

THE EFFECT OF MATERNAL EMPLOYMENT AND CHILD CARE ON CHILDREN'S COGNITIVE DEVELOPMENT*

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This article develops and estimates a dynamic model of employment and child care decisions of women after childbirth to evaluate the effects of these choices on children's cognitive ability. We use data from the National Longitudinal Survey of Youth to estimate it. Results indicate that the effects of maternal employment and child care on children's ability are negative and sizable. Having a mother that works full-time and uses child care during one year is associated with a reduction in ability test scores of approximately 1.8% (0.13 standard deviations). We assess the impact of policies related to parental leave and child care on children's outcomes.

1. INTRODUCTION

Extensive research has shown that children's early achievements are strong predictors of a variety of outcomes later in life. The high achievers are more likely to have higher educational attainment and higher earnings and are less likely to have out-of-wedlock births, be on welfare, or participate in crime. For this reason, the issue of what determines ability of individuals at early stages of life is critical for the design of public policy aimed at improving labor market outcomes.

The effect of parental time inputs and child care (as well as child care quality) on children's development has been widely analyzed, especially in the psychology and sociology literature. Economists have also realized the importance of this question. For many years we have been trying to understand the determinants of individuals' labor market performance, in particular, wages. In spite of the vast research in this area, there is still a large component of wages that we have not been able to explain. Other related studies² have concluded that once people

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² See Keane and Wolpin (1997, 2001), Cameron and Heckman (1998), and Cunha and Heckman (2006).

reach a certain age, around 16–18 years old, most of what determines their later labor market performance has already been determined. In other words, a set of unobserved (to the researcher) characteristics that determine a significant portion of wages, educational attainment, or other career outcomes are already present by age 16. These unobserved characteristics have often been called the individual's "cognitive ability" or "skill endowment." But their determinants remain largely a black box.

In this article we develop and estimate a dynamic model of employment and child care choices of mothers after childbirth and assess how these decisions affect children's cognitive outcomes using 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 and child care use on children's outcomes is that they have failed to fully control for potential biases that may arise as a result of one or both of 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 and (2) the child's cognitive ability itself may influence the mother's decisions of whether to work and/or place the child in day care.

Women are heterogeneous in their skill endowments, the constraints they face, and their tastes. Likewise, children are heterogeneous in their cognitive ability endowments. Some of these characteristics might be unobserved by the researcher. Mothers' decisions of whether or not to work and whether or not to use child care will clearly depend on these unobserved heterogeneous characteristics of both mothers and children. To illustrate this endogeneity problem, we lay out a couple of examples. In the case of (1), for example, suppose a woman with higher skill is more likely to have a child with high cognitive ability and also more likely to work. Then, a statistical analysis that does not account for endogeneity would overestimate the effect of maternal employment on her child's cognitive outcomes. In the case of (2), mothers of low ability children may choose to compensate them by spending more time with them, in which case mothers are more likely to work if they have high ability children. Again, the estimated effect of maternal employment on child's cognitive outcomes would be upwardly biased. This endogeneity problem makes evaluation of the effects of women's decisions on child outcomes very difficult.

In this article, we estimate a model of employment and child care choices jointly with a child cognitive ability production function. This type of estimation allows us to implement a correction for endogeneity in the sense that we can adjust for the fact that certain types of children are more likely to be put in child care and/or to have working mothers. Most importantly, we can use the model to assess the effects of counterfactual policy experiments.

Although a number of studies have estimated the effect of maternal employment or child care use on children's cognitive development, only some of them have tried to overcome the endogeneity problem by (1) using a very extensive set of control variables, (2) estimating fixed effects models, and/or (3) using instrumental variables. As we will discuss in detail in Section 2 none of these estimation methods provides a panacea for dealing with the problem of unobserved child

ability. Fixed effects and value added specifications³ often rely on assumptions that are in some cases stronger than OLS. In addition, neither fixed effects (child or household FE) nor value added models deal with the endogeneity problem that arises because current inputs may respond to lagged test score realizations. A few attempts to use IV have not been completely successful in the sense that the instrument is questionable (because one could easily argue that it is correlated with the child cognitive ability endowment)⁴ or it is too weak to identify plausibly sized effects of maternal inputs on child outcomes.

In this article, we pursue the alternative approach of estimating a structural model of maternal employment and child care decisions *jointly* with the cognitive ability production function using the sample of married mothers in the National Longitudinal Survey of Youth. This approach provides a plausible correction mechanism for the endogeneity problem under certain assumptions (which are clearly laid out and are not necessarily stronger than those required by approaches (1), (2), or (3) mentioned above). But most importantly, the structural approach allows us to assess the effects of counterfactual policy experiments. The latter would not be possible if one estimates the production function alone, regardless of the estimation strategy. In particular, we use the estimates of the model to evaluate the effects of policies related to parental leave, child care subsidies, and other incentives for women to stay at home after birth on women's labor supply and child care choices and children outcomes.

