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Employment and Child Care Decisions of Mothers and the Well-being of their Children*

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Abstract

This paper develops and estimates a dynamic model of employment and child care decisions of women after birth in order to evaluate the effects of mothers' decisions on children's cognitive ability. I use data from the NLSY to estimate the model. The results suggest that the effects of maternal employment and child care on children's cognitive ability are negative and rather sizeable. In fact, having a full-time working mother who uses child care during the first 5 years after the birth of the child is associated with a 10.4% reduction in ability test scores. Based on the estimates of the model, I assess the impact of policies related to parental leave, child care and other incentives to stay at home after birth on women's decisions and children's outcomes.

JEL Classification: D1, J1, J22.
Key Words: Female employment, child care and child development.

1. Introduction

In this paper I study how labor supply and child care decisions of women immediately after birth affect children's cognitive development. The effect of both a more rapid reemployment of mothers after birth and the increase in the number of working hours on children is theoretically ambiguous. On one hand, women thereby accumulate more labor market experience which leads, in general, to higher wages. This may yield benefits for children by providing extra income. On the other

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hand, a woman's earlier return to work reduces parental time investment in children during their early years. This may well have a negative effect on children, as there is evidence that these inputs promote healthy development. The medical and psychological literature have documented that maternal vocabulary and maternal cognitive stimulation are strong predictors of children's cognitive development[1]. Finally, it is not clear theoretically whether parental time is in fact better than an alternative provider's time. Hence, it is interesting to try to determine the net effect on children of both employment and child care decisions of women after birth.

There is an extensive literature on the impact of mothers' employment on children. Several disciplines including economics, psychology, sociology and demography have provided evidence of a positive relationship between human capital investment by parents in children and the ability and performance of these children. However, the results are still far from conclusive.

In this paper I use data from the National Longitudinal Survey of Youth (NLSY). A common limitation of previous studies that have used data from the NLSY to assess the impact of maternal employment on children's outcomes is that they have failed to fully control for potential biases that may arise from the following facts: (1) Women that work/use child care may be systematically different from women who do not work/do not use child care; (2) The child's cognitive ability itself may influence the mother's decisions of whether to work and/or place the child in daycare. These issues can be explained in the following way. Women are heterogeneous in both the constraints they face and their tastes. Likewise, children are heterogeneous in their cognitive ability endowments. While some of these characteristics are observable and recorded in the dataset, some of them are unobserved by the researcher. Mothers' decisions on whether to work and whether to use child care will clearly depend on these unobserved heterogeneous characteristics. Hence, children of working women or women who use child care may differ systematically from those whose mothers stay at home or do not use child care.

To illustrate the sample selection bias problem, I will lay out a couple of examples. In the case of (1), a woman with higher skills is more likely to have a child with high cognitive ability and also more likely to work. Then, a statistical analysis would attribute the effect of this woman's higher skills to employment, and the estimated effects of maternal employment on her child's cognitive outcomes would be upwardly biased. In the case of (2), mothers of low ability children may choose to compensate by spending more time with them, i.e. they are less likely to work. Again, the estimated effect of maternal employment on child's cognitive outcomes would be upwardly biased.

Clearly, this sample selection issue makes evaluation of the effects of women's decisions on child outcomes very difficult. In my model, estimation of the child's cognitive ability production function, which includes mother's time and child care use as inputs, jointly with the mother's work and child care decision rules enables me to implement a selection correction, in the sense that I can adjust for the fact that certain types of children are more likely to be put in child care and/or to have

[1] See for example, National Institute of Health. "Results of NICHD Study of Early Child Care", Reported at Society for Research in Child Development Meetings.

working mothers. I model individuals who make sequential choices about work and child care in each period following birth instead of modeling a one-time decision.

One can think of at least two other possibilities to solving the selection bias problem. The first is to run a regression of measures of the child's cognitive ability on several inputs which include mother's employment and use of child care by using instrumental variables for both of these decisions. This, of course, is an attempt to solve for the potential endogeneity of both choices to unobserved characteristics (of both mothers and children). In this case I would argue that it is very difficult to come across valid instruments for both employment and child care choices. Just to mention one example, child care costs or child care subsidies have been widely used as instrument variables in similar analyses. Yet, there is little exogenous variation (both cross-section and time-series) in either child care prices or child care subsidies, which makes it very difficult to use them as reliable instruments. Local area costs of child care are very likely to be correlated with factors such as wages and the local market characteristics that influence employment and child care choices, and are also likely to be correlated with tastes for child care in the region.

The second possibility is to run household fixed effects models in an attempt to get rid of household specific unobserved components (such as the child's ability endowment) that bias both the coefficient on employment choices and child care decisions[2]. However, as I will show in this paper, mothers do make time compensations for children depending on the child's ability. Hence, using a household fixed effect model in which it is assumed that siblings have the same ability endowments would not be appropriate. In conclusion, given the problems associated with instrumental variables and household fixed effects, structural estimation is almost a necessity.

My estimation provides estimates of the impact of mothers' work and child care decisions on child's ability and performance, which allows me to evaluate how policies related to parental leave, child care subsidies and other incentives for women to stay at home after birth affect women's labor supply, child care decisions and child outcomes.

The most important results of this paper are the following. First, the effect of maternal employment and child care on children's cognitive ability is negative and rather sizeable. In fact, having a full-time working mother who uses child care during the first 5 years after birth is associated with a 10.4% reduction in the child's test scores. Second, this effect is stronger for children with high ability endowments. In other words, there is a higher technological return to time spent with high ability children relative to low ability ones. Third, child care subsidies and a specific type of leave policy are detrimental for children yet increase the mothers' expected lifetime utility, whereas a baby bonus for the woman after the birth of a child would have positive effects on both mothers' welfare and children's test scores.

The paper is organized as follows: In Section 2 I present a brief summary of the related literature. In Section 3 I describe the structure of the model. Section 4 discusses the solution and estimation methods as well as some issues related to identification. Section 5 describes the NLSY data on

[2]This is, in fact, the approach adopted by James-Burdumy (1998) and Ermisch and Francesconi (2000).

which I estimate the model and highlights the overall patterns in the data. Section 5 presents the estimates of the model, evaluates its ability to fit the data and discusses the importance of unobserved heterogeneity. Section 7 presents the results from several policy experiments. Section 8 concludes.

2. Related Literature

Parental influence on children's health, cognitive development and academic achievement has long been recognized. In fact, several disciplines have presented evidence of the relationship between investment by parents in children and the ability and performance of these children. In this section I briefly summarize the main results of the studies published to date examining the impact of early maternal employment on child outcomes in the U.S. using data from the National Longitudinal Survey of Youth (NLSY). Many of these studies present simple correlations between maternal employment and children outcomes without controls for other variables or multivariate regression exercises with few or no measures of family and child characteristics. Some of these studies use small sample sizes or nonrandomly selected samples. Most of them do not control for self-selection of children into child care and/or the group of working mothers; a few of them control for variables such as mother's education and family income, but do not consider the possibility of selection on unobserved characteristics of mothers and children. Hence, most of these results should be interpreted with caution.

Desai et al. (1989) used 503 four year olds from the NLSY in 1986. Results from multivariate regression analysis show a statistically significant adverse effect of maternal employment on children's intellectual ability but only for boys in higher income families. Baydar and Brooks-Gunn (1991) analyzed 572 white 3-4 year olds (in 1986) and concluded that the effects of maternal employment differ, depending on the timing of the employment. The authors found that maternal employment during the first year of life has negative effects on PPVT scores while there is no effect of working in the second or third year. Mott (1991) analyzed 2,387 one to four year olds in 1986. He found maternal employment over 20 hours per week during the second quarter of the child's life to be negatively correlated with PPVT scores. Vandel and Ramanan (1992) studied 189 low income non-Hispanic second graders (in 1986) and found positive effects of maternal employment on Picture Individual Achievement Test (PIAT) and PPVT scores[3].

Parcel and Menaghan (1994) used 768 3-6 year olds whose mothers were employed in 1986. They found positive effects from mothers' employment during the first year or first three years on PPVT scores. Greenstein (1995) analyzed 2,040 4-6 year olds during 1986, 1988 and 1990. He performed different analyses by race and gender. He found an insignificant relationship between maternal employment and PPVT scores. Moore and Driscoll (1997) analyzed 1,154 five to fourteen year olds (in 1992) whose mothers were on AFDC during 1986-1990. The authors found that

[3] For a detailed description of these assessments see section 5.1.

maternal employment is associated with higher PIAT, although most of the effects are eliminated after controlling for maternal and household characteristics.

Harvey (1999) used children from 3 to 12 years old in 1986, 1988, 1990, 1992 and 1994. Her sample varies from year to year. She found a negative effect of maternal work hours on PPVT and PIAT scores for young children and a weaker or null effect at higher ages. Waldfogel et al. (2000) analyzed a sample of 1,872 children followed longitudinally from birth to age 7 or 8. They found small and persistent negative effects of maternal employment during the first year on children's cognitive outcomes for white children but not for African-American children. Finally, Han et al. (2001) used a cohort of 462 children followed from birth to age 7 or 8. They found that maternal employment in the first year has a negative but small effect on cognitive outcomes for white children, which persisted to ages 7 and 8.

Interestingly, a third of these studies predict a negative relationship between maternal employment and children's outcomes, another third predicts a positive relationship and the remaining fraction predicts that this relationship is either insignificant or varies depending on the group of children or the timing of maternal employment. As noted before, a common limitation of these studies is that they have not fully controlled for potential biases that arise due to the endogeneity of employment and child care choices. A few recent studies have tried to overcome this issue by either using a more extensive set of explanatory variables or using instrumental variables. Blau and Grossberg (1992) used 874 3-4 year olds in 1986. To correct for potential heterogeneity bias, they estimated their basic equation using instrumental variables for maternal supply[4]. However they use few plausible instruments. They concluded that maternal employment in the first year after birth is associated with lower PPVT scores, while the contrary is true for the second and third years of employment. Ruhm (2000) used a larger and more representative sample from the NLSY in an attempt to control for as many characteristics as possible which might otherwise bias the estimated effect of maternal employment on child outcomes. His results from multivariate regressions indicate that maternal labor supply during the first three years of the child's life is predicted to have a small negative effect on the verbal ability of 3 and 4 year olds and a significant negative effect on the reading and math achievement of 5 and 6 year olds.

Finally, James-Burdumy (1998) used 2,119 three to four year olds (in 1986 and 1988) to estimate a household fixed-effect model using instrumental variables to control for unobserved heterogeneity. She concluded that there is no effect of hours or weeks worked by the mother in years 1,2 or 3 on child test scores. In the case in which the unobserved ability endowments of children were assumed to be the same for children of the same mother, then a mother's fixed effect model would be a sensible framework. However, as I show in this paper, the effect of maternal employment on children differs by child type. Furthermore, mothers make time compensations for children depending on their ability type. In this case, using a fixed effect model would not be appropriate.[5]

[4]Instruments include fitted values from two-limit Tobit regressions for maternal supply.

[5]Ermisch and Francesconi (2000) used a sibling difference estimation strategy to assess the effect of mother's employment on children's cognitive ability using the British Household Panel Survey (BHPS).

3. The Model

To investigate these issues a model with the following attributes was used.

3.1. Choices

At each period[6] t after birth and before the child enters primary school, i.e. 5 years of age, the mother chooses whether to work full-time, work part-time or not work and whether to use childcare services or not. Formally, let each alternative $j \in J = \{(h_t, I_t^c) : h_t = f_t + \frac{p_t}{2} \text{ and } I_t^c = 0, 1\}$.The first component corresponds to the employment decision while the last component is related to the use of child care services. f_t, p_t and I_t^c are given by the following indicator functions:

$$\begin{aligned} f_t &= I\left[\text{woman works full-time in period } t\right] \\ p_t &= I\left[\text{woman works part-time in period } t\right] \\ & \quad \text{and} \\ I_t^c &= I\left[\text{childcare services are used in period } t\right] \end{aligned}$$

For simplicity, let us define:

$$d_t^j = I\left[\text{alternative } j \in J \text{ is chosen at time } t\right]$$

3.2. Utility Function

The current-period utility function for choosing alternative j is given by:

$$\begin{aligned} U_t^j = {} & \tfrac{1}{\alpha_1} c_t^{\alpha_1} + \alpha_2 h_t + \alpha_3 \left(\tfrac{A_t^\lambda - 1}{\lambda}\right) + \alpha_4 I_t^c + \alpha_5 h_t \left(1 - I_t^c\right) + \alpha_6 I_t^c (1 - I[\textstyle\sum_{\tau=1}^{t-1} I_\tau^c > 0]) \\ & + \alpha_7 I\left[t = 1\right] I_t^c + \alpha_8 I[t < 5] I_t^c + \sum_{j=1}^{6} \varepsilon_t^j d_t^j, \qquad \text{for } j = 1, ..., 6 \end{aligned} \tag{3.1}$$

with $c_t = w_t(500 h_t) + I^H - cc I_t^c$.

where c_t is consumption, α_2 is a non-pecuniary benefit/cost of working, A_t is child's cognitive ability which is known by the mother but unknown to the econometrician, α_4 is a non-pecuniary benefit/cost of using child care, α_5 is the disutility derived from working if child care is not available during that period, α_6 is the cost of initiating child care, e.g., search cost for the best daycare center, α_7 is an extra benefit/cost associated with using child care during the first quarter after birth and α_8 is an extra cost associated with using child care for children under one year old. ε^i is an alternative-specific random taste component with $j = 1, .., 6$ indexing each of the six possible choices. Finally, w_t is the mother's real hourly wage, I^H is her husband's average income during the period, and cc is the cost of child care services.

[6] Each period in the model corresponds to a quarter (three months).

3.3. Wage Formation

At birth, the woman's wage is w_0[7]. We assume that this wage corresponds to:

$$\ln w_0 = X_0\theta + \xi_0 \tag{3.2}$$

where X_0 is a set of observable characteristics that include education, age ,age squared and race that are assumed to determine the woman's wage at time $t = 0$ and ξ_0 corresponds to the woman's skill endowment[8].

