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ABSTRACT

The Career Costs of Children*

This paper analyzes the life-cycle career costs associated with child rearing and decomposes their effects into unearned wages (as women drop out of the labor market), loss of human capital, and selection into more child-friendly occupations. We estimate a dynamic life-cycle model of fertility, occupational choice, and labor supply using detailed survey and administrative data for Germany for numerous birth cohorts across different regions. We use this model to analyze both the male-female wage gap as it evolves from labor market entry onward and the effect of pro-fertility policies. We show that a substantial portion of the gender wage gap is explainable by realized and expected fertility and that the long-run effect of policies encouraging fertility are considerably lower than the short-run effects typically estimated in the literature.

JEL Classification: J1, J2, J31

Keywords: fertility, labor supply, occupational choice

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1 Introduction

In almost all developed countries, despite significant improvements over the last decades, women still earn less than men (see Blau and Kahn (1996), and Weichselbaumer and Winter-Ebmer (2005) for recent evidence). Women are also often underrepresented in leading positions, and their careers develop at a slower pace than those of men,[1] possibly because they are still more burdened by procreational activities and because the costs of having children for mothers' careers and lifetime earnings are substantial. One key question for investigation, therefore, is the magnitude of these costs and how they decompose into loss of human capital during interruptions and lower human capital investments. Another important question is how intended fertility, even *before* children are born, affects the type of career path a woman chooses. Addressing these issues requires an understanding of the dynamics of women's choices; the effects on career path sorting of unobserved fertility preferences and ability; and the possible interactions of intermittency patterns, work decisions, and fertility choices.

This paper addresses these questions. It makes three main contributions to the literature on fertility, female labor supply, and career choice. First, it develops a dynamic life-cycle model of the interaction between fertility choices, career choices, and labor supply choices over the female life cycle, which relates to the broad body of literature on fertility decisions, female labor supply behavior, and occupational choices. To date, however, such research has tended to address each of these issues in isolation, [2] so that few studies model fertility decisions and labor market choices

[1] See for instance Catalyst (2009).

[2] Early papers by Becker (1960), Willis (1973) and Becker and Lewis (1973) study fertility decisions and their dependence on household background variables in a static context; and several au-

jointly. Exceptions are Hotz and Miller (1988) and Gayle and Miller (2006) who develop a life-cycle models of fertility and female labor supply that connects wages and fertility through labor supply decisions. Closely related to our paper is also the work of Francesconi (2002), who derives a joint model of fertility and career choice that emphasizes the choice of part-time work, and Keane and Wolpin (2010), who analyze the different effects of welfare programs on women of different races. [3]

Our model builds on this literature by considering the fertility choice in a dynamic and life-cycle perspective, where women choose their labor supply and acquire (and lose) human capital. Our model allows for the endogenous timing of births and the number of children, as well as labor market participation, number of hours worked and wage progression. [4] A distinctive feature of our model is that it introduces occupation

thors, including Heckman and Willis (1976), Ward and Butz (1980), Rosenzweig and Schultz (1983), Wolpin (1984), Moffitt (1984), Rosenzweig and Schultz (1985), Hotz and Miller (1988) Cigno and Ermisch (1989), Blackburn, Bloom, and Neumark (1990), Hotz and Miller (1993), Leung (1994), Arroyo and Zhang (1997) and Altug and Miller (1998), propose dynamic models of fertility. Related literature on women's labor supply behavior, however, takes fertility decisions as a given or assumes it to be an exogenous shock; see, for example, Heckman and Macurdy (1980), Moffitt (1984), Blau and Robins (1988), Eckstein and Wolpin (1989), van der Klaauw (1996), Attanasio, Low, and Sanchez-Marcos (2008), and Blundell and Macurdy (1999) for an excellent survey.

[3]More reduced-form studies include Moffitt (1984) and Heckman and Walker (1990). For a focus on the role of state-dependence versus unobserved heterogeneity, see Hyslop (1999), Keane and Sauer (2009), and Del Boca and Sauer (2009).

[4]Some recent studies with a stronger macroeconomic orientation do consider fertility decisions and female labor supply in a simultaneous setting. For example, Caucutt, Guner, and Knowles (2002) and Olivetti (2006) focus on how the interaction between the marriage market and labor market (through changes in the return to experience) impacts fertility decisions. Likewise, Greenwood, Seshadri, and Vandenbroucke (2005) develop a model of fertility and labor supply in a general equilibrium setting to investigate the cause of the baby boom and link it to an increase in real wages

as an additional choice dimension and allows women to decide which career path to choose. To develop this feature, we build on the early work by Polachek (1981), [5] which emphasizes the important connection between expected intermittency and occupational choice. Like Polacheck, we also allow different occupations to have different entry wages and different rates of atrophy (skill depreciation) and wage growth. In our model, the initial occupational choice is affected by planned fertility and chosen so as to balance a potentially higher wage growth with higher atrophy rates. Thus, fertility affects career paths not only through reduced investments in human capital (modeled using a learning-by-doing approach), atrophy through intermittency, and part-time rather than full-time work, but also through initial career decisions about the type of occupation to choose.

The data used are for Germany, where individuals that choose to attend lower track schools at age 10 (about 65 percent of each cohort) enroll after graduation (and at the age of 15-16) in a 2-3 year vocational training program in one of 360 occupations within the German apprenticeship system, [6] We are therefore able to observe initial occupational choices for these individuals before fertility decisions are made, but conditional on individual preferences for having children. In addition, being administrative, our primary dataset allows precise measurement of wages, career interruptions, labor supply, and occupations, including initial choice, for many cohorts across different regions over several decades.

Our model and estimated parameters produce valuable insights into the different

and the invention of labor-saving household capital.

[5]See also Weiss and Gronau (1981) and Gronau (1988) for related studies.

[6]These occupations range from hairdresser to medical assistant to bank clerk, and two in three individuals of each birth cohort follow an apprenticeship-based career route (for details on the occupational choices of males and females, see Fitzenberger and Kunze (2005)).

components of the career costs of children, the contribution of fertility to explaining the male-female wage differential, and the short-run and long-run impact of transfer policies on fertility. For example, by decomposing the costs of children into their different elements, such as the costs from labor supply or wage responses, we show that about three-quarters of the costs result from the former and the remainder from the latter. Additionally, using a sample of comparable male cohorts who made similar educational choices, we run simulations that explain wage differences between women and men over the life cycle, and how these are affected by fertility decisions, We find that fertility choices can explain a large part of the wage gap. We also demonstrate that, in terms of unobserved ability, fertility leads to substantial changes in the labor force composition of working women over the age cycle, a selection process which tends to mitigate the differences between men and women in terms of observed wages.

Finally, we use our model to simulate the impact of pronatalist transfer policies. Most previous studies that investigate the effect of these policies on fertility are based on diff-in-diff designs and focus on short-term impacts. [7] In contrast, our model allows us to evaluate both short term and long term effects and to distinguish between responses at the intensive (i.e., fertility delay in reaction to announced policy) versus extensive margin (i.e., an increase in overall fertility). In doing so, we show not only that the long-run effect of a subsidy policy is considerably lower than the short-run effects estimated in the literature (by about a factor 5) but that such policies may also have a long-run impact on human capital accumulation and labor supply. For instance, we estimate the long-run intention-to-treat elasticity of human capital to child transfers to be close to -0.01.

[7] See, for instance, Milligan (2005), Laroque and Salanié (2008), Cohen, Dehejia, and Romanov (2010), and Lalive and Zweimüller (2009).

The paper proceeds as follows. Section 2 describes the institutional background and data sources and provides descriptive statistics on career profiles and fertility. Section 3 outlines the model and estimation strategy. Section 4 presents the results and evaluates the effect of fertility on careers and the gender wage gap, as well as the impact of transfer policies on fertility and women's career paths. Section 5 concludes the paper.

2 Background, Data, and Descriptive Evidence

2.1 Institutional Background and Data

Following fourth grade (at about age 10), the German education system tracks individuals into three different school types: low and intermediate track schools, which end after grade 9 and 10 (age 15/16), or high track schools, which end after grade 13. In the cohorts studied here, about one third of the cohort attends each of the three school types. Traditionally, only high track schools qualify individuals for university entrance, while low and intermediate track schools prepare them for highly structured 2 to 3-year apprenticeship training schemes that combine occupation-specific on-site training 3-4 days a week with academic training at state schools 1-2 days a week. [8] These programs, which train for both blue- and white-collar professions, cover many occupations that in the U.S. require college attendance (e.g., nurse, medical assistant, accountant). At the end of the training period, apprentices are examined based on centrally monitored standards, and successful candidates are certified as skilled workers in the chosen profession.

[8] For instance, training is only provided in recognized occupations, skilled training personnel must be present at the training site, and trainees must pass monitored exit examinations.

In our analysis, we concentrate on women who attend lower and intermediate track schools and then enroll in an apprenticeship training scheme after school completion. We follow these women throughout their careers for up to 26 years in the labor market. We draw on two main datasets (described in more detail in Appendix A): register-based data from the German social security records (IABS data) and survey data from the German Socio-Economic Panel (GSOEP). We use the IABS data to construct precise career profiles for the women studied from labor market entry (i.e., enrollment in apprenticeship training) onward, and the GSOEP data to measure their fertility behavior over their careers and as a source for family background and spousal information. The first dataset (IABS), which covers a 2 percent sample of all employees in Germany that contributed to the social security system between 1975 and 2001, provides detailed information on wage profiles, transitions in and out of work, occupational choice, education, and age, and identifies periods of apprenticeship training. For our analysis, we focus on females in West Germany born between 1960 and 1975 who have undergone vocational training within the apprenticeship scheme. The second dataset (GSOEP) provides detailed yearly information on socioeconomic variables for a representative sample of households living in Germany. From this source, we construct a sample from the same birth cohorts as in the register-based dataset, focusing again on women who have earned an apprenticeship certificate. Specifically, we gather information on birth year, employment status, part- or full-time work, actual and agreed-on work hours (per week), occupation, gross and net individual earnings, educational level, number of children and their birth years, whether a husband is present, and if so, his earnings. All analyses concentrate on the German population. Because the register data exclude the self-employed and civil servants, we exclude these groups from our analysis, as well as all individuals who have ever worked in East Germany. We provide more detail about the sample construction in Appendix A and give descriptive information for the two samples in Panels A and B of appendix Table A1. [9]

One important aspect of our analysis is that we not only consider women's occupational choices but can attach to each woman an occupation chosen before any fertility choices are made. Because the number of possible occupational choices is so large, we aggregate occupations into groups that reflect the tradeoff between careers that offer high wage growth but punish interruptions and careers that imply flatter profiles but lower atrophy rates. We develop this classification by first dividing individual tasks into three-digit occupations and then classify the occupations into three categories based on the dominant task, characterized as either abstract, routine, or manual. [10] Abstract tasks include such responsibilities as planning, notarizing, and law-related activities, research, IT/programming, educating and instructing, and managing. Routine tasks include handling machines, assembling, using a calculator, writing/using files forms, and archiving. Manual tasks entail activities like entertaining, hosting, repairing, driving, and nursing. Owing somewhat to their stronger complementarity to technology, abstract task requirements are likely to change at a faster pace than manual or routine tasks. For instance, occupations in the banking sector (classified as

[9] Earnings in both the IAB and GSOEP samples have been deflated using Consumer Price Index data for private households (German Statistical Office) and converted into Euros.

[10] Task information has been used elsewhere to investigate the interplay between technological changes and the change in the distribution of earnings (see, e.g., Autor, Levy, and Murnane (2003), Goos and Manning (2007), and Dustmann, Ludsteck, and Schoenberg 2009). The occupational grouping is constructed using a survey dataset that is representative of the West-German active labor force aged 15-65 (the Qualifikation und Berufsverlauf (German Qualification and Career Survey) for 1985/86) and includes information on tasks reported on the job. See also Gathmann and Schonberg (2010) and Black and Spitz-Oener (2010) for the development of similar indicators.

abstract) are likely to require constant updating because of rapidly changing information technologies or new financial products. Sales occupations (classified as routine), on the other hand, require a set of skills that must be acquired in the early stages of the career (like product knowledge and relational skills) but are unlikely to change much over time.

We show below that wages in abstract task-dominated occupations do indeed grow faster than those in routine or manual task-dominated occupations, but that atrophy rates in this category are also higher. The construction of the task indicators and the classification of occupations across the three groups are detailed in Appendix A, which also includes an illustration of how we classified the 20 most frequent occupations in our sample (Table A2). [11]

2.2 Occupational Choice, Labor Supply, and Fertility

In Table 1, we present descriptive statistics on occupational choice, wage growth, accumulation of work experience, atrophy rates, fraction of part-time and full-time work, age at birth of first child, and completed fertility for the whole sample by current occupation. About 45 percent of all women in our sample choose an initial occupation with more abstract tasks, while 25 and 30 percent, respectively, choose routine or manual occupations. The second row of the table presents the share in each occupation over all ages and cohorts. These proportions are similar to those for initial occupation, indicating that few women switch occupations during their careers.

