Charles University

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MASTER'S THESIS

Measuring the Effect of the Timing of First Birth on Mothers' Wages in the Czech Republic

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Declaration of Authorship

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Prague, January 2, 2019

Signature

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Abstract

This thesis investigates the effect of fertility timing on women's long-run wages. Following the work of Herr (2016), by considering fertility timing in terms of labour market experience at the first birth, we study the effect on wages observed in the window 15 to 20 years after the labour market entry. This allows us to build different models for two groups of mothers: those entering the labour force with and without a child. We come to the conclusion that there is no effect of fertility timing for women entering the labour force already having a child. For women entering the labour force childless, the estimated postponement effect differs depending on whether they have an earning partner or not. If they do, there is clear cost of fertility delay by one more year (contrary to expectations) associated with a decrease in wages by 1%. This finding is very likely connected to a trend of lengthy parental leaves in the Czech Republic. If a woman does not have a partner, we observe an insignificant effect of first birth delay, yet positive. Comparing the results for women living in versus out of Prague, we see no significant difference in the effects.

JEL Classification	J13, J31
Keywords	First birth timing, wages, mothers, Czech Republic

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Abstrakt

Tato práce se zabývá vlivem načasování prvního dítěte na dlouhodobé mzdy žen. Po vzoru studie publikované Herr (2016), odhadujeme vliv na mzdy pozorované v okénku 15 až 20 let od vstupu na trh práce pomocí načasování v podobě ženiny zkušenosti na trhu práce. Díky tomu můžeme vytvořit dva různé modely pro skupinu matek mající dítě při vstupu na trh práce and skupinu matek, které vstupují na trh práce bezdětné. Pro první skupinu není shledán žádný signifikantní efekt načasování dítěte na mzdu. Efekt pro druhou skupinu se liší v závislosti na partnerovi. Odložení prvního dítěte o 1 rok znamená pro ženu mající partnera jednoprocentní pokles ve mzdě. Tento překvapivý výsledek s největší pravděpodobností souvisí s českým trendem v dlouhých rodičovských dovolených. Efekt načasování pro ženy bez partnera je nesignifikatní, nicméně pozitivní. Při porovnávání výsledků pro ženy žijící v Praze a mimo Prahu, žádný signifikatní rozdíl v efektech není.

Klasifikace JEL	J13, J31
Klíčová slova	Načasování prvního dítěte, mzdy, matky, Česká republika

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Acronyms

CZSO The Czech Statistical Office

FTFYE Full-time full-year equivalent

PCA Principal Component Analysis

US The United States

Master's Thesis Proposal

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Proposed topic	Measuring the Effect of the Timing of First Birth on Mothers' Wages in the Czech Republic

Motivation In this work I will examine how timing of the first childbirth affects wages of women in the Czech Republic. Over last few decades this topic enjoyed a great popularity among both sociologists and economists. There is more and more pressure on closing the wage gap between men and women which is to a large extent driven by motherhood. Although this topic is widely discussed, only few studies attempt at quantifying the impact of timing of having a child on woman's wage and no such analysis has been done among the former communist countries.

The paper by Herr (2016), which is also the main reference for my master thesis, quantifies this effect for women in the United States. Firstly, the author proposed using relative timing (time point in one's career when a child is first present) instead of simple age at first birth and then she used it to estimate the effect. The results revealed that for women entering childless into the labour force there is a wage benefit for each year a woman delays her first birth. This applies to women with at least high school diploma. On the other hand, there is no relationship between timing and wages for women starting their career when already having a child.

From this point of view, there are many reasons why it is desirable to study the effect within the framework of the Czech labour market. First of all, the Czech labour market is more rigid than the one in the US, so the results can be different here than they are for the US. Second, the whole trend of length of parental leave is different here. In the US, women tend to spend as little time as possible off the labour market, whereas women in the Czech Republic often stay home for a longer period. Last but not least the difference lies in the social norms that women are tied with. In the US, there is bigger focus on the career, but here in the Czech Republic, there is still some prevalence of a belief that a woman is a primary caretaker of a child until the age of 2 or 3. All these differences can result in different power of effects of delayed childbirth.

Hypotheses

> Hypothesis #1: For childless women when first entering the labour force, there is positive effect on wages with delaying the first birth.
>
> Hypothesis #2: For women entering the labour force already having a child, the positive effect of delaying the first birth on the long run wages is not so significant and it might be even negative.
>
> Hypothesis #3: There are differences in strength of the effect for women working/living in Prague and women outside of Prague.

Methodology For testing hypotheses specified in previous section, I shall use a simple OLS. I will include all relevant factors in the regression that should control for (or should be correlated with) wage growth or for example women's individual characteristics such as education to reduce the omitted variable bias as much as possible and identify the true link between the timing of having a first child and wages. The effect will not be estimated in terms of age but rather woman's experience level as discussed before. So timing of entering the labour force will also play a role in defining the timing of having a first child. This relative timing should be more precise for estimating the effect on wages. To be more clear, the dependent variable will be the long run wage (wage measured in a window around 15 to 20 years after entering the labour force) and the main independent variable to be estimated will be the relative timing of the first birth, i.e. the difference between the age of first birth and age when entering the labour force (job experience level).

I will work with data gathered by the Czech Statistical Office (CSO). The raw dataset is accessible with special approval of the CSO and contains all information about households relevant for my analysis (more specifically it is a research "Household Income and Living Conditions").

Expected Contribution My master thesis will extend the original work of Herr (2016) and estimate the effect of first birth timing on mother's wages for the Czech Republic. Although the estimation framework is not that econometrically challenging, results from this simple regression can be useful not only from the academic point of view and does not have to be discussed only in sociological, political or entrepreneurial context, but above all it is relevant for mothers themselves in deciding when to start having a family.

Outline

1. Introduction: Motivation of the topic and literature review.
2. Situation in the Czech Republic: Sociological impact of the motherhood wage gap and labour market conditions.
3. Data: Description of the data with details about modifying the raw inputs from the CSO.
4. Model: Building a model for testing abovementioned hypotheses.
5. Estimation and Results: Discussion of baseline results and confront them with my hypotheses.
6. Conclusion: Summary of my findings.

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Author

Supervisor

Chapter 1

Introduction

This thesis investigates, how timing of the first birth affects long-term wages in the Czech Republic. Over last few decades, this topic enjoyed great popularity among both sociologists and economists. There is more and more pressure on closing the wage gap between men and women. Identification of the main factors that cause this wage differential is therefore absolutely crucial. It is believed that one of these most important factors is motherhood. Although this topic is widely discussed in many different, even political, spheres, there are surprisingly few studies focusing on estimating the effect of this factor on women's wages. There are some studies quantifying the effect using the data for the United States, nevertheless, no study focuses on estimating the effect for post-communist countries, e.g. the Czech Republic.

The paper by Herr (2016), which is also the main reference for my master thesis, quantifies this effect for women in the United States. The results revealed that for women entering the labour force childless there is wage benefit for each year a woman delays her first birth. On the other hand, there is no relationship between timing and wages for women starting their career when already having a child. From this point of view, there are many reasons why it is desirable to study the effect within the framework of the Czech Republic and its labour market. First of all, the Czech labour market is more rigid than the one in the United States, therefore results coming from American researches may predict absolutely different sentiment compared to the institutional and societal setting of the labour market in the Czech Republic. More specifically, the effect on women's wages can be smaller or it can be even missing. Second of all, trends in length of maternity and parental leave and the whole attitude towards gender roles in the Czech Republic is quite different from the United States. Women in the Czech Republic take longer parental leave and social norms with respect to motherhood vs. career are more traditionalistic. Concretely, on one side, there is a bigger focus on a career in the US, whereas here in the Czech Republic, there is still some prevalence of a belief that a woman is a primary caretaker of a child until the age of two or three. All these factors can lead to different results of analyses compared to the results valid for the labour market in the United States, which makes this topic desirable to analyze for the Czech Republic.

The object of this thesis is estimating the effect of fertility timing on long-run wages. We study the effect with the help of a simple OLS framework for two groups of mothers: women entering the labour force already having a child and women entering the labour force childless. For both groups of mothers, different models are built with different assumptions. For mothers entering the labour force already having a child, we do not assume any significant effect of fertility timing on long-run wages whereas mothers entering the labour force childless are hypothesized to enjoy a positive and significant return to fertility delay. Moreover, a group of mothers entering labour force childless forms a vast majority of the population and thus the thesis focuses more on them. Various bias scenarios are introduced to deal with problems arising from potential endogeneity of fertility timing for this group of mothers. Last but not least, the hypothesis about the difference in fertility timing effects for mothers living in Prague/out of Prague is tested solely using this bigger sample of mothers.

Our results show that women entering the labour force already having a child do not exhibit any fertility timing effect on long-run wages. The estimated effect for the larger sample of mothers (entering the labour force childless), on the other hand, differs depending on whether the mother has an earning partner. Estimation for women with an earning partner shows a negative postponement effect (opposite effect than expected) whereas women without an earning partner exhibit slightly positive postponement effect, yet insignificant. Regarding the difference in effects in/out of Prague, no significant dissimilarity is found. Altogether, the results from this study can be useful not only from the academic point of view and they do not have to be discussed only in sociological, political or entrepreneurial context, but above all, they are relevant for mothers themselves in deciding when to start having a family.

The thesis is structured as follows: Chapter 2 motivates the topic of this thesis and contains a wide-angle literature overview of studies focusing either on pay gap or measuring the fertility timing effect. Chapter 3 introduces the labour market in the Czech Republic and brings the problem introduced in Chapter 2 closer to what exactly will be analyzed. Moreover, the hypotheses are formulated at the end of this chapter. Chapter 4 describes the concrete methodology and introduces potential biases. Chapter 5 presents the data and describes the estimation method and Chapter 6 presents the results. Chapter 7 concludes.

Chapter 2

Literature Review and Motivation

This study examines how timing of the first childbirth affects long-run wages of women in the Czech Republic. Maternity and parental leave, or the impact of motherhood in general, is a widely discussed topic in recent decades. While it does not matter whether the investigated influence concerns the still-unclosed pay gap between men and women or the effect on wage growth after returning to work in general. This thesis analyzes only the impact on the long-run wage of a mother with respect to timing of the first birth. Although this topic enjoys great popularity among both sociologists and economists, only few studies attempt at quantifying the impact of timing of having a child on woman's wage and no such analysis has been done among the former communist countries.

This chapter is organized as follows. The girst part contains general literature overview of studies focusing on both the gender pay gap and then also the motherhood pay gap. With respect to this literature review, the second part builds on stylized facts derived from those studies and discusses problematic issues with regard to the pay gap. Next part narrows the motherhood problematic from the wide context into one specific issue that this thesis analyzes. Following part introduces the scope of this thesis in more detail and lastly, the reference study of this study is presented.

First, it would be appropriate to review some stylized facts about the gender or the motherhood pay gap. What is the reality with respect to wages of women and men (and mothers versus non-mothers) in relative terms and how this relative pay gap evolved over time. These trends that shift the pay gap to this or that direction are desirable to investigate both in Europe and in the

United States — that is why also overseas authors' views on this topic will be discussed. Of course, with respect to those trends, a lot of theories have been developed to explain the pay gap. Reviewing and discussing various theories will lay the foundations for this thesis and the motivation in particular.

A vast majority of studies concerning the gender or maternity pay gap with related issues focus on the United States. Although this thesis inspects women in the Czech Republic only, reviewing the US studies or studies from Europe can help in understanding the problem more deeply or draw some conclusions about this issue within the scope of a market economy in general. Blau & Kahn (2007) study the gender pay gap in the United States and how it evolved over time since the late 1970s. They argue that the gender pay gap narrowed but the pace at which the gap has been closing in the 1970s and the 1980s has come to a halt in the 1990s while the gap has been closing across all education and age levels. Grimshaw & Rubery (2015) on the other hand analyze the pay gap between mothers and non-mothers worldwide. In European countries, having one child has a small negative effect on wages, however, the wage penalty increases drastically with an increasing number of children. Additionally, the wage penalty for mothers with a strong job attachment is found to be very short — mothers tend to catch up non-mothers rather quickly. A study by Glauber (2012) expands the research behind the motherhood wage gap in the United States. The author finds that the wage penalty arising from having a child is the largest in female-dominated jobs compared to women working in male-dominated or even integrated jobs.

Until now, the discussion has been dealing with motherhood or gender pay gap in general. If we instead consider the pay gap between men and women working in the same position, the gender pay gap decreases a lot, however, it still does not close entirely. The Economist (2017b) says that this pay gap cannot narrow anymore at the high-paying level of jobs in developed countries due to the motherhood. Another article from The Economist (2017a) puts gender pay gap into numbers for three developed countries in Europe: Great Britain, France and Germany. Although the gender pay gap across all jobs ranges between 15% to 29% of men's wages, the gap decreases to 2.5%–3% when accounting for jobs at the same level and the same company. Moreover, men tend to earn more relative to women (taking into account only jobs in the same function and organisation) as we move from administrative/low-level jobs through professional and managerial/medium-level jobs to executive/top-level jobs. To compare these numbers from Europe to the comparable figures in the United States, we can make use of a report on the gender pay gap released by the GUCEW (2018). The gender pay gap among all jobs is 19% (in other words, a woman makes 81 cents for every dollar a man earns). When accounting for education, choice of major and job tenure, the gap narrows to 8% of men's wages (92 cents for one man's dollar). Madden (2012) measured the gap between men and women in one particularly high-paying organization, a stock brokerage firm in the United States, with relation to the potential productivity gap between the two genders. Brokers are compensated solely by commissions from sales, so the gender pay gap (18% to 20%) was a result of gender differences in sales. Using a natural experiment, it was found that the pay gap had not been the result of lower women's productivity in general but rather of achievement differences arising from discrimination by customers or by performance-support bias (women brokers were provided with different sales opportunities).