After childbirth, re-employment wages are described by the following process:

$$w_t = w_0(1-\delta)^t \exp(\phi_1 E_t + \phi_2 f_{t-1} + \phi_3 p_{t-1} + \phi_4(E_t * \text{ed}) + \epsilon_t).$$

where

δ is the depreciation rate of human capital, $E_t = \sum_{\tau=0}^{t-1} h_\tau$ is total work experience since birth, f_{t-1} and p_{t-1} indicate whether the woman worked full-time or part-time during the immediately preceding period, E_t*ed is an interaction term of woman's experience and her education at birth, and ϵ_t is a measurement error with $\epsilon_t \sim N(0, \sigma_\epsilon^2)$.

Log wages are then given by:

$$\ln w_t = \ln w_0 - \delta t + \phi_1 E_t + \phi_2 f_{t-1} + \phi_3 p_{t-1} + \phi_4(E_t * \text{ed}) + \epsilon_t \tag{3.3}$$

3.4. Child's Cognitive Ability Production Function

Each mother derives utility from her child's cognitive ability, which she can observe. The econometrician, on the other hand, has only approximate measures in the form of test scores. We assume that there is a cognitive ability endowment that is correlated with some observable and unobservable variables according to:

$$\ln A_0 = \gamma_1\xi_0 + \gamma_2\text{ed} + \gamma_3\text{race} + \gamma_4\mu + \gamma_5\text{BW} + \gamma_6\text{I[age<18]} + \gamma_7\text{I[age>33]} + \gamma_8\text{gender} + \omega_\kappa \tag{3.4}$$

where ξ_0 is the mother's skill endowment, ed is her education at birth, race is a dummy variable equal to 1 if the child is non-white, 0 otherwise , μ is the father's skill endowment[9], BW is child's

[7] w_0 is measured at birth as the average of the previous 18-month period hourly wages. We do this in order to avoid dealing with measurement error in initial wages.

[8] X_0 includes education, age and age squared (which proxy for experience) because these are variables that augment initial skill endowment in a human capital earnings function (see Willis (1986), Heckman and Sedlacek (1985), Keane and Wolpin (1997)). It is important to make a dichotomy between initial skill endowment and subsequent investments in order to get results that can be interpreted. In fact, the reason why AFQT scores are not included as part of X_0 is that these correspond to a mixture of the woman's initial ability endowment and subsequent educational inputs. If I introduce this variable in the wage equation, it would be both difficult to interpret that particular coefficient and less clear to interpret several other coefficients, in particular the coefficient associated to education in the cognitive ability production function (γ_2).

[9] I assume that the labor income of father i is given by: $\ln I_{it}^H = \beta_o + \beta_1 age_{it} + \beta_2 age_{it}^2 + \mu_i + \varepsilon_{it}$

birth weight, I[age<18] is a dummy variable that equals 1 if the mother is younger than 18, 0 otherwise, I[age>33] is a dummy variable that equals 1 if the mother is older than 33, 0 otherwise, gender is the child's gender and ω_κ corresponds to the child's cognitive ability type. I assume that $\kappa = l, h$, i.e., child's cognitive ability type can take two values, low or high. I also assume that the mother knows her child's specific random effect ω_κ, in other words, she knows $\ln A_0$.

By including education in equation (3.4) one can find out whether more educated mothers have a better technology for transferring human capital to their children.

Given this cognitive ability endowment, ability at time t will be given by:

$$\ln A_t = \ln A_0 + \gamma_9 E_t + \gamma_{10} C_t + \gamma_{11}(\ln A_0 * E_t) + \gamma_{12}(\ln A_0 * C_t) \tag{3.5}$$

where $E_t = \sum_{\tau=0}^{t-1} h_\tau$ (total experience) and $C_t = \sum_{\tau=0}^{t-1} I_\tau^c$ (total child care use).

Equation (3.5) implies that the child's initial ability endowment is moved about by mother's decisions regarding employment and daycare at every quarter t after birth. Additionally, interaction terms between the child's initial ability and mother's choices are included in order to allow the specification to be as flexible as possible, and in particular, to assess whether the effect of women's choices varies depending on the type of child.

The econometrician does not observe actual cognitive ability but has available a set of cognitive ability test scores from which she has to infer the child's cognitive type. Let S^A be the corresponding test scores and let it be specified as:

$$\ln S_t^A = \ln A_t + \eta_1 d_{1t}^A + \eta_2 d_{2t}^A + v_t \tag{3.6}$$

where d_{1t}^A and d_{2t}^A are cognitive ability test dummies, and v_t is a measurement error with $v_t \sim N(0, \sigma_v^2)$.

The mother knows the technological relation (3.5), as well as $\ln A_0$. This is equivalent to assume that she knows the distribution of test scores. In other words, there is no learning as the child grows up.

From the NLSY we can use the results of the Peabody Picture Vocabulary Test (PPVT) and the Picture Individual Achievement Test (PIAT)[10] as measures of cognitive ability.

3.5. Mother's heterogeneity

In order to take into account mother's unobserved heterogeneity as well, I will assume that women differ in their taste for work (α_2) and their taste for childcare (α_4)[11]. The corresponding preference

where age_{it} is father i's age in year t, μ_i is the father's skill endowment and ε_{it} is measurement error. Hence, the skill endowment is approximately given by:$\mu_i \approx \frac{1}{5}\sum_{t=1}^{5} \ln I_{it}^H - (\widehat{\beta}_o + \widehat{\beta}_1 age_{it} + \widehat{\beta}_2 age_{it}^2)$.The results of this regression are reported in Appendix 2.

[10] The PIAT contains a mathematical section and a reading section, both of which will be used in the analysis.

[11] Additionally, we have assumed that each woman is her own skill type as defined by equation (3.2).

parameter by type is given by:

$$\alpha_{i,k} = \alpha_{i1}\xi_0 + \alpha_{i2}\text{ed} + \alpha_{i3}\text{race} + \rho_i time + \overline{\alpha}_{i,k} \qquad \text{for } i = 2,4 \text{ and } k = l,h$$

where ξ_0 is the mother's skill type, ed is her education at birth, race is a dummy variable equal to 1 if she is black or hispanic, 0 otherwise, *time* is a cohort trend[12] and $\overline{\alpha}_{i,k}$ is the unobserved taste for work/daycare which is independent of the woman's personal characteristics. For simplicity, I assume that there are two different types in each case (low and high). This implies that women will be classified into 8 types[13] by unobserved characteristics of both them and their children. $\overline{\alpha}_{i,k}$ are parameters to be estimated.

3.6. The Individual's Optimization Problem

To close the model we assume that the random preference shocks $\varepsilon_t = \{\varepsilon_t^1, \varepsilon_t^2, \varepsilon_t^3, \varepsilon_t^4, \varepsilon_t^5, \varepsilon_t^6\}$ have a joint normal distribution $F(\varepsilon_t)$ and are serially uncorrelated. Define S_t as the state at period t that arises as a result of the decisions made up to t. The problem is characterized by three state variables that evolve endogenously: work experience since birth (E_t), work decision during the immediately preceding period (h_{t-1}) and total childcare used (C_t). These state variables evolve in the following way:

$$\begin{aligned}
&E_o = 0 \\
&E_{t+1} = E_t + h_t \\
&h_o \in \{0, \tfrac{1}{2}, 1\} \\
&C_o = 0 \\
&C_{t+1} = C_t + I_t^c.
\end{aligned}$$

There are also a set of fixed state variables, i.e., the ones that do not evolve endogenously. The mother's skill endowment as well as the child's ability endowment are part of these fixed state variables.

Further we can denote $S_t = \{E_t, h_{t-1}, C_t, \varepsilon_t\}$ as the state space at t and $\overline{S}_t = \{E_t, h_{t-1}, C_t\}$ as the deterministic part of the state space.

At any period after birth[14], the woman maximizes the expected present value of remaining utilities. The woman's optimization problem can be written in the following way. Define $V(S_t, t)$, the value function, to be the maximal expected present value of the rewards during the 20-quarter

[12] I introduce the cohort term in order to try to understand whether a change in these preference parameters over time has accounted for the increase in female labor participation rates and/or the raise in the average number of hours worked by married women with young children over the past three decades.

[13] The 8 corresponds to all the possible combinations of the two child cognitive ability types ω_κ, the two maternal tastes for work α_{2k} and the two maternal tastes for child care α_{4k}.

[14] Each period in the model corresponds to a quarter.

period following childbirth at period t, given the individual's state S_t and discount factor β.

$$V(S_t,t) = \max_{d_t^j} E\left[\sum_{\tau=t}^{20} \beta^{\tau-t} \sum_{j=1}^{6} U_t^j d_t^j | S_t\right]. \tag{3.7}$$

S_t contains all the relevant history of choices that enter the current-period utility functions and the realizations of all shocks at t. Maximization of (3.7) is achieved by choice of the optimal sequence of control variables $\{d_t^j : j = 1, ..., 6\}$ for $t = 1, ..., 20$.

The value function can be written as the maximum over alternative-specific value functions, each of which obeys the Bellman equation (Bellman 1957):

$$V(S_t,t) = \max_{d_t^j} \left\{V^j(S_t,t)\right\} \tag{3.8}$$

with $j \in J = \{(h_t, I_t^c) : h_t = 0, \frac{1}{2}, 1 \text{ and } I_t^c = 0, 1\}$. Alternative-specific value functions $V^j(S_t,t)$ are given by:

$$V^j(S_t,t) = U_t^j(c_t, d_t^j, A_t) + \beta E\left[V(S_{t+1}, t+1)|S_t, d_t^j = 1\right] \quad \text{for } t < 20 \tag{3.9}$$

At the terminal period, $T = 20$ quarters, when the child goes to primary school I assume the terminal period value function to be:

$$V^j(S_T,T) = U_T^j(c_T, d_T, A_T) + \sum_{\tau=a}^{65} (\beta^4)^{\tau-a}\left(\frac{1}{\alpha_1}\widehat{c}^{\alpha_1} + \alpha_2\right) + \sum_{\tau=5}^{65} (\beta^4)^{\tau-5} \alpha_3 \left(\frac{A_{T+1}^{\lambda} - 1}{\lambda}\right), \; T = 20$$

a is the age of the mother by the end of the 5-year period. A_{T+1} is the cognitive ability of her child by the end of the period, given the inputs at period T. Finally, $\widehat{c_i} = E(c_i|w_{iT}, E_{iT}, d_{iT}, I_{iT}^H, \xi_o)$ is the predicted consumption, which is a function of the state variables at T and accounts for the operativeness of the state vector at $T = 20$ for future behavior of the woman beyond the time span of the model. Specifically:

$$\widehat{c_i} = [E(h_t) * \overline{w}_{iT+1}] + \nu I^H$$

where I^H is the husband's average income, $\overline{w}_{iT+1}$ is the predicted wage of individual i at period T +1 given the state variables at T and the probability of employment status, $E(h_t)$, is given by a logit in various characteristics of the individual[15].

4. Solution and Estimation of the Model

4.1. Solution to the Individual's Decision Problem

The individual's optimization problem is solved recursively from the final period T. Consider an individual at period $T-1$ with particular values of the deterministic state space $\overline{S}_{T-1}$. In order

[15] Estimations of this logit are reported in Appendix 2.

to calculate the alternative-specific value functions (3.9) at T,the individual must calculate:

$$\begin{aligned} \text{Emax}(S_T) &= \text{Emax}(V_T^1, V_T^2, V_T^3, V_T^4, V_T^5, V_T^6|\overline{S}_{T-1}, d_{T-1}^j) \\ &= \int_{-\infty}^{+\infty} \max(V_T^1, V_T^2, V_T^3, V_T^4, V_T^5, V_T^6|\overline{S}_{T-1}, d_{T-1}^j) dF(\varepsilon) \end{aligned} \tag{4.1}$$

for each $j = 1, ..., 6$. Even when ε_t's are stochastically independent, the Emax function is, in general, a multivariate integral. Furthermore, given that each choice $j = 1, ...6$, leads to a different state at time T, Emax must be calculated at each of these six time T state points for each element of $\overline{S}_{T-1}$.

Having calculated (4.1), the value functions at $T-1$, $V^j(S_{T-1}, T-1)$, are known up to the random draws of the ε_{T-1}'s. The individual receives a set of draws at $T-1$ and chooses the alternative with the highest value. Before entering period $T-1$, the individual must calculate in a similar fashion, the expected maximum of the alternative-specific value functions at $T-1$ for every feasible state point:

$$\begin{aligned} \text{Emax}(S_{T-1}) &= E\left[\max_{d_{T-1}^j}[V^j(S_{T-1}, T-1)]\right] \\ &= E\left[\max_{d_{T-1}^j}(U_{T-1}^j + \beta \text{Emax}(S_T|d_{T-1}^j = 1))\right]. \end{aligned}$$

It is easy to see, that the functions $\text{Emax}(S_t)$ are determined recursively. We keep moving backwards, to compute the expected maximum of alternative-specific value functions at every t,which will take the general form:

$$\begin{aligned} \text{Emax}(S_t) &= E\left[V(S_t, t)\right] \\ &= E\left[\max_{d_t^j}[V^j(S_t, t)]\right] \\ & \quad E\left[\max_{d_t^j}(U_t^j + \beta \text{Emax}(S_{t+1}|d_t^j = 1))\right]. \end{aligned}$$

This backward solution for the Emax functions is repeated until $t = 0$, i.e., the moment of birth. Notice that calculating the $\text{Emax}(S_t)$ function for any given value of the state space involves a six dimensional integration with respect to the ε_t vector. This calculation is performed by Monte Carlo integration, i.e., for each draw of the ε_t vector from the joint distribution, $\max_{d_t^j}[V^j(S_t, t)]$ is obtained and the sample mean is used as a numerical approximation of $\text{Emax}(S_t)$[16].

Given the sequence of Emax functions, the choices that individuals make over the 5-year period after birth are determined by their initial conditions at birth and the sequence of shocks that

[16] The algorithm uses 20 draws.

are drawn. At birth, a woman receives a set of preference shocks, chooses from among the six alternatives the one with the highest alternative-specific value function and updates the state space, given that choice. A new set of draws is received during the second quarter after birth, the optimal choice is made, the state space is updated and the process is repeated until the end of the period.