[11]Other classifications are of course possible (e.g., into service, care, and industry occupations), but the allocation of occupations would still, to a certain degree, be arbitrary and circular because our model must allow for endogenous sorting into occupations. We therefore adopt a standard classification based on task content.

In the second block, we report initial wages at age 20 and real wage growth in each of the three occupation categories overall and after 5, 10, and 15 years of potential experience. Although women in more abstract occupations earn higher wages than those in the two other groups at the start of their careers (around 4 to 5 percent per year), on average, wage growth tends to decrease with potential labor market experience. For instance, after 15 years, wages grow by only 1.3 percent per year, although wages in abstract occupations grow faster at each level of experience than wages in the other two categories. In the next block, we report the accumulation of total labor market experience together with part-time and full-time experience, again by occupational category, evaluated after 15 years of potential labor market experience. As the figures in the table show, women who have chosen an occupation with predominantly abstract tasks have a higher labor market attachment and are more likely to accumulate full-time work experience. More specifically, after 15 years of potential work experience, total work experience is 1.3 years (nearly 10 percent) higher for women in abstract task-dominated than in routine task-dominated occupations. These women also have 1.6 (1.1) more years of full-time work experience than women in routine (manual) occupations.

The fourth block of Table 1 outlines the changes in daily wages after an interruption of 1, 3, and 5 years, where changes in work hours, firm size, and occupation are conditioned out. We evaluate the wage loss at about 17 percent per year in the first year, about 13 percent per year for a two-year interruption, and about 6 percent per year for a five-year interruption. The wage loss is highest for women in abstract occupations and lowest for women in routine jobs. These figures, however, are difficult to interpret causally as atrophy rates because work interruptions are associated with many factors that may impact wages. For instance, some women may choose to return to the labor market on a part-time basis or in a different occupation, implying a change in daily wages. Obviously, it is difficult to control for all these alternative reasons for wage decline, especially in a reduced form. Rather, the econometric methodology we develop below is designed to estimate the atrophy rate, taking into account both endogenous choices and these other factors.

Women in occupations dominated by abstract tasks have higher wages and wage growth and accumulate more labor market experience, but they are also older at the birth of their first child. Moreover, as shown in the last block of Table 1, a higher percentage remain childless or have only one child, compared to the two or more children borne by women in routine or manual task-dominated occupations. These figures suggest sizeable differences between women who choose different occupational careers at an early point in the life cycle in terms of future career patterns, labor force attachment, and fertility behavior. Again however, the figures cannot be interpreted causally because there is a selection of women into occupations, fertility behavior, and labor supply patterns based on fertility preferences and labor market abilities.

We now turn to changes in occupation over the life cycle. In Table 2, we report the transition probabilities for any of the three occupational groups between two consecutive years. The table shows a strong persistence of women in the initially chosen occupation: more than 98 percent are in the same occupational group as the year before. The annual transitions rates between full-time, part-time, and no work (for all ages) are given in appendix Table B1: in all occupations, persistence is very high (around 90 percent), indicating that few women change the intensity of work from one year to the next. Transition from full-time to no work and from part-time to no work is most common in routine jobs and least frequent in abstract jobs (5.6 and 6.6 percent versus 3.2 percent and 4.4 percent). Returning to work on a full-time basis is most frequent in manual jobs (4.7 percent).

3 A Life-Cycle Model of Fertility and Career Choice

In developing our model, we focus on key features and relegate technical details to Appendix B. Specifically, our model follows individuals from late adolescence to the end of life, with a focus on their occupational choices, labor supply decisions, and fertility choices (number of children and spacing of births). The individual i maximizes the flow of utility over the life-cycle:

$$V_{it} = \max_{\{c_{is}, n_{is}, l_{is}, o_{is}\}} E_t \sum_{s=t}^{T} \beta^s u_i(c_{is}, n_{is}, l_{is}, a_{is}, o_{is}, h_{is}) \tag{1}$$

where β is a discount factor, and E_t is the expectational operator conditional on information in period t. Each period lasts six months. We set life expectancy, T, to 80 years. Individuals gain utility from consumption c_{is} in each period s. As in Becker and Lewis (1973), the mother derives utility from the number of children n_{is}, which takes three values, zero, one or two, and we allow for individual heterogeneity in the utility gained. [12] Women also derive utility from leisure. In addition, we denote an indicator for labor supply, l_{is}, which can take four values: working full time (FT), working part-time (PT), being unemployed (U), or being out of the labor force (OLF). We allow the utility from consumption and leisure to vary with the number of children n_{is} and the age of the youngest child a_{is}, modeled through interaction terms. The variable o_{is} denotes the occupation in which the individual is working at time s. In our model, occupation is characterized by three features: a particular wage path, a specific atrophy process when out of work, and flexibility of

[12]In our empirical analysis, 2 corresponds to 2 children or more. For a model focussing on child quality, see Del Boca, Flinn, and Wiswall (2010).

part-time employment. We model this latter by allowing the arrival rate of part-time offers to depend on the occupation. Finally, the presence of a husband is denoted by the indicator variable h_{is}. The utility function is indexed by i because it differs between individuals through heterogeneity in the desire to have children.

We detail the exact specification of the utility function and how utility is affected by the different choices in Appendix B. Put briefly, we model the differences in the utility mothers gain from the presence of children under various career choices by adding a number of interactions between labor market choices and the presence of children. First, we allow for differences in the utility of leisure between full-time work and either working part time, not working, or being unemployed. Second, because some jobs are more demanding in terms of work hours or offer less flexibility to take time out for child care, we allow the utility of full-time work in each occupational group to depend on the presence of children. Third, we allow for different utilities from part-time work, not working, or unemployment when children are present (relative to full-time work), based on the age of the youngest child, defined as infancy (0 to 3 years), pre-school (4 to 6 years), or primary school (7 to 9 years). We also allow the utility from leisure to vary with occupational type, which captures the fact that in more demanding occupations, it may be more difficult to handle both part-time work and children. Our model thus allows occupational choice to depend on fertility not only through the balancing of intermittency and wage growth costs but also through preferences that reflect the ease with which some occupations allow labor market participation to be combined with child rearing.

The utility from consumption is linear. As we abstract from savings decisions, consumption equals (equivalised) household income, which is the sum of the wife's income and the husband's labor earnings, if present, divided by the number of adults in the household. The woman's income is composed of either labor earnings, unemployment benefits, or maternity benefits, depending on her labor market status (i.e., individuals who are out of the labor force receive no benefits):

$$c_{it} = (w_{it} I_{l_{it}=FT} + \lambda_{PT} w_{it} I_{l_{it}=PT} + b_{U,it} I_{l_{it}=U} + b_{M,it} I_{l_{it}=M} + I_{h_{it}=1} w_{it}^{H})/N_A \,, \qquad (2)$$

where w_{it} is the wage if the individual works full time, λ_{PT} is the fraction of the full-time wage if she is working part time and N_A is the number of adults in the household. We denote the benefits received if the individual is either unemployed or on maternity leave (labeled U and M) by $b_{U,it}$ and $b_{M,it}$, respectively. The husband's wage (if present) is denoted by w_{it}^{H}, which we allow to vary with the wife's age and occupation.

Overall, wages depend on human capital, x_{it}, occupation, o_{it}, and (unobserved) individual ability α_i:

$$\ln w_{it} = \alpha_i + \alpha_O(o_{it}) + \alpha_X(o_{it}) x_{it} + \alpha_{XX}(o_{it}) x_{it}^2 + u_{it}^{w} \qquad (3)$$

where u_{it}^{w} is an iid shock to wages. Because we allow for both a different intercept and different rates of return to human capital, the wage profile (as in Kim and Polachek (1994)) is specific to a given occupation. [13] Employment is characterized by working either full time or part time in one particular occupation. In each period, new offers arrive randomly that have three features- occupation, part time, or full time- and combine to form a "job". Combining occupation and labor supply choices gives $J = 6$ alternative "jobs," and the probability of receiving a job offer $j = 1, \ldots, J$ while in job j is denoted by ϕ_{ij}. While working, the individual accumulates human

[13] As the wage profile appears very flat after 15 years of work experience (see Table 1), we assume that there exists a threshold, $\bar{x}$, beyond which the marginal effect of human capital on wages is zero. We estimate this threshold along with the other parameters.

capital, which atrophies when out of work at a rate that is occupation specific. We also allow the atrophy rate to depend on the previous level of human capital, which in occupation i evolves as follows:

$$x_{it} = x_{it-1} + \rho(x_{it-1}, o_{it}) \tag{4}$$

where $\rho(x_{it-1}, o_{it}) = 1$ if the individual is working full time, $\rho(x_{it-1}, o_{it}) \in [0, 1]$ if working part time and $\rho(x_{it-1}, o_{it}) \leq 0$ if not working. Thus, individuals decide on an occupation by balancing the atrophy rate with the human capital growth rate over the life cycle, meaning that different occupations are optimal for different intermittency patterns.

Timing and Sequence of Choices. At the beginning of each period, the individual decides whether to have a child or not dependent on the future flow of utility associated with each outcome, subject to preference shocks for conceiving or not. We assume that these preference shocks follow an extreme value distribution such that the probability of conceiving, conditional on all observed characteristics, is logistic. If the woman decides not to conceive and is employed, she can end up in one of four different states: working in the same job, working in a different job, unemployed, or out of the labor force. In each period, when employed, she can be fired with probability δ. If she decides to conceive, a child is born in the next period with probability $\pi(age_M)$. We draw on medical evidence (e.g., Khatamee and Rosenthal (2002)) showing that the probability of conception depends on the age of the mother and declines with age. [14]

[14] Khatamee and Rosenthal (2002) estimate that a woman has a 90 percent chance of conceiving within a year at age 20, a 70 percent chance at age 30, and a 6 percent chance at age 45. After age

After the child is born, the mother takes maternity leave and is entitled to maternity benefits. At the end of the maternity leave, she has the opportunity to return to the same job. Alternatively, she may receive a different job offer or choose to be unemployed or out of the labor force. While unemployed, she is entitled to unemployment benefits and can either accept a job offer if one arrives, stay unemployed, or move out of the labor force. In accordance with the German welfare system at the time, unemployment benefits never expire (as long as no "acceptable" offers are turned down), with a replacement ratio at 0.55 (see Adda, Dustmann, Meghir, and Robin (2006) for more details). While out of the labor force, she receives no benefits, which may be preferable, especially for mothers with young children, because the job search requirement of receiving benefits means less leisure time.

At age 60, women retire and live an additional 20 years, deriving utility from consumption, leisure, and children. During that period, they receive no income. However, in a linear utility framework, such as ours, this is equivalent to assuming that individuals finance retirement through their own savings out of their gross wages, which includes pension contributions.

Initial Choice of Occupation. At age t_0, and before entering apprenticeship training, individuals decide on a specific occupation, comparing the expected flow of utility for each occupational type with the current cost, which depends on the region of residence and year effects, as well as a preference shock drawn from an extreme value distribution:

$$o_{it_0} = \arg\max_j [c(j, Region, Time_{t_0}) + \eta_{ij} + \beta^6 E_{t_0} V_{i,t_0+6}(j)]$$

where $V_{i,t_0+6}(j)$ is the flow of utility defined in (1) conditional on the choice of

50, the probability of conception is almost zero.

training occupation j. Because training lasts three years, the payoff is received six periods later. We assume that during apprenticeship, individuals cannot be dismissed, in line with training regulations in Germany that commit firms to fulfilling the entire period of the apprenticeship contract. We further assume that women begin making choices about fertility and labor market status once they have completed their training, an assumption in line with the very low teenage pregnancy rates in Germany. [15]

Unobserved Heterogeneity. As discussed above, the model allows for fixed unobserved heterogeneity in both ability and desired fertility. This heterogeneity is introduced as in Heckman and Singer (1984), using discrete mass points, which are estimated together with the relative proportion in the sample. We allow for two ability types through different intercepts in the wage equation and two desired fertility types through differences in the utility of the number of children. We also allow for a fraction of women to be unable to conceive, an unanticipated failure from which women do not learn. Based on medical evidence, we fix this proportion at 5 percent. [16]

3.1 Estimation

The model is estimated using indirect inference introduced by Gourieroux, Monfort, and Renault (1993), [17] which allows us to combine information from different data

[15]For instance, in 1998 in Germany, only 1.3 percent of women between 15 and 19 gave birth, compared to 5.2 percent in the U.S. (see UNICEF (2001)), and 4.7 percent between 15 and 18 in the UK (see http://www.fpa.org.uk/professionals/factsheets/teenagepregnancy).

