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ABSTRACT

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We investigate the importance of various mechanisms by which child care policies can affect life-cycle patterns of employment and fertility among women, as well as long-run cognitive outcomes among children. A structural life-cycle model of employment, fertility, and child care use is estimated using Norwegian administrative data. The estimation exploits a large-scale child care reform, which provided generous cash transfers to mothers who did not use formal child care facilities. Combining with administrative data on national test scores, we examine the effects of mother's behavior on long-run cognitive outcomes of children, via estimating a cognitive ability production function that corrects for the endogeneity of inputs. We find that the child care reform generates sizable changes in employment and fertility decisions, especially among low-education women. This leads to lower reading scores among children, primarily as a result of mothers shifting away from formal care and becoming employed. Simulation results suggest that a partial reform, in which workers are ineligible for cash transfers, can generate a more balanced impact on the population. The implications of tax policy and maternity leave are also investigated.

JEL Classification: D91, J13, J22

Keywords: child care, maternal employment, cognitive production function

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1 Introduction

The dramatic increase in labor force participation among women in the past few decades was accompanied by fundamental changes in how families raise their young children. Stay-at-home mothers became increasingly rare, and the use of non-maternal child care became increasingly common. In 1950, only 12 percent of married women with children under six were working in the United States; by 2000, this number had increased to over 60 percent (Blau and Currie, 2006). The labor force participation rate among married and cohabiting women with children has also risen substantially in European countries.[1]

In recent years, there has been an increasing advocacy for more government intervention in child care at early ages. In the State of the Union address in 2013, President Obama proposed to make "high-quality preschool available to every single child in America." In many other economies, child care reforms aiming to provide affordable child care have been or are being implemented (Bennett and Tayler, 2006). However, child care policies are costly to the government due to their generosity and broad coverage of the population. Changes to child care policies have also led to widespread concerns about the consequences for the wellbeing of children.

In this paper, we use a structural life-cycle model and a large-scale child care reform in Norway to understand the effect of child care polices on life-cycle decisions among women and long-run cognitive outcomes among children. There are a number of key questions being addressed: (i) What are the implications of child care policies for labor supply, child care use, and fertility decisions of women over the life cycle? (ii) What are the effects on long-run cognitive development of children, and which underlying mechanisms are important? (iii) What is the effective design of child care policy, and how does it relate to tax policy and other programs such as maternity leave programs?

Answering these questions has proven to be quite difficult, as there remains a large knowledge gap in the area. Existing research on the incentive effects of child care policies is largely confined to static analysis with an emphasis on maternal employment.[2] These studies do not address important issues such as human capital formation and fertility decisions. Although there exists a large literature on dynamic labor supply and fertility decisions (e.g., Moffitt (1984), Hotz and Miller (1988), Francesconi (2002), Gayle and Miller (2006), Adda, Dustmann, and Stevens (2011)),

[1]For instance, in Norway, the labor force participation rate among married and cohabiting women with children under 16 years of age increased from 17 percent in 1970 to over 80 percent in 2001 (Ljones, 1979; Statistics Norway, 2001).

[2]For instance, see Blau and Robins (1988), Connelly (1992), Michalopoulos, Robins, and Garfinkel (1992), Ribar (1992), Ribar (1995), and Averett, Peters, and Waldman (1997).

child care decisions are often overlooked. Traditionally, analysis of the effect of child care policies on children's cognitive outcomes has been limited by the lack of significant policy changes and detailed data.[3] Only recently much progress has been made by using specific policy reforms to indirectly evaluate the mechanisms that determine cognitive development (e.g., Bernal and Keane (2011), Dahl and Lochner (2012)).[4]

In this paper, we construct a discrete choice dynamic programming model to determine the importance of various mechanisms by which child care policies can affect life-cycle patterns of employment and fertility among women, as well as cognitive outcomes among children. In the model, the woman's fertility decisions are formulated jointly with labor supply and child care use decisions; both skill endowments and preferences are subject to heterogeneity. The budget constraint includes income tax, the deduction schedule of child care expenses, and major family transfer programs including maternity leave, child subsidy, and the cash-for-care program discussed below.

Our structural model is estimated using administrative data from Norway between 1993 and 2005. We exploit a large-scale child care reform in the period of study as a source of identification to the model.[5] In 1998, Norway implemented the Cash-for-Care reform (kontantstøtte), which provided cash to families with young children who did not use formal child care facilities. The reform resulted in a large exogenous change in the relative price of child care facilities. The child age restrictions on cash-for-care eligibility creates variations in exposure to benefits across child cohorts. In addition, the implementation of the reform generates notable differences in life-cycle exposure to benefits across women cohorts. By exploiting the above features and large-scale administrative data, we are able to select several key cohorts that can maximize the variation in the degree of exposure to the reform.

Combining with administrative data on national test scores beyond age 10, we study the implications of various policies for children's long-run cognitive outcomes. There is an extensive

[3] As a result, the literature has found inconclusive evidence that maternal employment can worsen child outcomes (Blau and Currie, 2006; Blau, 1999; Gregg, Washbrook, Propper, and Burgess, 2005). The literature is also relatively silent on the roles of the underlying mechanisms. On the one hand, maternal employment crowds out parental time with children. On the other hand, it increases family income, which affects child development directly or via the use of non-maternal child care.

[4] The above studies use welfare reform and the expansion of Earned Income Tax Credit, respectively. Also see, for example, Baker and Milligan (2010); Dustmann and Schönberg (2012); Carneiro, Løken, and Salvanes (2015) on evidence from maternity leave reforms, and Baker, Gruber, and Milligan (2008) and Havnes and Mogstad (2011) on evidence from child care reforms. These studies do not directly estimate the cognitive ability production function of children.

[5] In recent years, progress has been made in synergizing the methodological approaches undertaken by reduced-form and structural studies (e.g., Todd and Wolpin (2006), Attanasio, Meghir, and Santiago (2011), Ferrall (2012) on policy experiments; Chan (2013) and Blundell, Dias, Meghir, and Shaw (2013) on large scale reforms).

literature suggesting that the production of cognitive ability is determined by early inputs, and in the estimation of the production technology, it is important to correct for endogeneity bias resulting from unobserved child-specific endowment effects (Todd and Wolpin, 2003, 2007; Cunha, Heckman, and Schennach, 2010). Our cognitive ability production function accounts for the main features that are considered important by this literature. We address the potential source of endogeneity bias by a control function approach, where the estimated structural model is used to predict a mother's unobserved characteristics, in particular, skill endowment (and hence the child endowment), conditional on her observed behavior. Although our cognitive ability production is estimated "outside" of the structural model, it accounts for the unobserved heterogeneity of the mother and there are some practical advantages to this stepwise approach. This includes a more flexible production function to be estimated, less restriction regarding the woman's information set on each child's cognitive ability, and maintaining computational tractability even in the presence of endogenous fertility and multiple children.

Closely related to our paper is a recent important paper by Bernal (2008), who estimates a dynamic model of maternal employment and child care decisions using data from NLSY79.[6] Her model focuses on maternal decisions within the first five years after child birth.[7] We attempt to build upon Bernal (2008) along the following dimensions.[8] First, we incorporate fertility decisions, so that employment, child care use, and pregnancy depend on both the number and age of children, which are endogenous in the model. Second, we extend the model and data to a life-cycle framework, so as to analyze women's decisions both prior to and after child birth. Finally, by formally utilizing the child care reform in estimation, the identification strategy is potentially more robust than using pre-existing variations of women's behavior in the data to identify the model.

The key findings are summarized as follows. Child care policies have important implications for

[6] Del Boca, Flinn, and Wiswall (2014), Gayle, Golan, and Soytas (2014) and Griffen (2015) are important recent contributions. Del Boca, Flinn, and Wiswall (2014), households make labor supply decisions and decide on the allocation of parental time and pecuniary investments in child quality production. They emphasize the importance of parental time inputs on child development, and do not focus on other dimensions such as child care use, fertility, and unobserved heterogeneity. Focusing on explaining racial difference in the intergenerational transmission of human capital, Gayle, Golan, and Soytas (2014) estimate a dynastic model of parental time and monetary inputs in early childhood with endogenous fertility, home hours, labor supply, marriage, and divorce. Their results suggest significant returns to parental time investment in children mainly through improved education outcomes. Griffen (2015) builds on Bernal (2008) by considering heterogeneity in price and quality of child care programs. In addition, mothers can choose to enrol in Head Start, a federally funded preschool program for poor children. The above features are very important in the United States. By contrast, the Norwegian system is highly homogenous (see Section 2).

[7] The sample consists of mothers for the first five years after the birth of the child and who do not have an additional child during that period.

[8] Using cognitive scores from the preschool period, Bernal (2008) focuses on how early cognitive development can affect mothers' decisions. By contrast, we focus on how early post-natal intervention can affect the child's cognitive outcomes at a much later age. See the estimation section for more details.

the life-cycle decisions of women. For instance, by heavily subsidizing mothers, an early exposure to the cash-for-care reform can generate sizable changes in employment and fertility decisions, especially among low-education women. Counterfactual exercises suggest that if the implementation of the program begins at age 19, then by age 30, the program will have reduced the employment rate of these women by 3.1 percentage points (-5 percent), and increased the average number of children by 0.25 (+26 percent). In addition, although the reform substantially reduces child care use among mothers by 5.9 percentage points, the *overall* rate of child care use is almost unaffected due to increased fertility. Due to large behavioral effects on low-education women, on a per-person basis the reform is 1.6 times more expensive to implement among low-education women than high-education women; however, it generates smaller increases in utility among low-education women (both measured over a 12-year period).

We find that formal child care is substitutable from maternal care in the production of cognitive skills among high-education mothers, but much less so among low-education mothers. For instance, among low-education mothers, an additional year of being not employed and not using formal care between age 1 and 3 reduces the child's average reading test score (as measured beyond age 10) by 6.5 percent, or 0.15 sd, relative to an additional year of formal care use. The corresponding change in reading scores is almost zero among the children of high-education mothers. For both types of mothers, we also find that informal nonmaternal care leads to worse cognitive skills relative to maternal care. The primary cognitive skill being affected is reading instead of mathematics, although there is some evidence pointing to English skills (as a foreign language) as well. The implications of policy for the long-run cognitive development of children is somewhat mixed. Taking into account of various mechanisms, we find that the cash-for-care reform reduces the reading score by 0.03 sd among preexisting children of low-education mothers. Keeping income constant, the reduction would have been 0.043 sd due to mothers shifting away from formal care and becoming employed. The new children born under the reform tend to bring the average score even lower.

We examine several counterfactual policies as alternative options, including a partial cash-for-care program in which workers are ineligible for benefits, an expansion of the maternity leave program, and an introduction of income tax deductions for the presence of children. Although the partial cash-for-care program generates a larger work disincentive than the full program, it has a smaller effect on fertility, and is far less expensive to implement. In addition, if the full program is changed to a partial program, reading scores among children of low-education mothers will increase by 0.05 standard deviations. The maternity leave expansion and tax deduction tend to have a more balanced impact in the population, and their effects on children's reading scores are relatively small.

The paper is organized as follows. Section 2 provides institutional background of the reform. Section 3 describes the dynamic model. Section 4 presents the data, sample construction and summary statistics, followed by a discussion of identification and estimation strategy in Section 5. Section 6 presents estimation results and conducts counterfactual policy analysis. Section 7 concludes.

2 Institutional Background

Norway offers generous support to families with children. During the period of our study, in the first year since the birth of a child, parents were entitled to 42 weeks of parental leave with full compensation, or alternatively 52 weeks with 80 percent wage compensation.[9] After then and until the child turns to school age, family welfare policy focuses on the provision of subsidized child care. When the child becomes one year old, families have the option to use child care centers at a price that is heavily subsidized relative to the cost.[10] Our definition of formal child care is subsidized child care, which includes both public and private child care centers. Both public and private centers have the same price schedule for parental pay and are equally subsidized. The costs of a day care center are shared between the state, the municipality, and the parents. In 1998, the average monthly parental payment was approximately 3,500 Norwegian kroner (NOK - approximately 470 USD at the 1998 exchange rate). The Day Care Act (Barnehageloven) stipulates national standards regulating both public and private care centers. There are national requirements concerning size, child to staff ratio, staff qualifications, playground facilities, and total area within the center. The curriculum is centrally determined, with a strong focus on learning through social relationships both with other children and with adults in the day care centers.[11]

The cash-for-care reform was introduced in 1998. According to the legislation, there were three main purposes of this reform: give more freedom of choice to parents of form of care, provide

[9] In the period of study, four weeks out of the 42 weeks of paid parental leave were reserved exclusively for the father (paternity quota). Apart from the exclusive quotas, parents could share the remaining periods of parental leave between them as they desired, with the restriction that mothers and fathers could not both take leave at the same time. The majority of fathers (close to three quarters) take exactly four weeks of the quota (Cools, Fiva, and Kirkeben, 2015).

[10] Subsidized child care saw its largest expansion in the late 1970s supported by increased funding from the federal government. From a total coverage rate of less than 10 percent for 3 to 6 year old children in 1975, coverage had gone up to over 40 percent by 1985 (Havnes and Mogstad, 2011).

[11] Apart from formal child care which is strictly regulated and publicly subsidized, families may also choose informal care – care provided by nannies or close family such as grandparents. Informal care is ineligible for public subsidy and is not subject to public regulations.

parents with more time to be with their children, and redistribute to families that do not benefit from publicly subsidized day care (Kontantstttteloven §1 1998). From August 1st 1998 the cash-for-care benefit was available to children aged 1 (13 to 24 months), and from January 1st 1999 it was expanded to apply to children aged 1 and 2 (13 to 36 months). All parents with children in this age group who do not use publicly subsidized day care are entitled to the subsidy. To receive the full subsidy, the child must not attend a publicly subsidized day care center.[12] In addition, there is no obligation for parents who claim the benefit to stay at home and care for the children themselves. The subsidy is a flat, tax-free payment, paid out monthly from the month after the child is one year old (from month 13), until the month the child is three years old (36 months). The subsidy was set to 3,000 NOK per month in 1998.[13]. The subsidy was approximately equal to the state subsidy for a place in a day care center.

3 Economic Model

The decisions of the adult individual follow a discrete choice dynamic programming model, which is described as follows. In each decision period t (year), individual i chooses her level of labor supply, which involves no work ($h_{it}^p = h_{it}^f = 0$), part-time work ($h_{it}^p = 1, h_{it}^f = 0$), or full-time work ($h_{it}^p = 0, h_{it}^f = 1$). The employment indicator is denoted by $h_{it} \equiv h_{it}^p + h_{it}^f$. If the individual has less than three children, she can also decide whether to become pregnant ($p_{it} \in \{0, 1\}$). In addition, if her first or second child is between age 1 and 3, she faces a decision of whether to put that child in a formal child care facility ($c_{it} \in \{0, 1\}$).

The choice process is further simplified according to the underlying data structure and policy environment. If the individual has a child of age 0 (i.e., first year following birth), she cannot become employed or pregnant for that period. For a mother whose first and second child are *both* between age 1 and 3, both children will be in child care if the mother uses child care at all. Therefore, the total number of feasible choices can be 1, 2, 3, 6, or 12 depending on the state variables.[14] The key state variables that determine the choice set are the number of children ($n_{it} = 0, 1, 2, 3$) and the ages of the first and second child ($a_{1it}, a_{2it} = 0, 1, 2, 3, 4$).[15] The latter state variables are crucial

[12] Parents of children that attend publicly subsidized day care on a part-time basis may receive a share of the full benefit depending on weekly attendance. In the data, more than 80 percent of the benefit recipients use day care for less than 10 hours per week.