4.2. Estimation

Consider having data on a sample of individuals who are assumed to be solving the choice model previously described and for whom choices are observed in each of the periods $t = 1, ..., T$. In addition, as usual, wages are assumed to be observed only in the periods in which market work is chosen. Then, the joint probability of choosing alternative j and the corresponding (accepted) wage if market work is involved in alternative j is:

$$\begin{aligned} \Pr(d_t^j &= 1|w_t, \overline{S}_t) = \\ &= \Pr\left(U_t^j + \beta \mathrm{Emax}(S_{t+1}|d_t^j = 1) \geq U_t^k + \beta \mathrm{Emax}(S_{t+1}|d_t^k = 1)\right) \qquad \forall k \neq j \end{aligned} \tag{4.2}$$

namely, the probability that the alternative j value function exceeds the other five and that the wage that is accepted is the observed wage.

The likelihood contribution of each individual in the sample will then be given by:

$$L_i = \prod_{t=1}^{t=T} \left[\sum\nolimits_j \Pr(d_t^j = 1|w_t, \overline{S}_t)\right] .\phi(w_t|\overline{S}_t)^{(f_t+p_t)} \cdot f(S_t^A|E_t, C_t)^{I[S_t^A \ available]}$$

where $\phi(w_t|\overline{S}_t)$ is the likelihood of observing wage w_t given the state space at t, $f(S_t^A|\cdot)$ is the likehood of observing test score S_t^A given inputs in the production function of child's quality and $I[S_t^A\ available]$ is an indicator function equal to 1 if a test score is available in period t and 0 otherwise. The likelihood function for the sample is the product of these probability statements over people.

I have assumed that we have available a sample of individuals for whom choices $\{h_t, I_t^c\}$ are observed in each of the periods $t = 1, ..., 20$. Instead, the NLSY sample that I use contains individuals for whom employment choices are observed from $t = 1$ to $t = 20$ but child care choices are observed only from $t = 1$ to $t = 12$. To deal with this shortcoming I include the probability expressions that account for each possible child care use history after period $t = 12$ given the state space at $t = 13$ in the likelihood function[17]. Given that the number of possible histories increases significantly over

[17] For example, the probability of observing choice $\{f_{13}, p_{13}\}$ in $t = 13$ for every possible choice of I_{13}^c will be given by:

$$\begin{aligned} \Pr(f_{13}, p_{13}|w_{13}, \overline{S}_{13}) = \ & \Pr(f_{13}, p_{13}, I_{13}^c = 0|w_{13}, \overline{S}_{13}). \Pr(I_{13}^c = 0|\overline{S}_{13}) \\ & + \Pr(f_{13}, p_{13}, I_{13}^c = 1|w_{13}, \overline{S}_{13}). \Pr(I_{13}^c = 1|\overline{S}_{13}) \end{aligned}$$

where $\Pr(I_{13}^c = k|\overline{S}_{13}) = \frac{\Pr(f_{13}, p_{13}, I_{13}^c = k|w_{13}, \overline{S}_{13})}{\sum_{j=0}^{1} \Pr(f_{13}, p_{13}, I_{13}^c = j|w_{13}, \overline{S}_{13})}$, for $k = 0, 1$.

time and the estimation can become burdensome, I use semester periods for the last two years of the time span from birth to five years of age. In order to do this it is only necessary to adjust the discount factor when needed.

Recall that we allow for K different types of individuals. In this case, independence over time is conditional on type. Let π_k be the proportion of the kth type in the population. Then, the procedure will consist of finding the parameter vector that maximizes the weighted average of type-specific likelihood contributions where the weights are the type proportions π_k and are parameters to be estimated. In other words, the likelihood function is a mixture of the type-specific likelihoods, $\sum_{k=1}^{K} \pi_k L_{ik}$, where L_{ik} is the likelihood of person i's observed choice sequence, and corresponding wage and score (if market work and test score are observed) if person i is of tastes/endowments type k.

Maximizing the sample likelihood with respect to the parameter vector would yield consistent and asymptotically normal estimates. Evaluation of the likelihood itself requires the calculation of six-variate integrals[18]. In order to circumvent this problem, we use a GHK recursive probability simulator (Geweke, Keane and Runkle (1994)) of the choice probabilities and form a simulated maximum likelihood estimator[19].

4.3. Identification Issues

In the model, accumulated experience is correlated with the child's initial cognitive ability level because women with higher skill endowment (which affects the child's cognitive ability outcomes) will tend to have higher working experience. Identification of the selection model is provided by factors that shift experience but do not already affect child's ability. The basic intuition is that short run movements in mothers' and husbands' wage rates enter the mother's working and child care use decision rules, but do not directly affect child's ability.

On the one hand, I assume that only long lived components of parents' income affect child outcomes. Two main channels can be thought to link permanent variations in the earnings capacity of parents and children's outcomes. The first one is that these long lived factors affect household income, which in turn determines investments in children. The second one is that they may be di-

Let $\overline{S}_t'$ be the state space at the beginning of time t excluding C_t. The probability of observing a certain choice in period $t = 14$ will then be given by:

$$\begin{aligned}\Pr(f_{14}, p_{14}|w_{14}, \overline{S}_{14}) = \; & [\Pr(f_{14}, p_{14}, I_{14}^c = 0|w_{14}, \overline{S}_{14}', C_{14} = C_{13}+1).\Pr(I_{14}^c = 0|\overline{S}_{14}) + \\ & \Pr(f_{14}, p_{14}, I_{14}^c = 1|w_{14}, \overline{S}_{14}', C_{14} = C_{13}+1).\Pr(I_{14}^c = 1|\overline{S}_{14})]. \\ & \Pr(C_{14} = C_{13}+1) + \\ & [\Pr(f_{14}, p_{14}, I_{14}^c = 0|w_{13}, \overline{S}_{14}', C_{14} = C_{13}).\Pr(I_{14}^c = 0|\overline{S}_{14}) + \\ & \Pr(f_{14}, p_{14}, I_{14}^c = 0|w_{13}, \overline{S}_{14}', C_{14} = C_{13}).\Pr(I_{14}^c = 0|\overline{S}_{14})].\Pr(C_{14} = C_{13})\end{aligned}$$

where $\Pr(C_{14} = C_{13}) = \Pr(I_{13}^c = 0|\overline{S}_{13})$ and $\Pr(C_{14} = C_{13}+1) = \Pr(I_{13}^c = 1|\overline{S}_{13})$

[18] The probability expressions (4.2) are six-variate integrals.

[19] The algorithm uses 25 draws.

rectly correlated with children's skill endowments through genetic transmission or a better capacity to enhance the child's learning abilities. Both channels are incorporated in the model although no attempt is made to separate them.

On the other hand, components such as age of the mother at birth (and age squared), age of the father (and age squared), mother's previous period employment decisions and the child's age create short run wage variation in wages and tastes (for work and child care) but are assumed to not affect child outcomes. In general, we do observe in the data that women who are older when they have a child have higher wages and are more likely to work and more likely to put children in day care even conditional on their skill endowment and their children's ability. Although one might think that age of the mother could potentially be correlated with the child's ability endowment there is no strong evidence of this fact in either the medical or psychological literature, except when one is referring to teenage motherhood[20]. Furthermore, what I assume is that conditional on women's ability endowments, education, being older than 18 years and other personal characteristics, age does not affect the ability of the child.

An alternative way to estimate the effect of maternal employment and child care decisions on children's cognitive ability would be to estimate reduced form decision rules for both employment and child care choices together with a continuous outcome equation (test scores) and a wage equation. Appendix 1 outlines what the equations in this kind of setup would look like. From those, it is easier to see the exclusion restrictions that allow me to identify the key effects in my model. Variables that measure short-run variation in wages are assumed to enter employment and child care use decision rules while they do not directly affect child's outcomes. In particular, age of the mother at birth (and age squared), her employment decisions in the previous period, the child's age and the age of the father at birth (and his age squared) enter the work and child care probit but do not affect the test scores equation. It is interesting to note that in this case one would have to estimate 98 parameters as opposed to a total of 61 in the structural model.

5. Data

The data are taken from the 1979 youth cohort of the National Longitudinal Surveys of Labor Market Experience (NLSY). The NLSY consists of 12,686 individuals, approximately half of them women, who were 14-21 years of age as of January 1, 1979. The sample consists of a core random sample and an oversample of blacks, hispanics, poor whites, and the military. Interviews were first conducted in 1979 and have been conducted annually to the present. On a regular basis, the NLSY79 has collected pre- and postnatal care information from the sample of women as they became mothers. Using data from the NLSY79 Workhistory File, it is possible to construct a detailed employment history for each mother in the sample for the period surrounding the birth of

[20] The cognitive ability production function includes a control for very young mothers by introducing the indicator function $I[\text{age}< 18]$.

her child, i.e., up to four quarters[21] before birth and each quarter interval since the child's birth for a period of five years.

In 1986 a separate survey of all children born to NLSY79 female respondents began. In addition to the data on the mother from the NLSY79, the child survey includes assessments of each child as well as additional demographic and development information collected from either the mother or the child. A battery of child cognitive, socioemotional, and physiological assessments as well as a variety of attitude, aspiration and psychological well-being questions have been administered biennially for children of appropriate age.

5.1. Child Assessments

I use as a measure of the child's cognitive ability the score on the Peabody Picture Vocabulary Test (PPVT) and the Peabody Individual Achievement Test Reading Recognition subtest (PIAT-R) and Mathematics subtest (PIAT-M). Both assessments are among the most widely used for preschool and early school-aged children. The PPVT is a vocabulary test for standard American English and provides a quick estimate of verbal ability and scholastic aptitude. The PIAT-M measures attainment in mathematics. It consists of eighty-four multiple-choice items of increasing difficulty. It begins with such early skills as numeral recognition and progresses to measuring advanced concepts in geometry and trigonometry. Finally the PIAT-R measures word recognition and pronunciation ability. Skills assessed include letter matching, name recall, and the ability to read single words aloud.

The PPVT was administered to all children aged three and over. All age-eligible children were assessed in 1992, even if they had previously been tested. I examined the results for 3, 4 and 5 year olds. The PIAT-M and PIAT-R were administered to children 5 and over each survey year. I used data for children 5, 6 and 7 years old. The analysis is based on the "standard" cognitive assessment scores, which are transformations (on an age-specific basis) of the raw scores.

Table 1 displays average test scores in the NLSY by categories. The first three columns show average results for children age 3, 4 and 5 in the PPVT. Columns four to six show standard scores in the PIAT Math subtest and the last three columns show the scores in the PIAT Reading subtest for children 5, 6 and 7 years old. Simple t-tests indicate that, on average, children of older mothers (30 years or more) in the NLSY do better in all three tests, except the reading subtest for older children (7 years). Children of more educated women (more than 12 years of schooling) also perform better in all three categories, as well as children of white women in the NLSY. Results also indicate that children whose fathers are present for at least the first three years of their life exhibit higher test scores. With respect to family structure, we can observe that children with more than two siblings perform worse than only children or children with at most one sibling. Firstborns always do better, on average, in all three tests at all ages.

[21] A quarter consists of 13 weeks.

With respect to mother's employment one can observe that children of women working (full-time or part-time) during the fourth quarter after birth obtained higher scores on the three tests at all ages. Children of mothers that returned within the first six months after birth to work also performed better. However, if we classify children by working status of their mother, i.e., full-time vs. part-time, there is no significant difference in any test score between them. Finally, children in the sample[22] used in this paper obtained, on average, higher test scores at all ages for reasons that will become clear later.

Table 1

AVERAGE ASSESSMENT SCORES FOR CHILDREN IN THE NLSY

	PPVT			***PIAT - Math***			***PIAT - Reading***		
Child's age in months	36-48	48-60	60-72	60-72	72-84	84-96	60-72	72-84	84-96
Total NLSY	88.2	84.7	90.2	98.5	99.4	99.8	107.0	102.6	103.2
No. of observations	1790	2691	2788	2913	2917	2818	2840	2873	2810
Mother's Age									
0-30 yrs	87.7	84.0	89.9	97.9	99.2	99.6	106.4	102.2	103.0
30 or more years	91.4	88.0	94.1	102.1	101.3	101.8	110.7	106.0	104.7
ttest (Ho:mean1~=mean2)	2.3 **	3.5 **	2.9 **	5.0 **	2.8 **	2.5 **	4.7 **	5.8 **	1.8
Mother's Education									
0-12 years	81.2	72.3	83.2	93.0	94.5	95.7	100.3	98.8	98.5
More than 12 years	90.8	89.2	92.4	100.6	101.6	101.4	109.6	104.3	105.1
ttest	10.0 **	16.2 **	11.1 **	12.7 **	15.0 **	12.2 **	15.0 **	13.6 **	13.0 **
Mother's Race									
White	95.7	95.8	98.3	102.2	103.3	103.0	109.2	104.0	105.2
Hispanic-Black	79.6	73.0	83.6	94.7	96.0	96.8	104.8	101.3	101.2
ttest	19.5 **	28.6 **	22.0 **	13.9 **	16.6 **	14.7 **	7.6 **	67.0 **	8.6 **
Presence of father									
Present first 3 yrs	91.9	89.4	95.5	100.5	101.2	101.1	108.4	103.5	104.4
Otherwise	81.6	76.3	86.3	95.0	96.7	98.1	104.6	101.1	101.6
ttest	11.9 **	14.2 **	12.7 **	9.7 **	9.7 **	6.8 **	6.2 **	6.3 **	6.0 **
Number of Siblings									
0-1	92.2	90.6	94.7	100.8	101.5	101.7	110.3	104.0	105.2
2+	84.7	79.8	87.2	96.6	97.8	98.4	104.3	101.5	101.7
ttest	8.4 **	12.3 **	10.4 **	7.5 **	8.0 **	7.8 **	10.5 **	6.2 **	7.4 **
Birth Order									
Firstborn	92.8	91.3	92.6	100.6	101.1	101.1	110.8	104.2	105.2
Otherwise	85.2	80.7	87.8	97.0	98.2	98.7	104.2	101.4	101.5
ttest	8.5 **	11.9 **	6.7 **	6.3 **	6.3 **	5.7 **	11.4 **	7.1 **	8.1 **

NLSY and author's calculations.