Based on this literature review, there are several unanswered questions. Given the gender pay gap is still existing but to some extent closing, one can argue, whether there is still a potential to close it (The Economist, 2017b). The employer when deciding upon his or her employee's wage takes into account several issues, of course. To put it simply, the employer negotiates a wage which reflects a present value of *expected* future work of this particular employee. Or in other words, the employer values the "investment" with such a price that reflects the market and some characteristics of the worker. This includes, besides main decision elements such as education level, experience and other characteristics, also some perceived, or *expected*, factors that will affect future work. This applies only if the employer faces no strict "wage-assignment" tables as is often the case in the state sector and bargains with a potential employee about the wage rather freely.

Again, it is critical to emphasize that one assumption is crucial in order to capture these factors and to try to explain them in the context of this gender pay gap. The gender gap assumed here is a pay gap between men and women working in the same position, having similar educational and experience background. Of course, other academic or nonacademic sources can talk about the different definition of the pay gap, such as variance between average men's wage and average women's wage. This, of course, includes different variability of positions occupied by those men and women. Being this a legitimate definition too, it is, however, not within the scope of this paper to deal with this question. Having this in mind, some conclusions about the beforementioned factors can be made. From the side of the employer, lower bargained wage can reflect lower perceived value of the employee, or, the "investment". First of all, a lower value can reflect a stereotypical belief that women are less productive. Second of all, expected (or already realized) maternity and parental leave of a woman may also decrease her value for the firm in eyes of some employers (Grimshaw & Rubery, 2015). Last but not least, from the side of the employee, women can be sometimes less aggressive in wage bargaining, so women's wages can be pushed down on average also for this reason (Card *et al.*, 2015)[1].

The pay gap is a widely discussed topic for many years and social awareness with regard to female emancipation has exerted pressure on closing the pay gap for some discriminating reasons, including beliefs that, for example, women deserve less. The reasoning behind the productivity issue discussed before (that is, a woman is less capable compared to a man on the same position) has not much to do with discrimination anymore. The research behind differences in capabilities of males and females are subject of other studies — here, only the economic perspective will be discussed. Simple mechanism of a market economy can explain that if the employer believes a woman is less productive and offers lower wage than she deserves according to her capabilities (assuming a man on this position receives an equilibrium market wage, not a wage that is overvalued), some other employer can gain the whole "productivity buffer" of a women through offering slightly higher wage. This is true up to the value of the wage equal to the equilibrium wage received by men. The functionality of this mechanism is of course constrained by the assumption of a truly free job market, so in the theoretical case presented here, women's wages would converge to an equilibrium in a relatively short time. The real world and a labour market economy work slower, but over the decades, the tendency to close the gap for this particular reason must be at least in progress. As mentioned earlier,

[1] Card *et al.* (2015) show on the Portuguese data, that firm-specific pay premiums (which are correlated with measures of potential bargaining) received by women are on average only 90% of those received by men. Moreover, according to the authors, another thing that contributes to the gender pay gap is that women are less likely to work at high-paying firms. However, as mentioned before, this is subject to a different definition of the gender pay gap than assumed here.

studies analyzing potentially different productivities of men and women will not be reviewed here, however, one study already discussed before with regard to the gender pay gap can apply here. Madden (2012) measured whether the gender pay gap in sales commissions among stockbrokers results from different productivity and she proved it did not.

But from reviewed studies (focusing mainly on developed countries with a market economy), it is apparent that process of closing the gender pay gap has slowed down significantly or is even stagnating (Blau & Kahn, 2007; The Economist, 2017b;a). Then if the premise is true, one of the main factors driving the gender pay gap[2] is motherhood, which lowers the value of a woman to the firm[3] for reasons arising from either the *expected* motherhood or the fact that a woman is already having a child. The former can be an explanation for the pay gap between men and non-mothers, whereas the latter can be an explanation for differences in wages of mothers and non-mothers (the motherhood pay gap). Putting all this into context is not only useful for motivating the topic *per se*, but also for explaining how motherhood affects different types of pay gaps. This way, we can differentiate between various topics including the problematics of motherhood and lay the foundations for one particular topic that this thesis investigates.

Clearly, it is out of the scope of this paper to encompass the whole problematics of the gender pay gap, the motherhood pay gap etc. Instead, in relation to what has been said previously in this chapter, this study focuses solely on mothers and how their motherhood affects their long-run wages. Their wages will not be compared to those of non-mothers, i.e. the motherhood pay gap will not be analyzed. However, the problematics of a motherhood pay gap will be included (although non-mothers will not be included in the analysis) in a way that we will estimate the impact of postponing having a child on wages

[2]With regard to the definition of a gender pay gap assumed here (gap between men and women on the same position) and based on the literature review respecting this definition, expected or realized motherhood and lower bargaining power of women might be two of the most important drivers of the remaining gap. However, even if we do not assume the wide definition of a gender pay gap here (as a wage between all men and women), it can be (and it most certainly is) true that motherhood or other factors affect also this wider definition of a gender pay gap through occupation variability of men and women.

[3]And/or smaller aggressivity of a woman when bargaining over the wage as discussed before.

assuming there *is* some impact. If there is an estimated *zero* postponement effect, some conclusion about the motherhood pay gap can be drawn.

Therefore, this study is built on the assumption that wages grow fast at the initial stage of a woman's career and that the growth starts to stagnate later in a life of a woman, mostly only after she gives birth to the first child. Consequently, a woman faces some kind of a payoff that arises from the fact that if she delays her first child she can still enjoy the higher wage growth. Putting it differently, if a woman faces the high rate of return at the early stage of a career, we can define a "return" to fertility delay as a payoff a women gains by one more year of work experience (Herr, 2016).

This return to the postponement of a first child can be measured through the effect on long-run wages. Assuming different rates of wage growth before and after having a child and using an appropriate mathematical model (which will be introduced in Chapter 4) capturing all the assumptions, we can model the long-run wage (measured as annual wage X years from entering the labour force). The return to delay can be then easily estimated using the mathematical model.

Various studies attempt at quantifying the fertility timing effect for women in the United States. Miller (2011) and Buckles (2008) find that one year of fertility delay is associated with 3% increase in wages. Wilde *et al.* (2010) present a similar finding, that is, the postponement effect is significant only for high-skill women. Taniguchi (1999) finds that early child bearers face higher wage penalty since they interrupt their careers during the critical career-building period. Blackburn & Bloom (1990) explain higher wages earned by late child bearers by investment in human capital — late child bearers invest more than early child bearers.

The paper by Herr (2016), which is also the main reference for this master thesis, also quantifies this effect for women in the United States. Firstly, the author proposed using relative timing (time point in one's career when a child is first present) instead of simple age at first birth, as it is often a case in similar studies. The main explanatory variable is, therefore, the difference between a woman's age at first childbearing and age when entering the labour market. The explained variable is then long-run wage of the mother — the author uses a reported wage in the window of 19 to 24 years from entering the labour force. To estimate the model, Herr uses Ordinary Least Squares (OLS) method. Sign of the effect (positive/negative estimate) and size can then reveal how the above-described regressor affects long-run wages. The estimate can be also interpreted as a return to a one-year delay of the first birth in terms of increase in long-run wages. The results revealed that for women entering the labour force childless, there is wage benefit for each year a woman delays her first birth. This applies to women with at least a high school diploma. On the other hand, there is no relationship between timing and wages for women starting their career already having a child.

Herr (2016) uses a model that is sophisticated in many ways, not only in using relative timing instead of mother's age at first birth. The author also does not assume the same development of the effect (both size *and* sign of the estimate) for women having a child before and after entering the labour market. Among other changes and extensions of Herr's original model, also our analyzed sample of women differs significantly. For reasons discussed later in Chapter 3, we estimate the effect only for women entering the labour market after the year 1989, that is, they have reported wage in a window of 15 to 20 years from entering the labour force.

Chapter 3

Fertility and the Labour Market in the Czech Republic

With the collapse of the state-socialist regime in 1989, there has been a lot of changes in the lives of people inhabited in the area of the Czech Republic. End of a state (instead of a market) oriented economy brought a rather rapid transformation of the economy in the 1990s towards marketisation. This transformation provided rising economic growth, massive political changes with reorientation to the West and, more concretely, to the growing European Union. This reorientation influenced not only the way of life in the political sphere, but it had a huge sociological impact too. These overall changes affected family behaviour and in consequence also fertility rates and shifts in childbearing. It happened thanks to an economic transformation, new, market-oriented employment conditions and overall education boom among both women and men. New market-oriented era entailed many new job creations connected with a modernisation of obsolete industries and with services in general. Socialist era did not know unemployment and with the demise of the regime in 1989, employment rates have fallen significantly. In turn, market orientation did not mean only that a firm operates within a competitive environment but also that workers compete between each other to get a job since it is no longer possible to "allocate" a job to everyone at any price. Therefore the importance of education and especially university education has risen in the 1990s in order to increase individual employment opportunities and to secure income flows. This is of course mostly visible among medium and highly educated women. Low educated women still resort to early childbearing.

The attitude towards education influenced family structure and fertility, prolonged planned first birth among women and sometimes even changed women's priorities with regard to career/childbearing. Many women choose to attain some career position first to gain security and desirable income level and only after that they plan to have children. There are, however, aspects other than the importance of education with relation to a market-oriented economy that helped to redefine family structures, life priorities and, in turn, affected overall fertility rates after 1989. Before 1989, early marriage and early childbearing were supported and incentivised from the state, while at the same time opportunity costs of that were very low (Sobotka *et al.*, 2008). After 1989, as mentioned above, education became more and more important due to the changing labour market characteristics and uncertainty among young people. However, in addition to that, new family orders and patterns (extra-marital childbearing, childlessness, ...), that were much more socially acceptable after 1989, helped in a way to further delay average age at childbearing and to decrease fertility rates. Even though liberal views on abortion, extra-marital childbearing, divorces and so on, were prevailing already during the socialist era, the demise of the regime further eased the societal attitudes towards these non-traditional family issues. Also, widespread availability of contraceptives helped in this way to plan woman's childbearing precisely and to perfectly control her reproduction without the necessity of rather invasive abortion.

However, the idea of a family (the marriage and children) still enjoys great popularity. Some family policies developed after 1989 made childbearing and consequent parental leave more incentivised. Paid parental leave is extended up to the fourth year of a child, which is one of the longest paid parental leaves in the European Union (Sobotka *et al.*, 2008). Therefore, although the "Western" way of living (career orientation) and non-marital living arrangements has been increasingly popular in the Czech Republic, there are still some pro-family patterns anchored in the Czech society that are prevailing even after 1989. These may be either incentivising state policies for maternity and parental leave or prevailing norms and beliefs that a woman is a primary caretaker of a child and this is in a way her life "mission".

Still, the two competing forces do not even out: even though family-related behaviour and norms are more traditionalistic than in the Western countries and the trend of long parental leave is prevalent here, these effects are more than outweighed by already discussed effects of education, eased living arrangements etc., so the postponement of first birth and the decline in fertility rates are apparent after 1989. Sobotka *et al.* (2008) argue that the shift towards later parenthood reflects the Western trends:

- Fertility rates in the age group of mothers below 20 and 20–24 decreased by 78% and 74% respectively between the years 1990 and 2006.
- Fertility rates in the age group of mothers 30+ increased by 109% and share of 30+ mothers increased from 14% to 41% between the years 1990 and 2006.
- The mean age at first birth increased from 22.5 in 1990 to 26.9 in 2006.

All in all, the total fertility rate decreased rapidly from 1.9 children per woman in 1990 and reached the bottom 1.13 in 1999. This was partially offset later on when the fertility rate increased again to 1.53 in 2015[1]. Sobotka *et al.* (2008) argue that this strong decrease of fertility rates in the 1990s was mainly driven by delayed first birth. This postponement is visible among women born in the 1970s. Women born before, in the 1960s, had the main childbearing age before the collapse of the state-socialist regime and resorted to early childbearing as was the trend back then. After 1989, however, women in their early twenties abandoned fertility model of the previous generation and postponed their first birth. This led to the massive decrease in the total fertility rate in the 1990s. The new millennium compensated the fertility downturn due to second births of the 1970s cohort of mothers.

Another important point relates to the trend in parental leaves in the Czech Republic. In general, right after 6-months-long maternity leave, women (or men) are entitled to receive paid parental leave. Parental allowance is fixed and can be spread over 2 to 4 years. Employers, on the other hand, have to grant parental leave up to age 3 of the child. This, of course, suggests that women take the opportunity and spend time with their children at home instead of returning to work as soon as possible. Moreover, according to the CZSO (2016), the average time between births of the first and the second child was 4.4 years in 2015, although almost 65% of those mothers experienced the time between the first two births ranging between 1 to 3 years. Having in mind

[1]Updated information retrieved from World Bank data, World Development Indicators — Total Fertility Rates for the Czech Republic.

that an average number of children per woman is almost 2, an average woman in the Czech Republic might spend on the parental leave out of the labour market between 4 to 6 years.