[13] The subsidy was reduced to 2,263 NOK per month in 1999, before adjusted upward to 3,000 NOK per month in 2000 and then to 3,657 NOK per month from August 2003.

[14] For instance, if the individual's first child is aged between 1 and 3, and the second child is aged 0, then she can neither be employed nor pregnant, so she only faces a binary decision of whether to put the first child in child care.

[15] Child's age 4 is an absorbing state; for instance, for child 1, $a_{1it} = 0$ if $n_{it} = 0$ or $n_{it}p_{i,t-1} = 1$, else $a_{1it} =$

because the entitlement of cash-for-care benefits and maternity leave depends on children's age. The individual can have up to three children, and it is assumed that there are no child care choices related to the third child.[16]

Utility function. The "deterministic" part of the utility function takes the following form:

$$
\begin{aligned}
\bar{u}_{it} = {} & y_{it} + \alpha_h^p h_{it}^p + \alpha_h^f h_{it}^f + \alpha_c c_{it} + \alpha_p p_{it} + \alpha_{hc} h_{it} c_{it} + \alpha_{hp} h_{it} p_{it} \\
& + \alpha_{hn1} h_{it}^f n_{it} + \alpha_{hn2} h_{it}^p \mathbf{1}\{n_{it} > 1\} + \alpha_{cn1} c_{it} \mathbf{1}\{n_{it} \geq 1\}(n_{it} - 1) + \alpha_{cn2} c_{it} \mathbf{1}\{n_{it} \geq 1\} \mathbf{1}\{a_{1it} \geq 3\} \\
& + \alpha_{pn1} p_{it} \mathbf{1}\{n_{it} = 1\} + \alpha_{pn2} p_{it} \mathbf{1}\{n_{it} = 1\} \mathbf{1}\{1 \leq a_{1it} \leq 2\} \\
& + \max\{t - t_0 - 3, 0\}(\beta_{h1} h_{it} + \beta_{h2} h_{it}^f + \beta_p p_{it}) + \boldsymbol{x}_{cit}' \boldsymbol{\beta}_c c_{it} \\
& + \alpha_{hh} h_{i,t-1} h_{it} + \sum_{j=2}^{5} \mathbf{1}\{type = j\} \left(\mu_{hj} h_{it} + \mu_{pj} p_{it} \right).
\end{aligned}
$$

The individual's utility depends on her income (y_{it}), which is determined by a budget constraint that is discussed in detail below. She faces direct utilities of employment (α_h^p, α_h^f), child care use (α_c), and pregnancy (α_p). In addition, workers can face different utilities of child care use and pregnancy from nonworkers (α_{hc}, α_{hp}).

The utility parameters can have the following behavioral interpretation related to the form of child care. The choices represent three types of child care: maternal care (h=0, c=0); non-maternal informal care (h=1, c=0); formal care (c=1). Formal care is directly observed in the data. Maternal care and nonmaternal informal care are not directly observed but can be inferred from the data by combining women's labor supply decisions and formal child care choices. According to this formulation, the parameter α_c can be broadly interpreted as the utility of formal care relative to maternal care; $\alpha_c + \alpha_{hc}$ can be broadly interpreted as the utility of formal care relative to non-maternal informal care.

The model allows the utilities to differ by certain state variables. In particular, employment, child care use, and pregnancy depend on both the number and age of children, with corresponding

$\max\{a_{1i,t-1} + 1, 4\}$.

[16] We avoid modeling small categories because they provide limited identifying information regarding the underlying parameter(s) and do not justify the extra computational and modeling burden. The data related to the characterization of the model are described as follows. In the last period of the estimation sample (combining low- and high-education samples), only 5 percent of women have three children, and 2.5 percent have a third child aged 1 or above. Among all women with more than one child, 5 percent have births in consecutive years (first- and second-order births), and 80 percent have a birth gap between two and four years. Among all observations where child care choice is relevant, 82 percent involve child care choice for one child only. The estimated model is thus most useful for generating predictions that are related to the larger categories in the estimation sample. This does not preclude extending the model; for instance, it is possible to model up to four children in simulation exercises *after* estimation.

utilities captured by parameters $\alpha_{hn1}, \alpha_{hn2}, \alpha_{cn1}, \alpha_{cn2}, \alpha_{pn1}$, and α_{pn2}. The motivation is both methodological and empirical. Empirically, women's choice patterns differ nontrivially by number and age of children so the empirical model allows for some flexibility along these dimensions.[17] This is important given that the model is estimated by the method of maximum likelihood and the estimation procedure is based on matching the choice probabilities conditional on every state. Methodologically, the specification is consistent with the hypothesis that mothers care about the number and well-being of children, and provides multiple channels by which mothers can adjust their employment, child care, and fertility behavior according to the number and age of children.[18] For instance, if a mother cares about the well-being of the new child she may reduce labor supply after giving birth, and she may even adjust her pregnancy pattern based on the child's age. In both cases, the mother's preferences related to children's well-being will be reflected in the corresponding utility parameters.

An alternative approach is to allow for a specific dimension of children's well-being, such as cognitive ability, to enter into the adult's utility function directly. This approach is tractable when there is one child (e.g., Bernal (2008)), but the problem becomes substantially more complicated when fertility is endogenous. The model will require stronger assumptions regarding the woman's information set on each child's cognitive ability. For the model to be tractable, the extra elements may need to enter in a highly stylized way, e.g., certain patterns of substitutability or complementarity may need to be assumed. More importantly, there are practical limitations due to data availability. We only observe a child's test score after age 10, which is well beyond the age when mothers make child care decisions. Because early measures of cognitive ability are unavailable, it is extremely hard to investigate dynamics, e.g., how cognitive ability feeds back into mother's behavior. In addition, due to the sample window (see Section 4), the majority of test scores of the second child and almost all test scores for subsequent children in our sample are missing. These limitations prevent us from adopting a more structural approach.

One main drawback of our approach is that we are unable to disentangle how much of the woman's behavioral response to the child care reform can be attributed to preferences for the

[17] Certain parameters, which may appear more arbitrary than the others, are chosen partly due to strong empirical evidence along certain dimensions. We conducted a number of sensitivity analysis with alternative specifications (e.g., including $h^p_{it} n_{it}$), and find qualitatively similar results.

[18] Although the utility function does not contain direct terms on the number of children (e.g., n_{it} and n^2_{it}), these parameters can be estimated under the current parametric assumptions, with qualitatively similar results. Preference for children is primarily identified from observed pregnancy patterns in the data. We normalize the preference for no-child to zero, so that the preference for the first child is reflected in parameter α_p. The parameter also reflects the direct utility cost of pregnancy. Preference for subsequent children is reflected in parameters α_{pn1} and α_{pn2}.

cognitive ability of her children. For example, given the monetary incentives of cash subsidies from the Norwegian reform, we expect mothers to reduce formal care and they may increase their labor supply. However, if mothers also care about children and if informal care is inferior to formal care, they may choose a smaller change in behavior. Because our estimation sample covers cohorts of women who are exposed to the reform to varying degrees, we are able to measure the *overall* behavioral response from the data. However, we are unable to disentangle the relative roles of both types of incentives. Despite this drawback, we will explain in Section 5.3 how information from the structural model can be combined with the reform to estimate a cognitive ability production function that is "outside" of the structural model. There are some advantages to this stepwise approach. It allows for a more flexible production function, requires less restriction regarding the woman's information set on each child's cognitive ability, remains computationally tractable, and accounts for unobserved heterogeneity of the mother.

The parameters β_{h1}, β_{h2}, and β_p capture the differential utilities of employment and pregnancy in the early life cycle, with t_0 being the first decision period of the model. The vector of covariates $\boldsymbol{x}_{cit}$ includes two socioeconomic characteristics that influence behavior exclusively through the relative value of formal/informal care use: (1) the coverage rate of formal child care facilities at the individual's municipality of residence; and (2) whether the individual lives close to her parents (=1 if they are in the same municipality, =0 otherwise).[19] The parameter α_{hh} captures the degree of state dependence in work preference. The panel feature of the data allows for the modeling of unobserved heterogeneity, which is characterized by several "types" of individuals that differ in unobserved permanent characteristics (e.g., Heckman and Singer (1984)). The model has five unobserved types of individuals ($j = 1, ..., 5$), and the type-specific utilities of employment and pregnancy for a type-j individual are denoted by μ_{hj} and μ_{pj}, respectively. For a type-1 individual, μ_{h1} and μ_{p1} are normalized to zero. The properties of the unobserved types will be discussed further in the section on wage equation.

Consider an individual who faces a given choice set. The utility of alternative k, where k is an index representation of the choices, is the sum of the "deterministic" choice-specific utility $\bar{u}_{it}(k)$

[19] Both covariates capture differences in the supply of formal/informal child care across regions. Given the nature of the data, these supply-side changes are not separately identified from changes in preferences. To allow for broad changes over time, a linear function of calendar year is also included (normalized to zero in 1998 and bounded by the observed years in the sample).

and a choice-specific preference shock ϵ_{cikt}:

$$u_{ikt} = \bar{u}_{it}(k) + \epsilon_{cikt}.$$

The vector of choice-specific shocks is denoted by $\boldsymbol{\epsilon}_{cit}$, and is assumed to follow an i.i.d. extreme value distribution with means at Euler's constant and standard deviations at $(\pi/\sqrt{6})\sigma_c$, where $\pi/\sqrt{6} \approx 1.2825$ is a normalization constant.

Budget Constraint and Wage Function. The individual's income is determined by the following budget constraint:

$$\begin{aligned} y_{it} = {} & w_{it}(h_{it} + h_{it}^f) - T(w_{it}(h_{it} + h_{it}^f), D_c(c_{it}, n_{it})) - (P_{c1} + \mathbf{1}\{1 \le a_{1it} \le 3\}\mathbf{1}\{1 \le a_{2it} \le 3\}P_{c2})\, c_{it} \\ & + Z_{it}B_c \times (\mathbf{1}\{1 \le a_{1it} \le 3\} + \mathbf{1}\{1 \le a_{2it} \le 3\})\,(1 - c_{it}) + B_n n_{it} + B_m w_{it} p_{i,t-1} h_{i,t-1}. \end{aligned}$$

Gross earnings is the product of the wage rate (w_{it}) and work hours ($h_{it} + h_{it}^f$). A full-time worker is assumed to work twice as many hours as a part-time worker, and part-time work is normalized to take one unit of time. The individual pays income and payroll taxes, which are determined by a piecewise linear tax function $T(.)$ as defined in the Data Section. Income tax is a function of gross earnings as well as the amount of deduction due to expenses related to child care ($D_c(.)$). The individual also receives a child subsidy that pays B_n per period per child. If she was employed and pregnant last period, she will be entitled to a maternity leave benefit that is equal to a proportional adjustment of wage, $B_m w_{it}$.[20]

If the individual uses a formal child care facility, she pays P_{c1} for the first child, and a discounted price P_{c2} for the second child. If she does not use formal child care, she may receive a cash-for-care benefit B_c for each child who is within the eligible age. However, she can only receive this benefit if the cash-for-care program is present (i.e., $Z_{it} = 1$). Denote τ_i as the decision period in the model where the reform is first implemented. Then, we have $Z_{it} = 1$ if $t \ge \tau_i$ and $Z_{it} = 0$ if $t < \tau_i$. In the data, τ_i is defined as the implementation calendar date of the reform less the individual's birth year.

[20]Lagged pregnancy status $p_{i,t-1}$ is defined from other state variables as follows: its value equals to one if $n_{it} = 1$ and $a_{1it} = 0$, or if $n_{it} = 2$ and $a_{2it} = 0$.

The log wage equation is given as follows:

$$\ln w_{it} = \beta_{w0} + \beta_{we1}\mathcal{E}_{it} + \beta_{we2}\mathcal{E}_{it}^2 + \beta_{w1}x_{wit} + \sum_{j=2}^{5} \mathbf{1}\{type = j\}\mu_{wj} + \epsilon_{wit}$$

The wage depends on the individual's work experience ($\mathcal{E}_{it}$) as defined by cumulative periods of employment (part-time or full-time) since the first decision period, and the unemployment rate in her municipality of residence (x_{wit}), which enters into the model through the wage equation exclusively. The log wage is subject to a normally distributed shock ϵ_{wit}, which has standard deviation σ_w and is serially uncorrelated and independent of the preference shocks.

The log wage also depends on an unobserved permanent component μ_{wj} that is specific to a type-j individual. For a type-1 individual, μ_{w1} is normalized to zero. Therefore, μ_{wj} is the permanent percent-difference in skill endowment between a type-j individual and a type-1 individual, all else being equal. For a type-j individual, her overall type-specific characteristics are given by the tuple $(\mu_{wj}, \mu_{hj}, \mu_{pj})$. Because of its role in the estimation of cognitive ability, we adopt a relatively flexible specification by allowing for five unobserved types, and also allow for the probability that an individual belonging to each type to differ by her observed characteristics (see Section 5.2).[21]

The modeling of unobserved heterogeneity serves the following purposes. First, individuals who consistently pursue different choices may differ substantially in unobserved permanent characteristics, and failure to control for this source of difference may result in biased estimates of policy effects.[22] Second, wage can be endogenous due to self-selection based on unobserved permanent characteristics (beyond the fact that only workers' wages are observed). Because the extensive margin of female labor supply is important, the panel of accepted wages needs to be corrected for self-selection before it can be used to recover the type-specific skill endowment ("ability") in the labor market, which is captured by μ_{wj}. Third, the structural model will be used to predict a

[21] Estimating multiple unobserved types can be demanding due to computational burden and requirements on data. This is feasible in our analysis due to a relatively large sample size (a total of 1,743 women; see Section 4) and the fact that the cognitive ability production function is not jointly estimated with the structural model. In Bernal (2008), a joint estimation procedure is performed with two unobserved skill endowment types and a sample of 529 mothers. Her sample includes women who live with their husband or coresident male for the first five years after the birth of the child and who do not have an additional child for five years after the birth of the child. The sample contains quarterly data on employment for up to five years after child birth and child care (an indicator variable including formal or informal care) up to three years after child birth. Del Boca, Flinn, and Wiswall (2014)'s sample consists of 105 one-child households and 132 two-child households, which are separately used for estimation. Although they perform a joint estimation approach, due to sample size and the short panel that they consider (i.e., two waves of Letter-Word score data and three waves of parents' data), they do not model unobserved heterogeneity in their analysis.

[22] For instance, in Chan (2013)'s empirical analysis, he finds that structural models with unobserved heterogeneity tend to generate lower behavioral elasticity measures than models without such features.

woman's unobserved skill endowment in the labor market *conditional* on her observed behavior. This information will enter into the cognitive ability production function as a control function, based on the premise that a mother's skill endowment should be highly correlated with her child's unobserved endowment effect.