[22] The sample is described in detail later in this section.

Table 1 (cont)

AVERAGE ASSESSMENT SCORES FOR CHILDREN IN THE NLSY (Continuation)

	PPVT			***PIAT - Math***			***PIAT - Reading***		
Child's age in months	36-48	48-60	60-72	60-72	72-84	84-96	60-72	72-84	84-96
Mother's employment									
Working 4th qtr bef. birth	90.9	88.5	95.1	100.6	101.2	101.3	109.5	103.7	105.0
Otherwise	83.2	77.7	86.4	94.7	96.5	97.7	102.4	100.8	100.5
ttest	8.2 **	11.2 **	12.2 **	10.2 **	10.0 **	8.2 **	11.6 **	7.3 **	9.5 **
Mother returns to work									
0-6 months after birth	90.8	89.9	96.2	101.4	101.3	102.1	110.2	103.7	105.6
6+ months after birth	85.0	78.2	87.2	95.2	97.0	97.8	103.1	101.0	100.8
ttest	6.0 **	12.3 **	10.6 **	10.7 **	8.7 **	9.1 **	11.3 **	6.3 **	9.6 **
Obs	1522	2336	1973	2493	2507	2419	2421	2473	2416
Works full-time	90.6	88.7	95.3	101.5	101.5	101.8	110.2	104.1	105.8
Works part-time	91.6	90.7	95.5	101.3	101.4	102.0	110.2	103.6	105.6
ttest	0.7	1.6	0.2	0.2	0.1	0.3	0.0	0.8	0.3
Obs	739	1196	835	1222	1161	1093	1192	1145	1092
Mother belongs to the sample	96.1	97.9	102.3	104.1	103.9	103.2	113.9	105.5	106.4
Otherwise	87.7	83.8	89.7	98.1	99.1	99.6	106.5	102.4	103.0
ttest	4.3 **	8.9 **	7.3 **	5.4 **	5.3 **	3.6 **	6.7 **	3.6 **	3.2 **

NLSY and author's calculations.

These simple correlations must be interpreted very carefully because we are not controlling for other variables different from the one we are classifying test scores by. They provide, though, an overall description of the main features of the test scores data available in the NLSY.

5.2. Employment and Child care after Birth

Maternal employment is measured in the following way. Women reporting between 75 and 375 hours of work per quarter (13-week period) are assumed to be working part-time, women reporting more than 375 hours of work per quarter are assumed to be working full-time and women reporting less than 75 hours of work per quarter are assumed to be staying at home during the period. Women that report having used at least 10 hours per week of some kind of child care service[23] are assumed to have used child care during the corresponding period.

Approximately 50% of mothers in the NLSY were working one year before birth (30% full-time and 20% part-time). The share of working women declines during the period of pregnancy (three quarters before birth) and only 38% of all mothers in the NLSY work until birth. During the first quarter after birth around 71% of mothers stay at home and one year after birth 23% of women

[23] Relative or non-relative, day care center, nursery/preschool, regular school.

are already back to work full-time and 16.5% are back to work part-time (almost as many working women as one quarter before birth). By the end of the 5-year period approximately 40% of women are back to work. The NLSY data indicate that only about 8% of pregnant women that are working before birth left the labor market during the first quarter of pregnancy. Approximately 12% leave during the second and third quarters while most of the working women, approximately 67%, work until birth.

5.3. The Sample

The sample of women used consists of women who worked during at least one of the three quarters of pregnancy and satisfy the following two criteria. First, they have only one child or did not give birth to a second child during the 5-year period. Second, they lived with a partner during the length of this period. The first requirement allows me to abstract from fertility decisions and the complications derived from having two preschool children for mothers' employment choices. The second requirement is necessary to avoid having to deal with welfare issues given the fact that single mothers are eligible for welfare benefits and this will clearly affect their employment decisions[24]. The final sample consists of 374 mothers and their children[25].

Table 2 displays the mean characteristics of women in the sample. Approximately 46% of women in the NLSY were working at some point during the first year after giving birth, while this proportion is equal to 78% in the sample.

Mothers in the sample were older than the average in the NLSY by less than a year and were also more educated by around one more year of schooling. About 28% of the sample was hispanic or black. In the sample, the hourly wage before birth was higher and equal to $6.75 (constant dollars of 1983). The average quarterly income of the spouse or partner was slightly higher in the sample ($4,463 vs. $4,307) but the difference is not statistically significant. Finally, women in the sample had on average 1.6 children, while women in the NLSY had 2.8 children on average.

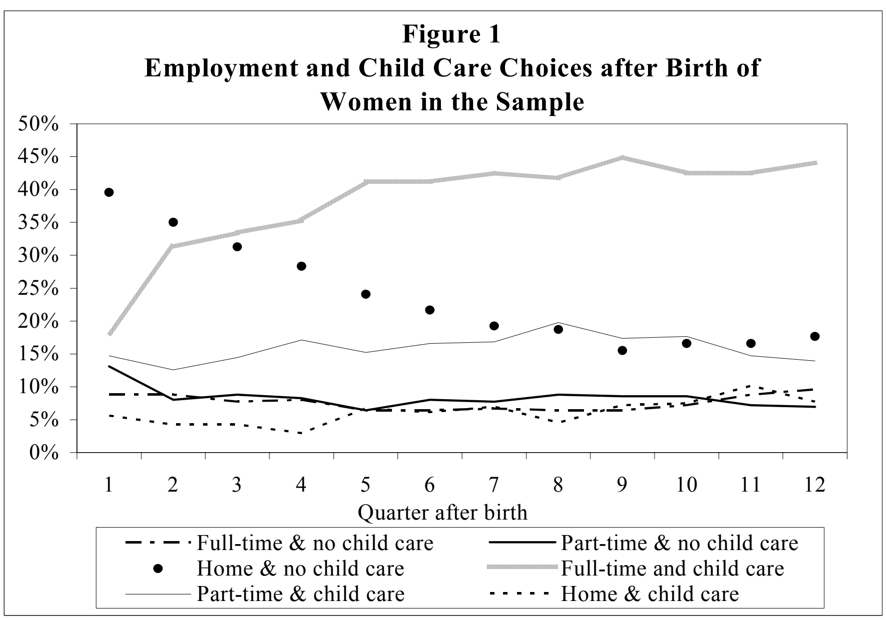
Figure 2 displays employment and child care choices after birth of women in the sample. During the first quarter after birth, about 40% of mothers stayed at home and did not use child care, 17.8% returned to work full-time and used child care, 15.2% returned to work on a part-time basis and used child care, 13.6% returned to work part-time but did not use child care, 8.7% worked full-time and reported to not have used child care during that period and, finally, around 5% of them remained at home and used child care.

[24] Both issues, fertility and welfare, are undoubtedly very important to analyze when trying to understand new mothers' employment decisions. However, the computational burden implied by the model would be immensely complicated by the introduction of either of these.

[25] From the original 4,814 mothers, 2,922 worked during pregnancy. From these, only 1,444 had a partner during the entire 5 year period after birth. From the 1,444, 499 did not have a second child before the fifth birthday of their first born. Finally, 125 observations have missing test scores data and have to be excluded for that reason.

Table 2 Mean Characteristics of Mothers in the Sample

Description	NLSY	Sample	ttest
Worked within 4 quarters after birth	0.46	0.78	14.63 **
	(0.004)	(0.021)	
Mother's age in years at birth	24.5	25.2	2.91 **
	(0.051)	(0.213)	
Mother's education in years at birth year	12.1	13.0	8.07 **
	(0.025)	(0.103)	
Hispanic or Black	0.47	0.28	7.76 **
	(0.004)	(0.023)	
Hourly wage before birth	6.15	6.75	2.1 *
	(16.60)	(23.70)	
Obs	5368	374	
Spouse or partner average quarterly income	4307	4463	0.91
	(54.1)	(162.1)	
Total number of children of mother	2.8	1.6	33.3 **
	(0.01)	(0.03)	
Father present at birth	0.55	1	-
	(0.004)	(0.0)	
Observations	4,814	374	



By the end of the first year after birth, 40% of these mothers were already back to work full-time and used child care, while only 26% still remained at home and did not use child care. The share of women working part-time with or without child care remained stable over the three-year period immediately following birth (about 15% and 9% respectively). Interestingly, the proportion of working women that remained at home after giving birth and used child care increased from 5% to 12% during this period. By the end of the first three years after birth, 40% of women were working full-time and used childcare and 19% continued to stay at home and did not use child care.

6. Estimation Results

The model is estimated by maximizing the likelihood function as written in section 4.2. In order to do this I first solve the dynamic programming problem for each individual given a type and then write the probability expressions derived by comparing current utilities plus discounted future flows of utilities during the remainder of the period. Recall that the number of types (K) is fixed at 8.

In assessing the model, I consider the reasonableness of the parameter values and the within-sample fit.

6.1. Inputs of the Model

Both the initial wage equation and the logit, for full-time and part-time probabilities in the terminal condition, are estimated before and used as inputs of the model. Given that all women in the sample were working at some point during pregnancy, initial wages are observed for everybody and it is straightforward to estimate this equation by OLS[26]. In addition, a logit on personal characteristics is estimated to determine the probabilities of working full-time or part-time by the end of the 5-year period and until retirement[27]. The results are presented in Appendix 2. The coefficient on accumulated experience is positive and significant, which means that the probability of working (full-time or part-time) after the child starts school increases with accumulated experience since birth. Similarly, the probabilities of working full-time and part-time increase with the age of the mother by the end of the period and average household income. On the other hand, being black or hispanic reduces the probability of working (either full-time or part-time) after the 5-year period following birth.

[26] Women with low education that are observed to be working are likely to have a high skill endowment. In this case, I expect the education coefficient to be biased downwards. However, this problem is not crucial because I am not modeling mothers' educational choices. The parameters that I need to be estimating consistently are those in technological relationships (3.4) and (3.5), since women make decisions based on these constraints. Furthermore, my results are not sensitive to changes in the specification of the initial wage equation.

[27] I expect the coefficient on experience to be subject to heterogeneity bias. In other words, women who work more during pregnancy are probably the ones with higher taste for work and would work more after the end of the 5-year period regardless of what they did within this period. It is worth mentioning, however, that my results are robust to various specifications of the terminal condition.

6.2. Parameter Estimates

Table 3 reports the estimates of the parameters in the utility function.

These results indicate significant heterogeneity among mothers' types. On one hand, with respect to tastes for work, one of the types dislikes work 50% more than the other type, as can be observed from the two different values of $\overline{\alpha}_2$ (-7.80 and -12.47). Interestingly, mother's skill type, her education and her race are not significant determinants of the mother's taste for work. It is possible to calculate the cost of working in terms of consumption units. For women with a high disutility from work, working full time during a given period reduces consumption by \$3,165.4 (while average consumption is equal to \$7,410), and for women with low disutility from work this reduction is equivalent to \$2,143.

Table 3: Estimation Results - Utility Function

Parameter	Estimate	Std. Errors
Consumption (α_1)	0.363337	(0.002078)
Mother's skill type on taste for work (α_{21})	0.029585	(0.227449)
Mother's education on taste for work (α_{22})	-0.007585	(0.034054)
Mother's race on taste for work (α_{23})	-0.034586	(0.253085)
Cohort trend in work preferences (ρ_w)	-0.001087	(0.002935)
Disutility from work ($\overline{\alpha_2}$) Type I	-12.475475	(1.841760)
Type II	-7.806053	(1.949133)
Utility from Child's ability (α_3)	0.138032	(1.381028)
Ability function (λ)	0.568200	(0.149655)
Mother's skill type in taste for child care (α_{41})	-0.010173	(0.124586)
Mother's education in taste for child care (α_{42})	0.002428	(0.037321)
Mother's race in taste for child care (α_{43})	0.051055	(0.174898)
Cohort trend in child care preferences (ρ_c)	0.003018	(0.002681)
Utility from childcare ($\overline{\alpha_4}$) Type I	-0.275665	(0.186625)
Type II	5.547423	(1.802276)
Cost of no childcare if working (α_5)	-3.708636	(0.061803)
Cost of initiating childcare (α_6)	-4.153411	(0.048892)
Extra cost of using childcare in qtr 1 (α_7)	-0.906821	(0.144037)
Extra cost of using childcare during 1st year (α_8)	-1.303910	(0.101233)
Childcare cost (cc)	161.376239	(0.023416)

Women are quite different in their tastes for child care as well. While one of the types derives disutility from child care (α_4=-.275), the other type derives a high utility from using child care in any given period (α_4=5.54). In the case of mothers not working, this corresponds to the value of leisure net of the loss from not staying with the child. This means, that for one type the value of the time spent with the child dominates and for the other type the value of leisure is more important. Again, mother's skill type, her education and race are insignificant in explaining differences in tastes for child care across women. The disutility from using child care for women who actually dislike doing so is equivalent to \$186.7 while, the utility of using child care in the case of women that like child care is approximately \$1,777.

The cost to a parent of working without using child care is \$1,034. The cost of starting child care is about \$1,151. The extra cost associated with having to use child care services during the first quarter after birth is \$266 and the extra cost of having to use child care for young children (one year old or younger) is approximately \$378. Finally, the cost of child care per quarter is estimated to be \$161 (dollars of 1983) which corresponds approximately to \$281 in 2001. Although this amount may seem small, it is important to remember that this estimation averages over various types of child care services which can have very different qualities and prices, including child care provided by relatives (which is in most of the cases free). Finally, note that the parameters on the cohort trend are not significant, which means that there are no significant differences in tastes for work or child care between women of younger and older generations.

