipation of treatment, often referred to as the *no anticipation* as-

¹⁵The definition of our treatment dummies, and therefore of the timing of pregnancies, is based on the observed quarter and year of childbirth, which we anticipate by 9 months in order to approximate the conception date. By doing so, we avoid assigning to the control group at time t those women who will deliver at time $t + 1$ but may have already changed their labour market behaviour in t because they know they are pregnant. This way, we account for possible anticipated responses with respect to the observed year of childbirth. The drawback is that in the treated group at time t there might be women who deliver in the first 9 months of year $t + 1$ but have yet to be affected by their pregnancy at time t if, for example, they realise late they are pregnant or in cases of preterm births occurring in $t + 1$. This measurement error could generate a bias toward zero in the motherhood penalty. If so, our findings are to be interpreted as lower bounds in terms of motherhood penalties.

sumption (Abbring and van den Berg, 2003). Therefore, we rule out the possibility that labour earnings and participation t years after school completion might be affected by the event of a childbirth $t + 1$ years after school completion, conditioning on all prior information. Notice that this assumption is violated if women giving birth in $t + 1$ are already pregnant in t , as they may, for instance, take the maternity leave already in t and act on their labour market participation. For this reason, we consider the treatment as starting not at the observed delivery date but 9 months earlier.¹⁶

For woman i , the observed labour market outcome j at time t can be written as

$$Y_{it}^j = \sum_{k=1}^K \sum_{r=1}^{\min\{t,R\}} \beta_{ir}^{jk} D_{ir}^k + \mu_t^j(X_{it}^j) + \epsilon_{it}^j, \quad (1)$$

where β_{ir}^{jk} is the effect of receiving the k -th treatment at time r on outcome j at time t , μ_t^j is a function of observed covariates X_{it}^j , and ϵ_{it}^j collects the individual- and time-varying unobservables. Following the example above, the parameter of interest for the evaluation of the effect of a second childbearing occurring 6 years after school completion on labour earnings 15 years after school completion is $\beta_{15,6}^{1,2}$.

The occurrence of childbearing k at time r after school completion is modelled as a function of a treatment-time specific index as follows

$$V_{ir}^k = \nu^k(Z_i^k) + u_{ir}^k \quad (2)$$

where ν^k is a function of observed covariates Z_i^k , which play a role in the decision of having a child in r , and u_{ir}^k denotes the individual and treatment-time unobserved heterogeneity. Equation (2) is a reduced-form expression not including the labour market outcomes of interest in its observable component. Selection into treatment k at time r occurs according to the following rules:

$$D_{ir}^1 = \mathbb{1}(R_i^1 = r | D_{ir'}^1 = 0, r' < r) \quad (3)$$

$$D_{ir}^k = \mathbb{1}(R_i^k = r | D_{ir'}^k = 0, D_{ir'}^{k-1} = 1, r' < r) \quad (4)$$

where $\mathbb{1}(\cdot)$ is the indicator function and $R_i^k = r$ whenever $r - 1 < V_{ir}^k \leq r$. Equation (3) is the selection into the treatment level $k = 1$, that is the first childbearing, which obviously may be taken by woman i at time r only if no other first pregnancies have occurred before r , at time $r' < r$. Equation (4) refers to following pregnancies after the first childbearing,

¹⁶Women delivering in the first 3 quarters of year $t + 1$ are assigned to the treatment group in year t .

which may only occur if woman i has already given birth for the $k - 1$ -th time ($D_{ir'}^{k-1} = 1$) and the k -th delivery has yet to occur at time r .

Because there are multiple treatments with different timings after school completion, a general formulation for the average effect at time t of the k -th delivery occurring in r versus the k' -th delivery in r'' can be written as

$$\text{ATE}_t^j [(k, r), (k', r'')] = \text{E} [Y_t^j(k, r) - Y_t^j(k', r'')],$$

where $k \in \{1, \dots, K\}$, $r \in \{1, \dots, R, \infty\}$ with $r \leq t$, and $k < k' \Rightarrow r < r''$. We may let $r'' = \infty$ to evaluate the effect in t of receiving treatment k in r versus not receiving treatment k' at all. Notice that our framework falls between the model by [Carneiro et al. \(2003\)](#), who specify multiple treatments evaluated at different times, and the one in [Fruehwirth et al. \(2016\)](#), where only one treatment is considered and the effect of the timing of treatment r is related to the outcome of interest over time t .

4.2 Identification

The identification of the treatment effect of a childbirth relies on properly accounting for unobserved, and possibly time-varying, heterogeneity across women that might affect the occurrence of a delivery and labour market outcomes at the same or at a later time. For example, women with a high degree of labour market attachment may be less inclined to start a family right after leaving school and more disposed instead to make an effort on their job to pursue their career, resulting in better labour market performances. However, their degree of commitment might change over time, for instance if they get married or if, when ageing, they change their preferences about childbearing.

In order to account for selection on time-varying unobservables, we need to specify the joint distribution of the unobserved components determining the outcome, ϵ_{it}^j , with $t = 1, \dots, T$ and $j = 1, \dots, J$, in Equation (1) and the selection into treatment, u_{ir}^k with $r = 1, \dots, R$ and $k = 1, \dots, K$, in Equation (2). Following the factor analytic dynamic model of [Carneiro et al. \(2003\)](#),¹⁷ we assume a factor structure in which the unobserved terms of both outcome and selection equations are composed of a latent trait called *factor*, representing the individual unobserved heterogeneity, and error terms that are conditionally independent given the factor. This type of structure greatly simplifies the problem of recovering the joint distribution of ϵ_{it}^j and u_{ir}^k , by assigning to the latent factor the task of capturing all the cross-equation dependence.

¹⁷See also [Heckman and Navarro \(2007\)](#), [Fruehwirth et al. \(2016\)](#), and [Cockx et al. \(2017\)](#).

We therefore rewrite the error terms in Equations (1) and (2) as

$$\epsilon_{it}^j = \alpha_t^j \theta_{it} + \varepsilon_{it}^j \quad (5)$$

$$u_{ir}^k = \lambda_r^k \theta_{ir} + v_i^k, \quad (6)$$

where θ_{is} , $s = t, r$ is the latent factor, collecting the unobserved differences across women that determine both the selection into treatments and the treatment effects. In this framework, unobserved heterogeneity is allowed to vary over time by means of both the factor distribution and a linear combination of the factor with time-varying coefficients, called *factor loadings*, denoted as α_t , $t = 1, \dots, T$, and λ_r^k , $r = 1, \dots, R$ and $k = 1, \dots, K$. The error terms ε_{it}^j and v_i^k are such that $E(\varepsilon_{it}^j) = E(v_i^k) = 0$, are independent of θ_{is} , $s = t, r$, and mutually independent for all j, t, k, r ; also ε_{it}^j is independent of $\varepsilon_{it''}^{j'}$ for all $j \neq j'$ and $t \neq t''$, and v_i^k is independent of $v_i^{k'}$ for all $k \neq k'$.