Following the existing literature on female labor supply, we allow the individual's partner to enter into the model in a parsimonious way. In particular, the partner's expected wage can be associated with the woman's behavior (e.g. Eckstein and Wolpin (1989); Van der Klaauw (1996); Francesconi (2002)).[23] In Bernal (2008), the partner's average income enters directly into the woman's budget constraint; in Francesconi (2002), the partner's expected wage is obtained as a linear combination of the woman's characteristics and enters into the woman's budget constraint. Due to concerns for assortative matching, we do not allow the expected wage to enter into the model exogenously. Thus, our approach is more similar to Francesconi (2002). We proxy the partner's expected wages by his average wage observed over the entire sampling period ("permanent wage") and his level of education. We then allow both the permanent wage and education level of the partner to affect the *distribution* of the unobserved type of the woman (see Section 5.2). This approach reduces the dimension of the state space, and still qualitatively captures the empirical association between the woman's observed employment decisions and her partner's expected wage. For instance, if there is substantive assortative matching, this will appear as a strong positive association between the partner's wage/education and the probability that the woman is of a higher skill endowment or "inherent ability" type (μ_{wj}).[24]

When conducting counterfactual policy simulations, we assume that the partner's expected wage is invariant to changes in the policy environment. The literature typically finds very small labor supply elasticity with respect to child care cost among men. To the extent that men's labor supply is inelastic especially at the extensive margin, this assumption is less restrictive than it otherwise would be.[25] One drawback is that fathers may change their active or passive time with

[23]When the utility function is linear and additive in earnings and under the assumption that partner's wages are realized after women's choices, only the partner's expected wage affects the woman's decisions (e.g. Eckstein and Wolpin (1989); Van der Klaauw (1996); Francesconi (2002)).

[24]This approach also allows for a negative association between the partner's wage/education and the probability that the woman has a higher taste for employment (μ_{hj}).

[25]For instance, Del Boca, Flinn, and Wiswall (2014) find that fathers' labor supply is invariant over a wide range of children's age (between 3 and 15). Over 95 percent of fathers work, except for one-child families with a child at 3 years of age (93.7 percent). In addition, the average weekly working hours range between 43 and 47 hours depending on the child's age. By contrast, mothers' labor supply varies widely by children's age: from 65 to 89 percent, and from 23 to 39 hours, respectively. More relevant in our context, by exploiting the Norwegian cash-for-care reform as a natural experiment, Bettinger, Hægeland, and Rege (2014) and Drange (2012) find that the reform had no significant effect on fathers' labor force participation.

children (Del Boca, Flinn, and Wiswall (2014)) even though they do not adjust their labor supply. It will be ideal if this feature can be incorporated into our model, but it is not possible due to lack of data. Nevertheless, Del Boca, Flinn, and Wiswall (2014) find that the amount of time input by fathers is roughly half of the time input by mothers over a wide range of children's age. The implications for child development is complex because they find that in one-child families, mothers' active time input is substantially more productive (in generating the child's cognitive ability) than fathers' active time input at pre-school age, but the evidence is more mixed at a later stage and for two-child families.[26] Despite the fact that we extend Del Boca, Flinn, and Wiswall (2014) by allowing for child care decisions and unobserved heterogeneity, the interpretability of the estimates in the cognitive ability production function will share the same issue as Bernal (2008).

Intertemporal Optimization Problem. At age t_0, the individual maximizes her expected present discounted value of utility from the current period to the end of the time horizon T:

$$\max E_{t_0} \sum_{t=t_0}^{T} \delta^{t-t_0} u_{ik_{it}t},$$

where δ denotes the discount factor, and k_{it} is the individual's choice at period t.[27] Generically, the intertemporal optimization problem can be written in recursive form as

$$V_{it}(\boldsymbol{S}_{it}, \boldsymbol{\epsilon}_{it}) \equiv \max_{k \in \mathcal{C}_{it}} \left[u_{ikt} + \delta E_t V_{i,t+1}(\boldsymbol{S}_{ik,t+1}, \boldsymbol{\epsilon}_{i,t+1}) \right], \tag{1}$$

where $V_{it}(.)$ is the value function with two sets of state variables $\boldsymbol{S}_{it}$ and $\boldsymbol{\epsilon}_{it}$, and $\mathcal{C}_{it}$ denotes the index representation of the choice set. The deterministic part of the state space $\boldsymbol{S}_{it} = (h_{i,t-1}, n_{it}, a_{i1t}, a_{i2t}, \mathcal{E}_{it}, type)$ is carried around explicitly as an argument in the expected value function, and may evolve (except for *type*) according to the intertemporal budget constraints. The error space $\boldsymbol{\epsilon}_{it} = (\boldsymbol{\epsilon}_{cit}, \epsilon_{wit})$ contains preference and wage shocks that are integrated out in each period of the backward recursion procedure. In the recursion procedure, the length of the time horizon is assumed to be 18 years.

The reform not only affects the static budget constraint (which determines u_{ikt}) but also the value function. Throughout the time horizon, the individual faces different policy environments

[26] They find that in general, the productivity of time inputs declines substantially with child's age. In addition, they find that the active time spent by parents in one-child families is more productive (in their scale, as high as around 0.16 for fathers and 0.24 for mothers), but the productivity of other types of parental time input in one-child and two-child families are generally much lower (lower than 0.1).

[27] The discount factor is set at 0.9 per annum.

before and after the cash-for-care reform. For each individual, the dynamic programming problem is solved twice – one assumes that the cash-for-care program is absent for all t ($Z_{it} = 0, \forall t$), and the other assumes that the program is present for all t ($Z_{it} = 1, \forall t$). Then, with the above two sets of value functions, the optimal choice at period t can be computed as

$$k^*_{it} \equiv argmax_{k \in \mathcal{C}_{it}} \left[u_{ikt}(Z_{it}) + \delta E_t V_{i,t+1}(\boldsymbol{S}_{ik,t+1}, \boldsymbol{\epsilon}_{i,t+1}, Z_{it}) \right].$$

where $Z_{it} = 1$ if $t \geq \tau_i$ and $Z_{it} = 0$ if $t < \tau_i$. Note that the indicator for the availability of cash-for-care benefits (Z_{it}) is a state variable. The above setup implies that when a decision is made at time t, the individual perceives the value of Z_{it} to stay fixed in the future.

4 Data

4.1 Construction of Data Samples

Our data are based on several administrative registers from Statistics Norway covering the entire resident population of Norway. Each register contains unique and consistent individual identifiers that allow us to match observations of the same individual across different registers. The Central Population Register, spanning from 1967 to 2010 and updated annually by the local population registries, provides information which allows us to link parents to their children. Given the additional information we have on each child's date of birth, we are able to construct fertility histories in each family. The earnings data are collected from tax records.[28] Below we describe the data we use and the construction of the final sample used in estimation.

Construction of Women's Panel. Our life-cycle model of women's behavior requires a panel data where we observe labor supply, child care choices, and fertility. For each woman in each year, we have information on her hours of work per week and labor earnings.[29] We also observe the individual's country of birth, education level, and municipality of residence. We include only women who were born in Norway. Education is defined at the level measured in 2009 to capture the highest completed level of education. Municipality of residence is used to define whether the

[28] Unlike those data from tax records available in most other countries, there is minimal attrition in the Norwegian income data due to the lack of need to ask permission from individuals to access their tax records. Also, our earnings data pertain to all adult individuals, and not only to jobs covered by social security.

[29] Hours of work per week is reported by the employer each year in one of the following categories: less than 20 hours, 20-29 hours, and 30 hours or more. Earnings is the sum of pre-tax labor income (from wages and self-employment) and work-related cash transfers (unemployment benefits and short-term sickness benefits). Labor earnings are deflator-adjusted prior to estimation.

woman lives in the same municipality as her parents and the local coverage rate of formal child care facilities.[30] We also use variables corresponding to spousal education and income, and the municipality of residence of the woman's mother.[31]

Child care choices among mothers are identified from two sources. After the cash-for-care reform in 1998, the cash-for-care register provides detailed benefit receipt for each child in every month. We can construct measures of child-specific child care usage from this register. For the years prior to the reform, child care attendance can be inferred using information on tax deductions for child care expenses from tax records of the parents (Black, Devereux, Løken, and Salvanes, 2014; Drange, Havnes, and Sandsør, 2014). Parents are allowed to deduct up to 25,000 NOK ($\approx$USD 4,310) from taxes in one calendar year for the first child for formal child care. We have access to this data from 1993 to 2005. For years when both sources are available, we define that the mother was using formal child care if she claimed less than 6 months of cash-for-care benefits (therefore using formal child care for at least half of the year) and the child care tax deduction for the household was over 10,000 NOK. Otherwise, the mother is defined as using formal child care when the child care tax deduction exceeded 10,000 NOK.

We construct two separate panels of women, one containing women with high school education and the other including women with college education. Structural estimation will be conducted on each sample separately, thereby allowing each parameter in the model to differ by education group. In the empirical analysis, each panel contains the first nine years of data since the beginning of the woman's decision-making process, which is defined as the expected age of school graduation. For low-education women, the first decision period starts from age 19. For high-education women, the first decision period starts from age 23.

The earliest and latest calendar years on which the panel data is based are 1993 and 2005, respectively. During this period, there were no other significant changes in income tax schedules and work-family related policies.[32] In addition, each panel differs by cohort composition so as to maximize the variation in exposure to the cash-for-care reform throughout the life cycle. In the Appendix, Table A1 lists the calendar years covered by each cohort in each panel. For low-education

[30] The municipality-level (smallest administrative unit in Norway) coverage rate is defined as the number of children aged between 1 and 3 who are in formal care, divided by the population within the same age range.

[31] For each woman, we link her partner's annual income and highest level of education over the sample period. See the subsection on construction of fertility histories for the household relation variable that is used for linkage.

[32] Prior to the period we study, there were large expansions in paid parental leave between 1986 and 1993. In 1986, Norwegian parents were granted 18 weeks of paid parental leave. In subsequent years, leave rights were gradually extended to 35 weeks in 1992 and to 42 weeks in 1993 (or 52 weeks with 80-percent pay). From 1993 to 2005, there were no changes to the parental leave policy. Fully-compensated parental leave was extended from 42 weeks to 44 weeks in 2006, and then to 46 weeks in 2009 (or 56 weeks of 80-percent compensation).

women, we select those who were born between 1974 and 1978. As a result, the 1978 cohort will have the longest exposure to the cash-for-reform (since age 20, or period 2); the 1974 cohort will have the shortest exposure to the reform (since age 24, or period 6). For high-education women, we select those who were born between 1970 and 1974. In this sample, the 1974 cohort will have the longest exposure to the cash-for-reform (since age 24, or period 2); the 1970 cohort will have the shortest exposure to the reform (since age 28, or period 6). For both panels, the earliest age in which the individual is exposed to the reform ranges from age 20 (1978 cohort) to age 28 (1970 cohort).

Construction of Fertility Histories. In administrative data, construction of fertility histories of women requires linking children with mothers. From the Central Population Register, we first select all children born between 1991 and 2010. For each child, we have information on the date of birth, as well as gender and birth weight obtained from the Birth Register. From the Birth Register, we also observe household relation at the time of birth. The household relation variable is later used to select mothers with "stable" household compositions as discussed further below.[33]

Information on the date of birth of each child is used to construct fertility histories. We exclude women who never had any birth by 2010, the last accessible year in the children's data. They account for only 8 percent of women in the women's panel, and their fertility decision may be constrained by other types of factors not captured by the model.[34] To avoid any left-censoring of fertility due to the way we construct the panel, mothers who had given birth prior to the age corresponding to the first period in the model are also excluded.[35] To keep the estimation tractable, we keep mothers with no more than three children. To focus on "stable" households and minimize impacts from changes to household compositions due to divorce and remarriage, we impose two additional selection restrictions. First, we exclude single mothers because there were other welfare programs targeted to single mothers (Mogstad and Pronzato, 2012). Therefore, women in our sample are either cohabiting or married at the time of every child birth.[36] Second, given the way

[33] One important advantage of the household relation variable in the Birth Register (especially when compared with data in the U.S.) is that it clearly distinguishes between cohabiting and married couples.

[34] In 2010, the high-education women in the analysis sample were between age 36 and 40, and the low-education women were between age 32 and 36. Note that we still have women who are non-mothers during the sample period: they are women whose first birth arrived by 2010 and after the last period in the sample.

[35] This implies that 1 percent of mothers in the low-education sample and 8 percent of mothers in the high-education sample are dropped.

[36] In the Norwegian administrative data, single mothers can be identified at the time of birth from the birth register. During the period we study, close to 50 percent of children were born when parents were married. Around 40 percent of children were born when parents were cohabiting. The remaining 10 percent consists of children born by single mothers or in other types of households. Note that the mother does not need to stay in the partnership after the

the father enters in the model, we drop mothers who ever gave birth to a child whose biological father is different from the father of her previous child. Combining with the first selection criteria, for each woman in the sample, all children have the same father living in the household at the time of every birth. This minimizes the potential impact of divorce and remarriage on fertility and early child investments.[37]

To ease computational burden in estimation, we use a 3-percent random sample of the matched women-children data. It consists of a balanced panel of 1040 women in the high-education sample and 703 women in the low-education sample.

The Test Score Data. From 2007 to 2010, we have data on national standardized test scores for all children at the beginning of grade 5 and 8 (at age 10 and 13, respectively).[38] These tests are mandatory and the test scores are used to provide feedbacks on teaching and inform policy makers on municipalities facing special challenges (Deborah, Lorna, William, and Claire, 2011). The tests include subjects on general reading in Norwegian, mathematics, and English. Because the tests are standardized and were graded externally, the test scores can be compared across cohorts and schools. We will explain our use of this data in detail in the estimation section.

Policy Environment. The income tax schedule ($T(.)$) is constructed from tax tables.[39] The unit of taxation in Norway is an individual. Standard deductions include basic allowance (equal to 20 percent of gross earnings with a ceiling at 32,600 NOK) and personal allowance of 25,000 NOK. The maximum annual tax deduction for child care expenses ($D_c(.)$) was 25,000 NOK for families with one child, and 30,000 NOK for families with more than one child. The base marginal tax rate, imposed on income after the above deductions, is 28 percent. Marginal tax rates of 37.5 percent and 51 percent are levied on individuals with net income greater than 248,000 NOK and 272,000 NOK, respectively. On top of the income tax, there is also a mandatory national insurance contribution, which constitutes 7.8 percent of gross earnings.

birth of a child.

[37] Compared to the initial sample consisting of all women in the relevant cohorts, women in our final sample are slightly more educated (13.74 mean years of education relative to 13.64 years in the initial sample) and have higher earnings on average (170182 NOK relative to 159470 NOK in the initial sample).

[38] The data implies that we observe grade 8 scores of children who were born between 1994 and 1997, and grade 5 scores of children who were born between 1997 and 2000. In estimation, grade 5 scores are used whenever available, otherwise (normalized) grade 8 scores are used.

[39] We thank Erik Sørensen for providing us with formulas to calculate income tax from annual labor earnings. The tax schedule is constructed using the schedule at 1998. There is no major tax reform in the period we study. Since the last tax reform in 1992, there have been some minor changes and most of the tax payers are unaffected by these changes (Aarbu and Thoresen, 2001).