[16]Data from the U.S. indicate that about 8 percent of women aged 15 to 29 have impaired fecundity (see Centers for Disease Control and Prevention (2002)), although some may give birth after treatment for infertility.

[17]See for instance Attanasio, Low, and Sanchez-Marcos (2008) or De Nardi, French, and Jones (2009) for recent applications to life-cycle models.

sources on career choices, wages, and fertility decisions over the life cycle. In this approach, the model is solved by backward induction (value function iterations) based on an initial set of parameters and then simulated for individuals over their life cycles. The simulated data provide a panel dataset used to construct moments that can be matched to moments obtained from the observed data. Using a quadratic loss function, the parameters of the model are then chosen such that the simulated moments are as close as possible to the observed moments. Because the focus of our model is on describing life-cycle choices, we remove regional means and an aggregate time trend from all our moments.

The full list of moments used to identify the model are detailed in Table 3. The first set contains the means of outcome variables like occupation, average wage by occupation, hours of work, or number of children, all computed at different ages ranging from 15 to 55. [18] These moments ensure that the model reproduces the basic trends (and levels) in the real data. Next, we use transition rates between periods across occupations and between part-time/full-time work, which help to identify the probability of receiving an offer, $\phi_{i,j}$ and the variance of the preference shock for each occupational choice. [19]

Just as marginal distributions of variables are not enough to recover their joint distribution, focusing on means is insufficient for identifying the model. We therefore use OLS regression coefficients to capture conditional moments that provide information on the link between several outcomes, including wages, fertility, occupation,

[18]We follow the cohorts from age 15 to 40. To completely characterize the life cycle, however, we also use supplemental data from slightly older cohorts to construct moments that describe wages and labor supply at ages 45, 50 and 55. We verify that at age 40, the labor supply and wages of these older cohorts are very similar to those of the younger ones.

[19]See for instance equation (7) in the appendix for a definition of these parameters.

and work experience. More specifically, to link wages, number of children, and occupational choice, we use coefficients from an OLS regression of log wages on age, age squared, dummies for number of children, occupational dummies, and the interaction between number of children and occupational choice. These regressions help identify the dynamic tradeoff between children and experience (atrophy rates and return to experience) and the interaction between occupation and fertility in the utility function (see equation (16)). We identify the atrophy rates in equation (4) using two sets of moments. First, we match the return to work experience on wages, which gives information on the return to human capital as defined in (3) and on atrophy. Second, we regress the change in log wages for individuals who interrupt their career on the duration of the interruption, dummies for experience levels, and the interaction of duration and experience. [20]

Our model also allows for unobserved heterogeneity in the level of wages (ability), as in equation (3), and in the utility derived from children (or desired fertility), as in equation (16). We model the heterogeneity as a mass point distribution and allow for a correlation between both dimensions. To identify the proportion of individuals in each "type", we regress the log wages on experience and occupation, compute the average wage residual for each individual, and then use the cross-sectional variance of this average- which is linked to the variance in ability- as a moment. We also regress the number of children on age to compute the average fertility residual and correlate it with the average wage residual to provide information on the correlation between ability and desired fertility.

[20] It should be noted that the auxiliary parameters obtained from the OLS regressions, both on the real and simulated data, are subject to bias because of endogenous labor supply or fertility decisions. However, because the model allows for such endogeneity, we can identify the underlying structural parameters.

4 Results

4.1 Model Fit

Overall, the model fits the sample moments well. Out of the 673 moments used in the estimation, we cannot reject the equality of the observed and simulated moments in over 58 percent of the cases at the 95 percent confidence level, even though, given the very large sample size, we measure a number of our moments with a high degree of precision. For instance, the proportion of women working full time at age 20 is 77 percent in the data, while the model prediction is 79.1 percent (see Table B2). Statistically, however, the equality of these two moments is strongly rejected, with a t-statistic of 15.5.

The model does match trends in labor supply and work hours, as well as number of children (Table B4) and spacing of births (Table B5) by age. It is also able to match wage profiles by age and initial occupation (Table B6) and the coefficients of a regression of log wage on work experience by occupation (Table B7). For a complete discussion of model fit and an extended set of tables, see Appendix B.3.

4.2 Estimated Parameters

The estimated parameters for the model are given in Tables 4 to 6, together with their asymptotic standard errors. In total, the model contains 161 parameters, which is rather parsimonious considering that we model five broad outcomes with (often) several categorical outcomes over the entire life cycle. These five outcomes- wages, hours of work, occupational choice, number of children, and spacing of each birth- are each a nonlinear function of age and of lagged endogenous variables.

The first three rows of Table 4 display the parameters of the (log) wage as a function of human capital. Compared to the OLS coefficients given in Table B7, the estimated coefficients imply a steeper wage profile for all occupations in terms of human capital, because our measure of human capital, unlike real experience, depreciates when the individual is out of work. Nonetheless, there is heterogeneity in the returns across occupation and time: at low levels of experience, the returns to human capital are similar across occupations but differ at 10 years of labor market experience, being highest in abstract occupations and lowest in routine occupations.

Table 5 outlines the atrophy rates, the loss of human capital resulting from a one-year interruption in work. In all three occupational groups, the stock of human capital depreciates at a slower pace early in the career, indicating that more experienced women in higher positions have more to lose. The results do not, however, imply per se that it is better to have children earlier. On the contrary, the return to human capital is highest at a low level of experience; that is, although wages at the start of a career do not decrease much when an individual is out of the labor force, foregone experience is more costly. In addition, because our model allows for interactions in the utility function between children and the presence of a father and only a quarter of women in the sample are married by age 23, fertility choices do not depend exclusively on monetary tradeoffs.

The occupational group with primarily abstract tasks exhibits the highest atrophy rates: individuals lose about 2 percent of their wages for each year of career interruption at between five and eight years of work experience and up to 3.2 percent at more than eight years. The other two occupational groups, in contrast, have atrophy rates of at most 0.7 to 1.2 percent per year. Thus, work interruptions later in the career are costlier in human capital in occupations dominated by abstract tasks, a finding consistent with the hypotheses that these tasks require frequent updating because they are more complementary to capital and technology and that the complexity of tasks performed increases with seniority. Although the estimated atrophy rates are smaller than the wage losses given in the descriptive statistics in Section II, we find the same qualitative pattern across occupation and experience profiles. [21]

Table 6 lists the parameters of unobserved heterogeneity in ability and fertility preferences based on four types of women who differ in labor market ability and preference for children. Whereas women of Types 3 and 4, who have a wage 7 percent higher than Types 1 and 2, rank higher on ability, women of Types 1 and 3 value children more. The first row of the table gives the estimated proportions of each type: Types 1, 2 (low ability), and 4 (high ability with a high preference for children) are most common, while Type 3 (high ability with a lower preference for children) is least common. The last three rows in the table, which show the proportion of each type in the three different occupational groups, provide evidence of sorting on ability; that is, women with higher ability are more likely to choose initial occupations requiring more abstract tasks.

The model offers two explanations for the lower fertility of women in better paid careers: (i) higher ability women with a lower taste for children are selected into more demanding jobs and (ii) the interaction between career and desired fertility makes children more costly for high ability women. The proportions in Table 6 also imply that desired fertility and ability are positively (rather than negatively) correlated (with a coefficient of 0.2), meaning that high ability women also have a higher preference for children. This finding suggests that it is not the combination of high ability and low preference for children that leads to women in better paid careers

[21]Similarly, Albrecht, Edin, Sundström, and Vroman (1999) show in a reduced-form context that atrophy rates estimated from cross-sectional data are larger than those estimated from panel data.

having fewer children but rather that for high ability women, the choice of steeper career paths is more costly in forgone utility through the sacrifice of fertility. [22]

4.3 Career Costs of Fertility

We now use our model to quantify the career costs of children by simulating them under two scenarios: (i) a simple matching of the model to the data and (ii) a conception probability set to zero. In this latter, women know ex ante that no children will ever be conceived and so base all decisions, including choice of occupational training, on that knowledge. We first present the career paths for both scenarios and then compute the costs of children as the net present value of income at age 15. [23]

Occupational Choice and Labor Supply. Figure 1 displays the differences in occupational choice at age 15. Women who know that they will remain childless are less likely to work in routine occupations and more likely to work in occupations involving mainly abstract tasks; specifically, this knowledge decreases the proportion of women in routine jobs by 3 percentage points (12 percent). Instead, these women choose an occupation with predominantly abstract (+1.7 percentage points) or manual tasks (+1.4 percentage points), which suggests that some of the career costs of having children are determined even before the children are born.

Figures 2 plots the difference in labor supply over the life cycle between the no-fertility scenario and the baseline scenario with children. As the figure shows, in the

[22] We report the remaining estimated parameters of the utility function and the arrival rates of offers in different states in Tables B11 and B12 in the Appendix.

[23] It should be noted that, because we are interested in the career costs for a single individual, we compute partial equilibrium results. The results might therefore differ if all women chose not to have children.

no-fertility scenario, women are more likely to work at any age; however, this difference, although just below 10 percent at age 20, increases to 45 percent when women reach their late thirties. Subsequently, it declines slightly as a higher proportion of mothers return to the labor market when their children become older. Hence, as shown below, the difference in labor supply is an important component of the overall costs of children. Fertility also affects the labor supply at the intensive margin: the difference between the two scenarios in the proportion of working women in part-time versus full-time employment increases with age, with about one in two working women in the no-fertility scenario choosing part-time instead of full-time employment by their early forties (see Figure 3). This effect of fertility on women's labor supply over the life cycle in turn impacts work experience and human capital: our evaluations of the long-run elasticity of work experience and of human capital to fertility (carried out at age 60) give estimates of -0.2 and -0.3, respectively.

Wages and Selection Over the Life-Cycle. Figure 4 plots the deviation of wages in the no-fertility scenario (where all women remain childless) from the baseline scenario. Here, and in the simulations below, we report average daily (rather than hourly) wages conditional on working. Hence, differences across scenarios result from differences in human capital accumulation, the number of hours worked per day, occupational choices, and differences in the ability composition of women who choose to work. As the figure shows, at age 20, the daily wages of women who remain childless are only about 5 percent higher than those of women with children, but the difference rises to 39 percent (0.33 log points) by age 40. [24]

[24] We also compute the difference in hourly wages when work hours are kept constant: by age 40, women in the no-fertility scenario have on average a 10 percent higher hourly wage than women with children.

Part of the difference between the two scenarios stems from the different composition of the labor force. There is a long tradition in economics- dating back to the seminal work of Heckman (1974) and including Blau and Kahn (1996), Blundell, Gosling, Ichimura, and Meghir (2007), Mulligan and Rubinstein (2008) and Olivetti and Petrongolo (2008) - of evaluating the extent of the selection of women into the labor market. Our model allows us to assess the role of fertility decisions during the life cycle in shaping the ability composition of women in the work force over the age cycle. In Figure 5, we present the ratios of working women of high versus low ability over the age cycle under both scenarios. Without fertility, this ratio is close to 0.7 and relatively stable, [25] but in the fertility scenario, the composition of working women changes quite dramatically with age. At age 20, the ratio is equal to 0.9, but it increases up to age 35, when high ability women are 2.5 times more likely to work than low ability women. It then decreases as mothers return to the labor market and rises again toward the end of the working life. This difference between the two scenarios stems from the fertility differential by ability group and the higher opportunity costs for high ability mothers of staying home.

Decomposing the Net Present Value of Fertility Choices. The graphs presented above show various aspects of the career costs of fertility in terms of occupational choice, labor supply, and wages. We summarize these costs by calculating their net present value at the start of the career, computed at age 15 for all earnings, w_{it}^S, unemployment benefits, $b_{U,it}^S$ and maternity benefits, $b_{M,it}^S$, where S indexes one of two scenarios, the baseline scenario $S = F$ or the no-fertility scenario $S = NF$. We define an indicator variable $I_{X_{it}^S}$, which is equal to one if X is true under scenario

[25] In the overall population of women in our sample, including those who do not work, this ratio equals 0.57 (see Table 6), which is lower because of positive selection into the labor market.

S. We then calculate the net present value for individual i:

$$NPV_i^S = \sum_{t=0}^{T} \beta^t \left(w_{it}^S I_{work_{it}^S} + b_{U,it}^S I_{Unempl_{it}^S} + b_{M,it}^S I_{Mat.Leave_{it}^S} \right) . \tag{5}$$

We evaluate the relative costs of children by computing $1-NPV^{NF}/NPV^{F}$, using an annual discount factor of β=0.95. These costs reflect the difference in earnings, labor supply, and occupational choice induced by the presence of children. The overall costs of children (comparing the baseline scenario with the no-fertility scenario) are about 64 percent of the net present value of income at age 15 (see Table 7).