The key findings of this article are the following. First, the average effect of maternal employment and child care on children's cognitive ability is negative and rather sizable. In fact, having a full-time working mother who uses child care during one of the first five years after childbirth is associated with a 1.8% reduction in the child's test scores (around 0.13 standard deviations). 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. However, we also find that mothers get diminishing marginal utility from child ability and will therefore have an incentive to compensate children with relatively low initial ability endowments. We find that the latter effect is big enough to counteract the former. Third, the estimated effect of household income since the birth of the child is quantitatively small, and statistically insignificant, given controls for mother's education and mother's AFQT scores. This is consistent with a view that permanent income is significant in determining parental investment in children and hence the children's achievement, whereas transitory income is not. But we make no attempt to disentangle the extent to which the mother's education and AFQT coefficients reflect genetic transmission of maternal ability to the child vs. the impact of household permanent income on investment in children. Fourth, child care subsidies and a specific type of maternity leave policy are detrimental for children's cognitive development yet increase the mothers' expected lifetime

³ In the value-added approach, the test score in period t (S_{ijt}) is a function of the outcome in period $t - 1$ and the inputs in period t , the idea being that the lagged test score proxies for the child's ability at the start of a period.

⁴ For example, Blau and Grossberg (1992) use work experience prior to childbirth as the instrument for maternal employment.

utility, whereas a baby bonus received by the household after the birth of a child would have positive effects on both mothers' welfare and children's test scores.

The article is organized as follows. In Section 2, we present a brief summary of the related literature. In Section 3, we describe the structure of the model. Section 4 discusses the solution and estimation methods. Section 5 describes the NLSY data on which we estimate the model and highlights the overall patterns in the data. Section 6 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

A number of prior studies, mostly in the developmental psychology literature, have used NLSY data to assess the effect of maternal employment and child care use on children's cognitive development. Comprehensive reviews of this literature can be found in Love et al. (1996), Blau (1999), Lamb (1996), Haveman and Wolfe (1994), and Ruhm (2002).⁵ A significant fraction of these studies provide results that are difficult to interpret in terms of effects of specific inputs.⁶ Most of these studies present simple correlations between inputs and child outcomes and do not include additional controls for family characteristics and/or child characteristics. In most cases, no control for the endogeneity problem associated with the fact that children whose mothers work/use child care may be systematically different from children whose mothers do not work/do not use child care was implemented.

Bernal and Keane (2007) summarize the results reported in this literature. Of the papers that use the NLSY data to assess the effect of maternal employment on child cognitive outcomes, roughly a third report positive effects, a third report negative effects, and the remaining report either insignificant effects or effects that vary depending on the group studied or the timing of inputs. Similarly, of the papers that evaluate effects of day care use (and/or day care quality) on children's outcomes, estimated effects range from positive to negative and are in most cases either insignificant or vary with the specific sample used or the quality of day care.

Reasons for the diversity of these results may include the wide range of specifications that are estimated, as well as the common limitation of failing to control for potential biases that may arise due to the endogeneity of employment and child care choices. However, a few studies, which we discuss below, have implemented corrections for the endogeneity problem by (1) using a very extensive set of control variables, (2) running household or child fixed effects models, and/or (3) using instrumental variables.

⁵ There are several papers, such as Rosenzweig and Wolpin (1994), Rosenzweig and Schultz (1983), Todd and Wolpin (2003), and Cunha and Heckman (2006), on the general topic of the specification/estimation of child cognitive (and/or noncognitive) ability production functions. We summarize here only studies related in particular to parental time and child care inputs during *early* childhood.

⁶ Some studies show associations between clusters of child care arrangements and children's development instead of assessing the impact of each input (e.g., Howes and Rubinstein, 1981; Peterson and Peterson, 1986; Studer, 1992). In some other cases, coefficient estimates or signs of the estimated effects are not provided by the authors (e.g., Howes and Rubenstein, 1981).

To make the exposition of the literature more clear, it is useful to consider the following specific framework, which at least implicitly, seems to underlie most of the papers in the literature. The following equation can be interpreted as a cognitive ability production function:

$$(1) \quad \ln S_{ijt} = \alpha_1 T_{ijt} + \alpha_2 C_{ijt} + \alpha_3 G_{ijt} + \alpha_4 X_{ijt} + \mu_j + \delta_{ij} + \varepsilon_{ijt},$$

where S_{ijt} is the child's cognitive outcome for child i of mother j at age t .⁷ T_{ijt} is a measure of the maternal time inputs up through age t .⁸ C_{ijt} is a measure of nonmaternal time input (i.e., child care), and G_{ijt} represents goods inputs used in the production of child's ability. X_{ijt} is a set of controls for the child's initial skill endowment.⁹ The error components, μ_j and δ_{ij} are family and child effects that capture parts of the *unobserved* skill endowment of the child. And finally, ε_{ijt} is a transitory error term that can be interpreted as measurement error.

A fundamental problem is that the maternal time input T and the goods inputs G are not directly observed. Most papers have dealt with this issue by using maternal employment and/or child care use in place of maternal time. Some studies, however, include one or the other of these variables without examining both.¹⁰ Similarly, some papers have ignored G , whereas a few have used income of the mother or the HOME environment index (which measures not only physical characteristics of the household but also features of the parent-child relationship) as a proxy.¹¹ A few papers, such as Rosenzweig and Wolpin (1994), Todd and Wolpin (2003), and James-Burdumy (2005) discuss in detail the relationship between a child ability production function and the estimating equation by pointing out the difficulty in interpreting the coefficients in the latter when proxies are used for maternal time and goods inputs.