Data on other policy parameters are briefly described as follows. The child subsidy (B_n), which is not taxable, is 970 NOK per month (11,640 NOK per year) for each child under 18 years of age. The annual subsidized cost of formal child care for the first child (P_{c1}) is fixed at 28,325 NOK; when two children are in formal child care, the total cost ($P_{c1} + P_{c2}$) is 45,202 NOK (Rauan, 2013).[40] If the mother was working and pregnant in the last period prior to child birth, she will be entitled to maternity leave benefits for one year at 80 percent of annual earnings prior to child birth.[41] The cash-for-care benefit (B_c) is 3,000 NOK per child per month (tax-free). Because benefit eligibility is based on the age of the child and our modeling period is a calendar year, we make the following simplifying assumptions to aggregate the cash-for-care benefit to an annual level. We assume that the child is eligible for the benefits for three consecutive calendar years from age 1 to 3, with an annual benefit given at 24,000 NOK. Therefore, the total amount of benefits the child is eligible for is the same as the actual amount before recoding.[42]

4.2 Sample Characteristics

In Table I, we report the choices made at each age by low-education women and high-education women, respectively.[43] Among low-education women, the employment rate is only 8.7 percent at age 19 (year 1 of the model). Because almost no one have children, the initial (formal) child care usage rate is zero. By age 23 (year 5), the employment rate has increased rapidly to 60.2 percent, and the pregnancy rate has also increased noticeably to 13.2 percent; however, the overall child care usage rate remains very low at 1.7 percent due to the low average number of children per individual (0.29). The employment rate starts to fall steadily beyond age 23, as the number of mothers continues to increase. At age 27 (year 9), the employment rate and pregnancy rate are 57.3 and 17.4 percent, respectively, and an individual has 0.93 children on average. The overall child care usage rate increases to 11.2 percent, and the child care usage rate among mothers with young children (at least one child between age 1 and 3) is 26.8 percent.

[40] The price schedule for an additional child is discounted if the first child is in child care. The price is nationally regulated. There are small regional differences in the price schedule mainly driven by the prices paid by extremely low-income households who are eligible for additional subsidy on the cost of child care (Black, Devereux, Løken, and Salvanes, 2014). The average household income in our sample far exceeds the income cutoffs eligible for these additional subsidies.

[41] Given that the model does not include prior earnings as a state variable, we assume that mothers who are eligible for maternity leave benefits will make a wage draw (w_{it}) in the first period after child birth. The benefit amount is then $B_m w_{it}$. Because w_{it} is normalized as part-time earnings, we use the sample proportion of full-time workers to part-time workers to adjust it upward. The proportional adjustment is set to be $B_m = 0.8 \times 1.5 = 1.2$.

[42] In the data, we observe many individuals who receive cash-for-care benefits for three consecutive calendar years. This is primarily due to children born in the middle of the calendar year. Nevertheless, in sample construction, the child care use variable is defined in the same manner as described in the data section.

[43] In Appendix Table A2, we also present summary statistics of other selected variables that are used in the analysis.

The basic choice patterns are qualitatively similar among high-education women. However, there are also some differences, such as more intensive fertility behavior and child care use. At age 23 (year 1 of the model), the employment rate is 34.7 percent, and almost none of the individuals have any children. At age 27 (year 5), the employment rate and pregnancy rate have increased rapidly to 68.4 percent and 17.3 percent, respectively. In addition, an individual has 0.42 children on average, and the overall child care usage rate is 7.5 percent. At age 31 (year 9), the employment rate drops to 64 percent, although the pregnancy rate increases slightly to 19.4 percent. The overall child care usage rate increases substantially to 24.2 percent, as a result of both a high average number of children per individual (1.22) and a high child care usage rate among mothers with young children (47.6 percent).

It is potentially interesting to compare the sample with US women, where a similar class of models has been applied. For instance, consider Keane and Wolpin (2010), who base their estimation on women from NLSY79. In their sample, teenage pregnancy is common; by age 20, white women already have an average of 0.28 children. However, given that the pregnancy rate is generally lower (usually between 4 and 8 percent), the first age at which white women have had one child on average is 27, which is similar to low-education women in Norway. Another interesting difference is the high teenage employment rate. The most rapid increase in the employment rate among white women occurs between age 16 and 18 (from 30 percent to 63 percent), and the employment rate increases steadily afterwards, to 72.6 percent at age 30-33.[44]

5 Identification and Estimation

5.1 Policy Reform and the Structural Model

The cash-for-care reform resulted in a large exogenous increase in the relative price of formal child care facilities. In the Data Section, we discussed the selection of women cohorts, who are different in the degree of life-cycle exposure to the reform. In the discussion below, we will focus on the child age restrictions on cash-for-care eligibility, which also create variations in exposure to benefits across child cohorts. In the model, the cash-for-care program is restricted to children between age 1 and 3. For children who are born in 1994 or earlier, they are never exposed to benefits because

[44] Unfortunately, the child care choices are not directly comparable, as the child care variable in NLSY79 is an indicator for whether nonmaternal care (formal or informal) is used for at least 10 hours per week during the last month (Bernal, 2008). In Bernal's sample of NLSY79 women, the child care (formal or informal) usage rate is around 60 percent by the end of the third year after child birth.

they are aged 4 or older when the program starts in 1998. For children who are born in 1995, they turn age 3 in 1998, which implies that they are exposed to a maximum of one year of benefits. By a similar argument, children who are born in 1996 are exposed to a maximum of two years of benefits, whereas children who are born in 1997 or later are exposed to a maximum of three years of benefits.

Because the reform was announced around 6 months before implementation, the reform was unanticipated by mothers whose children were born in 1998 or earlier, as the pregnancy decision was made one year prior to child birth. Therefore, there is natural variation in the exposure to benefits (from zero to three years) among mothers whose children were born between 1994 and 1998. This variation results in different incentives for employment and child care use. In addition, for mothers whose children were born in 1999 or later, they faced the same benefit exposure as mothers whose children were born in 1997 and 1998, but the reform was *anticipated* when the pregnancy decision was made. As a result, there is a notable difference in fertility incentives between women in 1997 and 1998. These sources of variations can help identify the effect of the reform on employment, child care use, and fertility.

Apart from the above policy features, the identification argument of the structural model is rather standard and has been discussed in the literature. For instance, because wages are observed for workers only, the distributional assumptions on the choice and wage shocks are important for identification, as in a similar class of models. Nevertheless, exclusion restrictions are included for robustness – these include the local unemployment rate in the wage equation, and the local child care coverage rate and proximity to grandparents in the utility function. Note that the income tax schedule creates piecewise-linearity in the budget constraint; in addition, the policy reform affects the budget constraint and decisions in various ways as described above.

5.2 Likelihood function of the Dynamic Programming Model

The model is estimated by the method of maximum likelihood. To compute the likelihood function, the unobserved types have to be taken into account and integrated out. The probability that the individual belongs to type j takes the following multinomial logit form:

$$Pr(type = j|\boldsymbol{x}_{ai}) = \begin{cases} \frac{\exp(\boldsymbol{x}_{ai}\boldsymbol{\beta}_{aj})}{1+\sum_{l=2}^{5}\exp(\boldsymbol{x}_{ai}\boldsymbol{\beta}_{al})} & \text{if} \quad j = 2,3,4,5; \\ 1 - \sum_{j=2}^{5} Pr(type = j|\boldsymbol{x}_{ai}) & \text{if} \quad j = 1. \end{cases} \tag{2}$$

The vector of covariates $\boldsymbol{x}_{ai}$ includes a unit constant as well as the partner's permanent income (defined as his average income over the sample period) and his level of education. We expect both characteristics to be positively associated with the probability that the individual belongs to a "high-ability" type, reflecting potentially assortative mating.

The parameter set consists of utility function parameters $\boldsymbol{\alpha} \equiv (\alpha_h^p, \alpha_h^f, \alpha_c, \alpha_p, \alpha_{hc}, \alpha_{hp}, \alpha_{hn1}, \alpha_{hn2}, \alpha_{cn1}, \alpha_{cn2}, \alpha_{pn1}, \alpha_{pn2}, \beta_{h1}, \beta_{h2}, \beta_p, \boldsymbol{\beta}_c, \alpha_{hh}, \sigma_c)$, wage equation parameters $\boldsymbol{\beta} \equiv (\beta_{w0}, \beta_{we1}, \beta_{we2}, \beta_{w1}, \sigma_w)$, and type-specific parameters $\boldsymbol{\mu} \equiv (\mu_{h2}, ..., \mu_{h5},\ \mu_{p2}, ..., \mu_{p5},\ \mu_{w2}, ...\mu_{w5},\ \boldsymbol{\beta}_{a2}, ..., \boldsymbol{\beta}_{a5})$. There are 49 parameters in total. To facilitate interpretation of the estimation results, we rank the types according to the unobserved "ability" in the wage equation in descending order, so $\mu_{w5} < \mu_{w4} < \mu_{w3} < \mu_{w2} < \mu_{w1} \equiv 0$ (i.e., type-1 individuals have the highest ability). Although the types are discrete, the tuple $(\mu_{hj}, \mu_{pj}, \mu_{wj})$ differs across types so the unobserved taste for work, taste for pregnancy, and ability can be correlated.

The likelihood function is constructed as follows. Consider individual i in period t. Conditional on the wage w_{it} (observed for workers) and state variables $\boldsymbol{S}_{it}$ (which includes the type), the alternative-specific value to alternative k that is *exclusive* of the preference shock can be defined as follows:

$$\bar{V}_{ikt}(w_{it}, \boldsymbol{S}_{it}) \equiv \bar{u}_{it}(k; w_{it}, \boldsymbol{S}_{it}) + \delta E_t V_{i,t+1}(\boldsymbol{S}_{ik,t+1}, \boldsymbol{\epsilon}_{i,t+1}). \tag{3}$$

Due to the distributional assumption for the choice shock, the choice probability is

$$P_{ikt}(w_{it}, \boldsymbol{S}_{it}) \equiv \frac{\exp(\bar{V}_{ikt}(w_{it}, \boldsymbol{S}_{it})/\sigma_c)}{\sum_{l \in \mathcal{C}_{it}} \exp(\bar{V}_{ilt}(w_{it}, \boldsymbol{S}_{it})/\sigma_c)}. \tag{4}$$

Given observed choice k_{it}, which includes information about work status h_{it}, the likelihood contribution is

$$L_{ik_{it}t} = \begin{cases} P_{ik_{it}t}(w_{it}, \boldsymbol{S}_{it}) f(w_{it}|\boldsymbol{S}_{it}) & \text{if} \quad h_{it} = 1, \\ \int P_{ik_{it}t}(w, \boldsymbol{S}_{it}) f(w|\boldsymbol{S}_{it}) dw & \text{if} \quad h_{it} = 0, \end{cases} \tag{5}$$

where $f(.)$ is the probability density function of the wage equation.[45] In a panel with N individuals

[45] For nonworkers, the integral is computed using a Gauss-Hermite quadrature.

and T periods, the log likelihood function is

$$LL = \sum_{i=1}^{N} \ln \sum_{j=1}^{5} Pr(type = j|\boldsymbol{x}_{ai}) \prod_{t=1}^{T} L_{ik_{it}t}. \tag{6}$$

5.3 Cognitive Ability Production Function

5.3.1 Accounting for the Endogeneity of Inputs

Our objective is to obtain unbiased estimates of the determinants of the child's cognitive ability, as measured by his/her test score beyond age 10. Before discussing the full empirical specification, the key sources of potential bias and identification are first highlighted. For illustration purposes, consider the following stylized model:

$$s_{iT} = \gamma_0 + \boldsymbol{x}_{si}^{'}\boldsymbol{\gamma}_1 + \boldsymbol{Y}_{it}^{'}\boldsymbol{\gamma}_2 + \nu_i + \epsilon_{siT}, \tag{7}$$

where s_{iT} denotes child i's cognitive ability at child's age T, $\boldsymbol{x}_{si}$ is a vector of child-specific covariates, $\boldsymbol{Y}_{it}$ denotes a vector of inputs by the child's mother (such as income and the time spent at home) at child's age t, ν_i represents the child's unobserved endowment effect, and ϵ_{siT} is a pure transitory shock. We consider the case where the measurement period of cognitive ability (T) is much later than the period of maternal inputs (t).

Because the child endowment ν_i is positively correlated with the mother's unobserved ability, which determines the mother's behavior, $\boldsymbol{Y}_{it}$ is endogenous and is correlated with ν_i. We address this potential source of endogeneity bias by a control function approach, where the structural model is used to predict a mother's unobserved characteristics conditional on her observed behavior. More precisely, we control for the unobserved effect ν_i using the following conditional mean as a covariate:

$$\begin{aligned} E(\nu_i|\boldsymbol{Y}_{it}, \boldsymbol{x}_{si}) &= \delta E(\mu_i|\boldsymbol{Y}_{it}, \boldsymbol{x}_{si}) \\ &\approx \delta \sum_{j=1}^{5} \mu_j Pr(\mu_j|\boldsymbol{Y}_{it}, \boldsymbol{x}_{si}) \\ &= \delta \sum_{j=1}^{5} \mu_j \frac{Pr(\boldsymbol{Y}_{it}|\mu_j, \boldsymbol{x}_{si})Pr(\mu_j|\boldsymbol{x}_{si})}{\sum_{l=1}^{5} Pr(\boldsymbol{Y}_{it}|\mu_l, \boldsymbol{x}_{si})Pr(\mu_l|\boldsymbol{x}_{si})}, \end{aligned} \tag{8}$$

where μ_i denotes the mother's unobserved ability. Suppose the mother belongs to one of the five discrete unobserved types (i.e., $j = 1, ..., 5$) in the structural model. Then, for each child, the above conditional mean can be computed, as the conditional probability $Pr(\boldsymbol{Y}_{it}|\mu_j, \boldsymbol{x}_{si})$ and type probability $Pr(\mu_j|\boldsymbol{x}_{si})$ can both be retrieved directly from the structural model. Although the types are discrete, given that the conditional mean summarizes information on the mother's unobserved ability given her observed behavior, its value is a function of $\boldsymbol{Y}_{it}$ and differs across mothers. The parameter δ, which is expected to have positive sign, captures the relationship between the mother's unobserved ability and the child endowment effect.

In our analysis, the measurement of cognitive outcomes occurs at a much later age than maternal inputs. The emphasis on long-run effects of maternal inputs implies that potential feedback mechanisms play a limited role in the analysis.[46] Nevertheless, if mothers have full information on their children's endowment ν_i, they may exhibit different tendencies to work subject to the level of ν_i (controlling for mother's ability). We test for this implication by including the conditional mean of the mother's unobserved work preference into the cognitive ability production function. The coefficient on this covariate will provide some evidence for the importance of such mechanisms.

5.3.2 Empirical Specification

Let s_i be the test score of the first child of individual i. We first consider the following empirical specification:

$$ln(s_i) = \bar{s}_i + \gamma_y \ln \sum_{a=0}^{3} y_{ia} + \gamma_h \sum_{a=1}^{3} h_{ia} + \gamma_c \sum_{a=1}^{3} c_{ia} + \gamma_{hc1} \sum_{a=1}^{3} h_{ia}(1 - c_{ia}) + \epsilon_{si}, \tag{9}$$

where $\bar{s}_i$ represents the time-invariant characteristics of the child:[47]

$$\bar{s}_i = \gamma_0 + \boldsymbol{x}_{si}^{'}\boldsymbol{\gamma}_1 + \delta_w \sum_{j=1}^{5} \mu_{wj} Postprob_i(\mu_{wj}) + \delta_h \sum_{j=1}^{5} \mu_{hj} Postprob_i(\mu_{hj}). \tag{10}$$

The covariates in equation (9) include the logarithm of total mother's income between child's age 0 and 3, total years of maternal employment between child's age 1 and 3, total years of formal child care use between child's age 1 and 3, and total years of employment *and* no formal child care between child's age 1 and 3.[48] The time-invariant term $\bar{s}_i$ includes a set of demographic

[46] This stands in contrast with Bernal (2008), where cognitive scores at an early age and maternal inputs from the same periods are used. In her model, the feedback mechanism (e.g., cognitive outcomes affect maternal inputs) is the primary object of interest.