To better understand the sources of these costs, we decompose the total costs into two components: the contribution of labor supply and the contribution of wages (see rows 2 and 3 in Table 7). [26] According to this decomposition, three quarters of the costs (i.e., 49 percent of the total 64 percent costs of children) result from differences in the labor supply and about one quarter (16 percent) from differences in wages. Thus, although wages are important, the larger source of the costs of children is the unearned wages of women who drop out of the labor force for considerable periods in their career.

In the third and fourth blocks of Table 7, we decompose the contribution of wages further into the three sources of wage differentials in our model: occupational choices, atrophy when out of work, and labor market experience. The contribution of atrophy to the daily wage disadvantage in the fertility scenario is 13 percent (2 percent of the total 16 percent of wage-induced costs). The contribution of occupational choices at the beginning of the career represents nearly 20 percent of the overall costs, which suggests that a substantial portion of the wage-induced career costs of children is

[26] As in standard Oaxaca-type decompositions, there are two alternative reference groups, but in the table, we present the average of the two.

already determined before fertility decisions are made through occupational choices conditioned on expected fertility patterns.

4.4 Fertility and the Gender Gap

Having shown that fertility leads to a sizeable reduction in life-cycle earnings and affects women's wage profiles throughout their careers, we now examine the extent to which the gender gap in earnings can be explained by fertility. To do so, we compare the wages of men of similar qualifications (i.e., men belonging to the same birth cohorts, having the same education (lower or intermediate secondary school), enrolled in an apprenticeship training scheme before labor market entry, and observed from labor market entry onwards) to those of the women studied. We compute this difference for the average daily (rather than hourly) wage, which we believe is the most appropriate measure because it includes the change from full-time to part- time work as an important margin of fertility adjustment (see Figure 3).

In Figure 6, we show the observed daily wages for working males (solid line) and females (dashed line by age), as well as the predicted profile for females from our model (dotted line). The fact that the observed and predicted wages for females are very similar suggests a good model fit. As the figure shows, whereas men's daily wages increase monotonically with age, women's increase up to age 27 but then decrease and only begin increasing again after age 38. Although the dynamics of female wages are highly complex because of the varying degrees of ability-based selection over the age cycle (illustrated above), overall, this compositional change tends to narrow the gender wage gap. On the other hand, the gap increases as women reduce the number of hours worked between ages 25 and 45 and as women with lower labor market experience and depreciated skills return to the labor market once their children are older. As the figure also illustrates, the log wage gap is substantial, ranging from 0.15 log points for females in their twenties to more than 0.6 log points in their forties.

To assess the contribution of fertility to the gender wage gap, we first compute the counterfactual careers of women who remain childless and condition decisions on that knowledge from the start of their careers. We can then compute the average wage (conditional on working), which in Figure 6 is labeled "Predicted Females, No Fertility." The log wage gap now reduces considerably (to about 10 percent) up to age 30, and increases to about 30-35 percent at age 40. Hence, fertility patterns and expectations account for a substantial part of the gender wage gap, especially for women over 30. [27]

What explains the remaining wage gap? First, even adjusting for fertility, occupational choices for males and females differ, with only one overlapping occupation among the 10 most frequent choices (own calculations, based on 1998 data). If wages in the "male" occupations grow faster than in the "female" occupations, this "segregation" may contribute to the observed wage gap. Second, on the demand side, even in our "childless" scenario, wages and firm-side induced investments in human capital, as well as the career paths offered to females, may be set in expectation of later career interruptions, which again may partly explain the increasing gender gap.

[27] These findings are in line with Bertrand, Goldin, and Katz (2010) who, using different techniques, show that fertility-induced differences in the labor supply of MBAs explains a large part of the male-female annual earnings differential. Rosenzweig and Schultz (1985) and Goldin and Katz (2002) who illustrate the impact of fertility shocks on labor market participation and wages.

4.5 The Effect of Pro-Fertility Policies on Fertility and Women's Careers

Because in many countries, fertility is encouraged- typically in the form of tax relief or transfers - a stream of literature has evolved on the effects of such policies on fertility, and sometimes on labor supply. [28] Some of this research, which typically identifies these effects based on policy changes, nonlinearities in the tax and transfer system, regional variation, and/or changes or differences in entitlements across family characteristics, reports considerable effects of these policies on total fertility. The focus of this literature, however, tends to be limited to short-run responses to fertility because of two important problems: First, it is difficult in many datasets to track women affected by such policies over an extended period, and until the completion of their fertility cycle. Second, and more important, because data become contaminated over time by other factors that affect the fertility and careers of particular birth cohorts, making a causal statement about the effect of a policy some years after its implementation requires restrictive assumptions. Hence, extant studies pay little attention to long-term consequences and how fertility behavior is affected at the extensive and intensive margins. [29] Yet, despite their complexity, the long-run effects are extremely important for policy evaluation. For instance, a newly introduced policy

[28] See, for instance, Cohen, Dehejia, and Romanov (2010) who investigate the effect of Israel's child subsidy program on fertility; Laroque and Salanié (2008) who study the impact of child subsidies in France on total fertility and labor supply; Haan and Wrohlichc (2011) who estimate the effect of child benefits on fertility and employment in Germany; Milligan (2005), who investigates the impact of a new lump sum transfer to families that have a child; and Sinclair, Boymal, and de Silva (2010) who analyze the effect of a similar policy on fertility in Australia.

[29] One notable exception is Parent and Wang (2007) who follow a cohort of Canadian women over their fertility cycle and find that the long-run response is low compared to the short-run response.

affects different cohorts differently, depending on where women are in their career and fertility cycle: young women about to enter the labor market can adjust not only their fertility behavior but also their occupational choices and entire career paths, whereas older women, having already made most career decisions, have fewer opportunities to adjust. The effects of the policy will also change over time as more women use it as a basis for their fertility and career choices. At the same time, transfer policies may affect decisions other than fertility, like labor supply, occupational choices, and human capital investments. Yet these "secondary" effects, despite being important for assessing the full impact of these policies, are often neglected.

To help fill this void, we use our life-cycle model to evaluate the effect of an increase in child transfers; specifically, the short-run and long-run effects of an unanticipated but permanent policy that doubles the transfer for each child from 1,220 to 2,440 Euros yearly. Drawing on longitudinal data for women from many birth cohorts, we build an economy made up of women in their productive years, assumed to be between the ages of 14 and 60. Each year, a new birth cohort of 15-year-old females enters the economy while the one that has just turned 60 exits. After 45 years, the economy is populated entirely by women who entered after policy implementation and reaches a new steady state.

Figure 7 plots the number of children born every year, compared to a baseline without the increase in child subsidy, which takes place in year 4. We observe a spike in the number of children born, with a 10 percent increase in total fertility in the first year of the policy, followed by a muted long-term response of about 2 percent. The peak in the earlier years of the policy occurs as young cohorts permanently increase their fertility rate while older cohorts present at the introduction of the policy take advantage of it to have an additional child before reaching menopause.

The short-run response corresponds to a short-run elasticity of 0.1, a figure consistent with that found in the literature using different econometric methodology. For instance Milligan (2005) find a benefit elasticity of fertility of 0.107 for Canada, Cohen, Dehejia, and Romanov (2010) show that a doubling of the child subsidy leads to an increase in fertility of about 17 percent, and Laroque and Salanié (2008) report that an increase in child subsidy of 1,800 euros per year increases fertility by 14 percent. In the long term, however, the impact of this policy is very different, with a far more modest increase in the number of children born.

In Table 8, we show the effect of the policy on women from three different birth cohorts: those unaffected by the policy, those who have just begun their careers, and an intermediate cohort that is 30 years old when the policy changes. We present evidence on completed fertility, human capital, and labor supply. Although the long-run effect of the policy is to increase overall fertility, the policy also shifts births forward, decreasing the age at first birth from 27.4 to 26.8 and the age at second birth from 32.2 to 31.6. Cohorts affected by the policy also accumulate less human capital, a decrease of about 0.6 percent, and the (intention-to-treat) elasticity of human capital with respect to child benefits is about -0.01. Occupational choice, however, is not sensitive to such a policy, which is not surprising given the relatively modest effect it has on long-run fertility.

5 Conclusions

Because it touches many core areas, including women's career choices and human capital acquisition and the gender wage gap, fertility is an area of key importance in labor economics. Policies aimed at increasing fertility, particularly, may have consequences not only for career choices and human capital investment but also labor market participation, all of which must be accounted for during policy evaluation. In this paper, we develop and estimate a model of fertility and career choice that sheds light on the complex decisions and interactions determining fertility choices and how these interact with career decisions. One unique feature of our analytical context is that women make career choices at a pre-fertility stage, which allows us to assess how careers are influenced by expected fertility and the degree to which the career costs of children are affected by pre-fertility decisions.

The first important insight generated by our analysis is that career choices are correlated with fertility: women in high-growth/high-atrophy occupations have lower fertility. In fact, career choices may be affected by fertility even before fertility is realized; that is, the choice of initial occupation is influenced by projected fertility; most particularly, the balancing of preference for children with the opportunity costs of labor market involvement. At the same time, however, women who choose steeper career profiles and have fewer children are more likely to be of the high ability type. Yet these women also have a higher preference for children, which suggests that, on average, women with better careers pay a high price in disutility for having fewer children.

We also show that the costs of fertility are substantial: in the data analyzed, fertility reduces women's life-cycle earnings by 64 percent, mostly because of reduced participation in the labor market at both the extensive and intensive margins (i.e., women who have children have a lower life-time participation and more part-time work). Fertility also affects wages through career choice, atrophy, and less accumulation of human capital. Interestingly, however, it also has strong composition effects along the age cycle in terms of unobserved heterogeneity. That is, because higher ability women have fewer children and a higher tendency to participate in the labor market, the composition of working women is heavily skewed toward high ability women at the peak of their reproductive cycle but not at the beginning or after their children are grown. When all these observations are taken together, fertility can explain a large portion of the gender wage gap between comparable males and females, which could be roughly halved if women had no children and conditioned their career choices on this knowledge.

Finally, because our model enables assessment of the effect of transfer policies on fertility, labor supply, career choice, and human capital investment, we can identify the long-term policy effects that are so difficult to pinpoint in a reduced-form analysis, as well as the different channels by which the policy affects decisions. We find, for instance, that although the immediate total fertility effects identified for a child subsidy policy are comparable to those in the literature, the long-run effects are far smaller. Any such policy, however, also affects the accumulation of human capital, an aspect largely ignored in prior literature but one worthy of more serious investigation.