The specification described in Equations (5) and (6) is a combination of the factor structures assumed by [Carneiro et al. \(2003\)](#) and [Fruehwirth et al. \(2016\)](#). Differently from their framework though, we assume that common unobservable traits are collected in a single factor rather than in a multidimensional set of latent variables.¹⁸ It is worth noting that the factor loadings in the treatment selection equations, λ_r^k , vary according to the treatment timing r , thereby allowing unobserved heterogeneity to determine the choice of having a child differently over time. However, we assume that unobserved heterogeneity cannot affect labour market outcomes at time t in a different manner according to the treatment timing r . We do so by imposing the implicit constraint $\alpha_{tr}^{jk} = \alpha_t^j$, $r = 1, \dots, R$, $k = 1, \dots, K$, which rules out essential heterogeneity ([Heckman et al., 2006](#)).¹⁹

Because the factor structure here described represents a special case of that proposed by [Carneiro et al. \(2003\)](#) combined with the the dynamic structure assumed by [Fruehwirth et al. \(2016\)](#), their identification results related to the factor analysis can be invoked directly and specialised to fit the case of a single latent factor. In addition, [Carneiro et al. \(2003\)](#) point out that factor models are identified by arbitrary normalisations and suggest that a set of selection-free measurements reduces the degree of arbitrariness while providing greater interpretability. We adopt this strategy and rely on predetermined information

¹⁸While the identification results, recalled later in this section, would hold for our case with multiple factors as well (see [Fruehwirth et al., 2016](#)), this further extension would make the estimation of our model computationally intractable, given the high number of treatment and selection equations.

¹⁹[Fruehwirth et al. \(2016\)](#) also specify time-varying factor loadings in the selection equations. In addition, they consider essential heterogeneity, differently from [Carneiro et al. \(2003\)](#).

to specify the additional measures

$$M_i^l = \omega^l(S_i^l) + \xi^l\theta_{i1} + e_i^l \quad l = 1, 2, \quad (7)$$

where M_i^l are information of woman i that are predetermined with respect to school completion and fertility choices. Specifically M_i^1 is a dummy variable equal to 1 if the woman worked for at least one day in the year before the one of school completion. M_i^2 is the number of siblings the woman had when she was 14 years old. The last two columns of Table 1 report the sample means of these two variables. Furthermore, ω^l collects a linear combination of observed covariates S_i^l , ξ^l is a factor loading and e_i^l is a zero-mean error term independent of S_i^l and θ_{i1} , which is taken at the first period. Both measures should be of help in pinning down the distribution of the factor θ , since M_i^1 and M_i^2 are likely to be determined by a series of unobserved characteristics, like labour force attachment and financial constraints for M_i^1 and family background, genetics, and social values for M_i^2 , which in turn are possibly strong determinants of fertility choices and labour market participation.

The final objective is the nonparametric identification of the joint distribution (up to a scale normalisation) of the latent factor and error terms for each outcome j , treatment k and time of treatment r , that is the joint distribution of $(\theta_{i1}, \dots, \theta_{iT}), (\epsilon_{i1}^j, \dots, \epsilon_{iT}^j), v_i^k$, and (e_i^1, e_i^2) , defined in Equations (5)-(7). In the following, we first discuss the identification strategy for a simplified factor structure where the latent trait in (5)-(7) is assumed to be time-constant, that is $\theta_{is} = \theta_i, s = t, r$. The results for this restricted model are then used to derive the identification in the case of a time-varying latent factor.

4.2.1 Time-Constant Latent Factor

In order to illustrate the rationale of the identification strategy, we break down the identification discussion in three main steps.

The first step consists in identifying the joint distribution of $(\epsilon_i^j, u_{i,r}^k, \boldsymbol{\vartheta}_i)$, where $\epsilon_i^j = (\epsilon_{i1}^j, \dots, \epsilon_{iT}^j), \boldsymbol{\vartheta}_i = (\vartheta_i^l, \vartheta_i^l)$, with $\vartheta_i^l = \xi^l\theta_i + e_i^l$. Nonparametric identification of this distribution is obtained following Heckman and Smith (1998), once the conditions required for Theorems 1 and 2 by Carneiro et al. (2003) are satisfied. Most of these requirements are assumptions and regularity conditions that we assume to hold (see Heckman and Smith, 1998, for further details), while we discuss here the requirement of exclusion restrictions. In Carneiro et al. (2003), having a continuous variable that is included among the set of observed determinants of one outcome but excluded from the others is enough

to satisfy a support condition necessary to prove the non-parametric identification.²⁰ We therefore use in $\nu^k(Z_i^k)$ and in $\omega^l(S_i^l)$, in Equations (2) and (7), the employment rate, the unemployment rate, and the total fertility rate of the region and at the time the woman was born. These regional rates will also enter $\mu_t^j(X_{it}^j)$, but measured at the time t in which the labour market performance is evaluated.²¹ Table 4 elucidates in detail the set of exclusions across equations. It is worthy to note that the sequentiality of the births gives rise to a set of exclusion restrictions that can be used to differentiate the set of covariates in the selection equations across k :

$$\begin{aligned}\nu_i^1(Z_i^1) &= \nu^1(Z_i), \\ \nu_i^2(Z_i^2) &= \nu^1(Z_i) + \gamma_R^2 \bar{R}_i^1 + \gamma_B^2 B_i, \\ \nu_i^3(Z_i^3) &= \nu^1(Z_i) + \gamma_{R_1}^3 \bar{R}_i^1 + \gamma_{R_2}^3 (\bar{R}_i^2 - \bar{R}_i^1) + \gamma_S^3 G_i,\end{aligned}\tag{8}$$

where Z_i is a set of woman i 's characteristics listed in Table 4, \bar{R}_i^k is the realised time elapsed since school completion and the occurrence of the k -th childbearing, B_i is a dummy variable equal to 1 if the first delivery was a twin delivery, and G_i is a dummy variable equal to 1 if the first two children are of the same gender. We create these treatment-specific exclusion restrictions exploiting the fact that the k' -th delivery can occur only conditional on the k -th childbearing, with $k' > k$.

The second step concerns the identification of the factor loadings. Once the joint distribution of $(\epsilon_i^j, u_{it}^k, \theta_i)$ is identified, cross moments can be used to identify the factor loadings and, following Carneiro et al. (2003), we use the information provided by the variance-covariance structure, assuming covariances are non-zero. In order to clarify the illustration, first consider the covariance between ϵ_{i1} and u_{i1}^1 :

$$\text{cov}(\epsilon_{i1}^1 u_{i1}^1) = \alpha_1^1 \lambda_1^1 \text{V}(\theta_i) = \lambda_1^1 \text{V}(\theta_i),\tag{9}$$

where clearly a normalisation is needed and we take $\alpha_1^1 = 1$. In order to identify the full structure of factor loadings in the outcome equations, we take the covariances between error terms of selection equation and outcome equations at subsequent times:

$$\text{cov}(\epsilon_{it}^1 u_{i1}^1) = \alpha_t \lambda_1^1 \text{V}(\theta_i), \quad t = 2, \dots, T.$$

²⁰See Assumption A-3 in Carneiro et al. (2003) and its comment at page 378.

²¹See Bhargava (1991) and Mroz and Savage (2006) for discussions on how the time-variation of exogenous variables helps to identify the causal impacts of endogenous variables in dynamic discrete time panel data models.