[47] The empirical results from the structural model indicate that the conditional means of unobserved heterogeneity for work and pregnancy preferences are highly correlated. Thus, only one of them is included in the equation.

[48] One potential drawback of our specified production function is that it ignores other inputs in cognitive production function which may become important after early childhood (such as school inputs). If additional years of child care also induces the mother to send her child to good schools, our estimates can be interpreted as capturing the average change in cognitive ability from an additional year of formal child care, taking into account of the potential correlation

characteristics $\boldsymbol{x}_{si}$ including parental education, child's gender, birth weight, whether the mother is under age 21 in the year of the child's birth, whether the child has any young siblings, father's permanent income, and whether the grandparents live in the same municipality. It also contains the conditional means of the mother's unobserved ability μ_{wj} and work preference μ_{hj}, which are both computed from the structural model. Estimation is carried out in two stages. First, the conditional means corresponding to each child are computed using the structural model.[49] Then, the model is estimated using ordinary least squares, using the mother's actual inputs as well as the conditional means as covariates. In the data, we focus on the first child of each mother only. For each child, there are three different subject scores: reading, mathematics, and English. Estimation is carried out separately for each type of score, using the same set of covariates.

Our preferred empirical specification is given as follows:

$$\begin{aligned} lns_i = \bar{s}_i + \gamma_y \ln \sum_{a=0}^{3} y_{ia} + \gamma_{hc1} \sum_{a=1}^{3} h_{ia}(1-c_{ia}) + \gamma_{hc2} \sum_{a=1}^{3} (1-h_{ia})(1-c_{ia}) \\ + meduc_i \times \left(\gamma_{y0} \ln \sum_{a=0}^{3} y_{ia} + \gamma_{hc10} \sum_{a=1}^{3} h_{ia}(1-c_{ia}) + \gamma_{hc20} \sum_{a=1}^{3} (1-h_{ia})(1-c_{ia}) \right) + \epsilon_{si}. \end{aligned} \tag{11}$$

Under this specification, formal child care use is considered as a benchmark, and it is compared against two other choice patterns: (i) employment *and* no formal child care (γ_{hc1}); (ii) nonemployment *and* no formal child care (γ_{hc2}). We expect $\gamma_{hc1} < \gamma_{hc2}$ as the former option implies less maternal time with the child, all else being equal. This specification also allows for the effects of maternal inputs on cognitive ability to be heterogeneous across the mother's education level; for instance, mothers with high education may be more effective in caring for the child on their own, or utilizing financial resources for their child.

between additional year of child care and subsequent school inputs. Nevertheless, there is compelling evidence that early life environments are critical for skill formation (see Heckman and Mosso (2014) for a review).

[49] In the empirical model, the conditional probabilities ($Postprob_i(.)$) are conditional on all information in the panel data that are used for structural model estimation. This includes the mother's choices, wages (observed if employed), covariates, and cohort. This yields the "best" summary of the mother's unobserved type given the data available. The conditional probabilities are computed by applying Bayes rule on the likelihood contribution in equation (5) (i.e., $\prod_{t=1}^{T} L_{ik_{it}t}$) and type probabilities in equation (2). The conditional means are then normalized with respect to type-1 individuals in the high-education subsample.

6 Estimation Results

6.1 Structural Model Estimates

Tables II and III report estimates from the structural model for low-education women and high-education women, respectively. The utility costs of employment and pregnancy are negative and rather sizable, but the utility cost of child care use is relatively small (around 150,000 NOK per year in both samples). However, the actual choices depend not only on the utility function coefficients but also the standard deviation of the choice shock (σ_c), which is twice as high among high-education women (170,000 NOK) than low-education women (87,000 NOK). There is a positive interactive utility of being employed and using child care, which reflects a tendency to choose both options simultaneously. Likewise, there is a tendency to be pregnant while being employed, especially among high-education women. Family size also plays a role in determining utility costs; for instance, in both samples, the utility cost of work is higher by approximately 50,000 NOK/year per additional child (α_{hn1}), while the utility cost of child care use is lower by roughly the same amount per additional child (α_{cn1}). The coefficients on exclusion restrictions indicate that a higher child care coverage rate in the local area is associated with more child care use; among high-education women, proximity to grandparents is associated with less (formal) child care use. In the wage equation, the local unemployment rate tends to negatively affect low-education women only. The return to work experience is slightly higher for high-education women than low-education women (10.2 versus 9.3 percent per year, respectively).

The type-specific coefficients (type-2 to type-5) are presented in descending order by the woman's unobserved skill endowment in the wage equation (μ_w), and the estimates can be interpreted as *differences* from type-1 individuals. The unobserved skill endowment varies widely by type. For instance, the permanent skill endowment difference (in wage) between type-5 and type-1 individuals is roughly 54 percent among low-education women, and 71 percent among high-education women. These are large differences, as the standard deviation of the wage shock is only around 20 percent. By contrast, the unobserved work and pregnancy preferences (μ_h and μ_p) are subject to less variations across type. Although individuals with lower unobserved skill endowment tend to have lower utility costs of work and pregnancy, there are also exceptions. The type probability estimates indicate all the types are important. The unconditional type proportions (from type-1 to type-5) for low-education women are 7.98, 26.12, 29.68, 11.99, and 24.23 percent, respectively; for high-education women, the type proportions are 10.24, 24.17, 25.35, 29.37, and 10.87 percent, respectively. Consistent with assortative matching, the partner's education level and permanent income (as measured by the average income during the sample period) are both *positively* associated with the probability that the woman belongs to a high skill endowment type.

Although the models for low-education and high-education women are separately estimated, the skill endowment estimates are measured in the same unit so they can be combined as follows. First, type-1 women in the low-education and high-education samples have a log wage intercept of 5.392 and 5.604, respectively. This implies that the skill endowment in the latter group is 21.2 percent higher (5.604-5.392=0.212) than the former group. Because the skill endowment estimates of other types are measured relative to type-1 individuals, we can combine these estimates with the unconditional type proportions to compute the average difference in skill endowment between low-education and high-education women, which is 16.36 percent.

6.1.1 Model Fit

Figure 1(a) and 1(b) show the fit of the model to the sample of low-education and high-education women, respectively. The subfigure on the left shows the employment rate, part-time work rate, full-time work rate, and pregnancy rate; the subfigure on the right shows the child care usage rate among all women, and the child care usage rate among mothers with at least one child aged between 1 and 3. Twenty simulations per individual are conducted, and simulated outcomes are reported until year 15 of the model.

The simulated outcomes exhibit a reasonably good fit to the data. The simulations capture the essential data patterns including the peak of employment in the data, and the rising pregnancy and child care usage rates during the sample period. The model tends to overpredict full-time work in later periods, but it predicts part-time work closely. Among low-education women, the model also tends to slightly underpredict the pregnancy rate. The model exhibits a good fit not only to the overall child care usage rate but also the usage rate among mothers with young children. It also predicts the evolution of state variables as well as the wage among workers reasonably closely.[50]

6.1.2 Generosity of Government Benefits and Family Size

Table IV reports the simulated present discounted values (PDV) of gross earnings and net government benefits received by individuals within the first twelve years of the model.[51] The government

[50]Results are available upon request.

[51]The results are computed based on 20 simulated histories per women in the sample.

benefits include maternity leave benefits, cash-for-care benefits (for mothers in the post-reform period), and child subsidy, which are subtracted by income and payroll tax after taking into account of deductions. Among low-education women, the average PDV of gross earnings is 681,280 NOK, with a standard deviation of 347,980 NOK. The average PDV of net government benefit received is only -23,360 NOK, with a standard deviation of 176,160 NOK. This implies an average tax rate (net of benefits) of merely 3.4 percent. Somewhat surprisingly, despite the fact that high-education women have substantially higher gross earnings (961,500 NOK), they face an even lower average tax rate (0.8 percent).

The remaining columns of the table compare the outcomes by family size (defined as the number of children in year 12). For a woman who has no children by year 12, her average tax rate is 27.4 percent if she has low education, and slightly higher at 29.4 percent if she has high education. These figures are consistent with the structure of the income tax system in Norway. In both samples, as family size increases, gross earnings reduce slightly but the net government benefit increases substantially. On average, among low-education women, an additional child is associated with an increase of PDV net government benefit by around 150,000 NOK; among high-education women, the average increase is around 200,000 NOK. With such large discrepancies, the average tax rate drops substantially to around 10 percent among women with one child, and even becomes *negative* among women with two or more children – they receive more benefits than payment of taxes during the period. The above results confirm that the benefit system in Norway is strongly pronatal, which underlines the importance of modeling fertility decisions; more evidence will be provided in subsequent sections.[52]

6.1.3 The Role of Unobserved Heterogeneity

In Table V, we report the proportion of variance of individuals' outcomes that can be explained by unobserved types, which reflects the economic significance of unobserved permanent individual characteristics in the data panel. A high proportion indicates a high degree of segregation across different unobserved types of individuals, whereas a low proportion indicates that idiosyncratic shocks play a large role in determining outcomes. The following outcomes are considered: PDV gross earnings, PDV net government benefits, PDV utility, and number of children. Using the variance decomposition formula, we compute the proportions of variance by the end of year 6 and

[52] Unobserved heterogeneity plays a limited role in the discrepancies of PDV benefits across family size. Around 64 percent of the variance of PDV benefits is explained by family size, although only 25 percent of the variance is explained by type (discussed below).

year 12. In each time period, two policy scenarios are considered: the "baseline scenario" is the policy environment in which the model is estimated, and the counterfactual "no CFC" scenario assumes that there is no cash-for-care program at all in the model. The difference between both scenarios will reveal how the (removal of) cash-for-care program can affect the degree of segregation in individuals' outcomes over time.

The results suggest that although idiosyncratic shocks dominate most of the outcomes in the early stage (e.g., by year 6), unobserved types tend to play a bigger role in the long run. For instance, consider the baseline policy scenario for low-education women. Unobserved types explain only 32.6 percent of the total variance in PDV gross earnings by year 6, but 50.8 percent of the variance by year 12. Somewhat surprisingly, these numbers are comparable to Keane and Wolpin (2010), who are based on a similar class of model using data from the United States (NLSY79).[53] By year 12, unobserved types explain only 25.2 percent of the variance in PDV net government benefit, which suggests that the redistribution process is weakly associated with individuals' unobserved types. By contrast, during the same period, the variance of PDV utility that can be explained by unobserved type is 55 percent. Unobserved types can only explain 24.5 percent of the variance in the number of children (measured in year 12).

Among high-education women, the proportion of variance of PDV gross earnings that can be explained by unobserved types is strikingly similar to low-education women (32.7 and 50.5 percent by year 6 and 12, respectively). Although idiosyncratic shocks play an even larger role in determining government benefits and the number of children, unobserved types are critical in explaining the total variance of PDV utility (81.6 percent by year 12).

The removal of the cash-for-care program has a small effect on the proportions of variances by year 6, but there is some effect among low-education women by year 12. Among these women, unobserved types explain more of the variance in PDV gross earnings (52.2 percent) and net government benefits (30.7 percent). There is a noticeable impact on utility, where 59.4 percent of the variance can be explained by unobserved types. These results suggest that the cash-for-care program can mitigate the degree of segregation in individuals' long run outcomes.

[53]There are six unobserved types in their model. For instance, they find that unobserved types explain 61 percent of the variance in full-time wage offer at age 30.

6.2 Test Score Estimates

Table VI reports estimates from regressions of children's reading test scores (measured around age 10) based on empirical specifications in equations (9) to (11).[54] A comparison between the first two columns show the degree of bias when the regression fails to control for the mother's unobserved type. The elasticity of test score with respect to mother's income is overestimated by 50 percent (0.052 in column 1, versus 0.033 in column 2). By contrast, the coefficients on maternal employment and formal child care use remain similar. All else being equal, an additional year of maternal employment will reduce children's reading score by 4.3 percent, or 0.1 standard deviations. This is similar to Bernal (2008)'s estimate of 0.07 standard deviations. Interestingly, an additional year of formal child care use will *improve* children's reading score by 4.9 percent. Although Bernal (2008) finds that child care use will reduce children's test scores, the results are not directly comparable, as her definition of child care includes *informal* care. The remaining estimates suggest that for each increase in the mother's unobserved ability (μ_w) that is equivalent to a 10-percent increase in the mother's wage, the child's reading score will be higher by 2.23 percent (0.055 standard deviations).[55] By contrast, the coefficient on the conditional mean of the mother's unobserved work preference (μ_h) is slightly positive, but statistically insignificant. Therefore, relative to the "ability" channel, this suggests that mothers of high-endowment children only have a small tendency to work more. The education background of both parents plays a similar role in affecting the child's reading score (coefficients for mothers and fathers are 0.121 and 0.106, respectively).[56]

Column 3 adds another variable – years of "employed and no formal care use" – as an additional covariate. The covariate measures the length of time that the child does not attend a formal child care facility but has a working mother. The new coefficient is negative and statistically significant (-0.078), and the original coefficients on maternal employment and formal child care use become

[54]The estimation sample includes the first child of the mother with nonmissing test scores. There are 643 such children, of which 218 have low-education mothers, and 425 have high-education mothers. Both post-natal maternal employment and child care use are constructed directly from the mother's choices in the data. Post-natal income is constructed from the mother's gross earnings in the data, plus government benefits less income tax which are both computed from the model's budget constraint.

[55]Note that this is an effect keeping a set of other factors, including mother's education, constant. Appendix Figure A1 reports the distribution of the conditional mean of unobserved skill endowment predicted by the structural model.

[56]The average difference in log reading score between children of low-education and high-education women is 0.18, or approximately 0.45 sd (3.07-2.89=0.18; see Appendix Table A2). Although the summary statistics are not directly comparable, Griffen (2015) finds that the average difference in children's cognitive skills (measured at pre-school ages) between a mother with a high school diploma versus a college degree is 0.7 sd. Note that in addition to parental education background, a set of demographic characteristics ($\bar{s}_i$) is controlled for in all specifications. The estimated coefficients (for our preferred model in Column 4) are presented in Appendix Table A4.

close to zero. Column 4 adds yet another variable – years of "not employed and no formal care use" – as a proxy for the length of time that the mother spends to care for the child on her own. In this specification, the coefficients on years of "employed and no formal care use" and years of "not employed and no formal care use" measure, relative to formal child care, the effects of an additional year of informal nonmaternal care and maternal care, respectively. Moreover, these variables are interacted with mother's education level, allowing the effects to be heterogeneous. Among low-education mothers, an additional year of being employed and not using formal child care will reduce the test score by 14.3 percent, and an additional year of being *not* employed and not using formal child care will reduce the test score by 6.5 percent.[57] Among high-education mothers, the corresponding changes in test scores are -6.4 percent (-0.143+0.079=-0.064) and +0.2 percent (-0.065+0.067=0.002), respectively. These results indicate that the use of formal child care is largely substitutable from maternal care in the production of reading skills among high-education mothers but much less so among low-education mothers. Among all children, informal nonmaternal care leads to worse reading skills relative to maternal care. Although income tends to have a larger effect on test scores among high-education mothers than low-education mothers (0.028+0.029=0.057, versus 0.028), the difference is not statistically significant.