This discussion is crucial for the analysis of the effect of first birth timing on long-run wages in various ways. The first and most important outcome of the factual analysis in this section is that it places a clear restriction on a sample that should be used to estimate the effect. Next, it allows us to make a hypothesis about the size of the effect compared to the reference study. Last but not least, evidence-based facts about shifts in family-related behaviour and the postponement of first birth send a clear signal about how women control their reproduction for career/education related reasons (this applies mostly to medium and high educated women). We can then use this information for hypothesis statements and model construction (use of some specific variables further in our analysis). Moreover, stylized facts presented above might help us when interpreting the results.

Building on this section and Chapter 2, several hypotheses can be formulated and further tested.

1. For childless women when first entering the labour force, there is a positive effect on wages with delaying the first birth.
2. For women entering the labour force already having a child, the effect of first birth timing is not significant.
3. There are differences in strength of the effect for women working/living in Prague and women outside of Prague. Concretely, women in Prague enjoy a higher (more positive) return to one more year of fertility delay.

There are many reasons why it is desirable to study the effect within the framework of the Czech labour market. First of all, the Czech labour market is more rigid than the one in the US, so the results can be different here than they are for the US (presented in Chapter 2). Second, the whole trend of the length of parental leave is different here. In the US, women tend to spend as little time as possible off the labour market, whereas women in the Czech Republic often stay home for a longer period. Last but not least, the difference lies in the social norms that women are tied with. In the US, there is a bigger focus on a career, but here in the Czech Republic, there is still some prevalence of a belief that a woman is a primary caretaker of a child until the age of 2 or 3. All these differences can result in different power of effects of delayed childbirth. As mentioned above (see hypothesis 3), the effect for mothers living or working in Prague might be closer in magnitude to the results for the US. Women in Prague might face higher return to fertility delay since wages grow faster before having the first child compared to other regions in the Czech Republic.

Chapter 4

Methodology

As already discussed in Chapter 2, this study assumes that wages grow fast at the initial stage of a woman's career and that the growth starts to stagnate later in a life of a woman, mostly only after has her first child. Through simplification of a complex wage development of a woman into only two rates of a wage growth — *before* and *after* the first child — we can easily estimate the payoff a woman gains by one more year of work experience. Herr (2016) also discusses that by delaying the first birth, women accumulate the human capital, which in turn favours her when she decides to return back to the labour force after the maternity leave. This is also connected to a woman's motivation connected to low transaction costs of looking for a better-quality job before motherhood. This return to fertility delay can be measured through the effect on long-run wages. The model by Herr (2016) uses two important features compared to other studies in this field. Firstly, the author proposes using relative timing (time point in one's career when a child is first present) instead of simple age at first birth. Secondly, it also does not assume the same development of the effect (both size *and* sign of the estimate) for women having a child before and after entering the labour market.

4.1 Model

First, a model for women entering the labour market before having a child will be discussed (we will call them post-work mothers). With respect to what has been said earlier, it is assumed that the rate of wage growth before the first child, g_1, is higher than the rate of wage growth after the first child, g_2 (see Chapter 2). For women entering the labour market before having a child (a vast majority of a sample), we can model the long-run wage as an initial wage W_0 plus different rates of wage growth multiplied by the relevant number of years:

$$W_{20} = W_0 + g_1 C_1 + g_2 t_{rest} \tag{4.1}$$

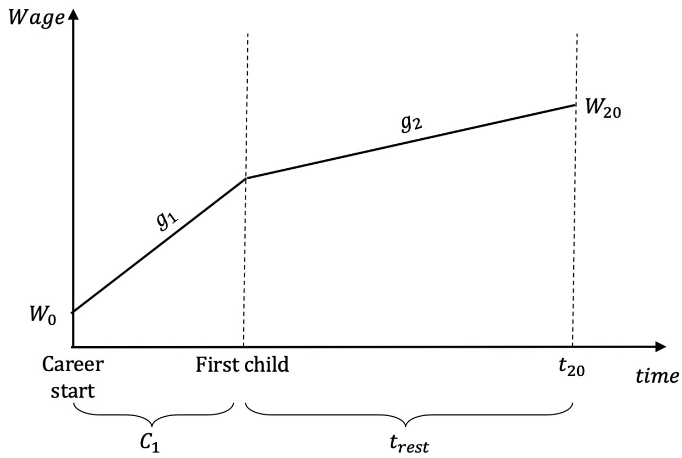
whereW_{20} is wage observed 15–20 years after the labour market entry, t_{rest} is the number of years between time-point where W_{20} is observed and the year of the first birth and C_1 is the fertility timing expressed as a number of years between the first birth and the labour market entry (timing in terms of labour market experience). The whole time between the labour market entry and the point of W_{20} identification can be denoted as t_{20} so that we can rewrite Equation 4.1 as

$$\begin{aligned} W_{20} &= W_0 + (g_1 - g_2)C_1 + g_2 t_{20}, or \\ W_{20} &= W_0 + \beta_1 C_1 + g_2 t_{20}. \end{aligned} \tag{4.2}$$

This is again, of course, relevant only for mothers already building their careers — women who have a child before the labour market entry are not taken into account yet for clarity. From the mathematical notation in Equation 4.2 it is now clear that the β_1 parameter (measuring the effect of fertility timing C_1 on long-run wages) is just equal to the difference between the two rates of wage growths, before and after having a child. This parameter can be also interpreted as a return to one year of fertility delay in terms of a long-run wage increase. The above model is illustrated in Figure 4.1.

Clearly, C_1 expresses woman's labour market experience at the time point of her first child's birth. The model assumes that the rate of wage growth is constant over the initial period up to the time of the first birth, no matter how long this period can be. Similar assumption holds for g_2, that is, the rate of growth after giving first birth is held constant up to the time where W_{20} is observed (15 to 20 years after the labour market entry in this case). Hypotheses then assume that the difference between the two rates of wage growth ($\beta_1 = g_1 - g_2$) is given by the timing of the first birth — going back to the graph, if a woman delays her child by one more year, then the ending wage W_{20} will be increased by $\beta_1 * 1$, which is exactly the return to one more year of

Figure 4.1: Wage development for women with first birth after the labour market entry



fertility delay. The hypothesis presented in the previous chapter states that for women entering the labour market before having a child, this β_1 is significant and positive.

Before the model for women entering the labour market *after* having a child is established, several notes about using relative timing, C_1, should be pointed out. The model could be rebuilt and instead of using relative timing, simple age of a woman could be used. Herr (2016) discusses various implications of using age instead of relative timing, such as for example potential bias in estimation of β_1 when both groups of women (with the first child before *and* after entering the labour force) are included in the sample. We do not go into detail and replicate discussion about the bias and estimation here. However, it should be noted here, that using relative timing in terms of labour market experience allows us to estimate different slopes on C_1 for both groups of mothers.

Another crucial point connected to the logic of the model is that we do not want to reflect the mechanism of how C_1 influences long-run wages. If variables explaining this mechanism were included in the model, part of the effect of C_1 would be absorbed by these variables. The wage growth after having the first child, g_2, can be smaller than initial wage growth for various reasons. Some of them were introduced in Chapter 2, such as reduced experience level after giving birth as perceived by an employer. Another factor might be for example lower labour supply. Therefore, including variables reflecting woman's labour supply would, in turn, affect the desired estimate of β_1. Last minor note concerns the sign of C_1. In the subsequent section, a model for mothers having the first child before entering the labour force will be introduced — C_1 for these women is therefore negative, which should be borne in mind throughout introducing the model.

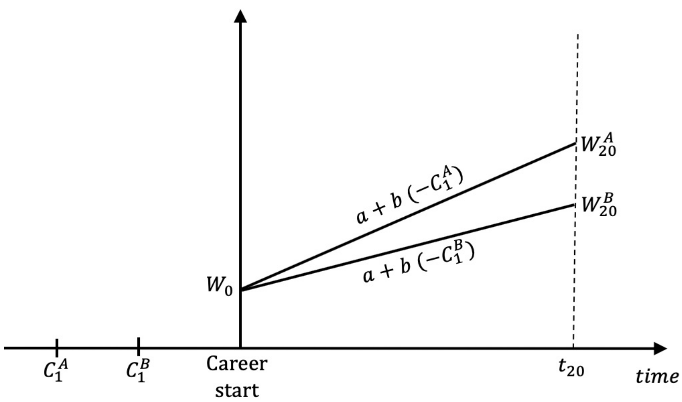
For the population of mothers having their first child before entering the labour force (we will call them pre-work mothers), we establish an indicator to distinguish between the two populations of mothers, I_{LF}:

$$I_{LF} = \begin{cases} 1 & \text{if } C_1 \leq 0 \\ 0 & \text{if } C_1 > 0. \end{cases} \tag{4.3}$$

Before establishing the model mathematically, discussion about the possible direction of C_1 effect on wages is in place. For this population of mothers, the effect is not that straightforward. It might be the case that age of the first child affects subsequent wages; the older the first child at the woman's labour market entry, the higher the wage afterwards. The reasoning behind it might be that with older children, mother's labour supply behaviour resembles the behaviour of a childless woman — she does not have to work shorter hours in order to take care of her children. However, again referring back to Chapter 3, the hypothesis about this population of mothers says that there is no link between the age of the first child (logically equal to $-C_1$) at the mother's labour market entry and subsequent wage path.

For pre-work mothers, there is only one rate of wage growth, valid for the whole period t_{20}. Similar graph as in Figure 4.1 is presented below:

Figure 4.2: Wage development for women with first birth before the labour market entry

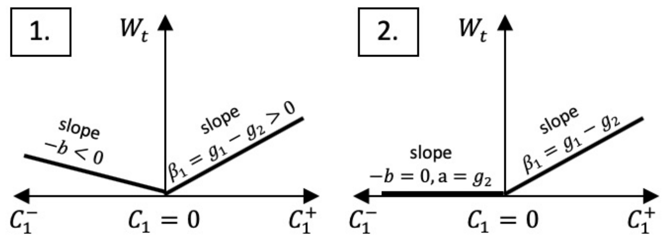


In the above graph, there are two wage developments for two different mothers. Mother A has an older child and in this particular case enjoys higher wage growth afterwards. To model the wage growth of pre-work mothers, $g_{I_{LF}}$, depending on C_1, we use the following equation:

$$g_{I_{LF}} = a + b * (-C_1), \tag{4.4}$$

where $-C_1$ is the age of the first child at the career starting point and $a, b \geq 0$ are parameters fixed for all mothers. Figure 4.2 shows the case, where the link between C_1 and consequent wage path exists, that is $b \neq 0$. More concretely, Figure 4.2 shows the case where $b > 0$ — the older the first child at the career start, the higher subsequent long-run wages. However, the hypothesis about pre-work mothers formulated in the previous chapter clearly states, that there is no link, that is, $b = 0$. The graph below shows the link between the two main parameters to estimate — β_1 and $-b$. These are the estimates measuring the postponement effect for post-work mothers and the effect of age of the first child at the career start for pre-work mothers. The postponement effect, β_1, expresses how much long-run wages increase if we increase C_1 by one more year. For pre-work mothers, C_1 is negative, so the effect of increasing age of the first child at the career starting point (implicitly equal to $-C_1$) by one more year is expressed by b. These two effects for post-work and pre-work mothers are graphically summarized in Figure 4.3:

Figure 4.3: Wage development for women with first birth before the labour market entry



The first picture shows the case where the older the first child at the career starting point, the higher subsequent long-run wages, that is $-b < 0$. The second picture, on the other hand, summarizes the first two hypotheses formulated in Chapter 3, $b = 0$ and $\beta_1 > 0$. Now, by putting together models for the two populations of mothers, we build the combined model for estimating the effect of first birth timing on wages:

$$W_{20} = W_0 + (1 - I_{LF})(\beta_1 C_1 + g_2 t_{20}) + I_{LF}(a + b(-C_1))t_{20} \tag{4.5}$$

To make the above model work, there is one crucial requirement — the period where the wage development is measured have to be the same for all women, i.e. t_{20} is held constant across observations. As has been discussed in the previous chapter, the ideal length of this period should be 15 to 20 years for the Czech Republic, although t_{20} suggests that only period of 20 years should be taken into account. In the following chapter, we take W_{20} as a wage of women 15 to 20 years after the labour market entry to boost our sample but we still consider t_{20} to be constant for all mothers.

In reality, simple equations and graphs presented above in this section can suffer from several biases. Scenarios presented in Section 4.3 can help in identifying plausible biases that can be present in the model. The first discussed bias is inspired by Herr (2016), the second one extends the original model and presents a more realistic decision-making process of women in the Czech Republic. Before all scenarios are introduced, it is crucial to model the optimal timing of the first birth. After building this optimal C_1, it will be clearer how the bias scenarios are built and consequently treated.