Table 4: Estimation Results - Wage Equation

Parameter	Estimate	Std. Errors
Depreciation rate (δ)	-0.004263	(0.000518)
Experience (ϕ_1)	0.010082	(0.001067)
Previous full-time exp (ϕ_2)	0.019212	(0.003611)
Previous part-time exp (ϕ_3)	0.015191	(0.002371)
Experience*Education (ϕ_4)	0.000011	(0.000060)
Measurement error (σ_ε^2)	0.437863	(0.009286)

Table 4 shows the estimates of the wage equation parameters. The experience effect on wages indicates that wages increase by 1% with each additional quarter of experience, which is in line with previous estimates implying that each additional year of experience increases wages by 4% (see Moffit (1984) and Blau and Kahn (1997)). The depreciation is equivalent to 0.4% per quarter, while having worked full-time during the preceding period increases wages by 1.9% and working part-time increases wages by 1.5%.

The estimation results for the cognitive ability equation are displayed in Table 5. All inputs turn out to have the expected sign and most of them are statistically significant. Estimates of γ_1 to γ_5 have the expected signs. The positive coefficient on education implies that better educated mothers have a better technology for transferring human capital to their children. The fact that the age dummies come out insignificant is in favor of my identification assumption according to which the age of the mother creates short run variation in wages (affecting employment and child care decisions) but does not directly affect the child's cognitive ability. These results also indicate significant heterogeneity among children's ability types. High ability type children are 19% more able than low ability ones (4.79 vs. 4.60).

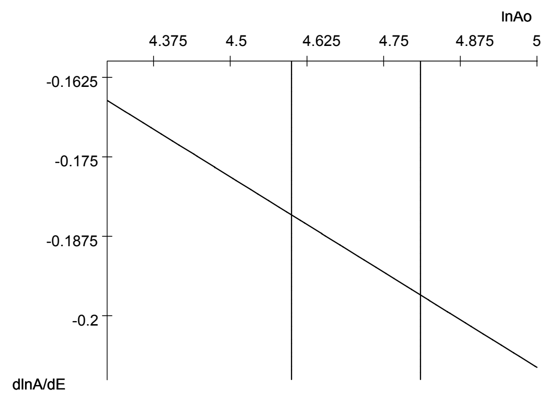
Table 5: Estimation Results - Cognitive Ability Production Function

Parameter	Estimate	Std. Errors
Mother's skill type (γ_1)	0.001767	(0.000911)
Mother's education (γ_2)	0.001250	(0.000201)
Child's race (γ_3)	-0.004503	(0.000657)
Father's Skill (γ_4)	0.000060	(0.000069)
Child's birth weight (γ_5)	0.000081	(0.000127)
Mother's too young dummy (γ_6)	-0.007141	(0.024160)
Mother's too young dummy (γ_7)	0.007355	(0.029520)
Child's gender (γ_8)	0.000521	(0.000567)
Cognitive ability Type I	4.603163	(0.070898)
Type II	4.796719	(0.071798)
Experience (γ_9)	0.000913	(0.000286)
Childcare Usage (γ_{10})	-0.001780	(0.002453)
Experience*lnA$_o$ (γ_{11})	-0.000599	(0.000207)
Childcare Usage*lnA$_o$ (γ_{12})	-0.000312	(0.000122)

In order to understand the net effect of experience or child care use on a child's cognitive ability, one has to take the derivative with respect to the relevant explanatory variable. For instance, the net effect of experience will be given by: $d\ln A_t/dE_t = 0.000913 - 0.000599\ln A_0$.

Figure 2 plots this equation, i.e., the effect of mother's working experience on the child's cognitive ability, as a function of unobserved skill endowment ($\ln A_0$). We are only interested in the relevant range of $\ln A_0$ which, given the estimated parameters, is between 4.60 and 4.81 in the sample (the region between the vertical lines). This means that the net effect of experience on a child's cognitive ability is between -0.184% and -0.197% per quarter. In fact, $d\ln A_t/dE_t$ evaluated at the average of $\ln A_0$ is -0.192%. This implies that an additional year of mother's work experience is associated with a 0.8% reduction in a child's test scores. Further, note that given that $\gamma_{11} < 0$, the technological return on time spent with the child is higher in the case of high ability children.

Figure 2- Effect of Working Experience on Cognitive Ability



The estimates imply that mother's provide a more stimulating environment than any alternative day care provider, and that this effect is stronger for higher ability children[28]. Note, however, that given the specification of the utility function, i.e., the CRRA functional form for child's cognitive ability, we are allowing for a compensation effect in the sense that parents may compensate low ability type children by devoting more time to them, depending on the curvature parameter λ. The net effect can only become clear by studying individuals' choices, which we do in the next section.

Similary, we can calculate the net effect of child care use on a child's cognitive ability: $d\ln A_t/dC_t = -0.001780 - 0.000312\ln A_0$. The effect of total child care use on a child's cognitive ability as a function of unobserved skill endowment ($\ln A_0$) is plotted in Figure 3.

As can be observed, the net effect of child care use on a child's cognitive ability in the relevant range of $\ln A_0$ is between -0.3214% and -0.3281% per quarter. The net effect evaluated at the average of $\ln A_0$ is equal to -0.3258%. This implies that an additional year of child care use is associated with a reduction of approximately 1.3% in test scores. Again, given that $\gamma_{12} < 0$, there is a higher technological return to having high ability children spend less time at child care than in the case of low ability children. The intuition in this case is the same. However, the magnitude of this technological difference is considerably smaller in this case than in the case of maternal employment.

In sum, the total effect of an additional quarter of working experience and child care on children's test scores is -0.51%[29]. Furthermore, the model implies that if a woman were to work full-time and

[28] I also find that high ability children are in fact associated with high ability mothers. In this case, this result could also be interpreted as highly skilled mothers time inputs having stronger positive effect on children.

[29] Appendix 3 shows the results from running the cognitive ability equation as shown in section 2 by OLS using the same sample of women. Given that two interaction terms are included, i.e., working experience and child care interacted with log(mother's initial wage) and mother's education, one needs to take the derivate of log(scores) with

use child care during the first 5 years after the birth of her child (which is the choice of more than 35% of the women in the sample), the total impact of both her decisions on her child's cognitive ability would be approximately a 10.4% reduction in test scores[30].

Figure 3 - Effect of Child Care Use on Cognitive Ability

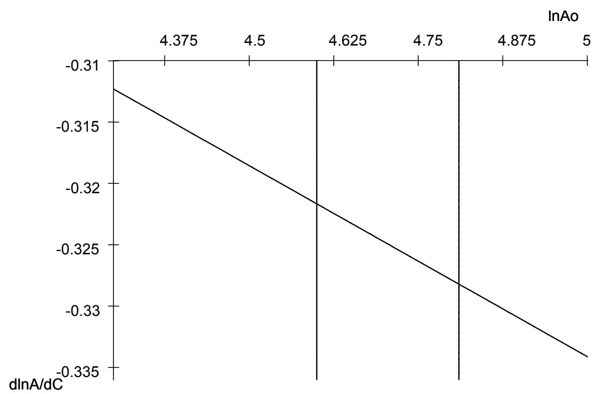


Table 6 shows the estimates of type proportions and the discount factor. Children of low cognitive ability endowment correspond to approximately 35% of the sample and are approximately 19% less able than high ability types. Most of the mothers (86%) dislike having to use child care while 58% of them have a high distaste for work. Finally, the discount factor is estimated to be 0.99, which is reasonable since a period in the model is equal to three months.

Table 6: Estimation Results - Type proportions and discount factor

Parameter	Estimate	Std. Errors
High disutility from work $\pi_{\alpha 2l}$	0.585030	(0.166318)
Low disutility from work $\pi_{\alpha 2h}$	0.414970	(....)
Low utility from child care $\pi_{\alpha 4l}$	0.860325	(0.178919)
High utility from child care $\pi_{\alpha 4h}$	0.139675	(....)
Low ability types $\pi_{\omega l}$	0.353814	(0.168029)
High ability types $\pi_{\omega h}$	0.646186	(....)
Discount factor	0.993960	(0.216958)

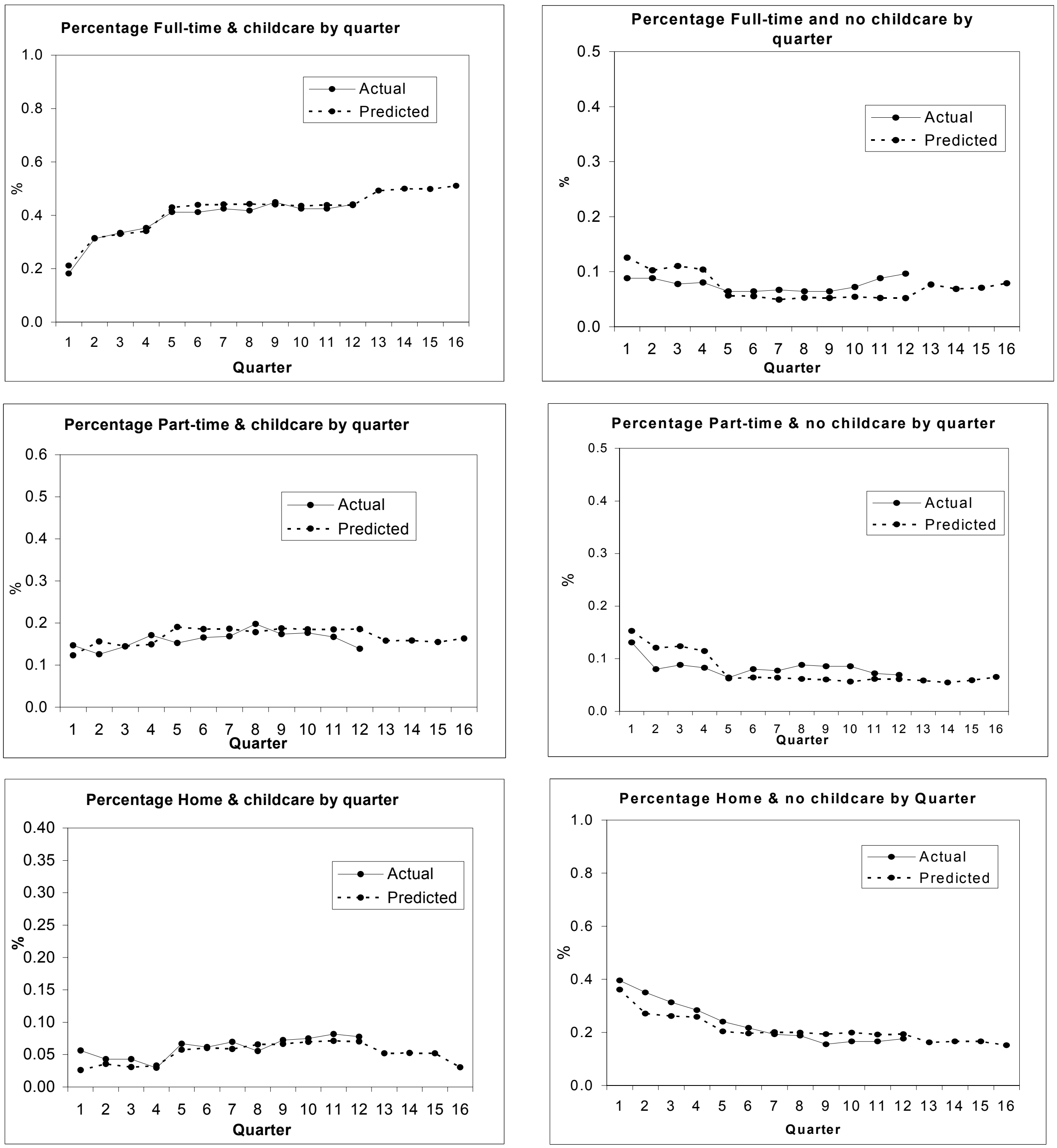
respect to employment and child care in order to obtain the net effect of mother's decisions on the child's cognitive ability. Evaluated at average log initial wages and average education level, this effect is approximately -0.09% per quarter.

[30]This is equivalent to a reduction of 0.73 standard deviations in cognitive ability test scores.

6.3. Model Fit

Figure 4 depicts the fit of the model to the choice distributions in Figure 1, based on a simulation of 8,000 individuals.

Figures 4 - Model Fit to Choice Distributions



As can be observed, the model matches the data quite well, in particular, in the case of the most chosen alternatives, i.e., working full-time or part-time and using child care, and staying at home without child care. Table 7 shows the within-sample χ^2 goodness-of-fit test statistics[31]. The tests confirm the graphical results, with the fit being rejected in very few periods. Further evidence of the model fit to the data is provided by additional graphs in Appendix 4. Figures 1 and 2 display actual and predicted wages by mother's education and age. As can be observed, both fit the data quite closely. Figures 3a-3c depict actual and predicted log average scores by age. Again, the model does a good job in matching test scores.[32]

Table 7 - Chi-squared Goodness-of-fit Tests

	CHOICE								
Qtr.	Full-time & no child care	Part-time & no child care	Home & no child care	Full-time & child care	Part-time & child care	Home & child care		Row	
1	4.099	1.183	1.250	1.584	1.740	13.350	*	23.21	*
2	0.733	5.084	8.741	0.004	2.208	0.548		17.32	*
3	3.663	3.796	3.813	0.025	0.000	1.856		13.15	*
4	2.016	3.325	0.915	0.170	1.174	0.148		7.75	
5	0.370	0.015	2.499	0.267	2.832	0.588		6.57	
6	0.509	1.500	0.842	0.634	0.789	0.011		4.29	
7	2.410	1.065	0.136	0.211	0.644	0.768		5.23	
8	0.939	4.348	0.278	0.551	0.811	0.591		7.52	
9	0.988	3.810	2.775	0.070	0.371	0.186		8.20	
10	2.211	5.566	2.097	0.089	0.153	0.154		10.27	
11	5.931	0.696	1.350	0.149	0.625	1.194		9.95	
12	6.154	0.405	0.549	0.012	4.362	0.277		11.76	*

* Statistically significant at 0.05

6.4. Understanding Unobserved Heterogeneity

As has been emphasized, there is significant heterogeneity among individuals by unobserved characteristics. It would be interesting to try to describe these types even if the model is silent on how types are determined. As was mentioned in an earlier section, according to the parameter estimates, there is a higher technological return of spending time with higher ability children but women derive higher marginal utility from spending time with lower ability children. Since these two effects go in opposite directions, whether there is or not a compensation effect from the part of the mothers towards low ability children is an empirical issue that we now turn to discuss.