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Table 1: Descriptive Statistics, by Occupation

	Routine	Abstract	Manual	Whole sample
Initial occupation	0.250	0.448	0.303	1
Occupation of work	0.253	0.528	0.219	1
Log wage at age 20	3.71	3.86	3.68	3.77
	(0.002)	(0.002)	(0.002)	(0.002)
Wage growth (annual)	0.0407	0.0421	0.0410	0.0415
	(0.196)	(0.185)	(0.216)	(0.195)
Wage growth, exp=5	0.0485	0.0551	0.0450	0.0510
	(0.187)	(0.156)	(0.196)	(0.175)
Wage growth, exp=10	0.0181	0.0240	0.0152	0.0208
	(0.187)	(0.206)	(0.223)	(0.206)
Wage growth, exp=15	0.00995	0.0147	0.0127	0.0133
	(0.206)	(0.195)	(0.211)	(0.200)
Total work experience after 15yrs	11.55	12.81	12.14	12.34
	(3.273)	(2.624)	(2.880)	(2.909)
FT work experience after 15yrs	10.32	11.92	10.86	11.29
	(3.907)	(3.348)	(3.570)	(3.617)
PT work experience after 15yrs	1.229	0.889	1.274	1.056
	(2.187)	(1.828)	(2.125)	(1.997)
Wageloss, interruption=1yrs	-0.136	-0.196	-0.166	-0.171
	(0.567)	(0.635)	(0.635)	(0.617)
Wageloss, interruption=3yrs	-0.204	-0.291	-0.262	-0.261
	(0.609)	(0.622)	(0.570)	(0.608)
Wageloss, interruption=5yrs	-0.215	-0.378	-0.339	-0.322
	(0.690)	(0.706)	(0.662)	(0.694)
Age at first birth	27.27	28.39	25.94	27.56
	(4.138)	(3.783)	(3.517)	(3.943)
No child (%) at age 40	14.39	20.08	14.86	17.58
	(3.067)	(2.544)	(4.164)	(1.787)
One child (%) at age 40	25.00	28.92	18.92	26.15
	(3.783)	(2.879)	(4.584)	(2.063)
Two or more children (%) at age 40	60.61	51.00	66.22	56.26
	(4.269)	(3.174)	(5.536)	(2.328)

Note: Standard deviation/standard errors in parentheses

Table 2: Annual Occupational Choice Transition

Occupation in year t	Occupation in year $t+1$		
	Routine	Abstract	Manual
Routine	98.3	1.2	0.5
Abstract	0.6	99.2	0.2
Manual	0.7	0.5	98.8

Table 3: Moments Used in the Estimations

Moments	Data Set
*Utility of leisure * utility of children*	
Proportion of full-time work, by age	IAB
Proportion of part-time work, by age	IAB
Proportion of full-time work, by age and initial occupation	IAB
Proportion of part-time work, by age and initial occupation	IAB
*ϕ, Utility of occupation * children*	
Annual transition rate between occupation	IAB
Annual transition rate between full-time, part-time and no work, by occupation	IAB
δ, ϕ_0, utility of leisure	
Average work experience, by age	IAB
Wage function & skill depreciation	
Average wage by age and by initial occupation	IAB
OLS regression of log wage on experience, by occupation	IAB
OLS regression of log wage for interrupted spells on duration and experience	IAB
OLS regression of log wage on age, number of children, occupation and experience	GSOEP
Trade-off between children and career interruption, by occupation.	
Proportion with no children, by age	GSOEP
Proportion with one child, by age	GSOEP
Proportion with two children or more, by age	GSOEP
Centiles of age at first birth	GSOEP
Centiles of age at second birth	GSOEP
Number of children at age 40	GSOEP
Average age at first birth, by current occupation	GSOEP
Average age at second birth, by current occupation	GSOEP
*Utility of children * husband presence*	
Proportion of childbirth within marriage	GSOEP
Opportunity cost of children & occupation	
IV regression of fertility on age and initial occupation (instrumented)	GSOEP
Unobserved heterogeneity in wages	
Variance of residual of log wage on occupation, age, work hours	GSOEP
Proportion of women with log wage residual < 1 std dev	GSOEP
Unobserved heterogeneity in wages and fertility	
Mean of residual of number of children on age — wage residual<0	GSOEP
Mean of residual of number of children on age — wage residual>0	GSOEP

Table 4: Estimated Parameters: Wages

Parameter	Routine	Abstract	Manual
		Wage equation	
Log wage constant	3.33 (0.006)	3.54 (0.0004)	3.32 (0.0072)
Human capital	0.131 (0.0012)	0.0986 (0.001)	0.114 (0.0009)
Human capital square	-0.00605 (6.3e-06)	-0.00304 (4e-05)	-0.00454 (4.2e-06)
Average return to human capital			
At 5 years of experience	7.1% (0.12)	6.86% (0.11)	6.9% (0.09)
At 10 years of experience	4.2% (0.12)	5.41% (0.12)	4.73% (0.09)

Note: The wage equation is defined as a function of human capital and not work experience. The former is allowed to depreciate when out of the labor force. Asymptotic standard errors in parenthesis.

Table 5: Estimated Parameters: Atrophy Rates

Parameter	Routine	Abstract	Manual
Percentage of wage lost per year of interruption			
Experience ≤ 4	-0.028% (2e-05)	-0.046% (2e-05)	-0.02%(1e-05)
Experience $\in [5, 8[$	-0.97% (0.2)	-2% (0.1)	-0.89%(0.3)
Experience >8 years	-0.74% (0.3)	-3.2% (0.6)	-1.2%(0.02)

Note: Asymptotic standard errors in parenthesis.

Table 6: Estimated Parameters: Unobserved Heterogeneity

Parameter	Type 1	Type 2	Type 3	Type 4
Proportion in sample	0.285	0.351	0.0912	0.274
	(3.16e-08)	(0.0145)	(0.00983)	(0.0145)
Log wage intercept	0	0	0.0692	0.0692
	-	-	(0.0078)	(0.0078)
Utility of children	1	1.9	1	1.9
	-	(1.4e-05)	-	(1.4e-05)
Total fertility	1.83	1.83	1.51	1.53
Prop in routine occupation	0.319	0.316	0.172	0.176
Prop in abstract occupation	0.349	0.367	0.52	0.504
Prop in manual occupation	0.332	0.317	0.308	0.32
Corr(Ability, Desired fertility)		0.2		

Note: Asymptotic standard errors in parenthesis. Proportions in given occupation are calculated at the start of the career.

Table 7: The Career Cost of Children - Percentage Loss in Net Present Value of Income at Age 15, with and without Fertility.

	Percentage loss
Total cost	-64.4%
Decomposition of total cost	
Labor supply contribution	-49%
Wage contribution	-16%
Decomposition of wage contributions to total cost, 1	
Contribution of atrophy	-1.9%
Contribution of other factors	-14%
Decomposition of wage contributions to total cost, 2	
Contribution of occupation	-3%
Contribution of other factors	-13%

Note: We include all wages, unemployment benefits and maternity benefits in the calculations. The discount factor is set to 0.95 annually.

Table 8: Effect of Increased Child Benefits

Effect at age 60	Age at start of policy		
	15	30	60 (Baseline)
Total fertility per woman	1.76	1.75	1.72
Age at first birth	26.8	27.4	27.4
Age at second birth	31.6	32.2	32.2
Human capital	15.3	15.3	15.4
Number of years working	25.6	25.6	25.7
Number of years working part-time	6.74	6.85	6.86
Proportion in routine occupation	0.265	0.265	0.265
Proportion in manual occupation	0.321	0.321	0.321

Note: Based on a benefit increase of 1,220 euros. Simulation performed over 8,000 individuals.

Figure 1: Effect of No Fertility on Occupational Choice at age 15

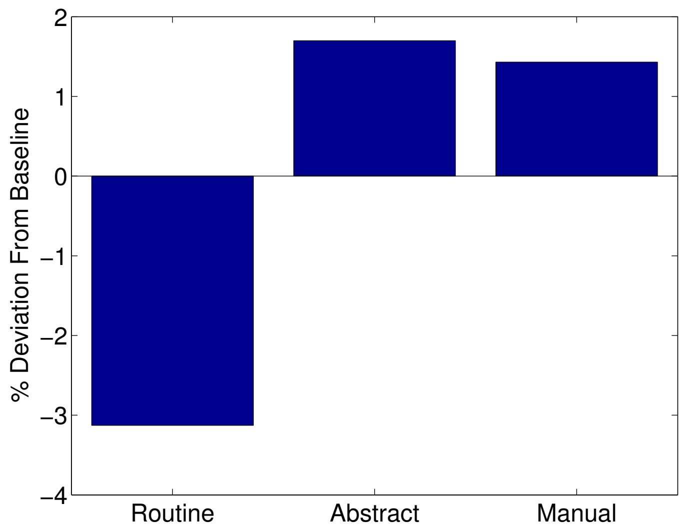


Figure 2: Effect of No Fertility on Labor Supply

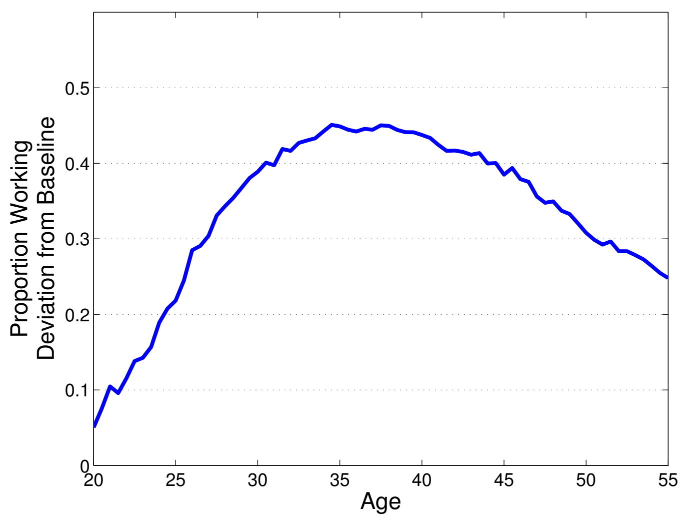


Figure 3: Effect of No Fertility on Part-Time Work

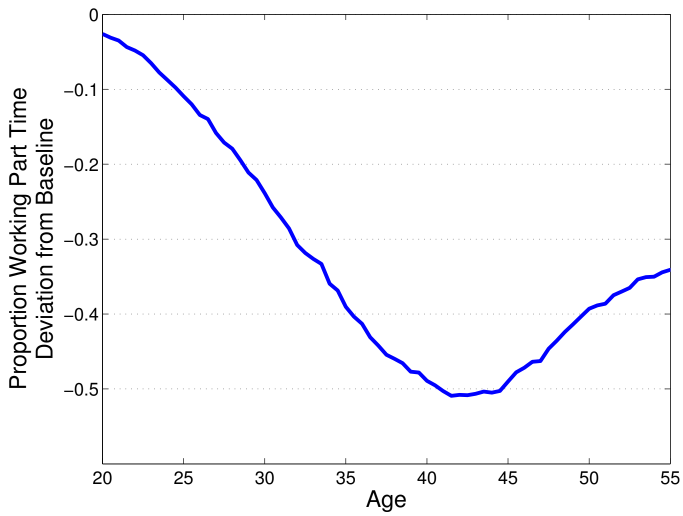


Figure 4: Effect of No Fertility on Wages

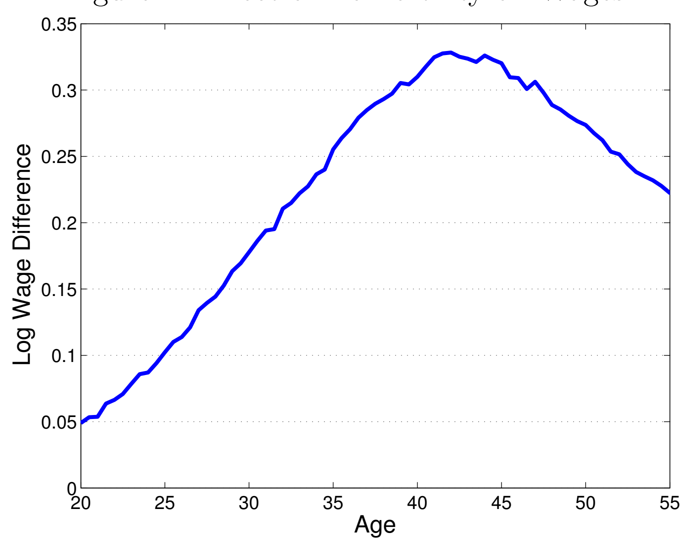


Figure 5: Ratio of High Ability to Low Ability Women, Conditional on Working

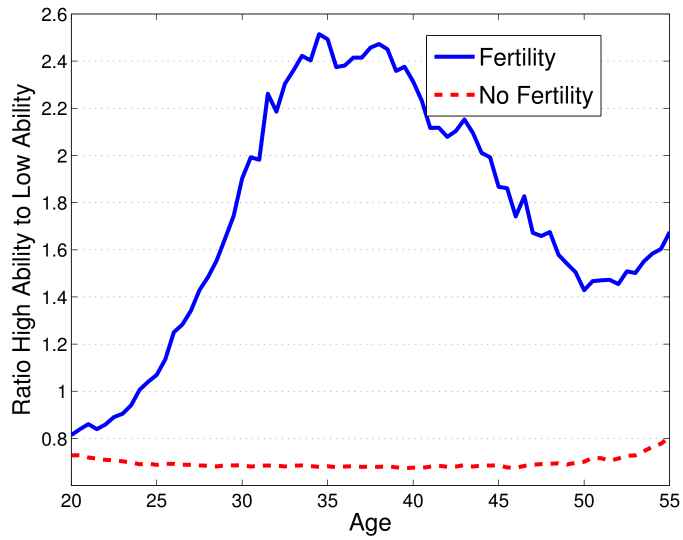


Figure 6: Effect of Fertility on Gender Wage Gap

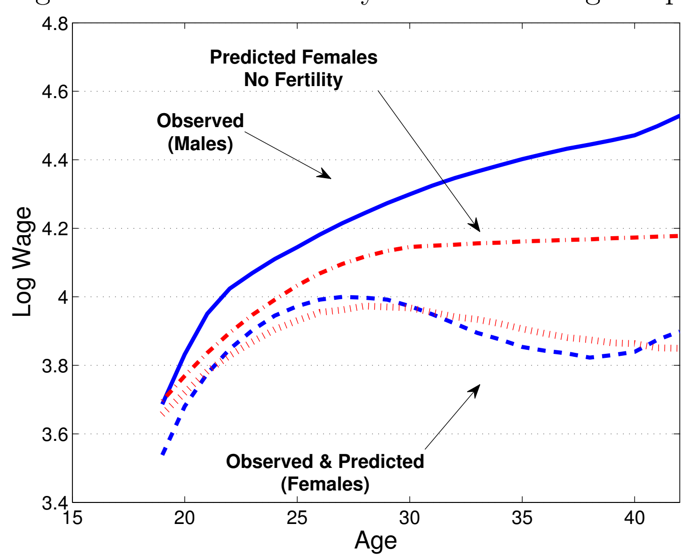


Figure 7: Effect of Increased Child Benefits on Number of Children, compared to Baseline