Table 4: Observed covariates and exclusions across equations

Regressors included in outcome, treatment, and measurement variables equations	Selection-free measurements		Treatments			Outcomes
	Employment 1 year before school completion	Number of siblings at 14	Timing 1st delivery	Timing 2nd delivery	Timing 3rd delivery	Labour market outcome t years after school completion
Age at school completion	–	Yes	Yes	Yes	Yes	Yes
Education (primary, secondary, tertiary)	–	Yes	Yes	Yes	Yes	Yes
Fraction of time at work 1 year before school completion	–	–	Yes	Yes	Yes	Yes
Mother's age at delivery	Yes	–	Yes	Yes	Yes	Yes
Number of siblings at 14	Yes	–	Yes	Yes	Yes	Yes
Mother's highest education	Yes	Yes	Yes	Yes	Yes	Yes
Mother at work at 14	Yes	Yes	Yes	Yes	Yes	Yes
Quarter of birth	Yes	Yes	Yes	Yes	Yes	Yes
Regional unemployment rate at t	–	–	–	–	–	Yes
Regional employment rate at t	–	–	–	–	–	Yes
Regional fertility rate at t	–	–	–	–	–	Yes
Regional unemployment rate at birth	Yes	Yes	Yes	Yes	Yes	–
Regional employment rate at birth	Yes	Yes	Yes	Yes	Yes	–
Regional fertility rate at birth	Yes	Yes	Yes	Yes	Yes	–
Twins in the 1st delivery	–	–	–	Yes	–	–
Time until 1st delivery	–	–	–	Yes	Yes	–
Spacing between 1st and 2nd delivery	–	–	–	–	Yes	–
First 2 kids of the same gender	–	–	–	–	Yes	–
IT-SILC wave (2005 or 2011)	Yes	Yes	Yes	Yes	Yes	Yes
Year of birth	Yes	Yes	Yes	Yes	Yes	Yes
Geographical area at birth (5 areas)	Yes	Yes	Yes	Yes	Yes	–
Geographical area at t (5 areas)	–	–	–	–	–	Yes
Year of observation	–	–	–	–	–	Yes
Indicators for timing to 1st delivery	–	–	–	–	–	Yes
Indicators for timing to 2nd delivery	–	–	–	–	–	Yes
Indicators for timing to 3rd delivery	–	–	–	–	–	Yes

Assuming $\lambda_1^1 \neq 0$, the ratios

$$\frac{\text{cov}(\epsilon_{it}^1 u_{i1}^1)}{\text{cov}(\epsilon_{i1}^1 u_{i1}^1)} = \alpha_t^1, \quad t = 2, \dots, T,$$

identify the factor loadings for the outcome equations. Then we can obtain λ_1^1 from any $\frac{\text{cov}(\epsilon_{it}^1 u_{i1}^1)}{\text{cov}(\epsilon_{i1}^1 u_{i1}^1)}$ and recover $V(\theta_i)$ from Equation (9). In a similar manner, ξ^1 and ξ^2 in Equation (7) can also be recovered. Notice that the information on the variance of ϵ_{it}^1 is left for the identification of $V(\varepsilon_{it}^1)$. It is straightforward to extend the strategy illustrated above to identify the factor loadings α_t^j , with $t, j > 1$, using the ratios $\frac{\text{cov}(\epsilon_{it}^j u_{i1}^1)}{\text{cov}(\epsilon_{i1}^1 u_{i1}^1)}$, and λ_r^k , with $r, k > 1$, using the ratios $\frac{\text{cov}(u_{it}^k u_{i1}^1)}{\text{cov}(\epsilon_{i1}^1 u_{i1}^1)}$.²²

With the identification of the joint distribution of $(\epsilon_i^j, u_{ir}^k, \vartheta_i)$ and of the factor loadings in hand, the third and final step consists in the nonparametric identification of the joint distribution of $(\theta_i, \varepsilon_i^j, v_i^k, e_i)$, where $\varepsilon_i^j = (\varepsilon_{i1}^j, \dots, \varepsilon_{iT}^j)$ and $e_i = (e_i^1, e_i^2)$. In order to illustrate the identification strategy rationale, consider a simple case where only one

²²At least three equations are needed to identify both λ_1^1 and $V(\theta_i)$. Carneiro et al. (2003) indeed show that, with L factors, at least $2L + 1$ measures are needed to identify the structure of factor loadings. In our model $L = 1$.

outcome is evaluated only in the first period $t = 1$, in which only the first childbearing, $k = 1$, can occur at the same time as the outcome evaluation, $r = t = 1$, and there are no measurements. The model described by Equations (1)-(2), (5)-(6), and (7) can be rewritten as

$$\begin{aligned} Y_i &= \beta D_i + \mu(X_i) + \epsilon_i \\ V_i &= \nu(Z_i) + u_i, \end{aligned}$$

and the final objective is to nonparametrically identify the distributions of θ_i , ϵ_i , and v_i .

In order to prove this result, [Carneiro et al. \(2003\)](#) rely on the following identification theorem by [Kotlarski \(1967\)](#): suppose there are two noisy measurements of the random variable θ_i , such that

$$E_{i1} = \theta_i + \epsilon_i^* \tag{10}$$

$$E_{i2} = \theta_i + v_i^*, \tag{11}$$

where ϵ_i^* and v_i^* are measurement errors. If ϵ_i^*, v_i^* , and θ_i are mutually independent, $E(\epsilon_i^*) = E(v_i^*) = 0$, and the characteristic functions of ϵ_i^*, v_i^* , and θ_i are non-vanishing, then it is possible to recover the distributions of ϵ_i^*, v_i^* , and θ_i from the joint distribution of E_{i1}, E_{i2} .²³

In order to apply the theorem by [Kotlarski \(1967\)](#), the joint distribution of ϵ_i, u_i and λ have to be identified, while α has to be normalised to 1. Then we can rewrite

$$\begin{aligned} \epsilon_i &= \theta_i + \epsilon_i \\ \frac{u_i}{\lambda} &= \theta_i + v_i^*, \end{aligned}$$

where $v_i^* = \frac{v_i}{\lambda}$. Then applying [Kotlarski's](#) theorem, the densities of θ_i, ϵ_i and v_i^* are nonparametrically identified, where ϵ_i is equal to ϵ_i^* in Equation (10) and the density of v_i can also be identified since λ is known. The above result can be easily extended to the rest of the outcome, treatment, and measurement equations.

4.2.2 Time-Varying Latent Factor

The generalisation to a time-varying factor θ_{is} , $s = t, r$, requires the nonparametric identification of the joint distribution of the error terms for each outcome j , $(\epsilon_{i1}^j, \dots, \epsilon_{iT}^j)$,

²³See also [Evdokimov and White \(2012\)](#) for more general conditions.

each treatment k , v_i^k , each measure l , e_i^l , along with the joint distribution of the vector $\boldsymbol{\theta}_i = (\theta_{i1}, \dots, \theta_{iT})$.

Let $F_{it} = F(\theta_{it}, \varepsilon_{it}^j, v_i^k)$ be the joint distribution of the unobservable random variables at time t , with $F_{i1} = F(\theta_{i1}, \varepsilon_{i1}^j, v_i^k, e_i^1, e_i^2)$, so that $\mathbf{F}_i = (F_{i1}, \dots, F_{iT})$ is the joint distribution to be identified. By sequential factorisation, \mathbf{F}_i can be written as

$$\mathbf{F}_i = \prod_{t=2}^T F(\theta_{it}, \varepsilon_{it}^j, v_i^k | \mathbf{F}_i^{t-1}) \times F_{i1},$$

where $\mathbf{F}_i^{t-1} = (F_{i1}, \dots, F_{i,t-1})$. This formulation shows that the joint distribution \mathbf{F}_i can be expressed as the product of distributions that are conditionally independent given past information. Therefore, once the distribution F_{i1} is identified, F_{i2} can be identified conditional on F_{i1} , which is then known; iteratively, identification of F_{iT} conditional on \mathbf{F}_i^{T-1} is obtained. In this respect, our strategy is similar to the one adopted by [Fruehwirth et al. \(2016\)](#).