[31] The χ^2 statistics have not been adjusted for the fact that the parameters of the model have been estimated.
[32] Test scores by mothers' characteristicas (not shown) fit the data fairly good as well.

Table 8 shows the proportion of mothers of low ability endowment children who work compared to the proportion of mothers of high ability endowment children who work. The right panel shows the same comparison in the case of child care use. One can observe that, on average, mothers of low ability children tend to work less and use less child care. For instance, during the first quarter after birth, 5 percentage points (8%) less women work and 5.29 percentage points less women use child care. The same is true for every period after birth.

Table 8 - Mothers' Compensation Effect

Choices by Child's Ability Endowment
(% of women choosing each alternative)

	Work			Child Care		
t	Low	High	Diff	Low	High	Diff
1	59.06	64.08	5.02	33.42	38.72	5.29
2	67.49	71.26	3.77	48.45	52.78	4.33
3	69.49	72.17	2.67	48.29	52.65	4.36
4	69.66	72.08	2.42	50.83	53.77	2.94
5	72.67	75.11	2.43	65.48	69.92	4.44
6	73.30	75.64	2.34	66.55	70.40	3.85
7	72.97	75.11	2.14	66.93	70.24	3.32
8	71.90	75.11	3.21	66.28	71.02	4.73
16	79.89	83.76	3.87	70.02	71.21	1.20

Based on a simulation of 8.000 individuals.

This pattern implies that parents of low ability children compensate by spending more time with them in spite of the higher technological return to investing in high ability type children. One can calculate experience and daycare use (in number of quarters) of mothers of low and high ability endowment children by the end of the fifth year after birth. In the case of the former group, average working experience is 10.84 quarters and average daycare use is 11.32 quarters. For the later group, average working experience is 11.51 quarters and average daycare use is 11.94 quarters. Again, on average, mothers of low ability children accumulate less experience and use less daycare than mothers of high ability children. Evaluated at the mean effect, this implies that the net average effect of experience and daycare use (over the first five years after birth) on scores is -5.6% in the case of mothers of low ability endowment children and -6.1% in the case of mothers of high ability endowment children.

This compensation effect can clearly create a selection bias problem in the sense that a high ability child will be more likely to be put in child care and/or have a working mother. In this case, an OLS regression of the cognitive ability production function (3.5) or a mother fixed effects model would yield upwardly biased estimates of the effect of child care on children's cognitive ability.

Appendix 5 presents results of OLS estimations of the cognitive ability production function using simulated data based on the model and the estimated parameters. Column (1) of the first table shows the OLS estimation of the same equation that was estimated in Appendix 3 (column (3)). Recall that in that case, the estimation was done using actual data from the sample. Interestingly, results from the estimation on simulated data seem to be very close to the estimation on actual data, except for a couple of exceptions like the estimated coefficient on education which seems considerably lower[33]. Again, once we calculate the total effect of employment and child care on child's cognitive development by taking the total derivative with respect to the corresponding variable, the net effect is approximately -0.15%[34]. Considering that the estimated effect from the structural parameters is -0.51% one can understand that the model is generating the same selection problem present in the data and it goes in the expected direction.

The second column shows the estimation of the same equation once we condition on both mothers' types and children's types (which are known in the simulation). One can observe that once we control for both types of heterogeneity, the estimated effect of experience and daycare on test scores more than doubles from -0.15% to -0.31% per quarter. The intuition for this is that we are presumably controlling for both sources of selection bias once we introduce both types in the regression, i.e., high ability mothers are more likely to have high ability children and more likely to work, and mothers of low ability children compensate for them by spending more time with them (which means that it is likely that working women have high ability children). Since both sources generate an upward bias it is natural to expect that once we control for both, the estimated effect is more negative. The third and fourth column of the same table show the same regression again, except types (mothers' and children's) are included one at a time. Column (3) includes mother's skill types while excluding child type dummies. Results are very similar to the original equation in column (1) but the total effect of experience and daycare increases from -0.15% to -0.2%. On the other hand, column (4) includes only children's ability types. In this case, the estimated effect increases to -0.27% per additional quarter of experience and child care use. This is interesting, in the sense that it suggests that children's unobserved heterogeneity accounts for a higher proportion of the bias in the original equation than mothers' heterogeneity.

Finally, the second table in Appendix 5 shows the estimation of the production function exactly as described by equation (3.5) conditional on the types used for simulation. In other words, it is the same equation estimated in the first table except the interaction terms now include children's endowment types. The results of the estimation on simulated data match quite closely the results from the structural estimation shown in Table 6. One can plot the net effect of experience on cognitive ability (not shown) and see that in the relevant range of $\ln Ao$ it is very close to the estimated effect in the structural model and plotted in Figure 2. In this case, the estimated average effect of one additional quarter of experience and child care use on children's test scores is -0.49%[35].

[33] These regressions are based on a simulation of 5,610 individuals whereas the actual data contains 374 observations. The fact that the size of the simulated data is bigger can be the reason that some coefficients turn out to be significant while they were insignificant when estimated on actual data.

[34] When estimated on actual data, the effect of an additional quarter of employment and daycare use was -0.09%.

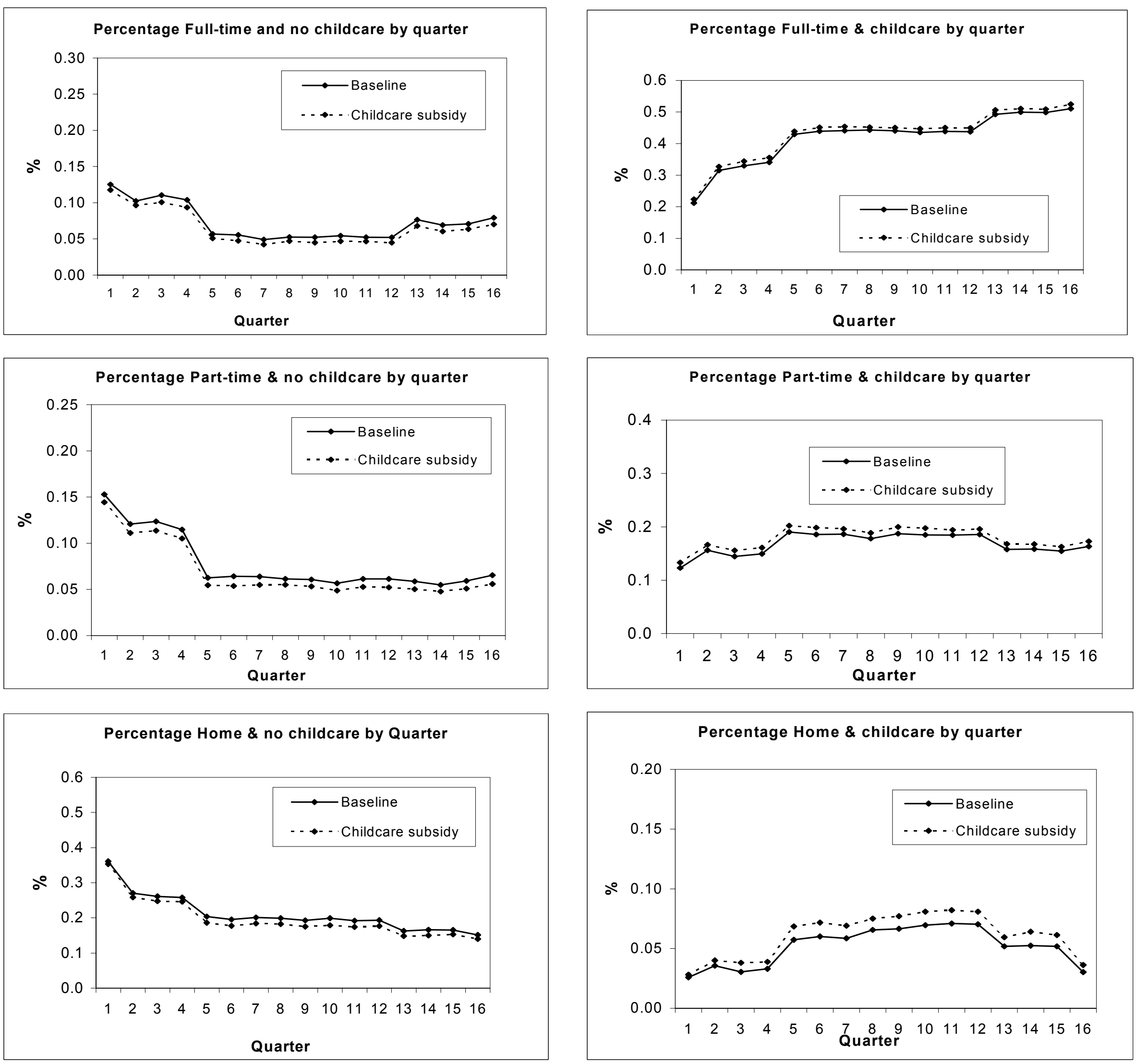
[35] These results might suggest that including unobserved child ability endowments nonlinearly might be a better

7. Policy Experiments

In this section we evaluate the effect of various policies on choice distributions and average test scores. To do this, we simulate the model under the baseline case using the estimated parameters described in the previous section and compare the results to the case in which a policy is introduced.

7.1. Child care Subsidy

Figure 5 - Choice Distributions (30% child care subsidy)



way to describe the cognitive ability production function.

The first experiment involves a 30% child care subsidy. In particular, the parameter cc is reduced from its estimated value of \$161.3 to \$112.9. The change in the choice distribution is displayed in Figure 5. As expected, the percentage of women choosing all alternatives that include child care increases with respect to the baseline case. On average, there is an increase of 3 percentage points per period in the number of women that now choose to use daycare.

However, a priori it is not obvious what will happen with employment choices once the subsidy is introduced. On the one hand, there is a substitution effect in the sense that the availability of cheaper child care might allow women to work. On the other hand, there is an income effect, in the sense that the subsidy increases household income and hence might induce a reduction in the hours of work. The overall effect of the subsidy is to increase the percentage of women working in almost every period after birth by less that 1 percentage point due to the fact that the combination of working and child care now has a higher payoff.

Table 9 displays the percentage difference of average log scores by ability type in the 30% child care subsidy case with respect to the baseline. The results indicate that the introduction of a subsidy is associated with a reduction in test scores for all ages and both types. Given the fact that child care has a negative effect on the child's cognitive ability, the incentive for mothers to move into child care alternatives is detrimental to children's scores even if it seems to increase parents' utility[36].

Table 9 - Average Log Scores by Childs' Types (30% Child Care Subsidy)

(% difference with respect to baseline)

	All Types	Low Type	High Type
PPVT1	-0.34	-0.20	-0.47
PPVT2	-0.27	-0.22	-0.32
PPVT3	-1.41	-0.23	-0.57
MATH1	-0.45	-0.13	0.03
MATH2	-0.35	-0.55	-0.14
MATH3	-0.45	-0.64	-0.27
MATH4	-0.25	-0.05	-0.47
READ1	-0.33	-0.22	-0.44
READ2	-0.13	-0.02	-0.24
READ3	-0.67	-0.76	-0.58
READ4	0.27	-0.13	0.67

Based on a simulation of 8000 individuals

[36] One can calculate the mother's mean expected present value of lifetime utility at t=1 and observe that it increases on average 0.1% once the child care subsidy is introduced.

7.2. Maternity Leave Policy

In order to assess a maternity leave policy, I will adopt a shortcut to avoid having to alter the state space. I analyze it by setting the wage depreciation rate δ at 0. This means that if the woman did not work for a few periods after birth, the re-employment wage is drawn from the same wage distribution she had before giving birth. In order words, it is not possible to discriminate against women on the basis of how long they were away from the labor market after birth.

Figure 6 - Choice Distribution (Wage Depreciation Rate set at 0)