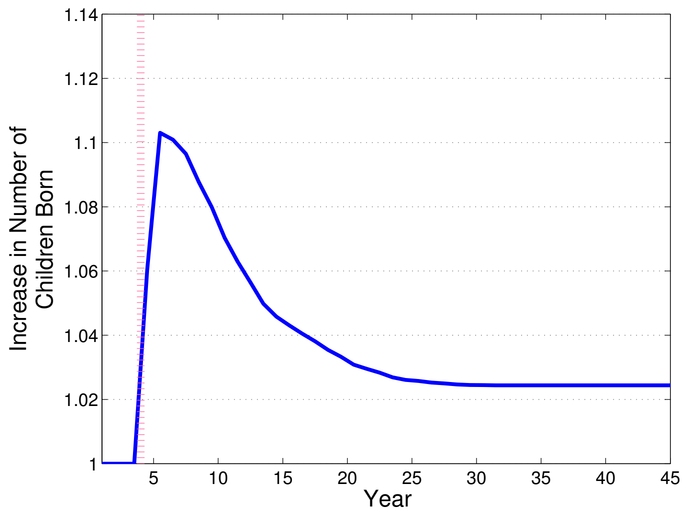
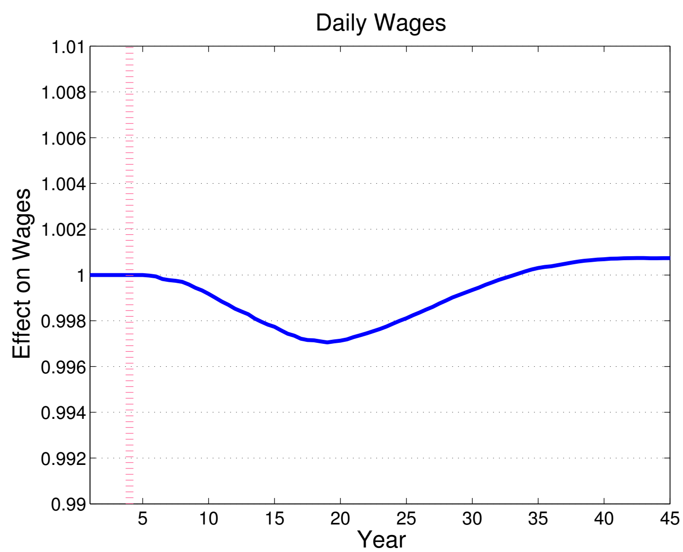


Figure 8: Effect of Increased Child Benefits on Daily Wages, compared to Baseline.



Appendix

A Data

As outlined in Section 2, our first dataset, from the German Institute for Employment Research (IAB: Institut fuer Arbeitsmarkt-und Berufsforschung), provides detailed information on wage profiles, transitions in and out of work, occupational choice, education, age, and periods of apprenticeship training. We use these data to compute the career histories of West-German females who have undergone vocational training within the apprenticeship scheme and belong to the 1960-1975 cohorts, meaning that the oldest individual in the first year of the survey (1975) is no older than 15, the earliest age of enrollment in an apprenticeship program. We transform the register data on periods of employment into biannual observations. Our final sample, used primarily to identify wage profiles and the transitions of working versus not-working women, comprises 72,430 women born 1955-1975 and observed from labor market (LM) entry until 2001. One unique aspect of this dataset is that it allows work histories to be observed from the start of the career onward and gives very detailed information about labor market experience.

The register data, however, do not include information on household background, fertility choices, number and age of children, and participation and work behavior by motherhood status. For these variables, we use yearly information on socioeconomic variables from the German Socio-Economic Panel (GSOEP), with a specific focus on the German (as opposed to immigrant) population. Specifically, we construct a sample from the same birth cohorts as in our register-based data (i.e., birth years 1955-1975), focusing again on women who earned an apprenticeship certificate and did not enroll in higher education. For these women, we compile information on birth year, employment status, part-time or full-time work, actual and agreed-on hours of work (per week), occupation, gross and net individual earnings, educational level, number of children and year of their birth, whether a husband is present, and if so, his earnings. Our final sample contains a total of 16,144 observations for 1,432 women, at least 500 in each age group between 21 and 38. For 50 percent of the women, we have data from 10 or more successive interviews. There are more than 1,000 births in the sample and about 9,700 periods of employment (after apprenticeship). Because the register dataset excludes the self-employed and civil servants, we exclude these groups from our analysis, together with individuals who have ever worked in East Germany, where fertility behavior was very different before German unification in 1989. We provide descriptive information on both the IAB and the GSOEP samples in Panels A and B of Table A1, respectively.

Although focusing on women with apprenticeship training allows us to attach a chosen occupation to each woman before fertility choices are made, the large number of possible choices requires that we aggregate them into groups based on the tasks involved (obtained from other data sources). Such task information is used elsewhere to investigate the interplay between technological changes and changes in the distribution of earnings (see, e.g., Autor, Levy, and Murnane (2003) and, Goos and Manning (2007)). Like Dustmann, Ludsteck, and Schoenberg (2009), we use survey information on tasks performed in three-digit occupations to classify jobs into three categories based on whether the dominant task is abstract, routine, or manual.

We construct the occupational grouping using the German Qualification and Career Survey (Qualifikation und Berufsverlauf) 1985/86, a representative survey dataset for the West-German active labor force aged 15-65, which includes information on tasks reported on the job. These data are also used by Dustmann, Ludsteck, and Schoenberg (2009), Gathmann and Schonberg (2010), and Black and Spitz-Oener (2010) in their analyses of the German labor market to develop task-based indicators of occupation. We construct task intensity indicators for each individual observation, which we then aggregate at 2-digit job levels, each categorized as involving mainly routine, abstract, or manual tasks (as described in Section 2). We then match this classification to our GSOEP and IABS data samples.

Because each job can include a variety of tasks, the task intensity indicators at the 2-digit job levels are constructed as follows:

1. We define 3 broad types of tasks X: Routine, Abstract, Manual ($X \in \{R, A, M\}$)

2. Each type of task X can involve a variety of tasks x_i ($i = 1, ..., n_X$). If a task x_i of type X is reported by an individual j: $x_i^j = 1$ (otherwise 0).

3. Sum of all tasks of type X reported by an individual j: $N_X^j = \sum_{i=1}^{n_X} x_i^j$

4. Total number of tasks (of any type) reported by an individual: $N^j = \sum_{X \in \{R,A,M\}} \sum_{i=1}^{n_X} x_i^j$

5. Intensity of type X tasks reported by individual j: $i_X^j = N_X^j / N^j$.

6. Each observation (j=1,...,N) belongs to a 2-digit job category Y. Task intensities are aggregated over all observations j in a 2-digit job category Y ($j \in Y$, n_Y observations). Task intensity of type X in job category Y: $I_X^Y = \frac{1}{n_Y} \sum_{j \in Y} i_X^j$

B Model and Numerical Solution

B.1 Formal Description of the Model

In our model, the dynamic choice depends on whether the individual is currently working or out of the labor force. If the individual is employed at the start of the period, she must decide whether or not to try and conceive a child. Hence, the overall value of work is given by

$$W_i(\Omega) = \max[W_i^C(\Omega) + \eta_i^C, W_i^{NC}(\Omega) + \eta_i^{NC}] \tag{6}$$

where η_i^C and η_i^{NC} are two preference shocks drawn from an extreme value distribution. The value of work and not conceiving a child is given by

$$\begin{aligned} W^{NC}(\Omega_i) &= u\left(w(X, O_i, \varepsilon) + Hw_H, O_i, H, N, age_K\right) \\ &\quad +\beta\delta EU(\Omega'_{ii}) \\ &\quad +\beta(1-\delta)\sum_j \phi_{i,j} E\max[\tilde{W}(\Omega'_{ii}), \tilde{W}(\Omega'_{ij}), \tilde{U}(\Omega'_{ii}), \tilde{O}(\Omega'_{ii})] \end{aligned} \tag{7}$$

With probability δ, the match resolves at the end of the period and the individual ends up unemployed. While still employed, however, she may receive an alternative offer (with a probability $\phi_{i,j}$) and choose between working, unemployment, or moving out of the labor force. It should be noted that a value function with a tilda represents the value function plus the preference shock assumed to follow an extreme value distribution (e.g. $\tilde{W}_i(\Omega'_{i,P}) = W_i(\Omega'_{i,P}) + \eta_i$).

The evolution of the state space is given by:

$$\Omega'_{ij} = \begin{pmatrix} age_M + 1 \\ X + \rho(i, X) \\ Occup' = j | Occup = i \\ N \\ I_{N>0}(age_K + 1) \\ H' \end{pmatrix}$$

Experience evolves as follows: If the individual is working, experience is incremented by 1 if employment is full time or by $\lambda_{PT} \in [0, 1]$ if part-time. If she is unemployed, experience depreciates at a rate dependent on both current occupation and level of experience. The presence of a husband is modeled as a first-order Markov process in which the transition rates are functions of the woman's age and occupation and the presence of children.

The value of conceiving a child and working is denoted by

$$\begin{aligned} W^C(\Omega_i) &= u\left(w(X, O_i, \varepsilon) + Hw_H, O_i, H, N, age_K\right) \\ &\quad +\pi(age_M)\beta EM(\Omega'_{i,P}) \\ &\quad +\delta(1-\pi(age_M))\beta EU(\Omega'_{ii}) \\ &\quad +(1-\delta)(1-\pi(age_M))\beta\sum_j \phi_{i,j} E\max[\tilde{W}(\Omega'_{ii}), \tilde{W}_j(\Omega'_{ij}), \tilde{U}(\Omega'_{ii}), \tilde{O}(\Omega'_{ii})] \end{aligned} \tag{8}$$

Conception occurs with probability $\pi(age_M)$, which declines nonmonotonically with the mother's age. We calibrate this function using medical data. The state space when pregnant evolves as

$$\Omega'_{i,P} = \begin{pmatrix} age_M + 1 \\ X + \rho(i, X) \\ Occup = i \\ N + 1 \\ age_K = 0 \\ H' \end{pmatrix}$$

i.e., a child is born next period and the age of the youngest child is set to zero.