4.2 Modelling C_1^*

Herr (2016) assumes that a woman chooses optimal C_1 (C_1^*) by maximizing the lifetime utility, which increases in lifetime earnings and decreases with delaying first birth. The cost of delaying first birth, $c(C_1)$, is according to Herr (2016) only dependent on simple taste for early motherhood. So the only thing that stops a woman from delaying first birth to infinity is the fact that she really wants to have a child. This comes from the main assumption of the model; a woman does not face a lower rate of wage growth *until* she has a first child. Without this cost, a woman would maximize her utility by not having a child at all. However, this cost is entirely non-material. This kind of women wants to work as long as possible and the only thing that stops her is her personal feeling.

With respect to what has been said about women living in the Czech Republic in Chapter 3, there might be another type of woman with the entirely different decision-making process. This study will, therefore, refine the optimal C_1 in a way that it will reflect the decision-making process of women living in the Czech Republic more precisely. The premise is as follows: women want to have children as soon as possible and the only thing that stops them is insufficient finance. This is actually one of the shortcomings of Herr's model. The author does not even consider increased expenditure related to having a child, which might be the one aspect that stops a woman from having a child immediately after leaving school for example. Therefore, to model C_1^*, this study will combine the two approaches; Herr's approach, which assumes that women equalize utility from lifetime earnings (y) and utility from having a child as soon as possible (the type 1 women), and this new added approach, where women choose to deliver the first child when they can afford it (the type 2 women).

Following the notation of Herr (2016), the type 1 woman maximizes:

$$\begin{aligned} U &= log(y) - c(C_1) = log\left(\int_{t_{20}} W_t e^{-rt} dt\right) - c(C_1) = \\ &= log\left(\int_0^{C_1} W_0 e^{g_1 t} e^{-rt} dt + \int_{C_1}^{t_{20}} W_0 e^{g_1 C_1} e^{g_2 (t - C_1)} e^{-rt} dt\right) - \\ &\quad -c(C_1), \end{aligned} \tag{4.6}$$

where y are lifetime earnings, $c(C_1)$ is cost of delaying the first birth, W_0 is a starting wage, g_1, g_2 are wage growths before and after having the first child, C_1 is a time point in a woman's career where she gives birth to her first child, t_{20} is a length of a woman's career and r is a discount rate.

There are various simplifying assumptions implicitly included, such as for example constant labour supply. Also, t_{20} should be the same for all women. By equalizing the marginal benefit of delay represented by the logarithmic term with the marginal cost of delay represented by $c(C_1)$, optimal C_1 for each woman i solves to:

$$C_{1i}^{*} = \frac{\beta_{1i} - \nu_i}{m_{1i} - m_{2i}}, \tag{4.7}$$

where $m_{1i}, m_{2i} \geq 0$, β_{1i} is the return to one more year of delaying the first birth or in other words the change in wage growths at the first birth, $g_{1i} - g_{2i}$, and ν_i is the taste for early motherhood[1]. This is the optimal C_1 for the type 1 woman. The second type of woman decides differently on C_1^* and it is assumed in this study that some portion of women in the Czech Republic follows this decision-making process. Keeping the notation of Herr, there is some fixed point in woman's career given by her desired wage at that point. This wage is objectively sufficient to bear increased costs related to having a child. For example, the level of maternity pay depends on this achieved wage level. Also, a woman can want to secure her future position in the labour market. Wage at this fixed point is then constant, W_{C_1}. Optimal C_1 for type 2 women is given by this W_{C_1} by the following formula:

$$C_{1i}^{*} = \frac{W_{C_1} - W_{0i}}{g_{1i}}. \tag{4.8}$$

Combining the two approaches, C_1^* is given as:

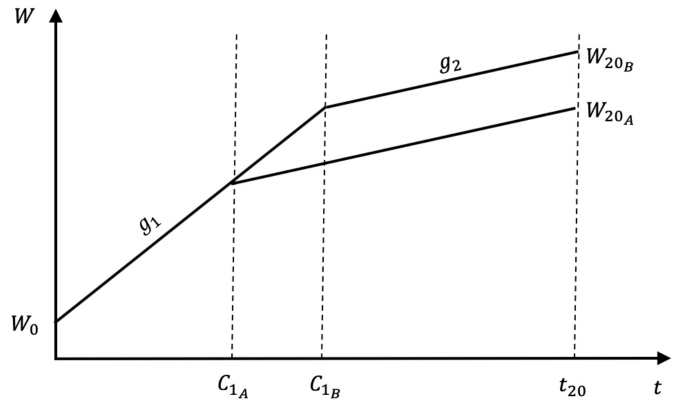
$$C_{1i}^{*} = \begin{cases} \frac{\beta_{1i} - \nu_i}{m_{1i} - m_{2i}} & \text{for type 1 women,} \\ \\ \frac{W_{C_1} - W_{0i}}{g_{1i}} & \text{for type 2 women.} \end{cases} \tag{4.9}$$

4.3 Potential Biases Captured in the Estimation of β_1

Scenarios presented below build on the model and reasoning behind the optimal C_1. The model constructed in Equation 4.5 assumes that C_1 is exogenous and parameters (g_1, g_2, a and b) that enter the model are the same for all women. However, taking into account only women with the first child after the labour market entry, we can think of some biases that can be present in the estimation of β_1, making the variable C_1 endogenous. For simplicity, compared women have the same starting wage in the following graphs and computations. Now, before introducing the bias scenarios, presenting the case without any bias is in place.

[1] See the calculation steps in the Appendix A.

Figure 4.4: No bias scenario



The return to one more year of fertility delay, β_1, is constant for all women in the no bias scenario, so both women experience the same g_1 and g_2 in Figure 4.4. The woman A decided to have her first birth earlier and the woman B had her first child later. We can observe their wage paths from their career starting point to the point t_{20} which corresponds to the twentieth year after the labour market entry. To compute the difference in the ending wages of the two women, we use Equation 4.2:

$$\begin{aligned} W_{20_B} - W_{20_A} &= (W_0 + \beta_1 C_{1_B} + g_2 t_{20}) - (W_0 + \beta_1 C_{1_A} + g_2 t_{20}) = \\ &= \beta_1 (C_{1_B} - C_{1_A}) = \beta_1, \end{aligned} \tag{4.10}$$

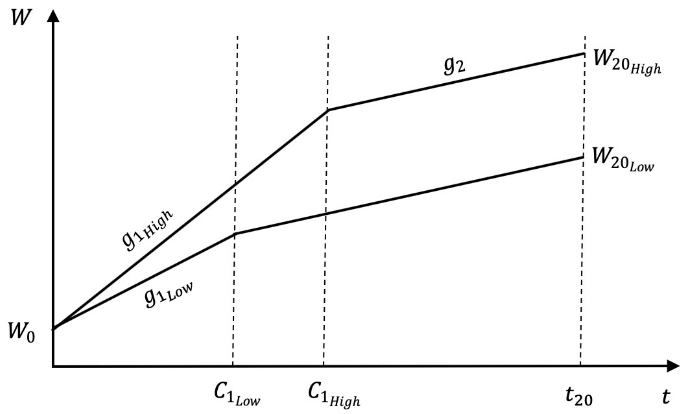
where we set the difference between C_{1_B} and C_{1_A} to 1 year for simplicity. Therefore, the estimation using OLS gives us in this case an unbiased estimate of β_1.

4.3.1 Bias I

In this scenario, we introduce the first plausible bias. It is assumed here that the correlation between C_1 and subsequent wage path is influenced by endogenous fertility timing. Specifically, women with higher ability might want to postpone their first child because they face higher return to fertility delay. In other words, their g_1 is higher than the wage growth of those with lower ability.

It is visible from Figure 4.5 that the woman with higher ability decided to

Figure 4.5: Bias I scenario



postpone her first birth in reaction to high return to fertility delay ($\beta_{1_{High}}$). This woman enjoys faster wage growth in the first period up to the point she has her first child ($g_{1_{High}} > g_{1_{Low}} \Rightarrow g_1$ is a function of ability, $g_1(ability)$). Consequent wage growth, g_2, remains the same for all women to allow $\beta_1(ability)$ to increase with ability. To compute the difference in the ending wage levels of the two women, the same approach as in Equation 4.10 is followed.

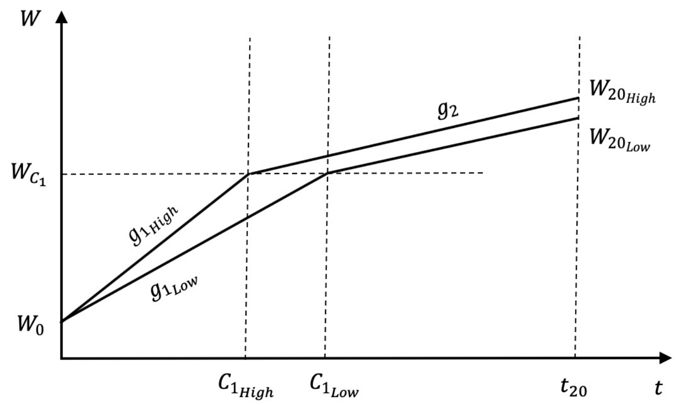
$$\begin{aligned}
W_{20_{High}} - W_{20_{Low}} &= (W_0 + \beta_{1_{High}} C_{1_{High}} + g_2 t_{20}) - \\
&\quad -(W_0 + \beta_{1_{Low}} C_{1_{Low}} + g_2 t_{20}) = \\
&= \beta_{1_{High}} C_{1_{High}} - \beta_{1_{Low}} C_{1_{Low}} = \\
&= \beta_{1_{High}} + C_{1_{Low}}(\beta_{1_{High}} - \beta_{1_{Low}}) = \\
&= \beta_{1_{High}} + C_{1_{Low}}(g_{1_{High}} - g_{1_{Low}}),
\end{aligned}$$

where again $C_{1_{High}}$ is normalized to equal $C_{1_{Low}} + 1$. Estimation without controlling for ability clearly creates an upward bias to the average return to delay.

4.3.2 Bias II

The second scenario shows exactly the possible bias inherent in the decision-making process of type 2 women presented in Section 4.2 with the combination of low/high ability type of a woman. Women in this scenario target some W_{C_1} and those with lower ability reach this target later than those with higher ability. The problem is depicted in Figure 4.6.

Figure 4.6: Bias II scenario



In this scenario, W_{C_1} is exogenously given and all women face the same level. This reflects the problem of making enough money to have a child that many families might face. Again, the woman with higher ability experiences fast wage growth ($g_{1_{High}} > g_{1_{Low}} \Rightarrow g_1(ability)$) but subsequent wage growth after having a child, g_2, is the same for both women. In consequence, $\beta_1(ability)$ is also increasing with ability as in case of the bias I scenario.

However, calculating the direction of bias now depends on a particular setting of model parameters. The wage difference computation starts the same:

$$\begin{aligned} W_{20_{Low}} - W_{20_{High}} &= (W_0 + \beta_{1_{Low}} C_{1_{Low}} + g_2 t_{20}) - \\ & \quad -(W_0 + \beta_{1_{High}} C_{1_{High}} + g_2 t_{20}) = \\ &= \beta_{1_{Low}} C_{1_{Low}} - \beta_{1_{High}} C_{1_{High}}. \end{aligned} \tag{4.11}$$

But now $C_{1_{High}}$ cannot be normalized that easily. The target level W_{C_1} has to be taken into account in the calculation of the difference between $C_{1_{High}}$ and $C_{1_{Low}}$.

$$W_0 + g_{1_{High}} C_{1_{High}} = W_{C_1} = W_0 + g_{1_{Low}} C_{1_{Low}} \Rightarrow$$

$$C_{1_{Low}} = \frac{g_{1_{High}}}{g_{1_{Low}}} C_{1_{High}}.$$

$$C_{1_{Low}} - C_{1_{High}} = 1 \Rightarrow \frac{g_{1_{High}}}{g_{1_{Low}}} C_{1_{High}} - C_{1_{High}} = 1 \Rightarrow$$

$$C_{1_{High}} = \frac{g_{1_{Low}}}{g_{1_{High}} - g_{1_{Low}}} \quad \& \quad C_{1_{Low}} = \frac{g_{1_{High}}}{g_{1_{High}} - g_{1_{Low}}}.$$

After substituting $C_{1_{High}}$ and $C_{1_{Low}}$ into Equation 4.11, we get:

$$\begin{aligned} \beta_{1_{Low}} C_{1_{Low}} - \beta_{1_{High}} C_{1_{High}} &= \beta_{1_{Low}} \frac{g_{1_{High}}}{g_{1_{High}} - g_{1_{Low}}} - \beta_{1_{High}} \frac{g_{1_{Low}}}{g_{1_{High}} - g_{1_{Low}}} = \\ &= g_2 \frac{g_{1_{Low}} - g_{1_{High}}}{g_{1_{High}} - g_{1_{Low}}} = -g_2 < 0 \end{aligned}$$

Under this scenario, regression of W_{20} on C_1 provides a negative coefficient that clearly understates the average β_1, which is of course positive ($\beta_{1_{High}}, \beta_{1_{Low}} > 0$).

Both biases, however, can be corrected by including a proxy for ability in the model. By comparing the models with and without this correction and by establishing the direction of the bias (upward bias versus downward bias), we can conclude something about the composition of women in our sample and their decision-making process. If the presence of a downward bias is proved, it can be concluded that there is a prevalence of type 2 women in the sample, with the decision-making process discussed in the bias II scenario. If, on the other hand, upward bias is detected in the estimation of β_1, the bias I is most probably present in the sample. In the following chapter, correction for these two kinds of biases is suggested and a proxy for ability is introduced.