The most important issue is that a significant fraction of papers in the literature estimate Equation (1) by OLS, ignoring the potential endogeneity of the inputs—that is, the potential correlation of the maternal work and day care use decisions, and the goods inputs, with the unobserved ability endowments, μ_j and δ_{ij} . A few

⁷ We use a log specification as we view Equation (1) as analogous to a standard human capital accumulation equation (such as Mincer) except at a young age and because cognitive ability test scores are positive.

⁸ This may be a scalar, as in a cumulative specification, or a specification where only average inputs or the current input matters. It may also be a vector, if inputs at different ages have different effects.

⁹ This might include mother's age, education, AFQT score, etc. (meant to capture the inherited ability endowment), and/or initial characteristics of the child such as gender, race, and birthweight.

¹⁰ For example, Vandell and Ramanan (1992) estimate the effect of maternal employment on child's cognitive outcomes but do not include child care arrangements as an additional input. Similarly, Caughy et al. (1994) assess the effect of child care participation on children's outcomes but do not include maternal inputs in their specification.

¹¹ Baydar and Brooks-Gunn (1991) estimate the effects of both maternal and child care arrangements but do not include goods/services in the specification of the production function nor a proxy for these such as household income. Desai et al. (1989) estimate the effect of maternal employment on children's achievement and include the average number of child care arrangements during the first 3 years after birth and household income as additional controls without much discussion of whether these should be considered additional inputs or the implications in terms of the interpretation of their estimated coefficients of this particular specification.

recent studies have tried to overcome this problem by using (1) an extensive set of explanatory variables to proxy for unmeasured endowments, (2) child or family fixed effects, or “value-added” models, and/or (3) instrumental variables.

Let us first consider the studies that have used extensive controls (like mother’s education, AFQT score, etc.), for the child’s skill endowment. Among others, Han et al. (2001), Baydar and Brooks-Gunn (1991), Parcel and Menaghan (1994), Vandell and Ramanan (1992), and Ruhm (2002) use an extensive set of observable characteristics of the child and the mother. In spite of this, these studies still obtain a diversity of results that make it difficult to draw conclusions. For example, Baydar and Brooks-Gunn (1991) report negative effects of maternal employment (in the child’s first year of life) on cognitive outcomes whereas Vandell and Ramanan (1992) report positive effects of early maternal employment on math achievement and positive effects of current maternal employment on reading achievement. Ruhm (2002) finds significant negative effects of maternal employment on math scores whereas Parcel and Menaghan (1994) report small positive effects of maternal employment on child’s outcomes.

Next, consider the studies that use fixed effects. James-Burdumy (2005) estimated household FE models using a sample of 498 sibling children in the NLSY. Her results indicate that the effect of maternal employment varies depending on the particular cognitive ability assessment used and the timing of employment.¹² Note that use of sibling differences eliminates the mother (or household) fixed effects μ_j from (1) but does not eliminate the child fixed effect δ_{ij} . It is plausible that mothers make time compensations for children depending on their ability type. In this case, using a household fixed effect model would not be appropriate, since maternal employment is correlated with the sibling specific part of the cognitive ability endowment. In addition, the FE estimator requires that input choices are unresponsive to prior sibling outcomes. If inputs of child i' are responsive to outcomes for child i , then ε_{ijt} will be correlated with those inputs.

Blau (1999) and Duncan and NICHD (2003) both study the effects of child care use and child care quality on child outcomes. Blau (1999) uses NLSY data whereas Duncan and NICHD (2003) use the NICHD Study of Early Child Care. They use very similar methodologies, including both a wide range of proxies for unmeasured child ability endowment (like mother’s AFQT and education), controls for many aspects of the home environment, and use of various fixed effects and value added specifications. Blau (1999) reports that child care inputs during the first three years of life have a small impact on child outcomes. Similarly, Duncan and NICHD (2003) find a modest positive effect of improved child care quality.¹³ Both these papers contain useful discussions of the limitations of fixed effects and value added

¹² Her FE estimates in some cases imply large effects of maternal employment on scores. According to the results in Table 5, an increase in maternal work hours from 0 to 2000 in year 1 of the child’s life would reduce the PIAT math score (measured at ages 3–5) by $(-0.00117) \times 2000 = -2.4$ points. However, James-Burdumy finds no significant effect of maternal employment after the first year, so her estimate of the effect of five years of full-time employment is relatively small.

¹³ In particular, a one standard deviation in child care quality causes a 0.04 to 0.08 standard deviation increment in child cognitive ability. Quality is assessed using the Observational Record of the Caregiver Environment (ORCE).

specifications. As they point out, neither approach is ideal for dealing with the problem of unobserved child ability. For example, the household FE estimator requires that input choices are unresponsive to the child specific part of the ability endowment. The value added model runs into the problem that estimates of lagged dependent variable models are inconsistent in the presence of fixed effects like μ_j and δ_{ij} . Neither approach, nor child fixed effects, deals with the endogeneity problem that arises because current inputs may respond to lagged test score realizations.¹⁴

Finally, consider the studies that have used instrumental variables, Blau and Grossberg (1992) and James-Burdumy (2005). Both of these papers look at effects of maternal work on child outcomes and do not examine effects of day care use *per se*. More importantly, the instruments used in both cases turn out to be too weak to estimate plausibly sized effects of maternal employment. A detailed discussion of this issue can be found in Bernal and Keane (2007). The conclusion is that it seems quite difficult to come across plausible instruments that are powerful predictors of both maternal employment and day care usage.