If the agent is unemployed, she first decides whether or not to conceive a child:

$$U(\Omega) = \max[U^C(\Omega) + \eta_U^C, U^{NC}(\Omega) + \eta_U^{NC}] \tag{9}$$

where the value of not conceiving a child is:

$$\begin{aligned} U^{NC}(\Omega_i) &= u\left(b + Hw_H, N, H, age_K\right) \\ &\quad +\beta(1-\phi_U)E\max[\tilde{U}(\Omega'_{ii}), \tilde{O}(\Omega'_{ii})] \\ &\quad +\beta\phi_U\sum_j \phi_{i,j} E\max[\tilde{U}(\Omega'_{ii}), \tilde{O}(\Omega'_{ii}), \tilde{W}(\Omega'_{ij})] \end{aligned} \tag{10}$$

At the end of the period, she is offered a new job with probability ϕ_U and decides whether to accept that position or remain out of work. The value of unemployment while conceiving is

$$\begin{aligned} U^C(\Omega_i) &= u\left(b + Hw_H, N, H, age_K\right) \\ &\quad +\pi(age_M)\beta EM^U(\Omega'_{i,P}) \end{aligned} \tag{11}$$

$$
\begin{aligned}
&+(1-\phi_U)(1-\pi(age_M))\beta E\max[\tilde{U}(\Omega'_{i,i}),\tilde{O}(\Omega'_{i,i})]\\
&+\phi_U(1-\pi(age_M))\beta\sum_j\phi_{i,j}E\max[\tilde{U}(\Omega'_{i,i}),\tilde{O}(\Omega'_{i,i}),\tilde{W}(\Omega'_{i,j})]
\end{aligned}
$$

The value of being out of work and trying to conceive a child is modeled as:

$$
\begin{aligned}
O^C(\Omega_i) &= u\left(Hw_H,N,H,age_K\right) \\
&+\pi(age_M)\beta EM^U(\Omega'_{i,P}) \\
&+(1-\phi_O)(1-\pi(age_M))\beta EO(\Omega'_{i,i}) \\
&+\phi_O(1-\pi(age_M))\beta E\sum_j\phi_{ij}\max[\tilde{O}(\Omega'_{i,i}),\tilde{W}(\Omega'_{i,j})]
\end{aligned} \tag{12}
$$

whereas the value of not conceiving is:

$$
\begin{aligned}
O^{NC}(\Omega_i) &= u\left(Hw_H,N,H,age_K\right) \\
&+(1-\phi_O)\beta EO(\Omega'_i) \\
&+\phi_O\beta E\sum_j\phi_{ij}\max[\tilde{O}(\Omega'_{i,i}),\tilde{W}(\Omega'_{i,j})]
\end{aligned} \tag{13}
$$

where ϕ_O is the probability of receiving an offer when out of the labor force. It should be noted that from this state, it is impossible to become unemployed and start claiming benefits. Maternity leave lasts for two periods during which the mother is not working and receives maternity benefit b_M. The value of maternity for a woman who previously worked is defined as

$$
\begin{aligned}
M(\Omega_i) &= u\left(b_M+Hw_H,O_i,H,N,age_K\right)+\beta u\left(b_M+Hw_H,O_i,H,N,age_K\right) \\
&+(1-\phi_O)\beta^2\sum_j\phi_{i,j}E\max[\tilde{W}(\Omega'_{ii}),\tilde{U}(\Omega'_{ii}),\tilde{O}(\Omega'_{ii})] \qquad (14)\\
&+\phi_0\beta^2\sum_j\phi_{i,j}E\max[\tilde{W}(\Omega'_{ii}),\tilde{W}(\Omega'_{i,j}),\tilde{U}(\Omega'_{ii}),\tilde{O}(\Omega'_{ii})]
\end{aligned}
$$

where the new state space is

$$
\Omega'_{j,M}=\begin{pmatrix} age_M+T_M \\ X+T_M\rho(i,j,U) \\ Occup=j \\ N \\ T_M \\ H' \end{pmatrix}
$$

$$
\begin{aligned}
M_{i,U}(\Omega) &= u(b_M + Hw_H, H, N)\frac{1-\beta^{T_M-1}}{1-\beta} \qquad (15)\\
&+\beta^{T_M}\left[(1-\phi_0)\beta EV_{iU}(\Omega_i') + \phi_0\beta\sum_j \phi_{i,j} E\max[\tilde{V}_{i,U}(\Omega_i'), \tilde{V}_j(\Omega_j')]\right]
\end{aligned}
$$

We define I_X to be an indicator variable taking the value of one if X is true and zero otherwise. We define γ as a vector of preference parameters. The utility function takes the following form:

$$
\begin{aligned}
u_i &= c_{is} + \gamma^1_{N,i} I_{n_{is}=1} + \gamma^2_{N,i} I_{n_{is}=2} + \gamma_{NH} I_{n_{is}>0\&h_{is}=1} \qquad (16)\\
&+\gamma^1_{PT} I_{l_{is}=PT} + \gamma^1_U I_{l_{is}=U} + \gamma^1_{OLF} I_{l_{is}=OLF}\\
&+I_{n_{is}>0}\sum_{i_O=1}^{O}\gamma_{i_o,FT} I_{o_{is}=i_o}\\
&+I_{n_{is}>0\&l_{is}=PT}\left[\gamma^1_{A,PT} I_{a_{is}\in[0,3]} + \gamma^2_{A,PT} I_{a_{is}\in[4,6]} + \gamma^3_{A,PT} I_{a_{is}\in[7,9]} + \sum_{i_o=1}^{O}\gamma_{i_o,PT} I_{o_{is}=i_o}\right]\\
&+I_{l_{is}=U}\left[\gamma^1_{N,U} I_{n_{is}=1} + \gamma^2_{N,U} I_{n_{is}=2}\right]\\
&+I_{n_{is}>0\&l_{is}=U}\left[\gamma^1_{A,U} I_{a_{is}\in[0,3]} + \gamma^2_{A,U} I_{a_{is}\in[4,6]} + \gamma^1_{A,U} I_{a_{is}\in[7,9]}\right]\\
&+I_{l_{is}=OLF}\left[\gamma^1_{N,OLF} I_{n_{is}=1} + \gamma^2_{N,OLF} I_{n_{is}=2}\right]\\
&+I_{n_{is}>0\&l_{is}=OLF}\left[\gamma^1_{A,OLF} I_{a_{is}\in[0,3]} + \gamma^2_{A,OLF} I_{a_{is}\in[4,6]} + \gamma^1_{A,OLF} I_{a_{is}\in[7,9]}\right]
\end{aligned}
$$

in which the first-line term is the utility i obtained from consumption (c_{is}) in period s. The individual also derives utility from the number of children. These parameters ($\gamma^1_{N,i}$, and $\gamma^2_{N,i}$) carry a subscript i because we allow for heterogeneity in the utility from children. Finally, we allow the utility from children to differ when a husband is present ($h_{is} = 1$), as indicated by the last term.

The second line of equation (16) is the utility of leisure, experienced when a woman is either working part time or not working. We distinguish here between women who are unemployed and those who are out of the labor force because the former may require time to search for a job. It should also be noted that because full time work is the baseline, we do not specify a utility level associated with that outcome. In the third line of equation (16), we allow the utility of full-time work in each occupation to depend on the presence of children, recognizing that some jobs may be more demanding in terms of work hours or offer less flexibility to take time out for child care.

The subsequent lines in equation (16) allow for different utilities obtained from part-time work or not working when children are present (relative to full-time work). In line 4, we allow mothers working part time to obtain utility from leisure (relative to full-time work) dependent on the age of their youngest child. Here, we distinguish between infancy (0 to 3 years), preschool (4 to 6 years), and primary school (7 to 9 years). We also allow the utility from leisure to vary with occupational type, captured by the last term in line 4. This variation accounts for the fact that in more demanding occupations, it may be more difficult to handle both part-time work and children. Line 5 allows the utility of leisure to vary with the number of children when the mother is unemployed, and line 6 allows it to differ with the age of the youngest child. Finally, lines 7 and 8 are similar to lines 6 and 7 when the individual is out of the labor force. Again, we expect the utility of leisure when unemployed to differ from that when out of the labor force because of job-seeking activities, especially when young children are present.

B.2 Numerical Solution to the Model

The model is solved by backward recurrence beginning at the end of life, which we set at 80 years. Between age 60 and 80, the individual is retired and infertile and therefore has no choices to make in terms of either labor supply or fertility. Prior to retirement, the individual is making choices about both these variables, although the probability of conception after age 55 is close to zero. We solve the model backward up to age 15, after which we solve for the optimal choice of initial occupation.

Because the state space of the model is large, we compute an age-specific value function - from age 15 to 80 - with a grid space of half a year. We allow women to have either 0, 1, or 2 children. We discretize the grid for the human capital stock to allow for four nodes and interpolate the value functions for the human capital values linearly between the nodes. To increase precision, we use a denser grid for low human capital value because the return to human capital is nonlinear. For example, in the data, we observe very flat wages after 15 years of experience. For the age of the youngest child, we choose a grid with four nodes, representing ages 0, 3, 6, and 9 years. For ages outside this grid, we interpolate the value functions linearly. This entire estimation is performed using the NAG e04ucf minimization routine together with the simplex algorithm.

B.3 Goodness of Fit

Tables B1 to B10 show the model fit along different dimensions, with the latter displaying the occupational choices both overall and in the initial period (at age 15). Both the initial and the overall proportion of women in each occupation are well fitted. Likewise, Table B3, which outlines the annual transition rate between occupations, indicates that persistence within occupational choice is closely fitted for all occupations. In Table B2, which shows the proportion of females in full-time work, part-time work, unemployment, and out of the labor force by age, the simulated proportions of females in full-time work and not working after age 20 are close to the observed proportions. Part-time work becomes more frequent with age both in the observed and simulated data, and the reverse holds for full-time work. The peak in the proportion of females out of the labor force at age 35 is also well matched.

The annual transition rates in work hours in each of the occupations is given in Table B1 in which the simulated data exhibit high persistence in each work-hour group, as in the observed data. The occupations also retain their relative persistence ranking in both full-time and part-time work. In the wage-experience profile for each occupation, given in Table B7, the simulated profile corresponds closely to the observed profile. Likewise, the returns to experience for both manual and abstract occupations are similar in both observed and simulated data, especially at low levels of experience. Table B8 shows the wage losses at return to work after interruption. Longer breaks from work and interruptions later in the career imply larger wage losses in both the observed and simulated data. Moreover, a change in hours of work at return to employment implies a wage adjustment in the simulated careers which corresponds closely to the observed change.

The profile of the number of children by age is well fitted in the simulated data (Table B4): females begin bearing children at the same time in both the observed and simulated data. The timing of a second child is also well fitted, although a slightly larger fraction of simulated females either remain childless or have more than one child. Finally, the simulated data for the link between wages, number of children, and occupation, outlined in Table B9 with routine jobs as the reference occupation, match a concave profile over age and exhibit a "child penalty" that, as in the observed data, is increasing in the number of children. The part-time time wages given in this table are also well matched.

Table A1: Descriptive statistics: IAB and GSOEP sample

	N	mean	sd	min	max
A. IAB SAMPLE:					
age at LM entry	72430	17.4	1.53	15	21
year of LM entry	72430	1984	4.89	1976	1996
birth cohort	72430	1967	4.53	1955	1975
age at end apprenticeship	72430	19.6	1.69	16	26
age at last observation	72430	32.8	5.25	16	46
year at last observation	72430	2000	3.71	1977	2001
work spells[a]	2664789				
gross daily earnings (in Euro)[a,b]	2654637	54.2	21.6	1	137
censored earnings[a] (% of earnings obs)	6205	0.23%			
PT work spells[a] (% of work spells)	381647	14.3%			
nonwork spells[a]	1646214				
unemployment spells[a] (% of nonwork spells)	205715	12.5%			
out of LF spells[a] (% of nonwork spells)	1440499	87.5%			
occupation of apprenticeship:	72409				
(1) Routine	18073	24.9%			
(2) Abstract	32421	44.8%			
(3) Manual	21915	30.3%			
B. GSOEP SAMPLE:					
age observed	16144	31.1	7.52	17	51
year observed	16144	1995	6.33	1984	2006
age at first observation	1432	23.8	5.96	17	50
age at last observation	1432	34.3	8.99	17	51
birth cohort	1432	1965	5.33	1955	1975
# years observed	1432	11.3	7.59	1	23
work spells [a]	9703				
PT work spells (% of work spells)	3095	31.9%			
monthly earnings (in Euro)[a]	8880	1450	666	31.7	7117
age mother when first child	810	26.0	4.39	18	40
age mother when second child	523	28.7	4.06	19	42
total fertility (age 39): # children	502				
0	78	15.6%			
1	124	24.7%			
2	216	43.0%			
≥3	84	16.7%			

[a] after apprenticeship

[b] daily earnings in IAB data are censored from above (if above the 'upper earnings limit'); censored daily earnings are included in earnings observations, with reported earnings=limit

Table A2: Most Frequent Occupations and Classification

Description	Proportion	Category
Secretaries/office clerks	25.80%	Abstract
Sales person/shop assistant	12.30%	Routine
Consultation hour assistant	7.65%	Manual
Nurse	6.01%	Manual
Bank specialists/professionals	5.35%	Abstract
Hairdresser	3.92%	Manual
Stenographer	3.27%	Abstract
Wholesale and retail sales people	3.02%	Abstract
Accountant, tax advisor	1.50%	Abstract
Design draftsman	1.38%	Abstract
Insurance specialists	0.98%	Abstract
Sewer	0.94%	Routine
Bookkeeper	0.90%	Abstract
Cook	0.87%	Routine

Note: These occupations represent 73% of all occupations in our sample.