For a given t , nonparametric identification of $\theta_{it}, \varepsilon_{it}^j, v_i^k$, conditional on \mathbf{F}_i^{t-1} , can be derived by the same three steps illustrated in the previous section for the case of a time-constant latent factor. The only difference relates to the normalizations required for the identification of the factor loadings. Consider, for instance, the covariance between ε_{it}^1 and u_{ir}^1 ,

$$\text{cov}(\varepsilon_{it}^1 u_{ir}^1) = \alpha_t^1 \lambda_r^1 V(\theta_{it}) = \lambda_r^1 V(\theta_{it}), \quad (12)$$

where clearly the normalisation is $\alpha_t^1 = 1$ and it occurs at every t . Then identification of the rest of the factor loadings is achieved in a similar way to that of a time-constant latent factor.²⁴

4.3 Estimation

The detailed discussion on the specifications of the outcome, selection, and measurement equations, and of the related distributional assumptions used to build the final likelihood function are discussed in Section B of the [Online Appendix](#). In addition, it contains the description of the Maximum Likelihood estimation of the model parameters and the approaches for modelling the distribution of the latent factor $\boldsymbol{\theta}_i$.

²⁴By assuming $\lambda_r^1 \neq 0$, the ratio $\frac{\text{cov}(\varepsilon_{it}^j u_{ir}^1)}{\text{cov}(\varepsilon_{it}^1 u_{ir}^1)}$ identifies α_t^j , $\frac{\text{cov}(\varepsilon_{it}^j u_{ir}^1)}{\text{cov}(\varepsilon_{it}^1 \varepsilon_{ir}^1)}$ identifies λ_r^1 and $V(\theta_{it})$ can be derived from Equation (12). Factor loadings for $k \neq 1$ can be identified using $\frac{\text{cov}(u_{ir}^k u_{ir}^1)}{\text{cov}(\varepsilon_{it}^1 \varepsilon_{ir}^1)}$, and similarly for every $r' \neq r$.

5 Estimation Results

The baseline model described in Section 4 was estimated under 4 different assumptions on the latent factor:

- (1) without unobserved heterogeneity;
- (2) with time-constant unobserved heterogeneity distributed as a mixture of 3 normals;
- (3) with time-constant latent factor with discrete distribution (10 support points);
- (4) with time-varying latent factor with discrete distribution (10 support points).

Table 5 reports some post-estimation statistics of these 4 models. When the presence of time-constant unobserved heterogeneity is accounted for, the log-likelihood value experiences a relevant increase. Approximating non-parametrically the distribution of the time-constant latent factor using either a mixture of 3 normals or a discrete distribution with 10 support points leads to very similar values of the log-likelihood. A [Vuong \(1989\)](#) test for non-nested models rejects the null hypothesis that the two models are equivalent in favour of the discrete distribution of the latent factor. The point estimates of the effects of interest are however very similar. When we take into account that the latent factor could be time-varying, there is a further important increase in the log-likelihood function and an improvement both in the Akaike Information Criterion (AIC) and in the Bayesian Information Criterion (BIC). In what follows, we present the estimation results only for the model with the time-varying latent factor, Model (4). The estimation results of the model without unobserved heterogeneity, Model (1), are reported in Section C of the [Online Appendix](#), whereas the results for Models (2) and (3) are available upon request.

In what follows, subsections 5.1 and 5.2 show the impact of childbearing and its timing on yearly labour earnings and the yearly fraction of days spent in employment. In Section D of the [Online Appendix](#), we report and comment on all the other estimation results (of selection-free measurement, fertility, and outcome equations) from the model with time-varying unobserved heterogeneity.

5.1 The Impact of Childbearing and Its Timing on Yearly Labour Earnings

Table 6 reports the estimated impact of childbearing and its timing on yearly labour earnings t years after school completion, with $t = 3, 6, \dots, 21$, when we control for time-varying unobserved heterogeneity. The reference individual is a woman who has not yet

Table 5: Summary statistics of the estimated models under different assumptions on the unobserved heterogeneity

	(1)	(2)	(3)	(4)
	Model without latent factor	Model with time-constant latent factor	Model with time-constant latent factor	Model with time-varying latent factor
Observations	9,387	9,387	9,387	9,387
Number of parameters	280	305	316	354
Log-likelihood	-135,752.6	-120,111.6	-120,063.9	-109,493.5
AIC	272,065.2	240,833.1	240,759.7	219,695.1
BIC	274,066.4	243,012.0	243,018.2	222,225.2
Distribution of the latent factor	–	Mixture of 3 normals	Discrete	Discrete
Number of support points of the latent factor	–	–	10	10
Vuong statistic: [§] Model (2) vs Model (3)			$z = -2.663$	

[§] We computed an unadjusted [Vuong \(1989\)](#) test for non-nested models to determine whether the model with the mixture of 3 normals, Model (2), and the model with the discrete distribution (with 10 support points), Model (3), for the unobserved heterogeneity could be statistically rejected against the other. The test statistic z equal to -2.663 means that we reject the null hypothesis that Models (2) and (3) are equivalent in favour of Model (3).

experienced the childbearing of corresponding childbearing t years after school completion.

By comparing the impact on earnings of the first childbearing with the ones of subsequent childbirths, it emerges that the first childbearing generates the highest penalties, both in the short and in the long run. For example, a woman having the first child between 4 and 6 years since school completion experiences a significant decrease in yearly labour earnings by €2,622 in the 6th year and further by €2,131, €1,587, and €1,964, respectively 9, 12, and 15 years since school completion.²⁵ Then, after persisting for about 9-12 years, the penalty in earnings disappears. The impact of the 2nd childbearing is relevant in the short run only and if it is delayed. For example, a woman having her second childbearing between 10 and 12 years after school completion faces a further significant penalty of about €1,005 in the 12th year after the school completion, but no longer-lasting impacts. Women having the second kid later than 12 years after school completion experience instead a slightly longer negative impact on earnings (at least 3 years longer). Understanding the impact of the third childbearing and its timing on earnings is more challenging since the identification is based on a much smaller number of observations. Although the point estimates indicate sometimes large negative effects of the third childbearing, the standard errors are wide and the estimated effects hardly show

²⁵Relatively to the average earnings of childless women, the decrease is of 16.2%, 11.1%, and 13.2%, respectively 9, 12, and 15 years since school completion. See Table D.6 in the [Online Appendix](#) for all the effects of the first childbearing relatively to the average earnings of childless women at different times since school completion.

any significance. We therefore refrain from drawing conclusions based on them.