Aside from the studies we have mentioned, several recent papers also estimate cognitive ability production functions, but for children who are old enough to be in pre-school or primary school (as opposed to child care). For instance, Liu et al. (2003) study 5–15 year olds, and Todd and Wolpin (2007) and Cunha and Heckman (2006) look at 6–13 year olds. Thus, none of these studies address how child care affects child outcomes.

3. THE MODEL

In this section, we present a structural model of married mothers' decisions about work and child care use, and how these affect child cognitive outcomes. The woman makes sequential choices about work and child care in each period t following the birth of a child and until the child goes to primary school at age 5.¹⁵ We will consider a woman who has a single child and ignore additional fertility decisions.¹⁶ In the model the time periods correspond to 3-month intervals. We

¹⁴ In addition, a key difficulty in interpreting the results in both Blau (1999) and Duncan and NICHD (2003) is that their specifications makes it difficult to infer any estimate of the effect of maternal time *per se*. Both studies include the HOME environment index, which includes both goods inputs, like books in the home, and time inputs, like how often the child is read to or talks with the mother while she does housework. Thus, the coefficient on whether the mother works or uses day care measures the effect of those variables holding the HOME index fixed.

¹⁵ In the model, mothers make all the decisions. Fathers' labor supply choices do not affect the child's cognitive ability and hence are not incorporated in the model, and fathers' income and education are taken as given. These assumptions allow us to avoid modeling the mother and father's joint labor supply decisions, which would significantly increase the complexity of the model. However, we allow fathers to matter in two dimensions: their income affects women's labor supply and child care choices, and the child's initial skill endowment is correlated with father's education.

¹⁶ In a model with multiple children, one would also have to specify how total maternal contact time is allocated among children and take a stand on the extent to which maternal time is a "public good" (i.e., do children get the same benefit from maternal time regardless of how many children are present?).

allow for three work options (full-time, part-time, or no work), whereas the child care choice is binary. That means that altogether there are $2 \times 3 = 6$ possible options in a woman's choice set.¹⁷ Formally, the choice set is denoted as: $J = \{(h_t, I_t^c): h_t = 0, 1, 2 \text{ and } I_t^c = 0, 1\}$, where h_t denotes hours of work (2 = full-time, 1 = part-time, 0 = no work), and I_t^c is an indicator for whether or not the woman utilizes child care in period t . Define d_t^j as an indicator function that equals 1 if alternative $j \in J$ is chosen at time t .

3.1. Utility Function. The current-period utility function given choice of option j is given by

$$(2) \quad U_t^j = \frac{1}{\alpha_1} c_t^{\alpha_1} + \alpha_2 h_t + \alpha_3 \left(\frac{A_t^\lambda - 1}{\lambda} \right) + \alpha_4 I_t^c + \alpha_5 h_t (1 - I_t^c) + \alpha_6 I_t^c \left(1 - \mathbf{1} \left[\sum_{\tau=1}^{t-1} I_\tau^c > 0 \right] \right) + \alpha_7 \mathbf{1}[t = 1] I_t^c + \alpha_8 \mathbf{1}[t < 5] I_t^c + \varepsilon_t^j d_t^j, \quad \text{for } j = 1, \dots, 6,$$

where consumption c_t is given by the budget constraint

$$(3) \quad c_t = 250 \cdot w_t \cdot h_t + y_H - cc I_t^c.$$

Here A_t is cognitive ability of the child generated by a production function that is defined below, w_t is the mother's hourly wage, y_H represents average husband's quarterly income, cc is the cost of child care, $\mathbf{1}[\cdot]$ represents the indicator function, and ε^j is an alternative-specific random taste component.

The utility function (2) has the common CRRA form in consumption. The parameter α_2 is the disutility from working. The mother gets utility from the child's cognitive ability, A_t , according to the CRRA function with parameter λ . An estimated $\lambda < 1$ would imply that mothers get diminishing marginal utility from child ability and will therefore have an incentive to engage in behaviors that compensate children with relatively low initial ability endowments.

The next set of terms in the utility function capture various aspects of the utility/disutility from child care use. This set of terms is necessary for the model to provide a good fit to the quantitative features of the NLSY data, in particular patterns of child care utilization. The parameter α_4 is a general nonpecuniary benefit/cost associated with the use of child care. The parameter α_5 is an extra disutility from working if child care is not available. The parameter α_6 is an extra cost of initiating child care if it has not been used before. This parameter captures the net effect of factors such as the cost of finding day care and the psychic cost of first time separation from the child. The parameter α_7 is an extra cost from using

¹⁷ We allow for the possibility that mothers work either full-time or part-time and do not use child care. This is the case of women whose partners/husbands take care of the child while they work. All other caregivers different from the mother's partner/husband are coded as child care (including older siblings, grandparents, other relatives, nonrelatives, etc.).

child care during the first quarter after birth ($t = 1$), and α_8 is an extra cost from using child care before the child is one year old ($t < 5$). Both of these parameters capture the fact that it is more difficult to find day care centers that will take infants, along with the fact that the psychic cost of separation from the child is greater when the child is very young.