Table B1: Goodness of Fit: Annual Transition Rate: Hours of Work

	From full-time work							
	Observed				Simulated			
	Full Time	Part Time	Unemployed	OLF	Full Time	Part Time	Unemployed	OLF
Routine	0.88	0.014	0.041	0.068	0.85	0.013	0.045	0.091
	(0.002)	(0.0006)	(0.001)	(0.001)				
Abstract	0.92	0.0089	0.022	0.053	0.91	0.0076	0.032	0.049
	(0.001)	(0.0003)	(0.0006)	(0.0008)				
Manual	0.89	0.014	0.034	0.065	0.88	0.01	0.039	0.067
	(0.002)	(0.0006)	(0.001)	(0.001)				
	From part-time work							
	Observed				Simulated			
	Full Time	Part Time	Unemployed	OLF	Full-time	Part-time	Unemployed	OLF
Routine	0.04	0.84	0.029	0.089	0.0036	0.84	0.063	0.089
	(0.002)	(0.003)	(0.002)	(0.003)				
Abstract	0.035	0.88	0.018	0.069	0.01	0.87	0.037	0.083
	(0.002)	(0.003)	(0.001)	(0.002)				
Manual	0.041	0.86	0.023	0.077	0.008	0.88	0.039	0.077
	(0.002)	(0.004)	(0.002)	(0.002)				
	From unemployment							
	Observed				Simulated			
	Full-time	Part-time	Unemployed	OLF	Full-time	Part-time	Unemployed	OLF
Routine	0.18	0.059	0.6	0.16	0.17	0.14	0.55	0.15
	(0.005)	(0.003)	(0.006)	(0.004)				
Abstract	0.25	0.05	0.53	0.16	0.25	0.094	0.47	0.18
	(0.006)	(0.003)	(0.007)	(0.004)				
Manual	0.28	0.056	0.5	0.17	0.29	0.097	0.42	0.2
	(0.009)	(0.004)	(0.01)	(0.006)				
	From out of labor force							
	Observed				Simulated			
	Full-time	Part-time	Unemployed	OLF	Full-time	Part-time	Unemployed	OLF
Routine	0.031	0.026	0.027	0.92	0.067	0.036	0	0.9
	(0.0007)	(0.0008)	(0.0009)	(0.001)				
Abstract	0.053	0.037	0.028	0.88	0.096	0.059	0	0.84
	(0.001)	(0.001)	(0.0009)	(0.002)				
Manual	0.044	0.031	0.023	0.9	0.063	0.023	0	0.91
	(0.001)	(0.0009)	(0.001)	(0.002)				

Note: Data source: IAB. Observed transition rates based on 925602 observations. Simulated moments based on 10,000 replications.

Table B2: Goodness of Fit: Hours of Work by Age

Age	Full-time		Part-time		Unemployed		OLF	
	Observed	Simulated	Observed	Simulated	Observed	Simulated	Observed	Simulated
20	0.769 (0.001)	0.791	0.0401 (0.0008)	0.0213	0.0836 (0.0006)	0.0151	0.107 (0.001)	0.173
25	0.615 (0.001)	0.598	0.0588 (0.0007)	0.0738	0.0639 (0.0005)	0.00632	0.263 (0.001)	0.322
30	0.375 (0.001)	0.382	0.109 (0.0007)	0.12	0.0588 (0.0005)	0.037	0.457 (0.001)	0.46
35	0.26 (0.001)	0.272	0.181 (0.0008)	0.175	0.0536 (0.0006)	0.0728	0.506 (0.001)	0.48
40	0.254 (0.002)	0.237	0.245 (0.001)	0.227	0.0492 (0.0008)	0.0665	0.452 (0.002)	0.469

Note: Data source: IAB. Observed moments based on 81343 observations. Simulated moments based on 10,000 replications.

Table B3: Goodness of Fit: Annual Transition Rate between Occupation

Occupation	Observed			Simulated		
	Routine	Abstract	Manual	Routine	Abstract	Manual
Routine	0.98 (0.001)	0.012 (0.0009)	0.005 (0.0006)	0.97	0.019	0.0091
Abstract	0.0058 (0.0005)	0.99 (0.0005)	0.0023 (0.0003)	0.0088	0.99	0.00052
Manual	0.007 (0.0008)	0.0055 (0.0007)	0.99 (0.001)	0.0066	0.009	0.98

Note: Data source: IAB. Simulated moments based on 10,000 replications.

Table B4: Goodness of Fit: Number of Children by Age

Age	No children		One child		Two or more	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
20	0.981 (0.008)	1	0.0178 (0.007)	0	0.0009 (0.0006)	0
25	0.65 (0.02)	0.667	0.255 (0.01)	0.241	0.0946 (0.009)	0.0916
30	0.315 (0.03)	0.33	0.305 (0.01)	0.302	0.38 (0.02)	0.368
35	0.16 (0.02)	0.187	0.266 (0.02)	0.248	0.574 (0.04)	0.565
40	0.14 (0.03)	0.117	0.259 (0.03)	0.197	0.601 (0.05)	0.686

Note: Data source: GSOEP. Simulated moments based on 10,000 replications.

Table B5: Goodness of Fit: Spacing of Births

Decile	Age at first birth		Age at second birth	
	Observed	Simulated	Observed	Simulated
10	21.1 (0.26)	21	23 (0.33)	24
20	22.6 (0.26)	22	24.9 (0.36)	25.5
30	24.2 (0.26)	23.5	26.1 (0.26)	27
40	25.2 (0.2)	25	27.1 (0.28)	28
50	26.4 (0.18)	26	28.3 (0.38)	29.5
60	27.4 (0.15)	27.5	29.5 (0.31)	30.5
70	28.5 (0.31)	28.5	30.6 (0.26)	32.5
80	30.3 (0.23)	31	31.8 (0.36)	34.5
90	32.3 (0.36)	34	33.5 (0.43)	37
100	39.7 (0.36)	40	41.2 (0.43)	40

Note: Data source: GSOEP. Simulated moments based on 10,000 replications.

Table B6: Goodness of Fit: Wage by Age and Initial Occupation

Age	Routine		Abstract		Manual	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
20	40.8 (0.09)	41.8	47.3 (0.08)	50.2	39.5 (0.09)	41.1
25	50 (0.08)	50.7	60.5 (0.07)	62.4	51.4 (0.07)	50.8
30	50.8 (0.09)	50.7	66.1 (0.07)	65.2	52.3 (0.08)	52.9
35	47.6 (0.1)	47.2	60.9 (0.09)	61.1	48.8 (0.1)	50.4
40	47.8 (0.2)	47.1	58.8 (0.1)	57.2	48.9 (0.2)	48.4

Note: Data source: IAB. Simulated moments based on 10,000 replications.

Table B7: Goodness of Fit: Log Wage Regression

Variable	Routine		Abstract		Manual	
	Obs.	Simul.	Obs.	Simul.	Obs.	Simul.
Experience	0.0574 (0.0005)	0.0602	0.0503 (0.0003)	0.06	0.0616 (0.0006)	0.0681
Experience^2	-0.00157 (2e-05)	-0.002	-0.00132 (1e-05)	-0.00145	-0.00192 (3e-05)	-0.0021
Constant	3.43 (0.003)	3.45	3.7 (0.002)	3.64	3.48 (0.004)	3.4

Note: Data source: IAB. Regression done on 183,917, 213,832, 497,245 and 190,198 observations respectively. Simulated moments based on 10,000 replications. Experience is real experience, defined as the number of years worked.

Table B8: Goodness of Fit: Log Wage Change Regression for Interrupted Spells

	Observed		Simulated.
Duration of interruption	-0.0062	(0.003)	-0.0019
Experience 5-8 years	-0.047	(0.01)	-0.053
Experience >8 years	-0.068	(0.02)	0.0043
Abstract	0.026	(0.01)	-0.024
Manual	0.045	(0.01)	-0.0011
Abstract, experience 5-8 years	-0.085	(0.02)	-0.006
Manual, experience 5-8 years	-0.083	(0.02)	0.0072
Abstract, experience > 8 years	-0.096	(0.02)	-0.053
Manual, experience > 8 years	-0.12	(0.02)	-0.0018
Part-time to full-time	0.37	(0.01)	0.54
Full-time to part-time	-0.41	(0.006)	-0.54
Duration, experience [5-8] years	-0.019	(0.004)	0.0034
Duration, experience >8 years	-0.03	(0.004)	-0.013
Constant	-0.026	(0.02)	0.0078

Note: Data source: IAB: Regression done on 52,958 observations. Simulated moments based on 10,000 replications. Experience is defined as the number of years worked.

Table B9: Goodness of Fit: Log Wage, Children and Occupation

Variable	Observed		Simulated
	Coeff	s.e.	Coeff
Age	0.16	(0.008)	0.14
Age square	-0.0022	(0.0001)	-0.002
Children = 1	-0.15	(0.02)	-0.093
Children $\geq$ 2	-0.39	(0.03)	-0.15
Abstract	0.14	(0.01)	0.22
Manual	-0.024	(0.02)	-0.015
Abstract * Child=1	0.057	(0.03)	0.054
Manual * Child=1	0.031	(0.04)	0.043
Abstract * Child$\geq$ 2	0.12	(0.03)	0.0081
Manual * Child$\geq$ 2	0.16	(0.04)	0.049
Part Time	-0.72	(0.01)	-0.59
Constant	1.1	(0.1)	1.7

Note: Data source: GSOEP. Simulated moments based on 10,000 replications.

Table B10: Goodness of Fit: Occupational Choices

Occupation	Observed		Simulated
		All periods	
Routine	24.5	(0.12)	24.7
Abstract	51.4	(0.15)	53.1
Manual	24.1	(0.11)	22.2
		At age 15	
Routine	25.8	(0.93)	26.5
Abstract	45.8	(0.88)	41.4
Manual	28.4	(0.81)	32.1

Note: Data source: IAB. Proportion for all ages based on 248,023 observations. Proportion at age 15 based on 27,979 observations. Standard deviation calculated through bootstrap in parenthesis. Simulated moments based on 4,000 replications.

Table B11: Estimated Parameters: Utility

Parameter	Estimate
Utility of work	
Utility of unemployment	2.78 (0.003)
Utility of out of labor force	48.8 (0.03)
Utility of part-time work	0.342 (0.0002)
Utility of occupation if children, routine	30.9 (5.8)
Utility of occupation if children, abstract	6.31 (1.3)
Utility of occupation if children, manual	0 (-)
Utility of unemployement if # child $\geq$1	25.1 (0.00048)
Utility of unemployement if # child ≥ 2	-24.8 (0.0082)
Utility of unemployement if age child ≤ 3	28.3 (0.00034)
Utility of unemployement if age child $\in]3,6]$	-129 (3e-06)
Utility of unemployement if age child $\in]6,10]$	101 (9.7e-07)
Utility of no work if # child $\geq$1	24 (0.066)
Utility of no work if # child ≥ 2	7.36 (0.012)
Utility of no work if age child ≤ 3	5.73 (0.0029)
Utility of no work if age child $\in]3,6]$	23.7 (0.00072)
Utility of no work if age child $\in]6,10]$	-3.38 (0.00081)
Utility of part-time work and children, routine	32.7 (0.043)
Utility of part-time work and children, abstract	34 (0.02)
Utility of part-time work and children, manual	33.3 (0.96)
Utility of part-time work and # children≥ 2	-16.1 (0.00064)
Utility of part-time work and age child ≤ 3	-23.2 (0.0004)
Utility of part-time work and age child $\in]3,6]$	21.1 (0.021)
Utility of part-time work and age child $\in]6,10]$	24.4 (0.049)
Utility of children	
Utility of one child	-1.5 (1.3e-05)
Utility of two children	-0.572 (3.3e-06)
Utility of children * not married	-80.2 (0.0801)

Note: Asymptotic standard errors in parenthesis.

Table B12: Estimated Parameters: Probability of Occupation and Hours of Work Offers

	Routine		Abstract		Manual	
Previous Status	PT	FT	PT	FT	PT	FT
Routine job PT	0.91	0.032	0.032	0.02	0.0007	0.0007
	(0.0011)	(0.00055)	(0.00055)	(2.4e-05)	(1.2e-05)	(1.2e-05)
Routine job FT	0.013	0.95	0.013	0.00029	0.021	0.00029
	(2.3e-06)	(4.6e-06)	(2.3e-06)	(5e-08)	(1e-07)	(5e-08)
Abstract job PT	0.007	0.007	0.96	0.00015	0.00015	0.021
	(6.6e-07)	(6.6e-07)	(1.3e-06)	(1.4e-08)	(1.4e-08)	(2.9e-08)
Abstract job FT	0.021	0.00073	0.00073	0.91	0.032	0.032
	(2.5e-05)	(1.3e-05)	(1.3e-05)	(0.0011)	(0.00055)	(0.00055)
Manual job PT	0.0003	0.022	0.0003	0.013	0.95	0.013
	(5.2e-08)	(3e-07)	(5.2e-08)	(2.3e-06)	(4.6e-06)	(2.3e-06)
Manual job FT	0.00016	0.00016	0.022	0.007	0.007	0.96
	(1.5e-08)	(1.5e-08)	(2.9e-07)	(6.6e-07)	(6.6e-07)	(1.3e-06)

Note: Semi-annual offer rates. Asymptotic standard errors in parenthesis. PT, FT: part-time and full-time job.