In the Appendix, Table A3 reports estimates from regressions of children's mathematics and English test scores, which are measured at the same age as the reading test score. Interestingly, across all specifications, neither mother's income nor work and formal child care use patterns have a significant impact on the mathematics score. However, there is a stronger association between the mother's unobserved ability and the child's mathematics score; for each increase in the mother's unobserved ability (μ_w) that is equivalent to a 10-percent increase in the mother's wage, the child's mathematics score will be higher by around 2.9 percent (0.073 standard deviations). Mother's education background becomes twice as important than father's education in determining the mathematics score (coefficients are 0.144 and 0.074, respectively).

The results on English scores are a somewhat weaker version of the results on reading scores. The signs of the key coefficients remain largely the same, but the coefficients generally become smaller and less significant. However, the role of the mother's unobserved ability becomes stronger. For each increase in the mother's unobserved ability (μ_w) that is equivalent to a 10-percent increase in the mother's wage, the child's English score will be higher by around 3.38 percent (0.087 standard

[57] Although these estimates are large, they do not necessarily translate into large policy effects because the policies need to have a strong impact on mother's work and child care use patterns simultaneously. See Section 6.3.2 for more discussions.

deviations). In addition, although mother's education background still plays a role in determining the score, father's education becomes unimportant (coefficients are 0.115 and 0.018, respectively).

Our estimates highlight the role of the quality of child care in determining children's cognitive development. Relative to formal child care, maternal care and informal care arranged by low-education mothers is presumably of lower quality. Consistent with this hypothesis, we find that both maternal and informal care used by low-education mothers have negative impacts on cognitive outcomes relative to formal child care. The negative effects are stronger among reading scores (and, to some extent, English scores) than math scores. This pattern is broadly consistent with findings from the literature emphasizing the importance of language environment in early childhood in shaping reading abilities later in life.[58]

6.3 Counterfactual Analysis

6.3.1 Effects on Adult Individuals

Table VII compares simulation results from several policy scenarios for both low- and high-education women in the 12th year of the dynamic model.[59] The baseline scenario (column 1) assumes that individuals are never subject to the cash-for-care reform, but other aspects of the policy environment remain the same as in the data. In subsequent columns, the following policies are implemented since the first period of the model: full cash-for-care benefits (column 2); cash-for-care benefits where workers are ineligible (column 3); an 10-percent increase of maternity leave benefits (column 4); an income tax deduction of 20,000 NOK for each child, up to two children (column 5).[60] Results are separately reported for low-education women and high-education women.

In the baseline scenario, low-education women have a slightly lower employment rate than high-education women (62.4 versus 67.8 percent). They have less than half the overall rate of formal child care use (9.8 versus 21.5 percent), and the usage rate among mothers with at least a child aged 1 to 3 is also lower (32.1 versus 49.6 percent). Low-education women also have a substantially lower pregnancy rate (9.8 versus 15.3 percent), and a lower average number of children by year 12 (0.95 versus 1.52). Although they have substantially lower gross earnings, the present discounted

[58]Studies have found that children from disadvantaged environments are exposed to a substantially less rich vocabulary than children from more advantaged families (Hart and Risley (1995), Fernald, Marchman, and Weisleder (2013)). For instance, at age three, children from professional families speak 50 percent more words than children from working-class families and more than twice as many compared to children from welfare families.

[59]Simulation results in the sixth year of the model are available in Appendix Table A5.

[60]The tax deduction is directly applied to the mother's gross earnings for the purpose of income tax calculations. It is independent of child care use.

value of net government benefits (i.e., benefits less income tax) received within the first 12 years is similar to high-education women and is close to zero.

Column 2 reports the effects of the cash-for-care reform. Among low-education women, the reform reduces the employment rate by 3.1 percentage points. This is largely due to a reduction in full-time work; as the rate of full-time work reduces by 5.1 percentage points, it is partially offset by an increase in part-time work by 2.1 percentage points.[61] Interestingly, the reform does not affect the *overall* rate of child care use. On the one hand, the child care usage rate among mothers with young children reduces by 5.9 percentage points; on the other hand, the reform is highly pro-natal, which substantially increases the fraction of women with young children (+8.3 percentage points). By the end of year 12, the reform has increased the average number of children by 0.25, representing a 26-percent increase. Although the reform generates a small negative effect on earnings, the present discounted value of net government benefits increases by a larger amount at an average of 70,000 NOK. This reflects not only cash-for-care benefits but also a reduction in income tax, as well as an increase in other types of government benefits due to increased fertility.

Column 3 reports the effects of a partial cash-for-care reform where workers are ineligible for cash-for-care benefits. The main purpose of the policy adjustment is to discourage mothers from becoming employed and not using formal care, which has a negative effect on children's cognitive scores (discussed in the next table). However, because workers are ineligible, the reform generates a large work disincentive among low-education women. The employment rate reduces by 4.6 percentage points, with reductions in both part-time and full-time work. The policy also reduces the usage rate of child care among mothers with young children (-3.0 percentage points), but the effects are concentrated among those who are *not* employed. The overall rate of child care use is unaffected. The policy is half as strong as the full reform in terms of increasing the number of children, but it is also half as expensive.

Column 4 reports the effects of an expansion in the maternity leave program. Among low-education women, the policy tends to reduce employment especially full-time work (-1.4 and -2.6 percentage points, respectively), as it promotes pregnancy which results in a larger number of children per women (+0.12 by the end of year 12). As a result of increased pregnancy, the overall rate of child care use increases by 1.2 percentage points. Column 5 reports the effects of introducing

[61] Previous empirical studies using the difference-in-difference approach document that the cash-for-care allowance decreased eligible mothers' full-time employment by 4 to 5 percent and decreased their labor force participation by 2 to 3 percent (Schøne, 2004; Drange, 2012). These are short-term effects identified by comparing mothers with children of the same age born in different time periods. In contrast, our model allows us to evaluate both short term and long term effects and to distinguish between responses at different points of a woman's life cycle.

an income tax deduction of 20,000 NOK per child (up to two children), a feature that is seen in other countries such as the United States. The deduction resembles an earnings-dependent tax credit for children. Because the policy reduces the effective tax rate for mothers, it increases employment especially part-time work (+1.4 and +3.3 percentage points, respectively). In addition, relative to the maternity leave expansion, the tax deduction results in a larger number of children per women (+0.15 by the end of year 12), and it also tends to encourage pregnancy at an earlier age. The overall rate of child care use increases by 1.6 percentage points. Both policies generate a similar increase in the present discounted value of net government benefits (+30,000 NOK).

The lower part of the table reports simulation results for high-education women. The policy effects are typically much smaller than low-education women. For instance, the full cash-for-care reform (Column 2) reduces the employment rate by 1.0 percentage point only, and it increases the average number of children by only 0.07 (a 4.6-percent increase). However, there is still a sizable reduction in the usage rate of child care among mothers with young children (-4.2 percentage points). Interestingly, despite a larger child care usage rate and family size in the baseline scenario, the cash-for-care reform generates a smaller increase in net government benefits than low-education women (+44,560 NOK). The effects of the partial cash-for-care reform (Column 3) are even smaller than the full reform, implying a minimal effect on high-education women. Due to higher earnings on which maternity leave benefits and income tax are calculated, the maternity leave expansion and tax deduction tend to be more generous for high-education women than low-education women. Nevertheless, both policies generate a smaller effect among high-education women. For instance, the maternity leave expansion reduces the employment rate by 0.5 percentage points, whereas the tax deduction increases it by 1.2 percentage points. Both polices have similar positive effects on the average number of children (+0.06 and +0.07, respectively), and slightly encourage child care use (+0.6 and +0.3 percentage points, respectively).

6.3.2 Effects on Children

Table VIII reports the effects of the above counterfactual policies on children's reading scores. To compute the effects on children, policy effects on mothers are first simulated, which are then used for computing the predicted change in reading scores based on estimation results in specification 4 of Table VI. The table reports changes in reading scores among "preexisting" children, who are defined as children who are born in *both* the baseline and counterfactual policy scenarios. Because the policies increase fertility, the table also reports the reading scores among "new" children, who are defined as children who are born in the counterfactual policy scenario only. The scores among "new" children can be systematically different from "preexisting" children due to differences in their mothers' post-natal choices as well as unobserved ability. Results are separately reported for the first child of low-education mothers and high-education mothers who are born by the 12th year of the dynamic model.

Among low-education mothers, the full-scale cash-for-care reform (column 1) reduces the average reading score of preexisting children by 1.24 percent, or 0.03 standard deviations, as a result of two forces acting in opposite directions. On the one hand, the reform increases income, which increases the average score by 0.56 percent. On the other hand, mothers tend to reduce formal child care use, and some of them become employed at the same time; this reduces the average score by 1.8 percent (1.22 plus 0.58 percent). In addition, as discussed earlier, the reform also encourages fertility. These new children constitute one-fifth of the preexisting children, and their average reading score is 0.47 percent lower than the average reading score of preexisting children in the *counterfactual* scenario. Therefore, the additional children born under the reform tend to bring the score even lower. The lower test score among new children is primarily due to differences in mothers' post-natal income and (employment and child care) choices.

By contrast, the partial cash-for-care reform (column 2) *increases* the average reading score of preexisting children by 0.72 percent. This amounts to a 2-percent increase (or 0.05 standard deviations) in test scores relative to the full reform. Although the policy reduces formal child care use, it also discourages nonusers of child care from working, which plays a large role in improving children's test scores (+2.21 percent). In addition, the new children born under the reform have a slightly higher score than preexisting children under the counterfactual scenario (+0.33 percent). Interestingly, this difference is primarily attributed to the increased fertility of high-ability mothers.

Both the maternity leave expansion (column 3) and income tax deduction for children (column 4) have a small effect on test scores of preexisting children. In both cases, the reduction in test scores due to changes in maternal employment and child care use are largely offset by the increase in income. Although the new children born under the maternity leave expansion have a similar test score to preexisting children, the new children born under the tax deduction have a noticeably lower score than preexisting children (-1.63 percent). Both the post-natal environment and mother's unobserved type contribute to the score difference (-1.21 and -0.42 percent, respectively).

The lower part of the table reports the effects on test scores of children of high-education mothers. The effects are largely along the "intensive margin", as the fertility effects are rather small. The full cash-for-care reform has a very small impact on preexisting children's test scores (column 1). Therefore, as a whole, it generates a disproportionately large negative impact on children of low-education mothers. By contrast, the partial cash-for-care reform (column 2) has a more balanced impact, improving the test scores of preexisting children of high-education mothers by 0.54 percent. Both the maternity leave expansion and income tax deduction have a positive effect on test scores, which is primarily due to an increase of mother's income.

7 Conclusion

In this paper, we used a structural life-cycle model to analyze the effect of child care polices on life-cycle decisions among women and long-run cognitive outcomes among children. In the model, women's fertility decisions were formulated jointly with labor supply and child care use decisions. Using Norwegian administrative data, we estimated the structural model by exploiting a large-scale child care reform in the period of study as a source of identification. By providing generous cash transfers to mothers who did not use formal child care facilities, the reform resulted in a large exogenous change in the relative price of child care facilities. The exposure to benefits varied across child and women cohorts. Combining with administrative data on national test scores, we further examined the effects of maternal inputs on long-run cognitive outcomes of children by estimating a cognitive ability production function. We accounted for the endogeneity of inputs by explicitly controlling for the mother's unobserved characteristics conditional on her observed behavior as predicted by the structural model.

We found that the child care reform generated sizable changes in employment and fertility decisions, especially among low-education women. If the implementation of the program begins at age 19, then by age 30, the program will have reduced the employment rate of these women by 3.1 percentage points (-5 percent), and increased the average number of children by 0.25 (+26 percent). The overall rate of child care use was almost unaffected due to offsetting effects from increased fertility and reduced child care use. These changes in women's behavior had significant intergenerational consequences, especially on children's cognitive reading ability as measured beyond age 10. Among low-education mothers, we find that an additional year of informal nonmaternal care and maternal care between age 1 and 3 (relative to formal care) reduced the child's average reading score by 14.3 percent (0.34 sd) and 6.5 percent (0.15 sd), respectively. Although these estimates are large, the policy effects on the next generation depends on the policy impact on mother's work and child care use patterns simultaneously. Taking into account of various mechanisms, the net effect of the cash-for-care reform among preexisting children of low-education mothers was negative and small. On the one hand, the reform increased income, which increased the average score by 0.56 percent. On the other hand, mothers tended to reduce formal child care use, and some of them became employed at the same time; this reduced the average score by 1.8 percent. Given that the reform also encouraged fertility, the new children born under the reform tended to bring the average score even lower.

Our findings have important policy implications, especially at a time when there is an increasing advocacy in many countries for more subsidized child care at early ages. Although our analysis was conducted in the Norwegian context where the quality of formal child care is relatively high, it allows us to broadly investigate the effective design of child care policy by conducting counterfactual policy evaluations. Our policy simulation indicates that child care policies are costly to the government through both increased expenditure on existing children and additional expenditure on "new" children due to fertility effects. Child care policies should also take into account of the potential consequences for the wellbeing of children. For instance, our policy simulation suggests that if the full cash-for-care program is changed to a partial program in which workers are ineligible for benefits, reading scores among children of low-education mothers will increase by 0.05 standard deviations (although mothers will face larger work disincentives). Effective design of child care policies should therefore strike a fine balance between impacts on life-cycle decisions of women and effects on children's development.

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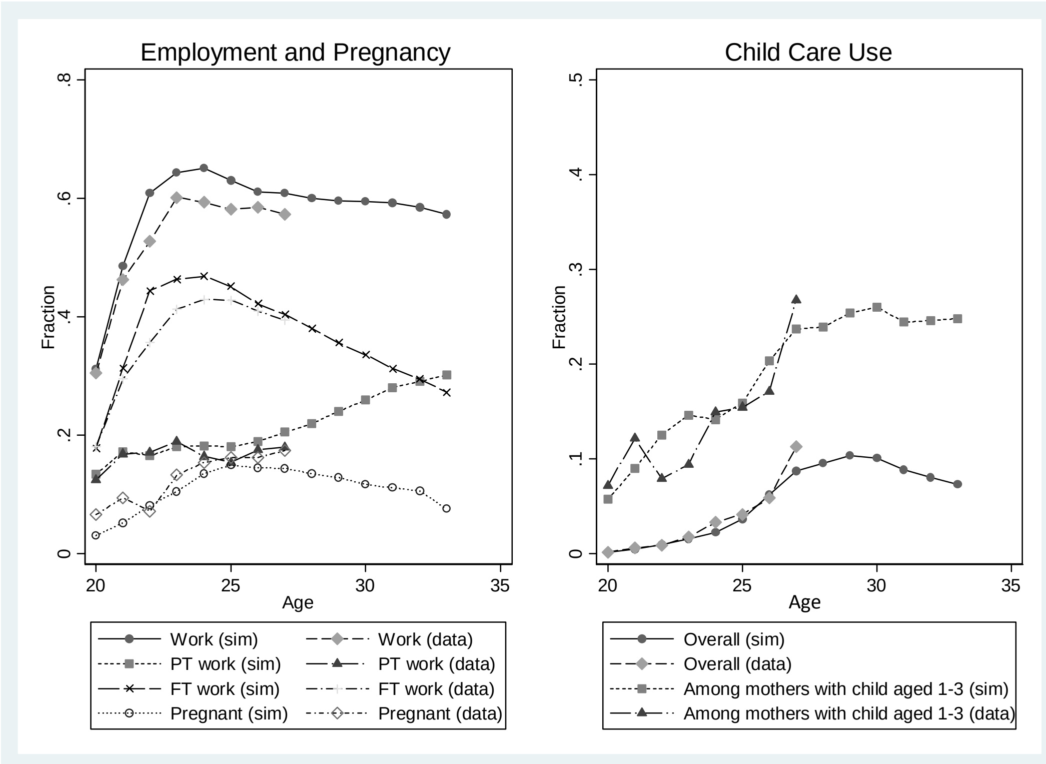


FIGURE 1(a). – Model Fit (Low-Education Women).