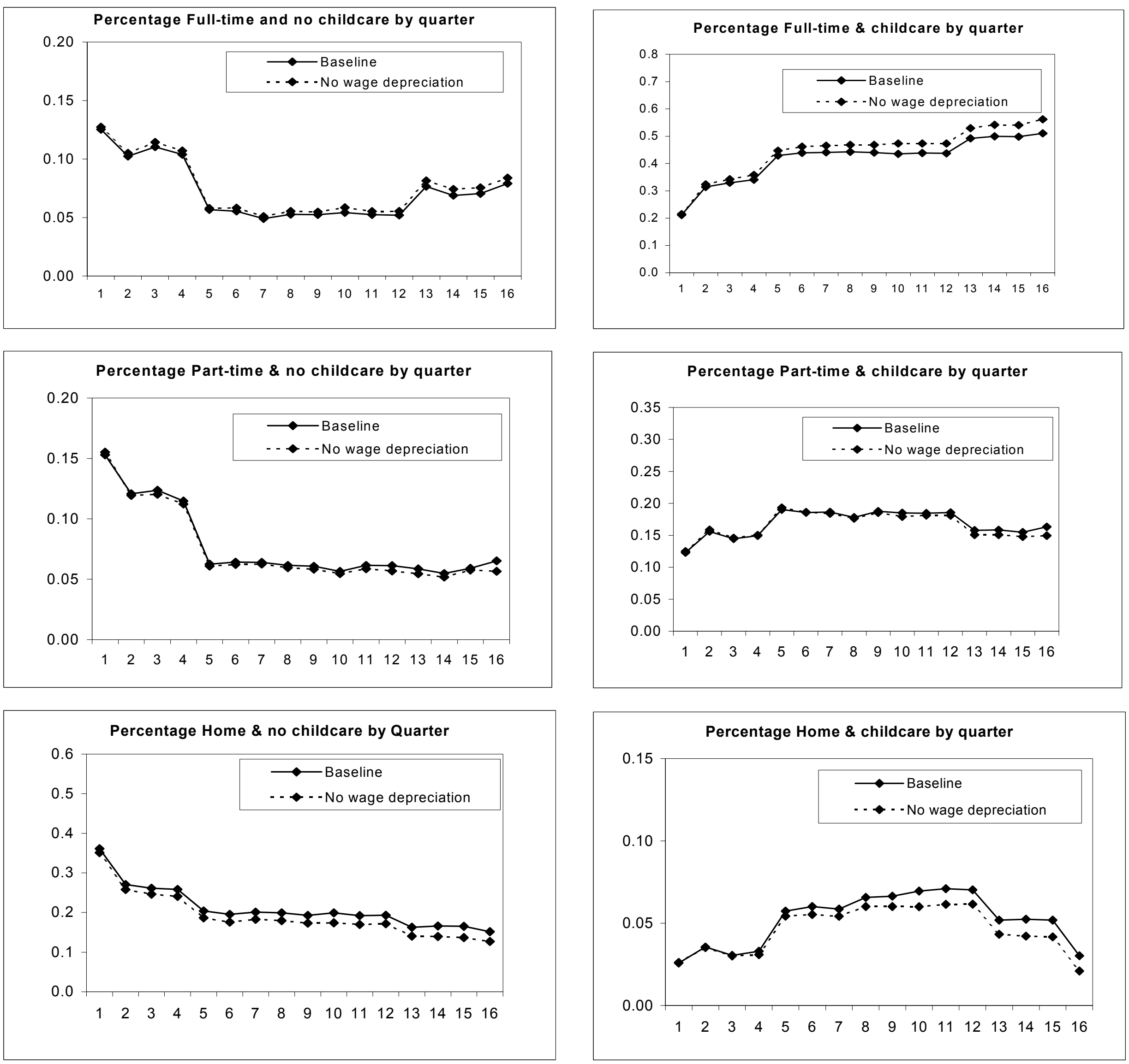


Figure 6 displays both the baseline choice distribution and the choice distribution once the wage depreciation rate is set at 0. As we can observe, a higher percentage of women choose to work full-time relative to the baseline case, while moving out from both home and part-time alternatives. In fact, in period 4 for example, the total percentage of women choosing to work increases by 1.95 percentage points and the proportion of mothers choosing to use child care raises by 1.68 percentage points.

The intuition behind this result is as follows. Women are still getting zero wages during the periods in which they are away from the labor market but the opportunity cost of staying at home has now increased relative to the baseline scenario. Foregone wages are higher during the current period and the discounted stream of future wages has increased as well. The expected gain derived from staying home with their children through their increased cognitive ability is not enough to compensate for the loss in foregone wages and, hence, women choose to work more.

As expected this has the effect of reducing average scores given that mothers are not only working more but also using more child care services and the additional income is not compensating for this detrimental effect. Average scores are reduced by approximately 0.2% to 0.5%, depending on the test and age of the child. Mothers' mean expected present value of lifetime utility at time t=1 is increased by 0.66% with respect to the benchmark case. It is difficult to assess whether this type of policy is effective or not given the fact that while it increases women's lifetime utility, it decreases children's test scores which are, in turn, correlated with their future wages.

7.3. Baby Bonus

Finally, we assess the impact on women's decisions and children's average test scores of a $250 quarterly baby bonus after the birth of a child and until he or she is 5 years old[37]. In this case, women move from working alternatives into home choices (choice distributions are not shown).

Table 10 shows the proportion of women who choose each alternative in the baseline case as well as in the $250 baby bonus scenario in period 4. The last column shows the difference (in percentage points) between these. As can be observed, there is a total reduction of proportion of women working (full-time and part-time) of 1.79 percentage points and a reduction of the proportion of women using child care of almost 1 percentage point. The same pattern can be observed for almost every period after birth until the end of the fifth year. As a consequence of the change in the choice distribution and the increase in household's income, average scores increase for all tests and all ages. On average, test scores increase by 0.2% to 0.7% depending on the test and age of the child. At the same time, women's mean expected present value of lifetime utility in period 1 increases by approximately 1%.

[37] To give a few examples, Australia just very recently implemented a baby bonus for a maximum of up to $2,500 per annum over five years. The minimum entitlement is $500 per year. In Singapore, the baby bonus amounts to $3,000 for the second child and $6,000 for the third child. Parents in Japan get a $70 allowance a month for the first two children until they enter pre-school.

Table 10 - Choices by Type in Period 4 ($250 Baby Bonus)

(% of people who choose each alternative)

	Baseline	Baby Bonus	Change (percentage points)
Full-time and no child care	10.39	9.87	-0.52
Part-time and no child care	11.48	11.58	0.09
Home and no child care	25.83	27.22	1.39
Full-time and child care	34.05	32.75	-1.30
Part-time and child care	14.95	14.88	-0.07
Home and child care	3.30	3.70	0.40
Work	**70.87**	**69.08**	**-1.79**
Child care	**52.30**	**51.34**	**-0.96**

Based on a simulation of 8000 individuals.

8. Conclusions

In this paper I focus on the labor supply and child care decisions of women immediately following birth, in order to evaluate the effects of mothers' decisions on the well-being of their children. In particular, I am interested in assessing the impact of both employment and child care decisions on children's cognitive ability. Previous studies have provided evidence that test scores measured early in a person's life have significant effects on future educational and labor market outcomes[38]. It seems at least interesting to try to understand whether there are any parental inputs that can enhance cognitive ability of individuals during their early stages of life. For this purpose I use data from the National Longitudinal Survey of Youth and, in particular, I look at the quarterly employment and child care histories of women after birth and until their child enters primary school at age 5. I assess the impact of these histories on Peabody Picture Vocabulary Tests scores and Peabody Individual Achievement Test scores (Math and Reading Sections).

The key issue dealt with in the paper is the potential endogeneity problem that arises as a result of the existence of unobserved characteristics of both mothers and children. In fact, women are heterogeneous in both the constraints they face and their tastes. At the same time, children are heterogeneous in their cognitive endowments. As we would expect, mothers' decisions with respect to working when children are young, and/or placing children in child care are influenced by these heterogeneous characteristics. Hence, children of working women or children of women who use child care will differ systematically from those whose mothers stay at home or do not use child care.

[38] Currie and Thomas (1999) show, for example, that men and women in the lowest quartile of the reading test score (PIAT in the NLSY) distribution have wages 20% lower at age 33 than those who scored in the highest quartile.

In my model, estimation of the child's cognitive ability production function, which includes mother's time and child care use as inputs, jointly with the mother's work and child care decision rules enables me to deal with the endogeneity problem. I model individuals that make sequential choices about work and child care in each period following birth instead of modeling a one-time decision. Once I have estimated the parameters of the model, I conduct an evaluation of policies such as parental leave and child care subsidies.

The results of the estimation suggest that the effect of maternal employment and child care during the first five years of life of the child is not negligible. In fact, an additional year of full-time work is associated with a reduction of test scores of about 0.8% while the impact of an additional year of child care use is a reduction of approximately 1.3%. This means that if a mother were to work full-time and use child care during the first 5 years of her child's life this would yield a 10.4% reduction in test scores. Furthermore, I find that this effect is stronger for high ability type children. In other words, there is a higher technological return to spending time with high ability children relative to time spent with low ability children.

The results of the policy experiments suggest that both child care subsidies and maternity leave entitlements can be detrimental for children, while increasing mothers' expected lifetime utility. On the one hand, child care subsidies provide incentives for women who derive high disutility from work and/or from child care to move into child care alternatives. This, has a negative effect on children's average scores. On the other hand, by setting the wage depreciation at 0, in other words, eliminating the possibility of discriminating against women on the basis of the number of periods they were away from the labor market after birth, children are made worse off. The intuition behind this is as follows. Given the fact that women do not receive a wage (or a portion of it) while away from the labor market and foregone wages are higher relative to the case in which the depreciation rate is nonzero, women decide to work more under the new scenario. Not only is the current foregone wage higher but so is the expected stream of future wages. Hence, if the gain derived from increased child's cognitive ability is smaller than the opportunity cost of staying at home, women choose to work more with the expected detrimental effect that this has on average scores.

Finally, the effect of a $250 quarterly baby bonus after the birth of a child and until his/her fifth birthday has a positive impact on both mothers and children. On the one hand, mean expected present value of lifetime utility of mothers is increased by 1% and on the other hand average scores of children increase by about 0.5%. The raise in household's income provides an incentive for women to move from working alternatives into home choices at the same time that it acts as a disincentive for the use of child care. Therefore, the net effect is to increase children's cognitive ability as well as mothers' utility.

In this paper, I have assumed that there is a homogeneous child care supply which includes several types of day care providers. An interesting extension of the model would include quality of child care as a choice variable of the mother. One might argue that the result according to which maternal employment has a significant and sizeable negative effect on children's cognitive ability is driven by the fact that most of the child care provided is of low quality. Clearly, introducing the quality of child care in the model might change the results in very interesting ways. A woman with higher wage might be able to purchase child care services of very high quality in which case it will not be so clear that her time investments will be as valuable.

Finally, one might think that different assumptions about what the mother knows about her child can possibly change the results. They way in which this would happen is not clear a priori. It could be possible that mothers know their child's ability endowment but there is a stochastic component in the cognitive ability production function which makes the outcome uncertain. Or one could allow for a learning process in which the ability endowment of the child is initially unknown by the mother and she uses actual test scores to gradually infer it. In either case, it is difficult to predict in which direction the results would change but both could plausibly describe parents' behavior.

Appendix 1

An alternative way to estimate the effect of mother's employment and child care decisions on the child's cognitive ability is to estimate reduced form decision rules for work and day care together with a continuous outcome equation (test scores) and a wage equation. In this appendix, I describe briefly how the work probit, child care probit, outcome equation and wage equation would look like in such a setup.

1) Work Probit:

$$\begin{aligned} V_f^* = \; & \beta_0 + \beta_1 \text{agem} + \beta_2 \text{agem}^2 + \beta_3 \text{educ} + \beta_4 \text{race} + \beta_5 f_{t-1} + \beta_6 p_{t-1} + \beta_7 E_t + \beta_8 C_t \\ & + \beta_9 t + \beta_{10} \mu + \beta_{11} \text{agef} + \beta_{12} \text{agef}^2 + \beta_{13} BW + \beta_{14} \text{gender} + \beta_{15} \text{I[age<18]} \\ & + \beta_{16} \text{I[age>33]} + \beta_{17} \xi_0 + \beta_{18} I[C_t{=}0] + \beta_{19} I[t{=}1] + \beta_{20} I[t < 5] + \varepsilon_f^* \end{aligned}$$

$$\begin{aligned} V_p^* = \; & \beta_{21} + \beta_{22} \text{agem} + \beta_{23} \text{agem}^2 + \beta_{24} \text{educ} + \beta_{25} \text{race} + \beta_{26} f_{t-1} + \beta_{27} p_{t-1} + \beta_{28} E_t + \\ & \beta_{29} C_t + \beta_{30} t + \beta_{31} \mu + \beta_{32} \text{agef} + \beta_{33} \text{agef}^2 + \beta_{34} BW + \beta_{35} \text{gender} + \beta_{36} \text{I[age<18]} \\ & + \beta_{37} \text{I[age>33]} + \beta_{38} \xi_0 + \beta_{39} I[C_t{=}0] + \beta_{40} I[t{=}1] + \beta_{41} I[t < 5] + \varepsilon_p^* \end{aligned}$$

where agem is the mother's age at birth, educ is her education, f_{t-1} and p_{t-1} are the previous period employment decisions, E_t is accumulated experience, C_t is child care use, t is the age of the child, μ is father's skill endowment[39], agef is the father's age at birth, BW is the birth weight of the child, gender is the child's gender, I[age<18] is a dummy variable that equals 1 if the mother is younger than 18, I[age>33] is a dummy variable that equals 1 if the mother is older than 34 years old, ξ_0 is the mother's skill endowment, $I[C_t = 0]$ is an indicator function that equals 1 if total child care use equals 0 in period t, $I[t = 1]$ is an indicator function that equals 1 if $t = 1$ and finally, $I[t < 5]$ is an indicator function that equals 1 if the child is younger than 1 year old.

2) Child Care Probit:

$$\begin{aligned} V_c^* = \; & \beta_{42} + \beta_{43} \text{agem} + \beta_{44} \text{agem}^2 + \beta_{45} \text{educ} + \beta_{46} \text{race} + \beta_{47} f_{t-1} + \beta_{48} p_{t-1} + \beta_{49} E_t + \\ & \beta_{50} C_t + \beta_{51} t + \beta_{52} \mu + \beta_{53} \text{agef} + \beta_{54} \text{agef}^2 + \beta_{55} BW + \beta_{56} \text{gender} + \beta_{57} \text{I[age<18]} \\ & + \beta_{58} \text{I[age>33]} + \beta_{59} \xi_0 + \beta_{60} I[C_t{=}0] + \beta_{61} I[t{=}1] + \beta_{62} I[t < 5] + \varepsilon_c^* \end{aligned}$$

3) Continuous Outcome Equation:

$$\ln S_t = ab0 + \beta_{63} E_t + \beta_{64} C_t + \beta_{65} (ab0 * E_t) + \beta_{66} (ab0 * C_t) + \beta_{67} \text{dPPVT} + \beta_{68} \text{dMATH} + \varepsilon_s^*$$

where

$$ab0 = \beta_{69} \xi_0 + \beta_{70} \text{educ} + \beta_{71} \text{race} + \beta_{72} BW + \beta_{73} \mu + \beta_{74} \text{I[age<18]} + \beta_{75} \text{I[age>33]} + \beta_{76} \text{gender}$$

and dPPVT and dMATH are dummy variables that equal 1 if PPVT and PIAT-Math respectively.

[39] As defined in Section 3.2.

4) Wage Equation:

$$\ln w_t = \beta_{77}\text{agem}+\beta_{78}\text{agem}^2+\beta_{79}\text{educ}+\beta_{80}\text{race}+\beta_{81}t+\beta_{82}E_t+\beta_{83}f_{t-1}+\beta_{84}p_{t-1}+\beta_{85}(E_t{*}\text{educ})+\varepsilon_w^*$$

Assume $\{\varepsilon_f^*, \varepsilon_p^*, \varepsilon_c^*, \varepsilon_s^*, \varepsilon_w^*\}$ have a joint normal distribution $F(\varepsilon)$ and are serially uncorrelated[40]. Together with the parameters in the variance covariance matrix, there a total of 98 parameters in the reduced form model as opposed to 61 parameters in the structural model.