Another factor closely related to the decision-making process depicted in bias scenario II or to the modelling of the optimal C_1 for type 2 women is a financial situation of a woman's partner at the time of first birth/conception. It can be the case that women do not target only their own wage level but they decide on having a child based on the whole household income. For purposes of estimation, it would be interesting to include partner's income from the time of first birth in the model and see whether it affects the correlation between C_1 and subsequent wage path of a woman. Due to positive assortative mating, wages of the two partners are often positively correlated which would then make the fertility timing eventually endogenous if women target partner's income when deciding on having a child. To eliminate such bias, one would ideally like to control for partner's wage at first birth (and include it in the regression).

The following chapter presents the data and shows the estimation steps to deal with modelled problems discussed above.

Chapter 5

Data Description & Estimation

In this chapter, we first introduce the dataset and relevant issues related to the structure of the dataset that can presumably pose problems. Continuing with sample selection criteria, report of our final sample follows with its summary statistics. We then discuss the definition and subsequent calculation of all variables mentioned in Chapter 4 that are used in the estimation. Then, the estimation procedure is presented together with the discussion of biases (introduced in Section 4.3 and their treatment in the estimation). Last but not least, robustness checks are developed with respect to discussed shortcomings of the data or lack of the data itself.

5.1 Data

We use the 2013 wave of the Statistics on Income and Living Conditions (SILC) data provided by the Czech Statistical Office (CZSO). Two raw datasets, made available with special approval of the CZSO, contain detailed information about household characteristics and socio-economic characteristics of each household member. Concretely, the first dataset includes information about 8275 households and the second dataset provides further characteristics about all 19105 household members including infants. Both datasets can be joined using unique household id number.

All data is cross-sectional and a vast majority of it captures the current state of households and household members, i.e. state as of 1st May 2013. These are the socio-demographic characteristics of individuals and households, characteristics of housing, household facilities, data on working, material, health conditions of adults and subjective perceptions of household/personal well-being in different areas of life (module “well-being”). All data on income (gross/net, household/individual) is combined for the full year 2012. There is also another variable, a coefficient assigned to all households and household members, that will be used throughout the whole estimation, robustness checks and summary statistics; it is a conversion factor to convert the results from the sample into the entire set in the population. All results and numbers regarding the sample will be therefore reported weighted, in relative numbers if not stated otherwise.

Another crucial note about the dataset of individuals (second dataset) is the structure of the information contained. The data are gathered as follows: the first observation within one household is the person in charge of the household and he/she is assigned number 1 in the variable describing the relationship to the person in charge (hereinafter referred to as the “relationship” variable). All subsequent observations within this one household are assigned a number from 2 to 8 depending on the type of a relationship; the two most important types of relationship is number 2 = partner/wife/husband and 3 = son/daughter. Another crucial parameter is a dummy variable denoting parents as 1 and non-parents as 0, where only parents whose children (dependent *or* economically active already) are still living in the same household are assigned number 1 (hereinafter referred to as the “parent” variable).

Now, the only way how to assign the oldest child to a mother (which is the first step in our analysis) in the same household is to allocate the oldest household member labelled 3 in the “relationship” variable to a woman labelled 1 or 2 in the “relationship” variable, where at the same time she is labelled 1 in the “parent” variable. This means, that this woman is either head of household and this child is her child for sure (the “relationship” variable indicates the link to the *head of household*) or partner/wife of the head of the family, where this child is direct child of the father presumably[1] and the mother has her own child in this household. For other women that have the parent variable equal to 1 but have different “relationship” variable, it is extremely difficult and uncertain to find out what household members are her children[2]. Either

[1]Because he is the head of the family and this child is assigned number 3 in the “relationship” variable.

[2]This means that she has the relationship to the head of the family either 3 = daughter of the head of the family, so her child would have had the “relationship” parameter 5 = grandson/granddaughter; or 4 = daughter-in-law of the head of the family, so her child

way, it is undesirable to include these mothers in our sample for two reasons: first, it is unclear how to find her child among other members of the household with certainty and second, these mothers with this kind of atypical family arrangement would presumably bring bias into our results.

This way we apply the first sample selection criteria and that is including into the sample only mothers that are either the head of household or a partner/wife of the head of household. A simple algorithm is then applied to find the oldest child (household member with a "relationship" variable equal to 3) and to assign this child and his/her age in particular to this mother.

Given this manual distribution of children, the allocation is precise only when the mother is at the same time the head of the family. However, in our final sample, this is the case for only 17% of women. In the rest of our sample, we have to rely on very limited auxiliary factors.

First, to check our manually drawn children and their ages to the selection of our mothers, we have at our disposal one other variable in the household dataset that contains the age of the oldest *dependent* child (however, this child still does not have to be the woman's offspring). Dependent children include preschool children, children studying elementary school or children preparing for future occupation — apprentices, students, up to the age of 25 inclusive. Checking the match of this variable and our manually drawn child's age watches over not only the correctness of our manual work but also controls for possible errors in the dataset. Fortunately, this check showed that all children young enough were matched correctly; the only discrepancy arose where the oldest child living in the household with his/her mother was already economically active. At this point, this manually allocated child might be the oldest child of the mother, but it is not marked as a "child" in the dataset, so the manual matching works better.

However, this check does not allow us to control for mothers marked as partners/wives of the head of household (women with a "parent" variable equal

would have had the "relationship" parameter 8 = other close/related person; or 6 = mother, mother-in-law of the head of the family, so her child would have had the "relationship" parameter 7 = brother/sister or 8 = other close/related person; or 7 = sister of the head of the family, so her child would have had the "relationship" parameter 8 = other close/related person; or 8 = other close/related person.

to 1 and a "relationship" variable equal to 2) and their children. We know for sure this woman has her child present in the household, and the only uncertainty arises in the case where the manually matched oldest child (oldest household member with the "relationship" variable equal to 3) is not *her* oldest child but a child of the father, the head of household. There is no possibility to check this alternative for sure in case of our dataset.

Nevertheless, we can compare the age of the oldest matched child to the length of the marriage of the head of household and his wife, which is also available in the household dataset. If the age of the oldest child is lower or equal to the length of the marriage, we can assume that the man at the head of household had this child with this woman. Out of 83% of women in our sample with the "relationship" variable equal to 2, only 17% is not married, so we cannot perform the check and 11% of women are married but the length of marriage is actually shorter than the age of the oldest child. The rest, 73% of women with the "relationship" variable equal to 2, is married and their oldest matched children were born after the marriage. For the 11% of women, the difference between the marriage and the oldest child's age is approximately 4.7 years, which is not that high and it can still be the case that this woman gave birth to the matched child.

Therefore, so far we cannot be sure in case of this 11% of women and this additional 17% of women that do not live in a marital relationship. The oldest child can be an exclusive offspring of the man in the current household if he had this child with some other woman before. The most likely reason for the breakdown of the former partnership with the father getting the full custody of the child is a divorce. However, Fafejta *et al.* (2014) argue that only 7% of children from divorced families end in their father's custody in the Czech Republic[3]. Based on this argumentation, it can be concluded that including women with the "relationship" variable equal to 2 in the final sample will not pose a serious problem to the results. However, we can perform the robustness check, where we exclude those 28% women from our sample, run the same regressions and see whether the results change dramatically (see Table B.3 and Table B.4 in Appendix B).

After correctly matching the oldest child to its mother, one last remark

[3]Statistics for the Czech Republic, year 2010.

concerning mothers entering the labour force already having a child is worth mentioning. With regard to what has been said about definition of the "parent" variable, it is crucial to have in mind that those mothers with their oldest child old enough do not have to have their children present in the household. This means that the sample of pre-work mothers used in our estimation can be actually reduced for this reason. Moreover, those mothers without their oldest child present in the household are then matched their second child for purposes of the estimation, so this creates another potential bias. Unfortunately, there is no way to test or check either pre-work mothers and already moved out children or the incorrectly matched second child to those mothers.

Of course, it can be the case that also post-work mothers do not have their first children present in household but it is highly improbable; since, as already mentioned in Chapter 3, we take into account women entering labour force 15 to 20 years prior to the year of 2013, this kind of a problem would arise for post-work mothers only if their first children left household at the age of 19 or less. However, according to Eurostat (2018), young people in the Czech Republic leave their parental households at the average age of 26.4. So the only question is how the estimation for pre-work mothers is affected by this dataset imperfection (this would, of course, have in turn effect on these mothers with their matched second child and probably their shift from pre-work mothers' sample to post-work mothers' sample).

In the end, it should be borne in mind that estimations for both samples might be influenced by this fact when interpreting the results. If there is this omission effect, the estimation for pre-work mothers will be affected probably more. However, this does not discredit results for this sample of mothers; with respect to uniqueness of such research using the data available for the Czech Republic, even the smallest results based on possibly imperfect dataset are a step forward to comprehension of how timing of children affects woman's economic background and a cornerstone for potential future research in this field.

5.1.1 Variable Definitions

With the use of the previous section, this subsection will provide definitions and descriptions of explanatory variables as well as the description of the main dependent variable, W_{20}.

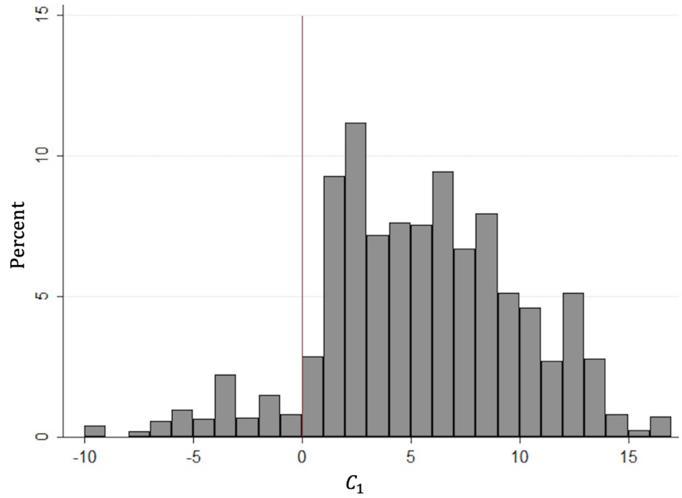
The main explanatory variable is the labour market experience at first birth, C_1. It is a difference between the age of a woman when having a first child and her age when starting her career. From the definition, C_1 is positive for women entering the labour market without a child and negative for women having a child before entering the labour market. To determine the size of this variable, we need two numbers; both in terms of a woman's age or year. The first number we already have; it is derived from the age of the oldest child in the year of 2013[4]. The second parameter, labour market entry, is yet to be determined.

The dataset for individuals provides us with two distinct variables connected to an individual's labour market entry; the first one is the year of labour market entry and the second one is a number of years worked. However, when comparing the two variables, it turned out that the two variables are not corresponding. Two explanations are at hand; one explanation can be that when asked, people recall their age when first having a job rather than calculating number of years they have been working so far; another explanation is the involvement of maternity and/or parental leaves — reported years worked might not include years on parental leave which consequently leads to discrepancy between the two variables. Therefore, we use the reported age/year at the labour market entry for the final calculation of C_1 . It is also possible to compare this reported age to possible age computed from the expected age at completion of education; the variable available in the dataset describing the completed level of education of an individual is an 8-degree variable[5], so the *expected* labour market entry year (defined as a year following the year of finishing the corresponding level of schooling) can be easily derived. This check is desirable because people might often consider their first part-time jobs as a labour market entry which eventually underestimates the real labour market entry with a full-time job. Fortunately, the reported and the expected age at labour market entry fit perfectly in most cases and the rest differs by a maximum of two years. Finally, C_1 is by computing the difference between the year/age at labour market entry and a year/age at first birth. The histogram of the final variable in the final sample (to be determined later) is presented in the Figure 5.1.

[4] Again, the data is cross-sectional, capturing the current state as of mid-year 2013.

[5] Ranging from no schooling level attained at all to postgraduate studies.

Figure 5.1: Histogram of fertility timing in terms of labour market experience (C_1 variable)



The dependent variable is a long run wage, W_{20}, which is a full-time full-year equivalent (FTFYE) of annual wage estimated (identified) in a window between 15 to 20 years after the woman's labour market entry (for the reasoning behind a selected window, see Chapter 3). Having in mind that both dataset show status as of mid-year 2013, it is then easy to filter only those women with the labour market entry year (defined in the previous paragraph) between 1993 and 1998, both outer years including. Both datasets then provide us with many variables describing earnings. Also, as mentioned in the beginning of this chapter, all data on income (gross/net, household/individual) is combined for the full year 2012[6].

Regarding the FTFYE of the true reported annual wage, a vast majority of the sample worked full-time (i.e. around 40 hours per week) and out of those working full-time, only a minority did not work a full year. Those, who worked full-time but not the full-year, spent part of the year either on parental leave or at home due to sickness, therefore creating full-year equivalent does not alter or damage the information that has been originally contained in the true reported annual wage. Concerning part-time workers, creating full-time equivalent also does not bring any kind of distortion to the estimation if we

[6]This means that in reality, we take into account women with the labour market entry 14 to 19 years prior to the date of identifying the long run wage. However, as all other data is reported as of 2013, we follow the window 1993 – 1998.

believe that if those mothers worked on the same position full-time they would not have earned more or less than this full-time equivalent. However, even if they did earn different wages, the proportion of part-time workers in our sample is negligible.