Table 6: Estimated coefficients of the impact of childbearing and its timing on yearly labour earnings (€)[§] with time-varying unobserved heterogeneity

Years since school completion	$t = 3$	$t = 6$	$t = 9$	$t = 12$	$t = 15$	$t = 18$	$t = 21$
<i>1st childbearing</i>							
$r \in [0, 3]$	-1,834.03*** (236.40)	-3,212.24*** (526.21)	-2,559.26*** (704.10)	-2,604.19*** (737.94)	-2,331.42** (1,077.02)	-1,080.35 (1,322.97)	-491.55 (1,463.45)
$r \in [4, 6]$	–	-2,621.51*** (271.99)	-2,130.72*** (496.23)	-1,586.62*** (555.28)	-1,963.94** (800.61)	-1,256.14 (996.71)	-750.21 (1,162.72)
$r \in [7, 9]$	–	–	-2,256.85*** (350.09)	-1,125.64*** (414.92)	-1,720.94*** (634.58)	-937.33 (828.13)	-1,256.05 (924.30)
$r \in [10, 12]$	–	–	–	-2,834.40*** (341.24)	-2,213.26*** (565.95)	-894.86 (787.18)	-1,556.78* (867.33)
$r \in [13, 15]$	–	–	–	–	-4,450.97*** (545.93)	-2,623.49*** (785.01)	-2,617.99*** (903.92)
$r \in [16, 18]$	–	–	–	–	–	-4,566.38*** (892.47)	-3,927.73*** (1,048.34)
$r \in [19, 21]$	–	–	–	–	–	–	-5,575.81*** (1,440.63)
<i>2nd childbearing</i>							
$r \in [1, 6]$	–	-1,046.39* (583.76)	-930.91 (948.34)	498.07 (967.53)	-79.32 (1,478.43)	638.75 (1,875.22)	108.47 (2,099.79)
$r \in [7, 9]$	–	–	-842.78 (528.85)	760.66 (676.51)	781.55 (958.95)	-203.66 (1,143.54)	-536.01 (1,450.03)
$r \in [10, 12]$	–	–	–	-1,004.77** (440.61)	-445.64 (760.81)	-660.05 (895.49)	-947.68 (1,026.63)
$r \in [13, 15]$	–	–	–	–	-1,750.19*** (633.64)	-1,800.30** (870.43)	-956.42 (970.38)
$r \in [16, 18]$	–	–	–	–	–	-3,533.57*** (790.41)	-2,432.67** (1,050.42)
$r \in [19, 21]$	–	–	–	–	–	–	-3,252.94*** (1,057.77)
<i>3rd childbearing</i>							
$r \in [1, \min(t, 12)]$	–	–	-1,249.88 (1,105.65)	-1,440.99* (873.39)	-2,672.65 (2,129.38)	-4,018.23 (2,465.06)	-3,668.91 (2,915.06)
$r \in [13, 15]$	–	–	–	–	-1,646.69 (1,337.10)	-1,645.88 (1,754.11)	-630.37 (1,749.66)
$r \in [16, \min(t, 21)]$	–	–	–	–	–	-1,654.57 (1,705.97)	-1,562.65 (1,350.86)

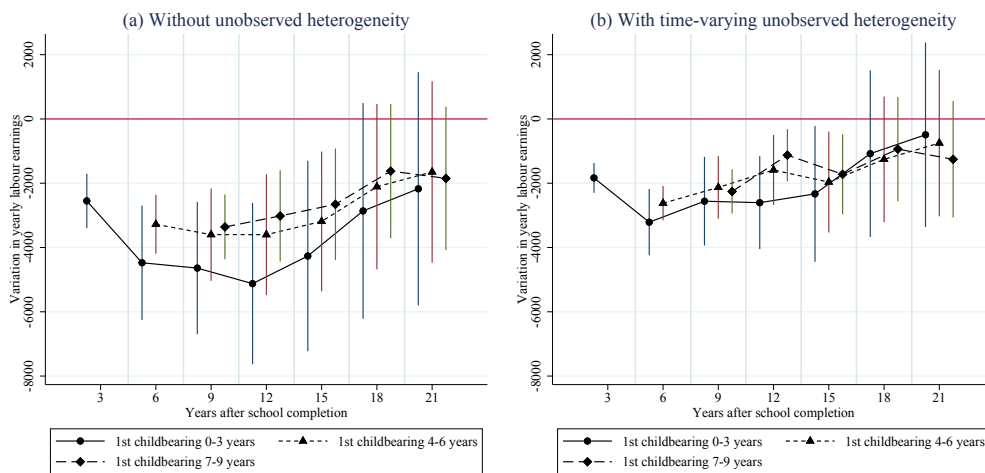
Notes: In bold the estimation results plotted in Graph (b) of Figure 1. *** Significant at 1%; ** significant at 5%; * significant at 10%. Standard errors are reported in parentheses.

[§] Yearly labour earnings are in 2014 prices. They are deflated by using the consumer price index gathered by ISTAT.

Figure 1 helps to visually quantify the magnitude and the duration of the impact of the first childbearing on labour earnings for births occurring at different times since school completion. Graph (a) of Figure 1 reports the results based on the model without unobserved heterogeneity. Graph (b) of Figure 1 shows instead the results based on the model with time-varying unobserved heterogeneity. Three points are worth of mention by looking at Figure 1 and Table 6. First, if we do not control for unobservable traits jointly

determining fertility choices and labour earnings, then the estimated impact of childbearing is downward biased. This result is compatible with the effect of omitted variables influencing fertility choices and labour earnings in opposite directions, such as a certain degree of labour market attachment, career orientation, family background, couple formation, and timing of marriage. In other words, if unobservables were not accounted for, the negative impact of childbearing on earnings would be overestimated because those women having one or more kids would have earned less, also in the counterfactual scenario without children.

Figure 1: The impact on labour earnings of the 1st childbearing 0-3, 4-6, or 7-9 years after school completion without unobserved heterogeneity (a) and with time-varying unobserved heterogeneity (b)



Notes: The vertical segments crossing the dots are 95% confidence intervals.

Second, Graph (b) of Figure 1 suggests that having the first child soon after school completion magnifies the negative effect on labour earnings: women conceiving the first-born 0-3 years after leaving school (similarly for 4-6 years) experience significant penalties at least up to 15 years since the diploma for at least, on average, 12-15 years after childbearing. Those conceiving the first child 7-9 years since school completion are instead able to catch up much faster with childless women by taking on average 6 years less. Their earning gap profile almost overlaps the profile of women giving birth immediately after school completion. Hence, women delaying the first child until the 7th-9th year after school completion avoid the loss of earnings that women having a child soon after leaving school experience in the preceding years.

Third, delaying too much the first child generates a substantial loss of earnings, at least in the short and medium run. Table 6 shows indeed that women delivering the first child 13-15 years after school completion face penalties of €4,451, €2,623, and €2,618 in the 15th, 18th, and 21st year after school completion, respectively. Relatively to the average earnings of childless women, the decrease is of about 30.0%, 17.4%, and 16.7%. Women experiencing the first childbearing later than 15 years after school completion suffer earnings penalties of similar magnitudes. A way of quantifying the cumulative effect of the first childbearing over time can come from summing up the coefficients over t . If we stick to the first 3 coefficients, that is about 6 to 9 years immediately after child birth, we get that women delivering the first kid 7-9 years since school completion face a cumulative penalty of €5,103,²⁶ whereas for women having the first child 0-3 (13-15) years since school completion the penalty is €7,605 (€9,692).²⁷ Hence, the penalty for women having the first child 7-9 years since school completion is 33% (47%) lower than that of women childbearing 0-3 (13-15) years since school completion.²⁸ Since the negative impact from delaying too much is large in both absolute and relative terms,²⁹ the large penalty cannot be explained by earnings that are higher in absolute value and therefore by a temporary absence from the labour market for maternal/parental leave being more costly in absolute terms. There might be however other explanations, like older women taking more time to recover from delivery, childbearing occurring in a key moment for the career progression, higher depreciation of human capital for women with larger work experience (Mincer and Ofek, 1982), or loss of most job skills because of the career interruption (Happel et al., 1984).

Summarising, the main findings about the impact of childbearing and its timing on yearly labour earnings are:

1. Women incur a sizeable and significant loss in labour earnings after childbearing.
2. Most of the negative effect and of its life-long duration come from the first childbearing, whilst further childbirths play a secondary and shorter-term role.
3. The timing of the first child matters. The loss in earnings caused by the first childbearing is minimised if it occurs between 7 and 9 years since school completion.