We allow the terms ε^i to be correlated across alternatives, to capture the fact that some alternatives are more similar than others. In particular, 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.

Turning to the budget constraint (3), note that earned income is given by $250 \times w_t \times h_t$, because part-time work (for a quarter) is defined as 250 hours and full time work as 500 hours. This grouping of hours is necessary to keep the choice set discrete. Keane and Moffitt (1998) argue that this particular grouping is desirable given that hours are very concentrated at 20 and 40 per week, and because much of the variation away from those figures is likely to be measurement error. The second term in the budget constraint, y_H , represents average husband's quarterly income, and finally the third term is the cost of child care.

Aside from the budget constraint, a woman faces two other constraints that influence her work and child care utilization decisions: her wage function and the child cognitive ability production function. We now turn to both these constraints.

3.2. Wage Formation. It is useful to first define w_o as the woman's "initial wage" prior to giving birth. This would be the actual wage for an employed woman, or a latent offer wage based on latent earnings capacity for a nonworking woman. We assume that the initial wage is a function of a vector of observable characteristics that include age, age squared, education, AFQT score¹⁸ and race. This yields the following initial wage function:

$$(4) \quad \ln w_o(\mu_o) = \mu_o + \theta_1 \text{age} + \theta_2 \text{age}^2 + \theta_3 \text{educ} + \theta_4 \text{AFQT} + \theta_5 \text{race} + v_{w_o},$$

where μ_o represents the mother's *unobserved* heterogeneity in the skill endowment. The mother's educational attainment at childbirth (*educ*) and *race* capture *observed* heterogeneity in the skill endowment, whereas *age* (the woman's age at the time of childbirth) captures movement along the life-cycle wage path for a woman of a given skill endowment. Finally v_{w_o} captures measurement error and it is assumed to be serially independent. In particular, we assume that $v_{w_o} \sim N(0, \sigma_w^2)$.

It is useful to define $\ln w_o(\mu_o) = \ln \bar{w}_o(\mu_o) + v_{w_o}$, so that $\ln \bar{w}_o(\mu_o)$ represents the persistent part of the woman's log offer wage at the time of childbirth. Then,

¹⁸ The AFQT is a standardized test adapted for the military and its goal is to ascertain test takers' general cognitive abilities.

after childbirth, the wage a woman can earn upon returning to work is given by the following process:

$$(5) \quad \ln w_t(\mu_o) = \ln \overline{w_o}(\mu_o) - \delta \cdot t + \phi_1 E_t \\ + \phi_2 f_{t-1} + \phi_3 p_{t-1} + \phi_4(E_t \cdot educ) + \phi_5 \tau_{st} + v_{w_t}.$$

Here, δ is the depreciation rate of human capital, so that $\delta \cdot t$ captures the percentage depreciation of a woman's offer wage (i.e., human capital level) if she leaves the labor force for t periods after childbirth.¹⁹ Acquiring work experience can counteract this depreciation. $E_t = \sum_{\tau=0}^{t-1} h_\tau$ 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, and $E_t \cdot educ$ is an interaction term of woman's experience and her education at birth. τ_{st} is a vector of local labor market conditions at time t in state of residence s ,²⁰ which includes the unemployment rate, the real hourly wage rate at the 20th percentile of the wage distribution in that state and the percentage of the labor force employed in the services sector. v_{w_t} is a stochastic term due to measurement error, which we assume to be distributed $v_{w_t} \sim N(0, \sigma_w^2)$.²¹ Finally, we assume a discrete distribution of unobserved types, i.e., we will assume two types μ_o , high and low. Type proportions, denoted by π_{μ_h} and π_{μ_l} respectively, are parameters to be estimated. We explain this further in Section 3.4.

3.3. Child's Cognitive Ability Production Function. Each mother derives utility from her child's cognitive ability, which she can observe. We assume that the child is born with a cognitive ability endowment A_0 , which is correlated with some observable and unobservable variables according to the following equation:

$$(6) \quad \ln A_0(\mu_s) = \mu_s + \gamma_2 educ + \gamma_3 race + \gamma_4 AFQT + \gamma_5 educfa + \gamma_6 1[age < 18] \\ + \gamma_7 1[age > 33] + \gamma_8 BW + \gamma_9 gender,$$

¹⁹ For women who were not working prior to giving birth, initial wages get depreciated by an additional amount, which is the total number of periods during which they were unemployed prior to giving birth.

²⁰ Recall that in the model a time period is a quarter (3 months) after childbirth. Hence the local demand variables included in the wage equation at period t correspond to those observed during the associated calendar period and vary by women depending on their delivery date and state of residence.