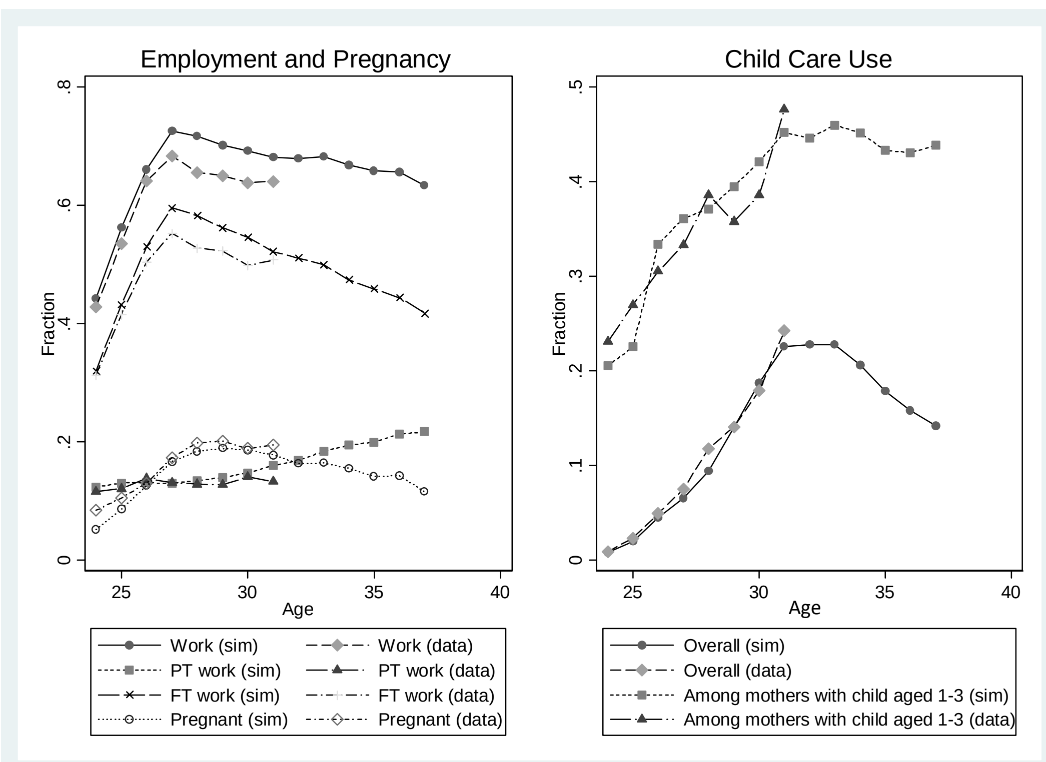


FIGURE 1(b). – Model Fit (High-Education Women).

TABLE I

OBSERVED CHOICES BY AGE

	Work (%)			Child Care Use (%)				
Age	PT or FT	PT	FT	Overall	Among Mothers[a]	Among Working Mothers[a]	Pregnant (%)	Number of Children
Low-education women:								
19	8.7	3.8	4.8	0.0	n/a	n/a	2.7	0.02
20	30.4	12.4	18.1	0.1	7.1	0.0	6.5	0.05
21	46.2	16.8	29.4	0.6	12.1	14.3	9.4	0.11
22	52.8	17.1	35.7	0.9	7.9	9.5	7.1	0.21
23	60.2	18.9	41.3	1.7	9.4	12.8	13.2	0.29
24	59.3	16.4	43.0	3.3	14.9	26.4	15.4	0.42
25	58.2	15.4	42.8	4.1	15.4	14.5	16.2	0.59
26	58.5	17.5	41.0	5.8	17.1	18.6	16.2	0.75
27	57.3	17.9	39.4	11.2	26.8	32.4	17.4	0.93
28	56.0	18.1	38.0	9.1	21.2	30.2	[b]-	1.10
High-education women:								
23	34.7	13.2	21.5	0.0	n/a	n/a	4.8	0.04
24	42.8	11.5	31.3	0.9	23.1	41.7	8.4	0.09
25	53.6	12.0	41.5	2.3	27.0	34.1	10.5	0.17
26	64.1	13.8	50.4	4.9	30.5	41.0	13.0	0.29
27	68.4	13.1	55.3	7.5	33.3	39.2	17.3	0.42
28	65.6	12.8	52.8	11.7	38.6	44.1	19.8	0.59
29	65.0	12.7	52.3	14.0	35.8	39.6	20.1	0.81
30	63.8	14.0	49.8	17.9	38.6	38.1	18.8	1.02
31	64.0	13.3	50.8	24.2	47.6	48.3	19.4	1.22
32	63.6	15.3	48.3	20.4	39.4	41.6	[b]-	1.41

a Mothers with at least one child aged between 1 and 3.

b Not computed from analysis sample.

TABLE II

STRUCTURAL MODEL ESTIMATES, LOW-EDUCATION WOMEN[a]

Utility function parameters:								
Basic parameters:			*Other interactions:*			*All other parameters:*		
Part-time work (α_h^p)	-340.24	(19.17)	α_{hn1}	-45.20	(5.32)	$\beta_{c1\ (coverage)}$	112.15	(42.30)
Full-time work (α_h^f)	-374.83	(14.93)	α_{hn2}	41.44	(7.63)	$\beta_{c2\ (grandparents)}$	-7.62	(10.98)
Child care use (α_c)	-148.95	(19.53)	α_{cn1}	47.78	(11.57)	β_{c3}	10.17	(2.38)
Pregnancy (α_p)	-349.76	(37.96)	α_{cn2}	94.61	(15.01)	β_{h1}	13.35	(5.10)
Work × Child care use (α_{hc})	54.86	(13.74)	α_{pn1}	-52.11	(28.54)	β_{h2}	20.19	(5.03)
Work × Pregnancy (α_{hp})	80.96	(27.24)	α_{pn2}	47.44	(12.35)	β_p	7.07	(2.98)
Work × Lagged work (α_{hh})	127.48	(13.09)						
Std.dev. choice shock (σ_c)	86.68	(6.89)						

Wage equation parameters:		
Intercept	5.392	(0.016)
Work experience	0.093	(0.003)
Work experience sq.	-0.012	(0.001)
Local unemployment rate	-0.154	(0.074)
Std.dev. wage shock (σ_w)	0.181	(0.002)

Type-Specific parameters:	Type 2		Type 3		Type 4		Type 5	
Utility function:								
Work (μ_h)	19.15	(11.79)	91.73	(12.05)	14.45	(11.27)	45.01	(9.46)
Pregnancy (μ_p)	31.99	(21.31)	103.21	(20.58)	-84.33	(19.37)	152.52	(20.49)
Wage equation:								
Intercept (μ_w)	-0.20	(0.02)	-0.34	(0.02)	-0.45	(0.03)	-0.54	(0.02)
Type probabilities (MNL):								
Intercept	1.42	(0.32)	1.58	(0.31)	0.01	(0.54)	1.70	(0.30)
Partner's education	-0.62	(0.56)	-1.02	(0.50)	-1.19	(0.63)	-1.00	(0.49)
Partner's permanent income	-0.38	(0.26)	-0.66	(0.24)	-2.53	(0.47)	-0.33	(0.22)

a Number of observations = 5624, log-likelihood = 6113. Standard errors are given in parentheses.

TABLE III

STRUCTURAL MODEL ESTIMATES, HIGH-EDUCATION WOMEN[a]

Utility function parameters:								
Basic parameters:			*Other interactions:*			*All other parameters:*		
Part-time work (α_h^p)	-535.48	(38.84)	α_{hn1}	-66.09	(7.57)	$\beta_{c1\ (coverage)}$	329.96	(56.34)
Full-time work (α_h^f)	-434.93	(22.42)	α_{hn2}	11.14	(12.09)	$\beta_{c2\ (grandparents)}$	-36.65	(10.46)
Child care use (α_c)	-151.34	(23.27)	α_{cn1}	53.59	(12.86)	β_{c3}	11.86	(2.36)
Pregnancy (α_p)	-621.26	(93.32)	α_{cn2}	154.62	(22.29)	β_{h1}	55.74	(7.68)
Work × Child care use (α_{hc})	84.78	(16.07)	α_{pn1}	326.73	(78.38)	β_{h2}	25.40	(5.18)
Work × Pregnancy (α_{hp})	448.26	(85.03)	α_{pn2}	107.84	(20.28)	β_p	25.91	(6.20)
Work × Lagged work (α_{hh})	285.36	(31.98)						
Std.dev. choice shock (σ_c)	170.34	(16.69)						
Wage equation parameters:								
Intercept	5.604	(0.008)						
Work experience	0.102	(0.003)						
Work experience sq.	-0.012	(0.001)						
Local unemployment rate	0.027	(0.054)						
Std.dev. wage shock (σ_w)	0.208	(0.002)						

Type-Specific parameters:	Type 2		Type 3		Type 4		Type 5	
Utility function:								
Work (μ_h)	-63.73	(18.78)	131.64	(25.80)	113.21	(18.52)	-30.87	(22.46)
Pregnancy (μ_p)	-204.58	(33.02)	240.47	(45.04)	293.17	(37.35)	28.37	(44.13)
Wage equation:								
Intercept (μ_w)	-0.31	(0.01)	-0.31	(0.01)	-0.53	(0.01)	-0.71	(0.02)
Type probabilities (MNL):								
Intercept	1.25	(0.18)	1.08	(0.19)	1.13	(0.18)	0.25	(0.23)
Partner's education	-0.55	(0.29)	-0.34	(0.31)	-1.05	(0.29)	-1.46	(0.36)
Partner's permanent income	-0.83	(0.13)	-0.58	(0.14)	-0.40	(0.12)	-0.47	(0.17)

[a] Number of observations = 8320 , log-likelihood = 9963. Standard errors are given in parentheses.

TABLE IV

SIMULATED AVERAGE TAX RATE BY FAMILY SIZE, YEAR 12

	Number of Children				
Variable	0	1	2	3	All
Low-Education Women:					
Proportion of individuals (%)	29.00	30.73	36.68	3.60	100.00
PDV gross earnings (1,000Kr)[a]	740.49	711.20	629.58	475.67	681.28
	(411.28)	(347.22)	(282.98)	(227.08)	(347.98)
PDV net government benefits (1,000Kr)[a]	-202.80	-58.12	120.15	256.67	-23.36
	(118.24)	(103.24)	(95.11)	(91.67)	(176.16)
Average tax rate (net of benefits)	27.4%	8.2%	-19.1%	-54.0%	3.4%
High-Education Women:					
Proportion of individuals (%)	12.89	25.44	52.78	8.88	100.00
PDV gross earnings (1,000Kr)[a]	1078.36	1004.82	932.43	840.50	961.50
	(480.25)	(445.85)	(360.59)	(260.86)	(398.68)
PDV net government benefits (1,000Kr)[a]	-316.81	-138.98	82.81	281.50	-7.48
	(153.20)	(140.19)	(124.79)	(117.47)	(214.31)
Average tax rate (net of benefits)	29.4%	13.8%	-8.9%	-33.5%	0.8%

a From year 1 to year 12. Standard deviations are in parentheses.

TABLE V

PROPORTION OF VARIANCE EXPLAINED BY UNOBSERVED HETEROGENEITY (TYPE)

	Baseline Policy Environment		If no Cash-for-Care	
Variable	Year 6	Year 12	Year 6	Year 12
Low-Education Women:				
PDV gross earnings (1,000Kr)	32.6%	50.8%	32.9%	52.2%
PDV net government benefits (1,000Kr)	18.2%	25.2%	20.4%	30.7%
PDV utility (1,000Kr)	37.0%	55.0%	38.8%	59.4%
Number of children	8.9%	24.5%	8.8%	23.8%
High-Education Women:				
PDV gross earnings (1,000Kr)	32.7%	50.5%	33.0%	50.5%
PDV net government benefits (1,000Kr)	10.2%	16.8%	10.9%	18.5%
PDV utility (1,000Kr)	65.1%	81.6%	65.3%	81.7%
Number of children	10.5%	19.1%	8.7%	21.7%

TABLE VI

LOG TEST SCORE REGRESSION ESTIMATES (READING)[a]

Variable	(1)	(2)	(3)	(4)
Ln(total mother's income, age 0-3)	0.052	0.033	0.039	0.028
	(0.032)	(0.035)	(0.035)	(0.049)
Years of maternal employment (age 1-3)	-0.041	-0.043	0.015	
	(0.023)	(0.024)	(0.035)	
Years of formal care use (age 1-3)	0.053	0.049	0.003	
	(0.016)	(0.016)	(0.026)	
Years of "employed and no formal care"			-0.078	-0.143
(age 1-3)			(0.035)	(0.043)
Years of "not employed and no formal care"				-0.065
(age 1-3)				(0.035)
Ln(total mother's income, age 0-3) ×				0.029
High education mother				(0.059)
Years of "employed and no formal care" in				0.079
age 1-3 × High education mother				(0.048)
Years of "not employed and no formal care"				0.067
in age 1-3 × High education mother				(0.042)
Conditional mean of mother's unobserved permanent component in:				
Log wage (skill endowment)		0.223	0.202	0.205
		(0.112)	(0.112)	(0.112)
Work preference (in NOK100,000)		0.026	0.028	0.025
		(0.032)	(0.033)	(0.036)
High education mother	0.154	0.121	0.127	-0.414
	(0.036)	(0.040)	(0.040)	(0.760)
High education father	0.112	0.106	0.109	0.102
	(0.037)	(0.037)	(0.037)	(0.037)
R-squared	0.226	0.231	0.237	0.242

a Number of observations = 643. For coefficients on other regressors, see the Appendix. Standard errors are given in parentheses.