Given that more than 70% of our sample exit education before they are 19 years old,

²⁶€5,103.43 = €2,256.85 + €1,125.64 + €1,720.94.

²⁷€7,605 = €1,834 + €3,212 + €2,559 and €9,692 = €4,451 + €2,623 + €2,618, respectively.

²⁸Figure D.1 in the [Online Appendix](#) displays these relative cumulative effects.

²⁹Table D.6 in the [Online Appendix](#) reports the effects of the first childbearing relatively to the average earnings of childless women at different times since school completion.

this means that the loss is minimised when they are between 26 and 28 years old. With respect to the previous literature on the effect of delaying the first childbirth (Miller, 2011; Karimi, 2014; Herr, 2016; Leung et al., 2016), we are indeed able to detect non-linearities in the impact of the timing of childbearing on earnings in the short and long run, thanks to the flexible specification of our dynamic treatment effect.

5.2 The Impact of Childbearing and Its Timing on the Yearly Fraction of Days Spent in Employment

Table 7 reports the point estimates of the impact of childbearing on the yearly fraction of days spent with a contract of salaried employment when we control for time-varying unobserved heterogeneity. The impact of the first childbearing on the fraction of time in employment for women childbearing soon after leaving school is not as long-lasting as the impact on earnings. Women conceiving the first-born 0 to 3 years after school completion spend a significantly lower fraction of time in employment than childless women: -8.1 p.p. six years after school completion. They however catch up soon with childless women. In the last year of observation, i.e. 21 years after school completion, they even spend more time in the labour market than childless women (+7.6 p.p. but not significant). A similar profile, but with a little longer-lasting negative effects, is also shown by women having their first-born from 4 to 6 years after school completion. Fitzenberger et al. (2013) found much larger negative effects for German new-mothers, ranging from 50 p.p. one year after the delivery to 20 p.p. five years after. There are at least two explanations for this quantitative difference. First, in our analysis we evaluate the impact on the fraction of days in a year covered by an employment contract, whereas Fitzenberger et al. (2013) look at whether the woman is at work. Their dependent variable is therefore more responsive to shocks and the point estimates are not directly comparable. Second, the maternity leave coverage is quite long (36 months of job-protected leave) in Germany and the detachment of new-mothers from the labour market induced by the childbirth could therefore be magnified.

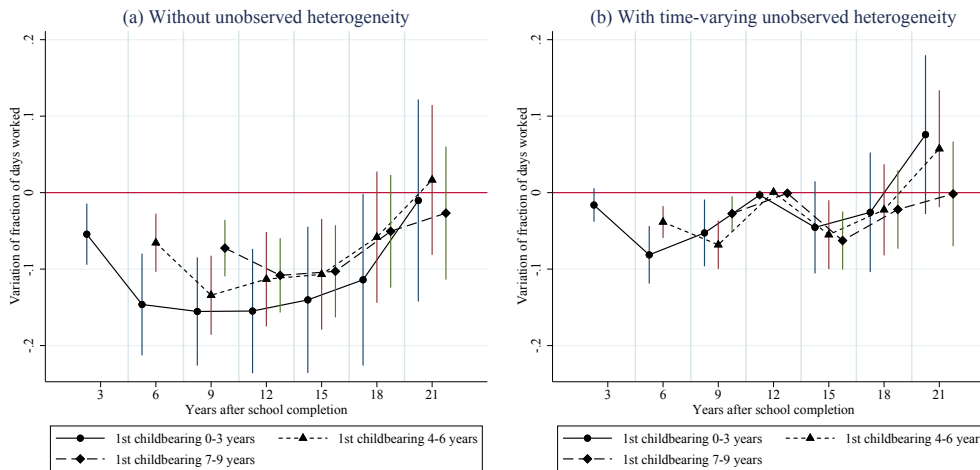
When looking at the impact of the first child on the fraction of days spent in employment, an optimal timing to deliver the first child emerges. The reduction in the time spent in employment is of smaller size and shorter-lasting for women having the first child 7-9 years after school completion. Graph (b) of Figure 2 helps comparing the impact of the first childbearing for women delivering the first child 7-9 years after school completion

Table 7: Estimated coefficients of the impact of childbearing and its timing on yearly fraction of days spent in employment with time-varying unobserved heterogeneity

Years since school completion	$t = 3$	$t = 6$	$t = 9$	$t = 12$	$t = 15$	$t = 18$	$t = 21$
<i>1st childbearing</i>							
$r \in [0, 3]$	-0.016 (0.011)	-0.081*** (0.019)	-0.053** (0.022)	-0.003 (0.003)	-0.045 (0.031)	-0.026 (0.040)	0.076 (0.053)
$r \in [4, 6]$	–	-0.038*** (0.011)	-0.068*** (0.016)	0.001 (0.002)	-0.055** (0.023)	-0.022 (0.030)	0.057 (0.039)
$r \in [7, 9]$	–	–	-0.027** (0.012)	-0.001 (0.002)	-0.063*** (0.019)	-0.022 (0.026)	-0.002 (0.035)
$r \in [10, 12]$	–	–	–	-0.004*** (0.001)	-0.085*** (0.017)	-0.027 (0.025)	-0.054 (0.033)
$r \in [13, 15]$	–	–	–	–	-0.095*** (0.017)	-0.083*** (0.026)	-0.085** (0.035)
$r \in [16, 18]$	–	–	–	–	–	-0.085*** (0.026)	-0.129*** (0.035)
$r \in [19, 21]$	–	–	–	–	–	–	-0.089** (0.044)
<i>2nd childbearing</i>							
$r \in [1, 6]$	–	-0.008 (0.023)	-0.059* (0.031)	0.005 (0.005)	-0.033 (0.044)	-0.019 (0.059)	-0.053 (0.072)
$r \in [7, 9]$	–	–	-0.032* (0.019)	0.001 (0.003)	-0.017 (0.027)	-0.039 (0.036)	-0.048 (0.047)
$r \in [10, 12]$	–	–	–	-0.001 (0.002)	-0.032 (0.022)	-0.054** (0.027)	-0.063* (0.036)
$r \in [13, 15]$	–	–	–	–	-0.006 (0.018)	-0.081*** (0.026)	-0.039 (0.033)
$r \in [16, 18]$	–	–	–	–	–	-0.102*** (0.026)	-0.110*** (0.036)
$r \in [19, 21]$	–	–	–	–	–	–	-0.071* (0.037)
<i>3rd childbearing</i>							
$r \in [1, \min(t, 12)]$	–	–	0.027 (0.050)	-0.005 (0.005)	-0.057 (0.049)	-0.063 (0.063)	-0.094 (0.078)
$r \in [13, 15]$	–	–	–	–	-0.052 (0.038)	-0.085 (0.052)	-0.043 (0.060)
$r \in [16, \min(t, 21)]$	–	–	–	–	–	-0.079* (0.044)	-0.106** (0.049)

Notes: In bold the estimation results plotted in Graph (b) of Figure 2. *** Significant at 1%; ** significant at 5%; * significant at 10%. Standard errors are reported in parentheses.