²¹ Note that we do not specify a single wage equation (instead of a pre-birth and post-birth equation) since we do not model the mother's entire human capital accumulation process, e.g., all education and work experience prior to childbirth. Instead, what the model is doing is relating the child's initial skill endowment to observed and unobserved characteristics of the mother. For example, children whose mother's had high initial wages are more likely to have higher levels of skill endowment. However, given that mothers had different ages and education levels, we age and education-adjust the wage rate (by specifying Equation (4)) before using it as a predictor of the child's skill endowment (for details, see Section 3.3). In this sense, equation $\ln w_o(\mu_o)$ should not really be thought of as a structural equation.

where $\mu_s \equiv \gamma_1 \mu_o + \omega_k$ is the child's *unobserved* skill endowment. This consists of a part that is correlated with the unobserved part of the mother's ability endowment (μ_o), and a part ω_k that is not. There is also a part of the child ability endowment that is correlated with a set of observed characteristics of the mother and the father: the mother's educational attainment (at childbirth), *educ*, AFQT score, and *race*,²² indicators for whether the mother was less than 18 or over 33 at the time of childbirth ($1[age < 18]$ and $1[age > 33]$), and the father's educational attainment (*educfa*). We include the age indicators in (6) because there is some evidence that teenage mothers (and old mothers) have less healthy children (i.e., there may be a direct physiological adverse effect), although some evidence also suggests that this association vanishes if one controls for mother's characteristics like education and income.²³ Finally, there is a part of the endowment that is correlated with observed characteristics of the child, although the only such observables we have are birthweight (*BW*) and *gender*, a dummy variable indicating the child is a male. In solving the dynamic programming problem and writing the likelihood function we assume a discrete distribution of types such that ω_k can take two values, low and high.

An additional assumption of the model is that mothers know their child's cognitive ability endowment. Thus, mothers know ω_k and $\ln A_0$. This creates a potential source of bias in the estimates of the cognitive ability production function in the sense that mothers can engage in compensating behaviors by spending more time (and using less child care) with low endowment children.²⁴ Although it is reasonable to assume that mothers know much more about the cognitive ability of their children than we do, assuming they have complete information is also unrealistic. It could be possible to consider extensions such as incorporating learning in the model or allowing ω_k to be a composite of two components, one of which is observed by the mother. However, we will not pursue either of these possibilities in this article.

Finally, the cognitive ability production function maps the child's initial ability endowment A_0 , along with subsequent home inputs (e.g., maternal time), into the child's (age adjusted) cognitive ability at time t , denoted A_t , according to

$$(7) \quad \ln A_t(\mu_s) = \ln A_0(\mu_s) + \gamma_9 E_t + \gamma_{10} C_t + \gamma_{11} \ln Y_t + \gamma_{14} \cdot t,$$

where $E_t = \sum_{\tau=0}^{t-1} h_\tau$ and $C_t = \sum_{\tau=0}^{t-1} I_\tau^c$ denote the mother's total quarters of work experience and child care use, respectively, since childbirth, $\ln Y_t$ denotes log cumulative household net income,²⁵ and t is the child's age at the time of the outcome. Equation (7) can be derived from a general specification of the child's ability production function in which ability at time t , $\ln A_t$, is given by an unrestricted function A of a vector \tilde{T}_{it} of period-by-period maternal time inputs up through period t , a vector of day care/pre-school time inputs (\tilde{C}_{it}), a vector of goods inputs

²² Race is a dummy variable that equals 1 if the child is nonwhite, 0 otherwise.

²³ See, for example, Lopez (2003) and Geronimus et al. (1994).

²⁴ In this case, a sibling fixed effect estimator would not deal with the problem because if mothers can see the endowment differences across their children they may treat them differently.

²⁵ Total household income net of child care expenditures.

(\tilde{G}_{it}), and the child's ability endowment (μ_s): $\ln A_{it} = A(\tilde{T}_{it}, \tilde{C}_{it}, \tilde{G}_{it}, \mu_s)$, under the following assumptions:

- (1) Only cumulative inputs matter instead of their timing, and the effect of the unobservable is constant over time. This simplification is quite familiar from the human capital literature, e.g., in the standard Mincer earnings function, only cumulative education and experience are assumed to affect human capital, and the unobserved skill endowment is typically assumed to have a constant effect on log earnings.²⁶
- (2) Cumulative inputs affect $\ln A_{it}$ linearly.
- (3) Maternal employment, E_{it} , reduces maternal contact time with the child and hence can be used as a proxy for maternal time inputs, T_{it} , which are not directly observed.²⁷
- (4) Finally, to deal with the fact that goods inputs (G_{it}) are, to a great extent, unobserved,²⁸ we use total household income as a proxy for G_{it} . In other words, we implicitly assume that households spend a fixed fraction of income on goods and services that enhance the child's cognitive ability.

Once we assume that only cumulative inputs matter and use assumptions (3) and (4), we obtain Equation (7), which is estimable, because all the independent variables are observable.²⁹

Finally, we include interaction terms between the child's initial ability and home inputs to allow the effect of inputs to vary by child type:

$$(8) \quad \ln A_t(\mu_s) = \ln A_0(\mu_s) + \gamma_9 E_t + \gamma_{10} C_t + \gamma_{11} \ln Y_t \\ + \gamma_{12}(\ln A_0(\mu_s) \cdot E_t) + \gamma_{13}(\ln A_0(\mu_s) \cdot C_t) + \gamma_{14} \cdot t.$$

The complete cognitive ability production function is obtained by substituting (6) into (8).