TABLE VII
EFFECTS OF COUNTERFACTUAL POLICIES, YEAR 12

		Difference from Baseline			
	Baseline (no Cash-for-Care)	Full Cash-for-Care	Partial Cash-for-Care	Expand Maternity Leave	Tax Deduction for Children
Variable	(1)	(2)	(3)	(4)	(5)
Low-education women:					
Work (%)	62.4	-3.1	-4.6	-1.4	+1.4
Part-time work (%)	24.5	+2.1	-1.0	+1.1	+3.3
Full-time work (%)	37.9	-5.1	-3.6	-2.6	-1.9
Child care (%)	9.8	+0.1	+0.0	+1.2	+1.6
Among mothers with a child aged 1 to 3 (%)	32.1	-5.9	-3.0	+0.1	+1.3
Among working mothers with a child aged 1 to 3 (%)	39.6	-7.7	+0.6	-0.3	+0.7
Pregnancy (%)	9.8	+1.4	+0.5	+0.7	+0.2
Has a child aged 0 to 3 (%)	38.0	+8.3	+3.9	+4.6	+3.9
Number of children	0.95	+0.25	+0.12	+0.12	+0.15
PDV earnings (1,000 Kr)[a]	697.20	-21.80	-25.69	-7.31	-2.36
PDV net government benefits (1,000 Kr)[a]	-75.16	+69.98	+36.74	+30.93	+29.81
PDV utility (1,000 Kr)[a]	359.69	+24.53	+12.46	+11.78	+8.42
High-education women:					
Work (%)	67.8	-1.0	-1.2	-0.5	+1.2
Part-time work (%)	19.3	+0.3	-0.1	+0.2	+0.7
Full-time work (%)	48.5	-1.3	-1.1	-0.8	+0.5
Child care (%)	21.5	-1.1	-0.2	+0.6	+0.3
Among mothers with a child aged 1 to 3 (%)	49.6	-4.2	-1.6	+0.0	+0.2
Among working mothers with a child aged 1 to 3 (%)	53.7	-4.1	+0.3	+0.1	+0.4
Pregnancy (%)	15.3	+0.0	+0.1	+0.0	-0.4
Has a child aged 0 to 3 (%)	54.1	+1.6	+0.7	+1.1	+0.2
Number of children	1.52	+0.07	+0.03	+0.06	+0.07
PDV earnings (1,000 Kr)[a]	969.34	-9.32	-10.73	-6.25	-3.53
PDV net government benefits (1,000 Kr)[a]	-42.90	+44.56	+19.02	+34.39	+29.30
PDV utility (1,000 Kr)[a]	1260.50	+34.30	+12.70	+27.90	+25.70

a From year 1 to year 12.

TABLE VIII

DECOMPOSITION OF POLICY EFFECT ON READING SCORES

Variable	Full Cash-for-Care (1)	Partial Cash-for-Care (2)	Expand Maternity Leave (3)	Tax Deduction for Children (4)
Children of Low-Education Mothers:				
Preexisting Children (born in both baseline and counterfactual, first child):				
Effect on reading test score	-1.24%	+0.72%	+0.18%	-0.07%
Due to:				
Ln(total mother's income, age 0-3)	+0.56%	+0.23%	+0.25%	+0.19%
Years of "employed and no formal care" (age 1-3)	-1.22%	+2.21%	-0.11%	-0.61%
Years of "not employed and no formal care" (age 1-3)	-0.58%	-1.71%	+0.04%	+0.35%
New Children (born in counterfactual only, first child):				
Fraction of new children to preexisting children	21.74%	11.05%	10.67%	12.21%
Reading test score relative to preexisting children (in *counterfactual* scenario):	-0.47%	+0.33%	+0.05%	-1.63%
Due to:				
Difference in mother's post-natal income and choices	-0.69%	-0.18%	-0.70%	-1.21%
Difference in mother's unobserved type	+0.22%	+0.51%	+0.75%	-0.42%
Children of High-Education Mothers:				
Preexisting Children (born in both baseline and counterfactual, first child):				
Effect on reading test score	+0.11%	+0.54%	+0.38%	+0.17%
Due to:				
Ln(total mother's income, age 0-3)	+0.59%	+0.31%	+0.36%	+0.21%
Years of "employed and no formal care" (age 1-3)	-0.50%	+0.22%	+0.02%	-0.04%
Years of "not employed and no formal care" (age 1-3)	+0.01%	+0.02%	+0.00%	-0.00%
New Children (born in counterfactual only, first child):				
Fraction of new children to preexisting children	3.82%	1.52%	2.66%	2.96%
Reading test score relative to preexisting children (in *counterfactual* scenario):	-0.73%	-0.52%	+0.24%	-2.46%
Due to:				
Difference in mother's post-natal income and choices	-0.01%	-0.21%	-0.19%	-0.41%
Difference in mother's unobserved type	-0.72%	-0.31%	+0.42%	-2.05%

APPENDIX TABLE A1

COHORT AND AGE COMPOSITION OF ANALYSIS SAMPLE[a]

Cohort/	Calendar Year												
age	1993	1994	1995	1996	1997	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**
							Low-education women						
1974	19	20	21	22	23	**24**	**25**	**26**	**27**				
1975		19	20	21	22	**23**	**24**	**25**	**26**	**27**			
1976			19	20	21	**22**	**23**	**24**	**25**	**26**	**27**		
1977				19	20	**21**	**22**	**23**	**24**	**25**	**26**	**27**	
1978					19	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**
							High-education women						
1970	23	24	25	26	27	**28**	**29**	**30**	**31**				
1971		23	24	25	26	**27**	**28**	**29**	**30**	**31**			
1972			23	24	25	**26**	**27**	**28**	**29**	**30**	**31**		
1973				23	24	**25**	**26**	**27**	**28**	**29**	**30**	**31**	
1974					23	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**

a The number in cells indicates the age of the woman. Boldface indicates the post-cash-for-care reform environment.

APPENDIX TABLE A2

SUMMARY STATISTICS OF SELECTED VARIABLES[a]

Variable	Low-Education Women	High-Education Women
Panel Data of Adult Individual:		
Yearly gross earnings (workers only, 100,000Kr)	1.78	2.19
	(0.47)	(0.65)
Local child care coverage rate (%)	48.26	49.98
	(11.52)	(11.53)
Grandparent lives close by (%)	67.86	48.07
	(46.70)	(49.96)
Local unemployment rate (%)	2.43	2.46
	(0.58)	(0.58)
Partner's education (=1 if more than high school) (%)	11.32	43.72
	(31.69)	(49.60)
Partner's permanent income (100,000Kr/year)	2.17	2.64
	(0.79)	(1.01)
Children Data for Test Score Regressions:		
Ln (Child's reading test score)	2.89	3.07
	(0.42)	(0.38)
Ln (Child's mathematics test score)	3.18	3.4
	(0.43)	(0.37)
Ln (Child's English test score)	2.97	3.15
	(0.40)	(0.36)
Child's gender (=1 if male) (%)	49.79	50.58
	(50.00)	(50.00)
Child's birth weight (grams)	3.53	3.50
	(0.56)	(0.57)
Mother under age 21 at birth (%)	6.84	0.00
	(25.26)	(0.00)
Young sibling born within 4 years of child's birth (%)	69.50	77.57
	(46.05)	(41.72)

a Standard deviations are given in parentheses.

APPENDIX TABLE A3

LOG TEST SCORE REGRESSION ESTIMATES (MATHEMATICS AND ENGLISH)[a]

	Mathematics		English	
Variable	(1)	(2)	(3)	(4)
Ln(total mother's income, age 0-3)	-0.038	0.008	0.015	0.025
	(0.037)	(0.053)	(0.036)	(0.051)
Years of maternal employment (age 1-3)	0.050		0.022	
	(0.038)		(0.036)	
Years of formal care use (age 1-3)	-0.019		-0.012	
	(0.028)		(0.027)	
Years of "employed and no formal care" (age 1-3)	-0.023	-0.021	-0.053	-0.083
	(0.038)	(0.047)	(0.036)	(0.045)
Years of "not employed and no formal care" (age 1-3)		-0.012		-0.018
		(0.038)		(0.036)
Ln(total mother's income, age 0-3) × High education mother		-0.042		0.003
		(0.063)		(0.060)
Years of "employed and no formal care" in age 1-3 × High education mother		0.037		0.065
		(0.052)		(0.050)
Years of "not employed and no formal care" in age 1-3 × High education mother		0.004		0.013
		(0.045)		(0.043)
Conditional mean of mother's unobserved permanent component in:				
Log wage (skill endowment)	0.290	0.297	0.338	0.343
	(0.120)	(0.121)	(0.116)	(0.116)
Work preference (in NOK100,000)	0.013	0.024	0.024	0.012
	(0.035)	(0.038)	(0.034)	(0.037)
High education mother	0.144	0.632	0.115	-0.003
	(0.043)	(0.824)	(0.041)	(0.781)
High education father	0.074	0.073	0.020	0.018
	(0.039)	(0.039)	(0.037)	(0.037)
R-squared	0.116	0.114	0.094	0.097

a Number of observations for mathematics and English score regressions are 661 and 657, respectively. For coefficients on other regressors, see the appendix table on socioeconomic covariates. Standard errors are given in parentheses.

APPENDIX TABLE A4

OTHER SOCIODEMOGRAPHIC COVARIATES IN LOG TEST SCORE REGRESSIONS[a]

Variable	Reading	Math	English
Child's gender (female=1)	0.120	-0.023	0.045
	(0.030)	(0.013)	(0.030)
Ln(birth weight)	0.188	0.325	0.206
	(0.085)	(0.090)	(0.087)
Mother under age 21 at birth	-0.023	-0.006	0.046
	(0.088)	(0.095)	(0.090)
Young sibling born within 4 years of child's birth	-0.011	0.059	-0.040
	(0.037)	(0.039)	(0.037)
Father's permanent income	-0.084	0.004	-0.011
	(0.035)	(0.037)	(0.036)
Grandparent lives close	-0.020	-0.016	-0.018
	(0.029)	(0.031)	(0.030)
Constant	0.928	-1.129	-0.535
	(1.125)	(1.206)	(1.164)
R-squared	0.242	0.114	0.097

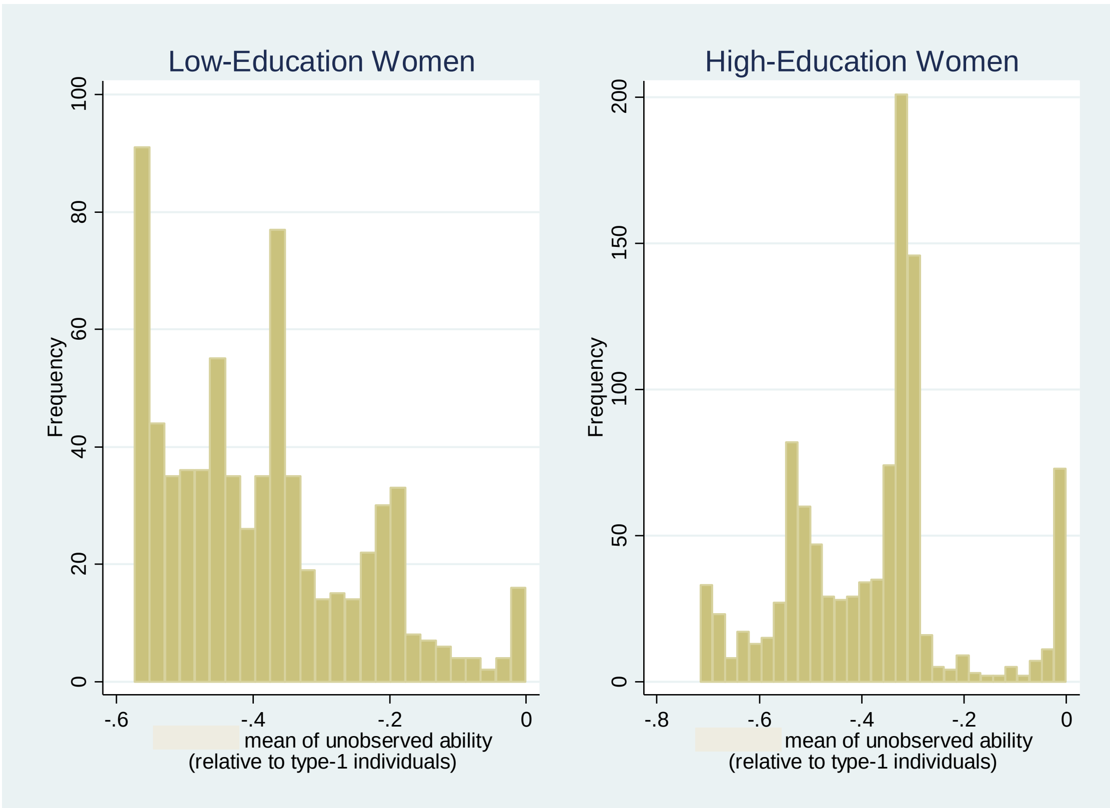
a The coefficients correspond to our preferred model with maternal education interactions. Standard errors are given in parentheses.

APPENDIX TABLE A5

EFFECTS OF COUNTERFACTUAL POLICIES, YEAR 6

		Difference from Baseline			
	Baseline (no Cash-for-Care)	Full Cash-for-Care	Partial Cash-for-Care	Expand Maternity Leave	Tax Deduction for Child
Variable	(1)	(2)	(3)	(4)	(5)
Low-education women:					
Work (%)	66.0	-2.5	-2.4	-0.5	-0.8
Part-time work (%)	18.4	-0.3	-0.9	+0.2	+0.1
Full-time work (%)	47.6	-2.2	-1.6	-0.7	-1.0
Child care (%)	2.6	+0.3	+0.2	+0.4	+0.9
Among mothers with a child aged 1 to 3 (%)	18.0	-3.4	-1.9	+0.5	+1.0
Among working mothers with a child aged 1 to 3 (%)	22.2	-4.4	+1.7	+0.9	+1.0
Pregnancy (%)	11.0	+3.3	+1.4	+1.5	+2.0
Has a child aged 0 to 3 (%)	21.7	+8.1	+3.8	+3.0	+5.3
Number of children	0.29	+0.09	+0.04	+0.03	+0.06
PDV earnings (1,000 Kr)[a]	362.76	-4.81	-5.74	-0.15	-1.55
PDV net government benefits (1,000 Kr)[a]	-60.72	+23.16	+11.97	+9.45	+10.71
PDV utility (1,000 Kr)[a]	142.25	+5.90	+4.36	+3.05	+0.34
High-education women:					
Work (%)	72.2	-1.1	-0.9	-0.7	-1.0
Part-time work (%)	13.7	-0.5	-0.4	-0.3	-0.5
Full-time work (%)	58.5	-0.6	-0.5	-0.4	-0.5
Child care (%)	10.1	-0.3	-0.2	+0.4	+1.2
Among mothers with a child aged 1 to 3 (%)	40.9	-4.4	-1.7	-0.3	+0.1
Among working mothers with a child aged 1 to 3 (%)	43.4	-4.5	+0.3	-0.3	-0.1
Pregnancy (%)	17.6	+0.9	+0.3	+0.7	+0.9
Has a child aged 0 to 3 (%)	36.9	+3.1	+0.9	+2.0	+3.8
Number of children	0.50	+0.04	+0.01	+0.02	+0.05
PDV earnings (1,000 Kr)[a]	517.31	-2.71	-2.90	-1.77	-3.64
PDV net government benefits (1,000 Kr)[a]	-58.64	+17.51	+6.98	+13.99	+12.97
PDV utility (1,000 Kr)[a]	525.34	+15.05	+6.45	+12.42	+12.01

a From year 1 to year 6.



APPENDIX FIGURE A1. –Distribution of the Predicted Mean of Woman's Unobserved Skill Endowment Conditional on Her Observed Behavior.