[40] We need two normalization for identification purposes. One in the child care probit and one in the work probit. This means that the total number of parameters in the variance covariance matrix is 13.

Appendix 2

Initial Wage Equation Estimation

	Log(Initial Wage)	
Age of mother at birth	0.0623	
	(0.03)	*
Age of mother at birth^2	-0.0003	
	(0.00)	
Race of mother	-0.1340	
	(0.06)	*
Education of mother	0.0575	
	(0.02)	**
Constant	-0.4533	
	(0.94)	
No. of observations	374	
R^2	0.24	

Estimated by OLS

Father's Labor Income

	Log(Father's Wage$_t$)	
Age of father in year *t*	0.1649	
	(0.02)	**
(Age of father in year *t*)^2	-0.0019	
	(0.00)	**
Constant	5.0330	
	(0.33)	**
No. of observations	1870	
R^2	0.15	

Estimated by OLS

Working Probabilities by the end of the 5-year period

	Full-time		Part-time	
Age at end of period	2.087		1.641	
	(0.53)	**	(0.55)	**
Age at end of period^2	-0.036		-0.030	
	(0.01)	**	(0.01)	**
Education at end of period	0.038		0.012	
	(0.02)		(0.01)	
Race of mother	-1.077		-0.854	
	(0.36)	**	(0.37)	*
Accumulated experience during the period	0.170		0.079	
	(0.02)	**	(0.02)	**
Average Household Income	2.8E-05		1.6E-06	
	(0.00)	*	(0.00)	
Estimation	Logit			
No. of observations	374		374	
Pseudo-R^2	0.25		0.25	

Accumulated experience is calculated as the sum of a dummy equal to 2 if the mother worked full-time during the period, 1 if she worked part-time and 0 otherwise.

Appendix 3

OLS REGRESSION - EFFECT OF MOTHER'S EMPLOYMENT AND CHILD CARE USAGE ON CHILDREN'S PERFORMANCE

	log(TEST SCORE)					
	(1)		(2)		(3)	
Mother's age dummy	-0.0169		-0.0157		-0.0146	
(=1 if mother's age<18)	(0.0241)		(0.0240)		(0.0241)	
Education of mother	0.0105		0.0105		0.0158	
	(0.0021)	**	(0.0021)	**	(0.0051)	**
Race of mother	-0.0752		-0.0742		-0.0738	
	(0.0086)	**	(0.0086)	**	(0.0086)	**
Sex of child	0.0139		0.0132		0.0132	
	(0.0076)	*	(0.0076)	*	(0.0076)	*
Log(Hourly Wage Mother)	0.0139		0.0465		0.0406	
	(0.0081)	*	(0.0176)	**	(0.0184)	*
Accumulated working experience of	0.0001		0.0019		0.0028	
the mother + total child care usage	(0.0002)		(0.0009)	*	(0.0019)	*
Log(Father's quarterly wage)	0.0209		0.0193		0.0197	
	(0.0056)	**	(0.0056)	**	(0.0056)	**
Child's birth weight	0.0001		0.0002		0.0001	
	(0.0002)		(0.0002)		(0.0002)	
Dummy PPVT Test	-0.0989		-0.0995		-0.0997	
	(0.0096)	**	(0.0096)	**	(0.0096)	**
Dummy MATH Test	-0.0472		-0.0468		-0.0468	
	(0.0090)	**	(0.0090)	**	(0.0090)	**
Log(Mother's Wage)*(Experience+Child care)			-0.0010		-0.0009	
			(0.0005)	*	(0.0005)	*
(Mother's education)*(Experience + Child care)					-0.0002	
					(0.0002)	
Constant	4.3444		4.3091		4.24745	
	(0.0495)	**	(0.0522)	**	(0.0756)	**
No. of observations	1304		1304		1304	
R^2	0.1783		0.1811		0.1819	

Mothers in the sample. OLS estimates. Number of observations is 1304. Evaluated on averages, the effect of an additional quarter of experience and child care on scores is **-0.09%** from equation (3).

Appendix 4

Figure 1 - Actual and Predicted Log(wages) by Education

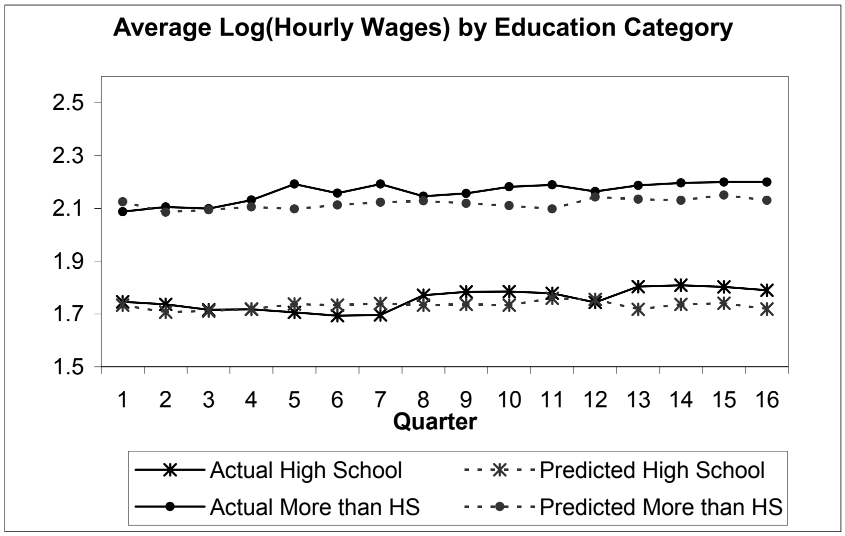
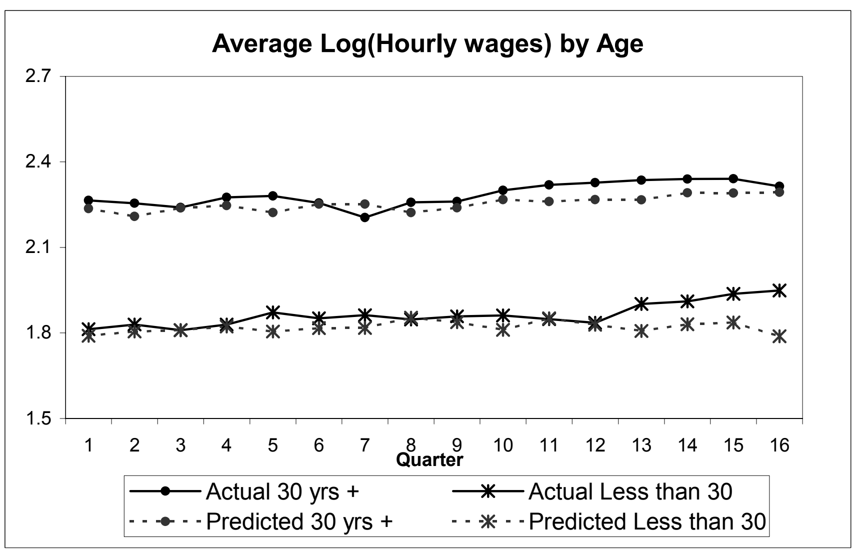
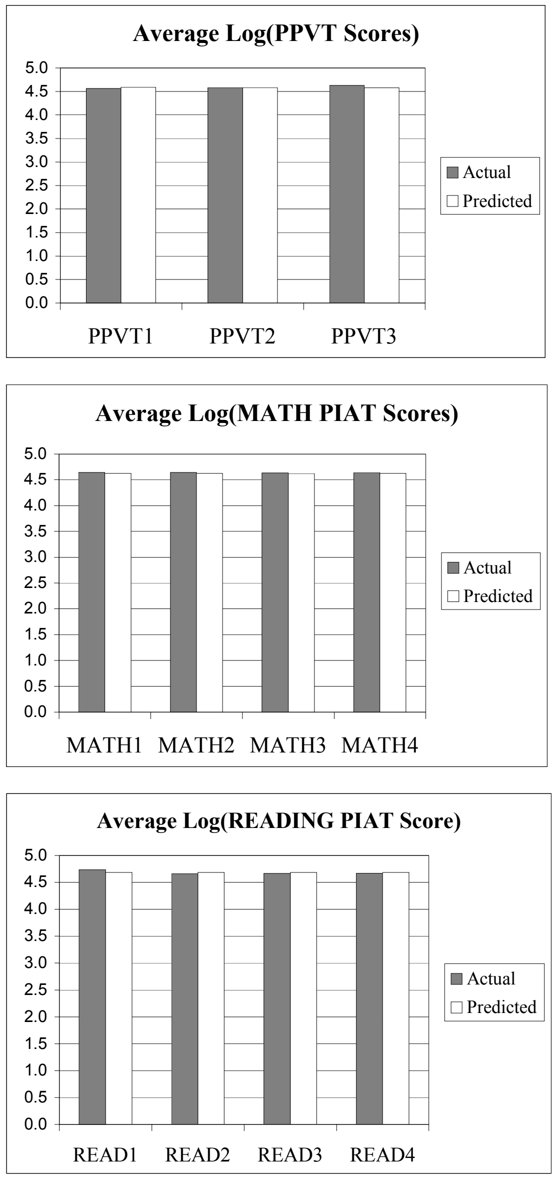


Figure 2 - Actual and Predicted Log(wages) by Age



Figures 3a-3c - Actual and Predicted Test Scores



Appendix 5

OLS REGRESSION IN APPENDIX 3 WITH AND WITHOUT CONDITIONING ON TYPES

(SIMULATED DATA FROM THE MODEL)

	Log (Test Score)			
	(1)	(2)	(3)	(4)
Mother's age dummy	-0.0169	-0.0137	-0.0300	-0.0081
(=1 if mother's age<18)	(0.0057) **	(0.0059) **	(0.0071) **	(0.0048)
Education of mother	0.0040	0.0023	0.0070	0.0021
	(0.0008) **	(0.0010) **	(0.0012) **	(0.0008) **
Race of mother	-0.0325	-0.0100	-0.0009	-0.0086
	(0.0015) **	(0.0016) **	(0.0020)	(0.0013) **
Sex of child	0.0032	0.0017	0.0024	0.0010
	(0.0015) *	(0.0014)	(0.0017)	(0.0011)
Mother's Skill Type (ξo)		0.0078	0.0247	
		(0.0034) **	(0.0046) **	
Log(Hourly Wage Mother)	0.0561			0.0053
	(0.0044) **			(0.0036)
Accumulated working experience of	0.0015	-0.0043	-0.0146	-0.0020
the mother + total child care use	(0.0004) **	(0.0011) **	(0.0014) **	(0.0004)
Father's Skill Type	0.0301	0.0005	0.0052	0.0018
	(0.0018) **	(0.0015)	(0.0018) **	(0.0014)
Child's birth weight	0.0001	0.0001	-0.0001	0.0000
	(0.0000) *	(0.0000) *	(0.0000)	(0.0000)
Dummy PPVT Test	-0.1161	-0.1202	-0.1230	-0.1188
	(0.0017) **	(0.0018) **	(0.0022) **	(0.0015) **
Dummy MATH Test	-0.0615	-0.0622	-0.0622	-0.0611
	(0.0017) **	(0.0017) **	(0.0021) **	(0.0014) **
(Mother's Skill Type ξ_o)*(Experience+Child care)		-0.0003	-0.0017	
		(0.0001) **	(0.0002) **	
Log(Mother's Wage)*(Experience+Child care)	-0.0010			-0.0002
	(0.0002) **			(0.0001)
(Mother's education)*(Experience + Child care)	-0.0001	-0.0001	-0.0002	-2.9E-05
	(0.0000) *	(0.0000) *	(0.0000) **	(0.0000) **
Dummy Child Type Low		4.6359		4.5894
		(0.0286) **		(0.0141) **
Dummy Child Type High		4.8362		4.7828
		(0.0286) **		(0.0142) **
Constant	4.46098		4.8392	
	(0.0170) **		(0.0391) **	
R^2	0.103	0.389	0.110	0.380
Effect of experience and child care on scores	**-0.15%**	**-0.31%**	**-0.20%**	**-0.27%**

Based on a simulation of 5,610 individuals given the estimated parameters

(1) Identical to regression in Appendix 3. (2) Conditioning on both mothers' and children's types.

(3) Conditioning on mother's types only. (4) Conditioning on children's types only.

OLS Regression of equations (3.4) and (3.5)

(Simulated Data from the Model - Conditional on types)

	log(TEST SCORE)	
Mother's skill type (ξ_o)	0.0036	
	(0.0016)	*
Education of mother	0.0019	
	(0.0003)	**
Race of mother	-0.0092	
	(0.0011)	**
Father's skill type (μ)	0.0001	
	(0.0001)	
Child's Birthweight	0.0001	
	(0.0001)	
Mother's age dummy	-0.0058	
(=1 if mother's age<18)	(0.0038)	
Mother's age dummy	0.0051	
(=1 if mother's age>33)	(0.0038)	
Gender	0.0014	
	(0.0010)	
Experience	0.0024	
	(0.0008)	**
Child Care	-0.0018	
	(0.0082)	
Experience*Child's ability endowment	-0.0008	
	(0.0001)	**
Child Care*Child's ability endowment	-0.0004	
	(0.0002)	**
Dummy PPVT Test	-0.1181	
	(0.0116)	**
Dummy MATH Test	-0.0600	
	(0.0011)	**
Dummy Child Type Low	4.6074	
	(0.0121)	**
Dummy Child Type High	4.8036	
	(0.0120)	**
R^2	0.38037	

Based on a simulation of 5,610 individuals given the estimated parameters reported in Tables 4 through 7 and conditioning on the types used for simulation. Evaluated on averages, the total effect of one additional quarter of experience and child care on test scores is **-0.49%.**

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