Of course, we do not observe actual cognitive ability of children but instead have a set of cognitive ability test scores from which one has to infer it. Let S_t^A be

²⁶ Admittedly, it would be desirable to use a more flexible specification that allows effects of maternal employment and child care to depend upon child's age. It is plausible to think that the production of human capital is very different during early childhood than during adulthood, and that the timing of inputs is particularly relevant during the former. This could be done, for example, by decomposing E_t and/or C_t into measures of employment and child care use when the child is in various different age ranges. Clearly, this would imply that the state space that the woman faces each period is not only characterized by cumulative work and child care decisions but also by these age-specific cumulative terms. Hence, this would considerably add to the computational burden of solving and estimating the model. Although we do not pursue this possibility in this article, Bernal and Keane (2007, 2008) find that child care inputs do not have any detrimental effect during the first year but have a negative and significant effect on children's cognitive achievements after year one.

²⁷ Let alone "quality" time with the mother.

²⁸ For example, the NLSY contains information on number of books in the home, but lacks other potentially important goods inputs like nutrition, health care, tutors, recreation, etc.

²⁹ Note that, comparing (1) with (7), the term $\alpha_4 X_t + \mu + \delta$ (i.e., the observed and unobserved parts of the ability endowment) has been subsumed in $\ln A_0(\mu_s)$. In addition, we drop ε because the dependent variable in (7) is the actual ability instead of a noisy test score measurement.

the (age adjusted) test scores³⁰ observed in period t and let measurement error be specified as

$$(9) \quad \ln S_t = \ln A_t + \eta_1 d_{1t} + \eta_2 d_{2t} + v_{st},$$

where d_{1t} and d_{2t} are cognitive ability test dummies³¹ that capture the fact that the means on the different tests differ, and v_{st} is a measurement error with $v_{st} \sim N(0, \sigma_v^2)$.

Finally, we will allow for observed and unobserved heterogeneity in a number of dimensions. We have already noted that women are heterogeneous in their unobserved skill type, given by μ_o , and that children are heterogeneous in their endowment type, ω_k in Equation (6). We will also allow mothers to be heterogeneous in their tastes for work (α_2) and tastes for child care utilization (α_4). Recall that the α 's are parameters of the utility function in Equation (2). Specifically:

$$(10) \quad \alpha_{i,k} = \alpha_{i1} ed + \alpha_{i2} race + \bar{\alpha}_{i,k}, \quad \text{for } i = 2, 4 \quad \text{and} \quad k = l(\text{low}), h(\text{high}).$$

$\bar{\alpha}_{i,k}$ is the unobserved component of tastes for work or child care. We assume that there are two different types in each case (low and high).³² That means that altogether there are a total $2^4 = 16$ child-mother types: two types of mother unobserved skill type, μ_o , two types of child endowment type, ω_k , and two types of each mother preference parameter, $\bar{\alpha}_2$ and $\bar{\alpha}_4$. Associated type proportions are denoted by $\pi_{\mu_h}, \pi_{\mu_l}, \pi_{\omega_h}, \pi_{\omega_l}, \pi_{\alpha 2_l}, \pi_{\alpha 2_h}, \pi_{\alpha 4_l}$ and $\pi_{\alpha 4_h}$, which are parameters to be estimated.

Finally, note that identification of the effects of interest relies on (1) the structure of the model being correct, (2) the distributional assumptions required to estimate the model being correct, and (3) certain exclusion restrictions in the sense that some variables enter some equations of the model and not others. For example, local labor market conditions, τ_{st} , enter the mother's employment and child care use decision rules whereas they do not enter the cognitive ability production function directly. That means that local demand conditions (measured by things like the local unemployment rate) enter the score equation only through their effect on hours of work, child care and household income, but not directly. Thus, we assume that variation in local labor market conditions might plausibly generate exogenous variation in employment and child care decisions of mothers although not being directly correlated with the child's ability.

For local demand conditions to be valid exclusion restrictions we require the following assumptions: (1) These local conditions are merely demand indicators, and cannot vary across regions due to changes in supply conditions. More specifically, we have to assume that a common shock to married women, e.g., a common

³⁰ We use the Peabody Picture Vocabulary Test and the Picture Individual Achievement Test (Math and Reading).

³¹ $d_{1t} = 1$ if S_t is a Peabody Picture Vocabulary Test score, 0 otherwise, and $d_{2t} = 1$ if S_t is a Peabody Individual Achievement Test (Math) score, 0 otherwise.

³² The fit of the model does not improve if the number of unobserved types is increased.

shock to tastes for work in a given period, cannot drive up or down variables such as the local unemployment rate; (2) there is no systematic variation in women's unobserved heterogeneity across localities, e.g., women in one state like to work more than women in another state, or if these differences exist, they are not big enough to influence local supply conditions to the extent that they would move the local demand measures.