The FTFYE of individual's gross income is eventually used in the final estimation. The net income includes various tax reliefs and other personalized deductions that would possibly bring bias into the estimation. Moreover, a type of gross income used in our estimation creates one additional huge sample selection criteria and that is the type of occupation itself. In the Table 5.1, there is a development of the sample size according to the chosen sample selection criteria. It can be seen that applying necessary conditions such as a woman being a mother, a woman entering the labour force in 1993 to 1998 or her relation towards the head of household decreases the sample to 638 women. The next criterion is exactly the type of occupation. For reasons argued in Chapter 2 about women as employees and how they bargain their wage with employers, it is reasonable to include only women that earn a salary from the main employment. The sample decrease from 638 to 438 (200 women) is therefore partly caused by the exclusion of self-employed women and women with secondary employment. There is also a considerable part of women that do not work at all as of the year 2012 although they entered their first job a long before — exactly 146 women out of those 200 excluded from the final sample are either on parental leave, receive a disability pension or are unemployed.

Table 5.1: Sample size development

Sample selection criteria	*Sample size development*
Whole dataset	19 105
Women, over 16 yrs	8 611
Labour force entry 1993-98	730
Mothers	654
“Relationship” variable 1, 2	638
Gross income from main employment	438

The last essential variable is determining the initial wage W_0 at the labour market entry. Establishing this wage is actually the most challenging process done in this estimation. Due to the cross-sectional structure of this dataset, this crucial variable W_0 is missing in our dataset. There are very limited possibilities how to treat this problem. One possibility is to substitute missing values of W_0 with starting wages of women entering the labour force in the year 2013. Matching of starting wages of those young women on the main estimation sample would be then based on similar characteristics of those two samples of women.

First, to establish the sample of women that recently started working, we again use the variable defined in the previous subsection (i.e. gross income from the main employment) and take women with the labour market entry year between 2011 and 2013. These women account for a really small portion of the whole dataset — 188 individuals. Wages of these young women have to be matched with the original sample of 438 women. To determine the matching between the young sample and the original sample, we compare time-invariant individual characteristics of every woman and then link the two samples in a way that each woman in the original sample of 438 women is matched with a woman from the young-women sample.

Regarding time-invariant characteristics, the dataset — household or individual — provides us with very few of them. We can use practically only the final attained education level (8-degree variable), age at labour market entry and a place of residence. Of course, a place of residence might change during the 15 to 20 years of one's career life but the trend in the Czech Republic is actually the opposite, so taking it as time-invariant is acceptable. Since there are more than one characteristics, a single "index" for each woman is then created to match the two samples using a Principal Component Analysis (PCA).

PCA reduces the data dimension with principal components that represent new artificial variable within the new coordinate system. Principal components help to keep the maximum amount of information from all variables while minimizing the dimension. PCA is an orthogonal analysis of a symmetric positive semidefinite covariance matrix of variables where the eigenvectors correspond to principal components and eigenvalues correspond to a proportion of explained variance. Eigenvalues are ordered from the largest to the smallest, and the eigenvector corresponding to the largest eigenvalue is then selected as the principal component, which is the desired index for discussed purposes of matching. With the PCA, we have the data basically in a new coordinate system where each axis represents a new artificial variable (the principal component). The first axis is the projection of the first principal component that explains the largest portion of the data (the principal component with the largest variance). Each component is then a linear transformation of individual variables.

We first estimate the first principal component for the original sample of women. The first component explains around 55% of variance in the data for the original sample of women. The same linear combination is then used to compute the index (principal component) for the sample of young women. After creating a single index for all women from both samples, Epanechnikov kernel matching is used to match the two samples based on the created indices and assign wages from the sample of young women to the original sample. Regarding the starting wages, we create full-time full-year equivalent (FTFYE) of the reported annual wages for the young-women sample as in case of the original sample of 438 women. Creating FTFYE does not bring any kind of a problem to our estimation, the same as in case of the original sample.

Finally, after the matching, almost all women from the original sample (now only 436 women[7]) are assigned these FTFY equivalents of reported starting wages from the sample of young women.

Before establishing additional variables correcting the biases discussed in the previous chapter or other factors of interest, it is crucial to differentiate in the estimation between the two wage paths modelled for pre-work and post-work mothers. The dummy indicator I_{LF} introduced in the previous chapter will serve this purpose.

Last but not least, it is necessary to establish a dummy variable indicating the place of residence for purposes of testing the third hypothesis stated in Chapter 3; women living either in a district of Prague, Prague-East or Prague-West will be assigned 1 in the *Prague* variable, all other districts will be assigned 0 (living out of Prague).

For purposes of summary statistics presented below, we introduce a new form of the education variable already discussed above — we construct a new

[7]Two women from the original sample of 438 women were not assigned any wage because they were outliers.

dummy variable, EDU, with 1 being "high school graduated" (high level) and 0 being "not high school graduated" (low level).

In the table containing the summary statistics of the whole sample (436 women), various characteristics in relation to the estimation or not are presented and divided into small subsamples. For example, women living in Prague, highly educated, with a first child born after the labour market entry have on average the highest wages and had their first child at the latest as expected. The biggest subsample contains higher educated post-work mothers not living in Prague, which is also expected with respect to the whole population. Division of the sample reveals a slightly unsettling fact — sample of pre-work mothers counts 43 women while practically all of it concentrates in the "Out-of-Prague" subsample. The last column reports gross income from the main employment (for the whole year 2012) of a woman's partner. However, the number of partners is always lower than the number of women as reported in the column Observ.

5.2 Estimation

Building on Equation 4.5 introduced in Chapter 4, the final equation to estimate using the Ordinary Least Squares method is as follows:

$$\begin{aligned} log(W_{20}) &= log(W_0) + (1 - I_{LF})\beta_1 C_1 + (-b)t_{20} I_{LF} C_1 + (a - g_2)t_{20} I_{LF} + X\gamma = \\ &= log(W_0) + \beta_1 C_1^{post-work} + \alpha C_1^{pre-work} + \delta I_{LF} + X\gamma, \end{aligned} \tag{5.1}$$

where $C_1^{post-work} = (1 - I_{LF})C_1$, $\alpha = (-b)t_{20}$, $C_1^{pre-work} = I_{LF} C_1$, $\delta = (a - g_2)t_{20}$ and X are additional control variables added to the estimation. As discussed in Section 4.1, $C_1^{post-work} > 0$ is a labour market experience at the time-point of having the first child with β_1 (being the most important parameter to estimate) representing the postponement effect of delaying the first child by one more year for post-work mothers. On the other hand, $C_1^{pre-work} < 0$ captures the age of the first child at the career starting point (with minus sign) for pre-work mothers with α expressing the effect of increasing age of the first child at a career starting point by one more year. The dummy variable I_{LF} indicates whether the mother belongs to pre-work/post-work sample and the δ estimate measures the difference in the wage growths closely around $C_1 = 0$

Table 5.2: Whole sample summary statistics

I_{LF}	*Prague*	*EDU*	Observ.	GI (CZK)	Age of first child	Age at LF entry	Age at first birth	C_1	$GI_{partner}$ (CZK)
Post-work	**Prague**	**Low**	10	213 169	13.3	18.2	23.6	5.4	300 041
			(2.8%)	*71 573*	*4.0*	*0.6*	*3.4*	*3.4*	*67 518*
		High	24	310 127	9.1	20.2	28.5	8.3	489 222
			(6.6%)	*205 116*	*3.8*	*2.4*	*4.3*	*3.9*	*237 590*
	Out-of-Prague	**Low**	132	157 524	12.5	17.9	23.2	5.3	303 641
			(30.8%)	*90 911*	*4.1*	*1.1*	*3.7*	*3.6*	*156 768*
		High	227	235 849	10.9	19.5	26.2	6.7	358 387
			(49.6%)	*114 560*	*4.3*	*1.8*	*4.0*	*3.8*	*195 864*
Pre-work	**Prague**	**Low**	1	-	-	-	-	-	-
			(0.2%)	-	-	-	-	-	-
		High	2	-	-	-	-	-	-
			(0.5%)	-	-	-	-	-	-
	Out-of-Prague	**Low**	15	173 342	21.4	22.8	19.1	- 3.6	274 127
			(3.8%)	*72 621*	*3.4*	*3.5*	*2.1*	*3.0*	*84 926*
		High	25	254 150	20.0	22.3	19.6	- 2.6	336 853
			(5.7%)	*170 623*	*1.9*	*2.8*	*2.2*	*2.1*	*124 091*

Note: Weighted averages according to sample weights. Numbers in italics represent standard deviation.
Absolute numbers of observations are not weighted — percentages below in the brackets then report weighted portion of the whole sample.

(fertility timing in terms of labour market experience) for post-work and pre-work mothers (it is a trend break in wage development for these two groups of mothers). These three estimates, β_1, α and δ, are directly connected to the modelled behaviour introduced in the previous chapter.

With respect to bias scenarios introduced in the previous chapter, other variables (proxies) have to be included in the estimation to correct for the potential biases captured in the estimation of β_1. The first bias scenario assumes that the correlation between C_1 and subsequent wage path is influenced by endogenous fertility timing, that is, women with higher ability tend to postpone their first birth in order to gain from a higher return to fertility delay they face compared to less able women. Estimation without controlling for ability would create an upward bias to the average return to delay. If, on the other hand, the bias II scenario is true, women target some exogenous wage level. More able women reach that target earlier than less able women, which consequently leads to a negative estimate of β_1 (hugely underestimating the true average effect) without controlling for ability. As discussed in the previous chapter, ability proxy has to be included to correct for both biases. Moreover, by comparing the models with and without this correction and by establishing the direction of the bias (upward bias versus downward bias), we can conclude something about the composition of women in our sample and their decision-making process. However, we do not have perfect measure fully accounting for ability, so we need to look for a proxy. The best proxy for ability available to us is the education dummy variable, EDU. It accounts for ability at least to some extent (although probably not fully), thus reducing the bias. Observing the effect of inclusion of the education variable on the estimate of first birth timing should then tell us what bias (if any) was prevalent in the estimation.

Other variables included in X are the $GI_{partner}$ (gross income from the main employment of a woman's partner) as discussed in the previous chapter and $CHILD_{count}$ variable denoting a total number of children of a mother as of 2013. A total number of children (that is the total number of household members with the "relationship" variable equal to 3) can also suffer from problems discussed at the beginning of this chapter — some of them does not have to be own children of a woman. However, a probability of such case is negligible, as pointed out above. The inclusion of the $CHILD_{count}$ variable might, in fact, filter out the effect of lengthy parental leaves on the long run wage,

W_{20}. The wage path model as presented in Equation 5.1 does not take into account possible years off where a woman does not gain any experience and therefore does not enjoy wage increments as modelled. The $CHILD_{count}$ variable proxying for the length of parental leaves can then also have an effect on β_1 estimate. Without taking it into account, g_2 (= wage growth of post-work mothers after having the first child) can be estimated to be much lower than it actually is which consequently leads to overestimation of β_1. This is true under all bias/no-bias scenarios. Moreover, we can expect that the effect of the $CHILD_{count}$ variable on long-run wages is negative.

The last variable included in X is the $GI_{partner}$. As discussed in the previous chapter, an important factor related to the decision-making process related to fertility timing is a financial situation of a woman's partner at the time of first birth. Since his income can be also positively correlated with a woman's wage (positive assortative mating), estimation without controlling for the partner's wage at the time of first birth might also result in a biased estimate of β_1. Although the estimation needs to deal with a rather limited dataset with only cross-sectional data and no such variable as partner's income from the time of first birth is available, we can add a proxy for partner's former wage which is his present wage. We do not assume any kind of income targeting in the bias I scenario, however, in the bias II scenario, women are targeting their own income. It can be true that apart from their own income, they also "target" their partner's income. So under bias II scenario, estimation without controlling for partner's income would produce a negatively biased estimate of β_1.

As mentioned in Section 5.1, Prague subsample of pre-work mothers is almost empty, so to test the third hypothesis (stating that there are differences in strength of the fertility timing effect for women working/living in Prague and women outside of Prague, see Chapter 3), only the subsample of post-work mothers will be used. To see the difference in β_1 between Prague and Out-of-Prague post-work sample women, we include an interaction term between $Prague$ variable and $C_1^{post-work}$ variable in the estimation together with the $Prague$ dummy variable. This will allow us to compare the effect of living/working in Prague on different magnitudes of β_1. Since we do not estimate this effect for pre-work mothers, Equation 5.1 needs to be simplified for post-work mothers only. Consequently, $C_1^{pre-work}$ and I_{LF} variables are left out from the estimation and $Prague * C_1^{post-work}$, $Prague$ variables are included. The following equation will be therefore estimated for the whole post-work subsample:

$$log(W_{20}) = log(W_0) + \beta_1 C_1^{post-work} + \beta_2 Prague * C_1^{post-work} + \theta Prague + X\gamma. \tag{5.2}$$

According to the first hypothesis stated in Chapter 3 (there is a positive effect on wages with delaying the first birth for post-work mothers), $\beta_1 > 0$ and significant. The third hypothesis about the magnitude of β_1 for women living in Prague/out of Prague can be then tested through β_2. If this hypothesis is true, β_2 should be positive and significant too.