Figure 2: The impact on the yearly fraction of days spent in employment of 1st childbearing 0-3, 4-6, or 10-12 years after school completion without unobserved heterogeneity (a) and with time-varying unobserved heterogeneity (b)



Notes: The vertical segments crossing the dots are 95% confidence intervals.

with the one for women delivering the first child soon after their diploma. If women delay the first birth up to the 13th year or more after school completion, the penalties in terms of labour market participation are, in the short and medium run, in line or even larger than those of women childbearing soon after school completion. [Frühwirth-Schnatter et al. \(2016\)](#) found something similar in terms of labour force participation for Austrian women who gave birth later in life. Moreover, our findings enrich the empirical evidence in [Bratti and Cavalli \(2014\)](#), who found that, in Italy, delaying the first birth increases the labour market participation of new mothers two years later. However, differently from us, [Bratti and Cavalli \(2014\)](#) did not study medium/long run effects and did not take into account that the impact of delaying the first child could be heterogeneous over the waiting time.

The second and third childbirths play a more distinctive role on the fraction of time spent in employment than they do on earnings, especially if they occur later in the career. A second childbearing 16-18 years after school completion significantly reduces the fraction of time spent in employment by 10.2 (11.0) p.p. in the 18th (21st) year after school completion. A third childbearing 16-18 years after school completion lowers the fraction of time spent in employment by 7.7 (10.6) p.p. in the 18th (21st) year after school completion. The magnitude of these effects are in line with those of previous stud-

ies. For example, [Angrist and Evans \(1998\)](#) found that the third child reduces the female employment probability by 9.2 p.p. in the US.

Summarising the main findings about the impact of childbearing and its timing on the fraction of time spent in employment:

1. Childbearing significantly reduces the yearly fraction of time spent in employment, although the effect is shorter-lasting than the one for earnings.
2. The timing matters. The reduction in the time spent in employment caused by the first childbearing is smaller if it occurs between 7 and 9 years since school completion, meaning that the minimisation will occur around 26-28 years of age, given that most of the women in our sample are out of school by the time they are 19. The impact of the second and third child is instead lower if the delivery occurs in the first 9 years and 15 years since the diploma, respectively.

6 Conclusions

We studied the impact of childbearing on labour market outcomes for Italian women. We exploited AD-SILC, a dataset obtained by merging the administrative archives with survey data. We set up an econometric model with multiple treatments (one for each childbearing), multiple time periods, and in which treatment effects are allowed to be heterogeneous according to the time in which a childbearing occurs since school completion. Compared to previous studies on the impact of fertility and its timing on labour market outcomes, our model was equipped to credibly deal with the fact that: i) women having children at different times after school completion might differ in unobservables jointly determining both fertility choices and labour market outcomes (dynamic selection); ii) it is policy relevant to identify, not only the short run effects, but also long run consequences of childbearing on female labour market outcomes; iii) the impact of delaying the childbearing could be non-linear over the elapsed time since school completion.

We find that childbearing has a negative and relevant impact on labour earnings and on the time spent in employment of Italian women. Most of the negative effect and of its life-long duration come from the first childbearing. Further childbirths play a role only in the short run. Thanks to the flexible specification of our dynamic treatment effect, we detect non-linearities in the impact of the timing of the first childbearing over the elapsed time since school completion. We find that the timing matters and penalties are

minimised if the first childbearing occurs between 7 and 9 years since school completion, corresponding to 26-28 years of age for most of our sample.

The negative and relevant impact on labour market outcomes calls for policy interventions aimed at weakening the work-family conflict implied by childbirths. Since it is especially the first child that generates negative effects and they are particularly long-lasting for women delivering soon after school completion, policies aimed at enlarging the access to affordable child care services and at increasing employment protection and stability for new labour market entrants would be desirable. Because of the larger employment instability and lower earnings, new labour market entrants are indeed more likely to be financially constrained and less likely to afford child care. This is a relevant concern in Italy for at least two reasons. First, the supply of public and inexpensive child care services is extremely limited, in terms of both number of children and hours per child (Del Boca, 2002). In order to promote the supply of child care services, the Italian government started in 2007 a 1 billion Euro program – called *Piano straordinario triennale*, co-sponsored by local governments (Regions) – to subsidise public and private daycare centres and other child care services (Gennari, 2013; Istituto degli Innocenti, 2014). Whether this program has been effective in improving the availability of public child care services is yet to be assessed and left for future research. Second, from the end of the 1990s until the beginning of the 2000s, the employment protection of new labour market entrants has largely decreased, as a consequence of a series of labour market reforms introducing different types of temporary contracts. Although the 2015 labour market reforms were aimed at recovering the open-ended contract as the benchmark form of job relation, the use of temporary jobs among young people is nowadays still quite larger than it was in the past.³⁰

Bratti and Cavalli (2014) found that delaying the first child raises the female labour supply both at the extensive and the intensive margins in Italy. On this basis, they concluded that “tempo policies” aimed at reducing the age at first birth to increase fertility may have negative effects on female labour supply. In our study we showed that the impact of delaying the first child is not homogeneous over the elapsed time since school completion and the negative consequences are larger if the first childbirth occurs either too early or too late. Hence if “tempo policies” are tailored on the elapsed time since school completion, they can still be effective in increasing fertility without compromising the labour market outcomes for women. For example, if policies aimed at reducing the

³⁰The fraction of employees from 15 to 24 years of age with a temporary position was equal to 56% in 2016, whilst it was 35.2% in 2006 (Eurostat, annual results of the Labour Force Survey, <http://ec.europa.eu/eurostat/web/lfs/data/database>).

age of first birth to increase fertility targeted women who left school since more than a decade, they would also generate positive aggregate effects on female labour supply and earnings.

References

- Abbring, J. H. and G. J. van den Berg (2003). The nonparametric identification of treatment effects in duration models. *Econometrica* 71(5), 1491–1517.
- Adda, J., C. Dustmann, and K. Stevens (2017). The career costs of children. *Journal of Political Economy* 125(2), 293–337.
- Amuedo-Dorantes, C. and J. Kimmel (2005). The motherhood wage gap for women in the United States: The importance of college and fertility delay. *Review of Economics of the Household* 3(1), 17–48.
- Anderson, D. J., M. Blinder, and K. Krause (2002). The motherhood wage penalty: Which mothers pay it and why? *American Economic Review* 92(2), 354–358.
- Angrist, J. D. and W. N. Evans (1998). Children and their parents' labor supply: Evidence from exogenous variation in family size. *American Economic Review* 88(3), 450–477.
- Bhargava, A. (1991). Identification and panel data models with endogenous regressors. *Review of Economic Studies* 58(1), 129–140.
- Blundell, R. and T. MaCurdy (1999). Labour supply: A review of alternative approaches. In O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics, Volume 3A*, Chapter 27, pp. 1559–1695. Amsterdam: Elsevier.
- Bratti, M. (2015). Fertility postponement and labor market outcomes. *IZA World of Labor* 117, 1–10.
- Bratti, M. and L. Cavalli (2014). Delayed first birth and new mothers' labor market outcomes: Evidence from biological fertility shocks. *European Journal of Population* 30(1), 35–63.
- Bratti, M., E. Del Bono, and D. Vuri (2005). New mothers' labour force participation in Italy: The role of job characteristics. *Labour* 19(1), 79–121.
- Bratti, M. and K. Tatsiramos (2012). The effect of delaying motherhood on the second childbirth in Europe.
- Browning, M. (1992). Children and household economic behavior. *Journal of Economic Literature* 30(3), 1434–1475.
- Carneiro, P., K. T. Hansen, and J. J. Heckman (2003). Estimating distributions of treatment effects with an application to the returns to schooling and measurement of the effects of uncertainty on college choice. *International Economic Review* 44(2), 361–422.
- Cigno, A. (1983). Human capital and the time-profile of human fertility. *Economics Letters* 13(4), 385–392.
- Cigno, A. and J. Ermisch (1989). A microeconomic analysis of the timing of births. *European Economic Review* 33(4), 737–760.

- Cockx, B., M. Picchio, and S. Baert (2017). Modeling the effects of grade retention in high school. GLO Discussion Paper No. 148, Global Labor Organization.
- Datta Gupta, N. and N. Smith (2002). Children and career Interruptions: The family gap in Denmark. *Economica* 69(276), 609–629.
- Del Boca, D. (2002). The effect of child care and part time opportunities on participation and fertility decisions in Italy. *Journal of Population Economics* 15(3), 549–573.
- Ermisch, J. (1990). European women’s employment and fertility again. *Journal of Population Economics* 3(1), 3–18.
- Evdokimov, K. and H. White (2012). Some extensions of a lemma of Kotlarski. *Econometric Theory* 28(4), 925–932.
- Felfe, C. (2012). The willingness to pay for job amenities: Evidence from mothers’ return to work. *Industrial and Labor Relations Review* 65(2), 427–454.
- Fernández-Kranz, D., A. Lacuesta, and N. Rodríguez-Planas (2013). The motherhood earnings dip: Evidence from administrative records. *Journal of Human Resources* 48(1), 169–197.
- Fitzenberger, B., K. Sommerfeld, and S. Steffes (2013). Causal effects on employment after first birth – A dynamic treatment approach. *Labour Economics* 25, 49–62.
- Fruehwirth, J. C., S. Navarro, and Y. Takahashi (2016). How the timing of grade retention affects outcomes: Identification and estimation of time-varying treatment effects. *Journal of Labor Economics* 34(4), 979–1021.
- Frühwirth-Schnatter, S., C. Pamminer, A. Weber, and R. Winter-Ebmer (2016). Mothers’ long-run career patterns after first birth. *Journal of the Royal Statistical Society: Series A* 179(3), 707–725.
- Gennari, S. (2013). Gli asili nido. In M. Stefani (Ed.), *Le normative e le politiche regionali per la partecipazione delle donne al mercato del lavoro. Questioni di Economia e Finanza (Occasional papers) No. 189*, Chapter 9, pp. 64–73. Bank of Italy.
- Grimshaw, F. and J. Rubery (2015). The motherhood pay gap: A review of the issues, theory and international evidence. ILO Working Paper No. 1/2015.
- Gustafsson, S. (2001). Optimal age at motherhood. Theoretical and empirical considerations on postponement of maternity in Europe. *Journal of Population Economics* 14(2), 225–247.
- Happel, S. K., J. K. Hill, and S. A. Low (1984). An economic analysis of the timing of childbirth. *Population Studies* 38(2), 299–311.
- Harkness, S. and J. Waldfogel (2003). The family gap in pay: Evidence from seven industrialized countries. In S. W. Polachek (Ed.), *Worker Well-Being and Public Policy*, Volume 22, pp. 369–413. Emerald Group Publishing.
- Heckman, J. and S. Navarro (2007). Dynamic discrete choice and dynamic treatment effects. *Journal of Econometrics* 136(2), 341–396.

- Heckman, J. J. and J. A. Smith (1998). Evaluating the welfare state. NBER Working Paper No. 6542, National bureau of economic research.
- Heckman, J. J., S. Urzua, and E. Vytlacil (2006). Understanding instrumental variables in models with essential heterogeneity. *The Review of Economics and Statistics* 88(3), 389–432.
- Herr, J. (2016). Measuring the effect of the timing of first birth on wages. *Journal of Population Economics* 29(1), 39–72.
- Hotz, V. J., J. A. Klerman, and R. J. Willis (1997). The economics of fertility in developed countries. In M. R. Rosenzweig and O. Stark (Eds.), *Handbook of Population and Family Economics*, Volume 1A, pp. 275–347. Elsevier.
- Iacovou, M. (2001). Fertility and female labor supply. ISER Working Paper No. 2001-19, University of Essex.
- Istituto degli Innocenti (2014). Monitoraggio del Piano di sviluppo dei servizi socio-educativi per prima infanzia. Centro nazionale di documentazione e analisi per l'infanzia e l'adolescenza. Litografia IP di Firenze.
- Karimi, A. (2014). Effects of the timing of births on women's earnings: Evidence from a natural experiment. Working Paper IFAU No. 2014:17, Institute for Evaluation of Labour Market and Education Policy.
- Killingsworth, M. and J. Heckman (1986). Female labor supply: A survey. In O. Ashenfelter and R. Layard (Eds.), *Handbook of Labor Economics*, Volume 1, Chapter 2, pp. 103–204. Amsterdam: Elsevier.
- Kotlarski, I. (1967). On characterizing the gamma and the normal distribution. *Pacific Journal of Mathematics* 20(1), 69–76.
- Lalive, R. and J. Zweimüller (2009). How does parental leave affect fertility and return to work? Evidence from two natural experiments. *The Quarterly Journal of Economics* 124(3), 1363–1402.
- Leopold, T. (2012). The legacy of leaving home: Long-term effects of coresidence on parent – child relationships. *Journal of Marriage and Family* 74(3), 399–412.
- Leung, M. Y. M., F. Groes, and R. Santaaulalia-Llopis (2016). The relationship between age at first birth and mother's lifetime earnings: Evidence from Danish data. *PLoS ONE* 11(1), 1–13.
- Michaud, P. and K. Tatsiramos (2011). Fertility and female employment dynamics in Europe: The effect of using alternative econometric modelling assumptions. *Journal of Applied Econometrics* 26(4), 641–668.
- Miller, A. R. (2011). The effects of motherhood timing on career path. *Journal of Population Economics* 24(3), 1071–1100.
- Mills, M., R. Rindfuss, P. McDonald, and E. te Velde (2011). Why do people postpone parenthood? Reasons and social policy incentives. *Human Reproduction Update* 17(6), 848–860.
- Mincer, J. and H. Ofek (1982). Interrupted work careers: Depreciation and restoration of human capital. *Journal of Human Resources* 17(1), 3–24.
- Mroz, T. A. and T. H. Savage (2006). The long-term effects of youth unemployment. *Journal of Human Resources* 41(2), 259–293.

- Pacelli, L., S. Pasqua, and C. Villosio (2013). Labor market penalties for mothers in Italy. *Journal of Labor Research* 34(4), 408–432.
- Rondinelli, C. and R. Zizza (2011). (Non)persistent effects of fertility on female labour supply. ISER Working Paper No. 2011-04.
- Taniguchi, H. (1999). The timing of childbearing and women's wages. *Journal of Marriage and Family* 61(4), 1008–1019.
- Tomes, N. (1985). Human capital and the time-profile of human fertility: Revisited. *Economics Letters* 17(1-2), 183–187.
- Troske, K. R. and A. Voicu (2013). The effect of the timing and spacing of births on the level of labor market involvement of married women. *Empirical Economics* 45(1), 483–521.
- Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica* 57(2), 307–333.
- Waldfogel, J. (1997). The effect of children on women's wages. *American Sociological Review* 62(2), 209–217.
- Waldfogel, J. (1998). The family gap for young women in the United States and Britain: Can maternity leave make a difference? *Journal of Labor Economics* 16(3), 505–545.
- Walker, J. R. (1995). The effect of public policies on recent Swedish fertility behavior. *Journal of Population Economics* 8(3), 223–251.
- Wilde, E., L. Batchelder, and D. T. Ellwood (2010). The mommy track divides: The impact of childbearing on wages of women of different skill levels. NBER Working Paper No. 16582.