Chapter 6

Results

All results in this chapter are reported in accordance with the estimation process presented in Section 5.2. This means that for each single (sub)sample estimation, we look at the main estimates of interest (β_1, α) and their development after including additional variables one by one. The β_1 estimate shows the effect of $C_1^{post-work}$ variable and thus represents the postponement effect of delaying the first child by one more year for post-work mothers. The α estimate, on the other hand, expresses the effect of increasing age of the first child at the career starting point by one more year.

Throughout this chapter, hypotheses are tested with the use of various types of samples, so no single estimation is used to test all hypotheses. The following list describes the use of all (sub)samples in this chapter, its size and a reason for considering it.

1. **Whole sample:** consists of both pre-work and post-work subsamples, thus counting 436 observations. Estimation done using this sample serves to test our two hypotheses concerning the effects of first birth timing on long-run wages for pre-work as well as post-work mothers. Therefore, both β_1 and α are present in the estimation using this sample. However, only α is discussed in detail, β_1 is dealt with later on.

2. **Post-work sample:** includes only post-work mothers and counts 393 observations. We look more closely on the β_1 estimate and how it develops when controlling for additional factors such as for example ability/education.

3. **Post-work sample — women with an earning partner:** represents a major subsample of post-work mothers, counting 266 women.

4. **Post-work sample — women without an earning partner:** complements the subsample above and the two together form the whole post-work sample of women. This subsample therefore counts 127 observations.

Estimations using the sample of post-work women *without* an earning partner and the sample of post-work women *with* an earning partner (the last two subsamples) serve to test suppositions based on the results from estimation done using the whole post-work sample.

All results are presented in the following manner. First, baseline estimates are presented, that is baseline estimation with no additional variables included. Second, we look how estimates change after inclusion of education dummy variable that should correct for both types of biases discussed in Chapter 4 — this estimation is called bias. The third estimation additionally includes $CHILD_{count}$ variable and the fourth estimation shows estimates from the regression where gross income of the partner is included.

The whole sample estimation is sufficient to test the first two hypotheses concerning the effect of first birth timing on long-run wages of both pre-work and post-work mothers. It is hypothesized that there is a positive postponement effect of delaying the first child on long-run wages for post-work mothers and no effect of increasing age of the first child at a career starting point for pre-work mothers. As presented in Equation 5.1 in the previous chapter, it is sufficient to include the dummy variable identifying the subsample (pre-work/post-work sample — I_{LF}) and an interaction term of this dummy variable with the main C_1 variable (which consequently creates $C_1^{post-work}$ and $C_1^{pre-work}$ variables). We then look closely on the post-work sample and test the bias scenarios introduced in Chapter 4. Also, as discussed in the previous chapter, the sample of pre-work mothers does not include a sufficient number of observations to test the third hypothesis dealing with the difference in first birth timing effects for women living or working in Prague/out of Prague. Again, to run pooled regression, it is sufficient to include the $Prague$ dummy variable and an interaction term of this dummy variable with $C_1^{post-work}$ variable, as shown in Equation 5.2.

6.1 Whole sample

Table 6.1 shows results from the whole sample estimation. Estimated effect of $C_1^{pre-work}$ variable (α estimates) show an interesting development. Baseline estimate is very significant and positive. With the inclusion of additional explanatory variables, a positive significant effect of $C_1^{pre-work}$ slightly diminishes. Nevertheless, since $\alpha = (-b)t_{20}$, rather positive α estimate means that increasing the first child's age at the career starting point has a *negative* effect on long-run wages. However, after adding the last variable, $GI_{partner}$, α loses significance and hypothesis about $\alpha = 0$ cannot be rejected — this is in line with the second hypothesis stated in Chapter 3 — for women entering the labour force already having a child, the effect of the first birth timing is not significant. The δ estimate representing the trend break around $C_1 = 0$ in wage developments of post-work and pre-work mothers is positive and insignificant in the baseline estimation. However, by adding control variables, the magnitude of the estimate decreases. Moreover, last regression $+GI_{partner}$ makes the estimate negative and significant. It implies that when comparing having a child right after versus right before entering the labour force, it is strictly better to have a child right after entering labour force ($g_2 > a$). So there is a positive return to fertility delay across the $C_1 = 0$ point.

All additional variables are significant in all consequent regressions. Education has a positive effect on long-run wages as well as partner's income, as expected. On the other hand, an increased number of children results in lower long-run wages, which is also an expected outcome. The main variable of interest for the sample of post-work mothers and the development of its estimate is discussed in the following chapter.

6.2 Post-work sample

Table 6.2 shows results from the estimation for the subsample of post-work mothers only. Development of β_1 estimates compared to Table 6.1 is almost the same. Baseline estimation results in positive, yet insignificant effect of $C_1^{post-work}$ variable. However, after adding other explanatory variables, β_1 becomes more and more negative and even significant which is counterintuitive. The results suggest that mothers who postpone children enjoy lower wages — each year of postponement corresponds to about -1% drop in wage 15–20 years

Table 6.1: Whole sample estimates (post-work + pre-work mothers)

	Baseline	Bias	+ Total kids	+ $GI_{partner}$
$C_1^{post-work}$	0.00483	-0.00266	-0.00584	-0.0133*
	(0.00542)	(0.00525)	(0.00558)	(0.00554)
$C_1^{pre-work}$	0.0567**	0.0371^{+}	0.0349^{+}	0.00392
	(0.0202)	(0.0207)	(0.0209)	(0.0238)
I_{LF}	0.0942	0.0268	0.0104	-0.163^{+}
	(0.0968)	(0.0968)	(0.0957)	(0.0953)
$l(W_0)$	1.061**	0.762**	0.763**	0.574**
	(0.168)	(0.171)	(0.172)	(0.206)
EDU		0.319**	0.321**	0.283**
		(0.0389)	(0.0389)	(0.0410)
$CHILD_{count}$			-0.0553	-0.0846*
			(0.0387)	(0.0391)
$GI_{partner}/100000$				0.0529**
				(0.0125)
Constant	-0.492	2.953	3.059	5.279*
	(2.021)	(2.046)	(2.057)	(2.453)
Observations	436	436	436	291
R^2	0.128	0.247	0.253	0.319

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

after the labour market entry. This negative effect is not predicted by any of the bias scenarios introduced in Chapter 4.

Table 6.2: Post-work sample estimates

	Baseline	Bias	+ Total kids	+ $GI_{partner}$
$C_1^{post-work}$	0.00471	-0.00267	-0.00513	-0.0131*
	(0.00540)	(0.00522)	(0.00556)	(0.00563)
$l(W_0)$	1.117**	0.830**	0.826**	0.558*
	(0.186)	(0.187)	(0.188)	(0.227)
EDU		0.314**	0.317**	0.278**
		(0.0396)	(0.0397)	(0.0435)
$CHILD_{count}$			-0.0424	-0.0858*
			(0.0413)	(0.0424)
$GI_{partner}/100000$				0.0518**
				(0.0129)
Constant	-1.161	2.142	2.279	5.472*
	(2.237)	(2.241)	(2.248)	(2.711)
Observations	393	393	393	266
R^2	0.131	0.248	0.251	0.299

Standard errors are in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Since no bias scenario predicts such results, we need to look closer what happens in the last regression. Note that there is a much smaller sample — out of 393 women in the post-work sample, only 266 have a working and earning partner (we added $GI_{partner}$ variable). This suggests that maybe the negative effect is already driven by *having* an earning partner — we can test it by repeating all estimates on the smaller sample of 266 women and on the remaining sample of 127 women without an earning partner (this is a sample of women who either do not have a partner at all or their partner does not earn). In fact, there might be behavioural differences between women in those two subsamples. Women with an earning partner can afford to spend many years on parental leave(s) and specialize in childbearing because their partner's income is sufficient to support the whole family, whereas women without an earning partner cannot afford this.

We first rearrange the estimation process and observe whether the development of β_1 is the same if we first add $GI_{partner}$ and only after that we add education and number of children variables. Concrete results are in the Table B.1 in Appendix B. The main finding is that $GI_{partner}$ already drives this negative effect; the only question is whether it is driven by the partner's income or solely by the fact that a woman *has* an earning partner. Now we compare estimates computed using a sample consisting of women either with an earning partner or without an earning partner. Above the baseline regression, we add a new regression (called Prague), where the $Prague$ dummy variable and an interaction term with the C_1 variable are present[1].

Baseline regression in the Table 6.3 reveals that β_1 is 2.5 times smaller and much closer to zero than in the Table 6.2, first column. By adding education (third column) and a variable indicating a number of children (fourth column) the β_1 estimate is much more negative compared to relevant columns in Table 6.2 and it becomes significant already in the + Total kids regression. However, adding partner's income does not change the β_1 estimate much, so the effect is not driven by partner's income itself but by the fact that a woman has an earning partner. If we instead estimate the same for women without an earning partner, the results are completely the opposite.

Table 6.4 shows results from estimation for women without partners only. Clearly, β_1 estimate is positive (however insignificant) in all regressions. Baseline regression shows that β_1 is much bigger than in previous estimations. In addition, in the second and third regression where additional variables are included, the positive postponement effect captured in β_1 becomes smaller and smaller. This estimation suggests that there is some indication that mothers without an earning partner behave according to the model introduced in this study since the β_1 estimate is positive. Moreover, it seems that controlling for ability (education) brings the estimate of β_1 towards zero, what suggests the bias I scenario. Nevertheless, the fact that this postponement effect is insignificant goes against the first hypothesis which clearly stated that it would be positive *and* significant (see Chapter 3).

Concerning expected effects of $CHILD_{count}$ and $GI_{partner}$ variables and how

[1]Table 6.2 with a Prague regression is presented in Appendix B, Table B.2.

Table 6.3: Post-work sample estimates — women with an earning partner

	Baseline	Prague	Bias	+ Total kids	+ $GI_{partner}$
$C_1^{post-work}$	0.00197	0.00122	-0.00691	-0.0119*	-0.0141*
	(0.00522)	(0.00503)	(0.00498)	(0.00603)	(0.00570)
$l(W_0)$	0.967**	0.759**	0.507*	0.489*	0.369
	(0.233)	(0.227)	(0.233)	(0.230)	(0.225)
$Prague * C_1^{post-work}$		-0.0174	-0.0138	-0.0119	-0.0141
		(0.0194)	(0.0203)	(0.0201)	(0.0164)
$Prague$		0.386*	0.368*	0.358*	0.347**
		(0.149)	(0.160)	(0.155)	(0.125)
EDU			0.296**	0.303**	0.281**
			(0.0450)	(0.0442)	(0.0427)
$CHILD_{count}$				-0.0734	-0.0867*
				(0.0471)	(0.0413)
$GI_{partner}/100000$					0.0486**
					(0.0130)
Constant	0.662	3.148	6.030*	6.412*	7.740**
	(2.795)	(2.725)	(2.785)	(2.747)	(2.691)
Observations	266	266	266	266	266
R^2	0.111	0.151	0.270	0.281	0.333

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 6.4: Post-work sample estimates — women without an earning partner

	Baseline	Prague	Bias	+ Total kids
$C_1^{post-work}$	0.0126	0.0103	0.00395	0.00285
	(0.0108)	(0.0113)	(0.0108)	(0.0113)
$l(W_0)$	1.141**	1.074**	0.761*	0.754*
	(0.288)	(0.297)	(0.292)	(0.294)
$Prague * C_1^{post-work}$		0.0297	0.0221	0.0239
		(0.0402)	(0.0381)	(0.0386)
$Prague$		-0.0728	0.0335	0.0180
		(0.298)	(0.284)	(0.288)
EDU			0.320**	0.318**
			(0.0826)	(0.0831)
$CHILD_{count}$				-0.0235
				(0.0656)
Constant	-1.498	-0.684	2.910	3.041
	(3.455)	(3.558)	(3.494)	(3.526)
Observations	127	127	127	127
R^2	0.132	0.139	0.234	0.235

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

their inclusion affects β_1 estimate as discussed in the previous chapter, it is clear now that $GI_{partner}$ (now looking only at Table 6.3, a fourth and a fifth column) does not change the β_1 estimate significantly. Instead, the whole negative postponement effect is given by the fact that the woman has an earning partner — inclusion of his income has then a negligible impact on the estimate of β_1. If we instead compare the development of the β_1 estimate between the third and the fourth column in Table 6.3 and Table 6.4, the inclusion of the $CHILD_{count}$ variable has an effect in both estimations. In the Table 6.3 in particular, the estimate changes drastically. Without $CHILD_{count}$, lengthy parental leaves are not accounted for and therefore g_2 is estimated to be much lower than it actually is. By controlling for parental leaves, the negative postponement effect is much bigger (in absolute value). The same applies to Table 6.4, where the logic follows the reasoning depicted in the previous chapter: without controlling for $CHILD_{count}$, g_2 is estimated to be much lower which consequently leads to overestimation of β_1.

To test the last hypothesis concerning difference in the postponement effects for women living or working in Prague/out of Prague, we look at the interaction term in both Table 6.3 and Table 6.4. For both subsamples of women (with and without an earning partner), the interaction term is insignificant, so the hypothesis cannot be confirmed — there is clearly no difference in the size (and significance) of the postponement effect for post-work mothers living in Prague/out of Prague.

6.3 Discussion

The negative postponement effect discussed in the previous section revealed rather counterintuitive behaviour. This outcome cannot be linked to any of the bias scenarios, because the postponement effect becomes negative only *after* adding corrective education variable. The results suggest that the wage development of mothers with an earning partner does not follow the model outlined in Chapter 4. The observed results cannot be explained by any of the bias scenarios, nor by assuming $g_2 > g_1$, that is, wage growth before the first child is actually smaller than after giving birth to the first child. As argued below, it might be the case that due to the specific institutional setup in the Czech Republic, Czech mothers wages follow different paths than wages of US mothers.

On the other hand, women without an earning partner follow the logic of wage path development depicted throughout this thesis, however, their postponement effect is insignificant. Moreover, since the postponement effect decreases with adding corrective variables, it can be concluded that wages of these women not only follow the logic of our model but also exhibit the behaviour introduced in bias I scenario. This means that more able and educated women tend to postpone their first birth in order to gain higher long-run wages because they face higher return to fertility delay.

Women with an earning partner do not exhibit such behaviour. On the contrary, it seems that our model does not fit them at all. The reason might be the following. Women in the Czech Republic tend to stay on parental leaves for an extremely long time compared to other countries. If we follow the behaviour in an average Czech family, women tend to have 2 children with 1–3 years in between each birth (for concrete statistics see Chapter 3). Consequently, a woman might spend 4–6 years on parental leave, loosing much of her originally gained experience which relatively disadvantages her on the labour market. After her return, she might have a problem with starting where she left off and rather starts to build her career from the beginning. This would, in turn, explain the negative effect of first birth postponement: the earlier a woman starts having children, the earlier she re-enters the labour market afterwards, and the more experience and tenure she has by the time of observation.[2]. The negative postponement effect could be thus interpreted as a positive after-children labour market experience effect. Women with an earning partner can afford to spend a long time on parental leave because their partner's income is sufficient to support the whole family. Consequently, these women do not face the model presented in Chapter 4 because the wage growth before having the first child is completely immaterial.

Our results show a very different effect of the first birth timing on wages compared to American studies in this field. The positive return to delay observed in these studies nicely demonstrates the trend in late childbearing. We also see this trend of late childbearing in the Czech Republic (see Chapter 3), however, it is connected to negative postponement effect, at least for women

[2]Remember, we measure W_{20} at a single point in time for all women, 20 years after the labour market entry.

with an earning partner, entering the labour force childless. Regarding the pay gap between men and women, mothers and non-mothers, our findings might actually help to understand it. Comparing the pay gap in general, mothers with an earning partner in the Czech Republic start building their careers again after returning to work and their experience and wage growth prior to the first birth is immaterial. For these women, motherhood has therefore significant impact on both definitions of pay gap — either comparing women and men or comparing mothers and non-mothers. If we instead take women without an earning partner, postponement effect is insignificant, that is, wage growths before and after having a child are the same. These mothers and non-mothers might consequently exhibit the same wage path development. The motherhood pay gap in this particular case might then arise only from the fact that the mother has to stay on a parental leave while she does not gain from modelled wage increments.

Chapter 7

Conclusion

This study estimates, how timing of first birth affects long-term wages of mothers in the Czech Republic. There is more and more pressure on closing the wage gap between men and women which is to a large extent driven by motherhood. Although this topic is widely discussed, only few studies attempt at quantifying the impact of timing of having a child on woman's wage and no such analysis has been done among the former communist countries.

The analysis extends the original work of Herr (2016), which studies the effect for women in the United States. First of all, in measuring the fertility timing, we use labour market experience at the time of the first childbirth instead of woman's age, which is widely used in similar studies. This actually suggests that the effect of fertility timing on long-run wages might be different for women having the first child before and after entering the labour force. Consequently, wage path development for these two groups of mothers is modelled differently and therefore the effect is estimated separately. The effect of fertility timing (labour market experience at the first childbirth) is examined on long-run wages defined as annual wage 15 to 20 years after the labour market entry.

Results suggest that for mothers entering the labour force after having a child (a minority of a sample), there is no link between fertility timing and subsequent wages, which confirmed our hypothesis. Interestingly, estimation showed that around the trend break at the labour force entry it is strictly better to have a child right after entering the labour force compared to having a child right before entering the labour force. However, estimation for women entering the labour force before having a child (a vast majority of a sample) revealed a striking result. Among these mothers, there is a difference in effects for mothers having an earning partner compared to those who do not have an earning partner. Estimation for women with an earning partner showed a negative postponement effect (one year of fertility delay is associated with 1% lower long-run wage), therefore these women do not exhibit behaviour depicted in our main model (nor cannot it be connected to any of the bias scenarios). Instead, it seems that this negative effect is caused by the trend in very lengthy parental leaves which makes earlier wage growth before having a child completely immaterial. Women with a partner can afford to spend a long time on parental leave, losing much of experience gained before. The only thing important is then the wage growth after returning to the labour market, which then results in a negative postponement effect.

Women without an earning partner, on the other hand, follow the logic of the modelled wage path. Their postponement effect is positive, however, insignificant. Moreover, it can be concluded, that there is an ability bias captured in the correlation between the fertility timing and subsequent wages. More concretely, more able and educated women tend to postpone their first birth in order to gain higher long-run wages because they face higher return to fertility delay. Concerning different effects for women living or working in Prague/out of Prague, it is estimated only for women entering the labour force without a child. Among these mothers, there is no significant difference in effects for women working/living in Prague and women outside of Prague.

Although the estimation is imperfect in many ways due to data limitations, with respect to uniqueness of such research using the data available for the Czech Republic, even the smallest results based on possibly imperfect dataset are a step forward to comprehension of how timing of children affects a woman's economic background. This thesis might then serve as a cornerstone for potential future research in this field. Results from this study can be useful not only from the academic point of view and they do not have to be discussed only in sociological, political or entrepreneurial context, but above all, they are relevant for mothers themselves in deciding when to start having a family.

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Appendix A

Calculation of C_1^*

A.1 Type 1 woman C_1^*

This computation follows Herr (2016). To maximize utility presented in Equation 4.6 in Chapter 4, we need to solve for the marginal benefit of fertility delay and the marginal cost of fertility delay. The marginal benefit of fertility delay is computed as a linear approximation of y, y'/y, where

$$\begin{aligned} y &= \int_{t_{20}} W_t e^{-rt} dt - c(C_1) = \\ &= \int_0^{C_1} W_0 e^{g_1 t} e^{-rt} dt + \int_{C_1}^{t_{20}} W_0 e^{g_1 C_1} e^{g_2 (t - C_1)} e^{-rt} dt = \\ &= \frac{W_0 (g_2 - g_1) e^{(g_1 - r) C_1}}{(g_1 - r)(g_2 - r)} + \frac{W_0 e^{(g_2 - r) t_{20}} e^{(g_1 - g_2) C_1}}{g_2 - r} - \frac{W_0}{g_1 - r}. \end{aligned} \tag{A.1}$$

The marginal benefit of fertility delay, MB, is then:

$$\begin{aligned} MB &= y'/y = \beta_1 - \frac{\beta_1 (g_{2i} - r)}{e^{(g_{2i} - r) t_{20}} - 1} C_{1i} \\ &= \beta_1 - m_{1i} C_{1i} \end{aligned} \tag{A.2}$$

The marginal cost of fertility delay is then assumed to be a linear function of taste for early motherhood and it is increasing with C_1.

$$MC = \nu_i + m_{2i} C_{1i}, \tag{A.3}$$

where both $m_{1i}, m_{2i} \geq 0$. By comparing the marginal benefit with the marginal cost, we get the final C_1^*, which is increasing with β_1 and decreasing with ν:

$$C_1^* = \frac{\beta_{1i} - \nu_i}{m_{1i} - m_{2i}}. \tag{A.4}$$

From Equation A.4 and Equation A.2, it is obvious that β_1 is present in both numerator and denominator (through m_{1i}). However, the numerator dominates for common values of g_2, r and t_{20}.

Appendix B

Additional Results

Table B.1: Post-work sample estimates — rearrangement

	Baseline	Bias	+ Total kids	+ $GI_{partner}$
$C_1^{post-work}$	0.00471	-0.00100	-0.00754	-0.0131*
	(0.00540)	(0.00498)	(0.00494)	(0.00563)
$l(W_0)$	1.117**	0.778**	0.582*	0.558*
	(0.186)	(0.229)	(0.226)	(0.227)
$GI_{partner}/100000$		0.0573**	0.0497**	0.0518**
		(0.0134)	(0.0119)	(0.0129)
EDU			0.270**	0.278**
			(0.0444)	(0.0435)
$CHILD_{count}$				-0.0858*
				(0.0424)
Constant	-1.161	2.755	5.011^{+}	5.472*
	(2.237)	(2.737)	(2.700)	(2.711)
Observations	393	266	266	266
R^2	0.131	0.186	0.285	0.299

Standard errors are in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

B.0.1 Robustness Check

We do not do the robustness check for pre-work mothers because of data limitations (too little sample). Therefore, we only compare Table B.3 to the table Table B.2, where Prague regression is added. Above that, we also compare

Table B.2: Post-work sample estimates (+ Prague)

	Baseline	Prague	Bias	+ Total kids	+ $GI_{partner}$
$C_1^{post-work}$	0.00471	0.00293	-0.00452	-0.00739	-0.0141*
	(0.00540)	(0.00560)	(0.00540)	(0.00575)	(0.00570)
$l(W_0)$	1.117**	0.987**	0.680**	0.673**	0.369
	(0.186)	(0.184)	(0.179)	(0.178)	(0.225)
$Prague \star C_1^{post-work}$		0.00493	0.00294	0.00489	-0.0141
		(0.0185)	(0.0168)	(0.0167)	(0.0164)
$Prague$		0.147	0.185	0.172	0.347**
		(0.165)	(0.142)	(0.139)	(0.125)
EDU			0.320**	0.323**	0.281**
			(0.0392)	(0.0393)	(0.0427)
$CHILD_{count}$				-0.0456	-0.0867*
				(0.0406)	(0.0413)
$GI_{partner}/100000$					0.0486**
					(0.0130)
Constant	-1.161	0.395	3.931^{+}	4.113^{+}	7.740**
	(2.237)	(2.204)	(2.140)	(2.136)	(2.691)
Observations	393	393	393	393	266
R^2	0.131	0.147	0.268	0.272	0.333

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table B.3: Post-work sample estimates — robustness check

	Baseline	Prague	Bias	+ Total kids	+ $GI_{partner}$
$C_1^{post-work}$	0.00628	0.00532	-0.00145	-0.00658	-0.0221**
	(0.00708)	(0.00740)	(0.00716)	(0.00738)	(0.00755)
$l(W_0)$	0.977**	0.887**	0.541*	0.540*	0.0381
	(0.215)	(0.206)	(0.211)	(0.209)	(0.266)
$Prague \star C_1^{post-work}$		-0.0000585	-0.00582	-0.00204	-0.0261
		(0.0235)	(0.0212)	(0.0214)	(0.0242)
$Prague$		0.138	0.225	0.199	0.422**
		(0.194)	(0.167)	(0.163)	(0.154)
EDU			0.316**	0.319**	0.266**
			(0.0463)	(0.0453)	(0.0517)
$CHILD_{count}$				-0.102*	-0.127*
				(0.0475)	(0.0556)
$GI_{partner}/100000$					0.0583**
					(0.0146)
Constant	0.531	1.608	5.589*	5.811*	11.82**
	(2.578)	(2.471)	(2.529)	(2.494)	(3.172)
Observations	300	300	300	300	190
R^2	0.103	0.113	0.224	0.242	0.305

Standard errors are in parentheses.

$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table B.4: Post-work sample estimates, women without an earning partner — robustness check

	Baseline	Prague	Bias	+ Total kids
$C_1^{post-work}$	0.0233*	0.0214+	0.0129	0.00881
	(0.0115)	(0.0121)	(0.0114)	(0.0115)
$l(W_0)$	1.046**	0.980**	0.626*	0.595*
	(0.292)	(0.301)	(0.292)	(0.289)
$Prague \star C_1^{post-work}$		0.0218	0.0168	0.0238
		(0.0393)	(0.0365)	(0.0362)
$Prague$		-0.00713	0.120	0.0397
		(0.288)	(0.269)	(0.270)
EDU			0.360**	0.342**
			(0.0854)	(0.0849)
$CHILD_{count}$				-0.121+
				(0.0650)
Constant	-0.421	0.375	4.450	5.067
	(3.498)	(3.612)	(3.490)	(3.465)
Observations	110	110	110	110
R^2	0.163	0.171	0.292	0.315

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table B.4 to the Table 6.4 in Chapter 6. If we first compare the estimations for the whole post-work sample, all estimates are more or less the same, especially with the inclusion of $CHILD_{count}$ variable, where the β_1 estimate is almost the same. Comparing the β_1 estimate in the fourth columns, we can notice that the estimate in the robust regression is somewhat higher in absolute value, nevertheless, this is compensated by lower estimated effects of other variables. When comparing regressions using the subsample of women without an earning partner, we can see that the β_1 estimate is now bigger in all regressions which then makes them significant in the baseline regression. However, with the inclusion of the education dummy and the $CHILD_{count}$ variable, β_1 is again insignificant. It can be, therefore, concluded that the inclusion of these potentially problematic mothers in our sample does not distort the results and the story behind it.