3.4. Solution and Estimation of the Model. Solution of the individual's optimization problem requires that we solve numerically for the value function at each point in the state space. Define Ω_t as the state at period t that arises as a result of the decisions made up to t . The model is characterized by three state variables that evolve endogenously: quarters of work experience since childbirth (E_t), the work decision during the immediately preceding period (h_{t-1}), and cumulative quarters of child care use (C_t). In addition, cumulative household net income should be part of the set of state variables that evolve endogenously. Cumulative income (Y_t) is given by

$$(11) \quad Y_t = \left[\sum_{\tau=1,t} w_{\tau}(E_{\tau}, h_{\tau-1}) \cdot h_{\tau} \cdot 250 \right] + t \cdot y_H - cc \cdot C_t,$$

where $w_{\tau}(E_{\tau}, h_{\tau-1})$ highlights the dependence of current wage on cumulative experience (E_{τ}) and the previous period employment choice ($h_{\tau-1}$). From that expression, it is clear that to solve the DP problem at t , we would have to keep track of $\{E_{\tau}, h_{\tau-1}\}_{\tau=1,t}$. For example, at $T = 20$ the number of endogenous state variables could be as large as 61. To reduce the state space we use the following approximation of log cumulative income:

$$(12) \quad Y_t = w_t \cdot E_t \cdot 250 + t \cdot y_H - cc \cdot C_t,$$

where current wage, w_t , is used as an approximation to the average wage of the woman from childbirth and up to period t .³³ Thus, cumulative household income can be easily constructed by using the three state variables in $\Omega_t = \{E_t, h_{t-1}, C_t\}$. The state variables are all incremented in the obvious way at each age t based on the work and day care use decisions at $t - 1$.

In addition, each woman has a set of individual specific state variables that stay fixed over time or that we assume evolve exogenously.³⁴ These include her skill endowment and her child's cognitive ability endowment, her race and education,

³³ In other words, we could have approximated cumulative labor income by multiplying the average wage since childbirth $((w_1 + \dots + w_t)/t)$ by total accumulated experience since childbirth. We use current wage instead of average wage (in which case we would have to keep track of additional state variables) since these should be very close, differing only because of depreciation and accumulation of experience.

³⁴ In a way that the woman anticipates.

and her husband's average income. As a result of these variables, each woman in the sample faces her own unique optimization problem.³⁵

We model mother's decisions from $t = 1$ (the first quarter after the child is born) until $T = 20$. At $T + 1 = 21$ the child reaches 5 years of age and goes to primary school. At that point the nature of the woman's decision problem changes fundamentally, so we will not model decisions beyond that point. Rather, we will assume a terminal period value function that is a function of the values of the state variables at $T = 21$:

$$(13) \quad V_{T+1}^j(\Omega_{T+1}) = U_{T+1}^j(c_{T+1}, d_{T+1}, A_{T+1}) + \sum_{\tau=a}^{65} (\beta^4)^{\tau-a} \left(\frac{1}{\alpha_1} \tilde{c}^{\alpha_1} + \alpha_2 \right) \\ + \sum_{\tau=5}^{65} (\beta^4)^{\tau-5} \alpha_3 \left(\frac{A_{T+1}^{\lambda} - 1}{\lambda} \right),$$

where $V_t^j(\Omega_t)$ denotes the value a person assigns to choosing alternative $j \in J_{st}$ at time t . Equation (13) says that the woman cares about the cognitive ability of her child and consumption,³⁶ which depends upon her own work experience (which will affect her future earning capacity) at time $T = 20$.³⁷

Estimation of the structural model requires that, at any given trial parameter vector, we solve the agent's dynamic optimization problem numerically by using the "backsolving" technique from $T = 21$ to 1.

In solving the woman's optimization problem, we assume that she has perfect foresight about aggregate local market conditions. In other words, women are forward-looking and know how future wages will be influenced by the local demand conditions they face.

Having solved the dynamic optimization problem at a particular value for the parameter vector of our model, we are now in a position to construct the likelihood function. Suppose we have data on a sample of individuals who are assumed to be solving the choice model previously described. The data consist of choices in each of the periods along with wages that are observed only when people choose to work. In addition, we have data on the test scores of children. We can write the

³⁵ However, in describing an individual woman's optimization problem, we suppress these variables in the notation, and focus only on the endogenously evolving state variables in Ω_t .

³⁶ In particular, $\hat{c}_i = E(c_i | w_{iT+1}, E_{iT+1}, h_{T-1}, y_{iH})$ denotes predicted consumption, which is a function of the state variables at $T + 1$ and accounts for the fact that the values of the state variables at $T = 20$ matter for the earnings capacity (and hence for future behavior) of the woman from that period on. Specifically:

$$\hat{c}_i = [E(h_{T+1}) * \bar{w}_{iT+1}] + v.y_H,$$

where y_H is the husband's average income, v is the probability of divorce in period $T + 1$, \bar{w}_{iT+1} is the predicted wage of individual i at period $T + 1$ given the state variables at $T + 1$, and the probability of employment status, $E(h_{T+1})$, is given by a logit in various characteristics of the individual. The results of this logit are reported in Appendix Table A.1.

³⁷ Estimation results are not sensitive to the specification of the terminal value function.

probability that a woman chooses alternative j at time t from her choice set J , as follows:

$$(14) \quad \Pr(d_t^j = 1 \mid \Omega_t) = \Pr(U_t^j(\Omega_t) + \beta E_{t-1} V_t(\Omega_t(\Omega_t, j)) \\ \geq U_t^k(\Omega_t) + \beta E_{t-1} V_t(\Omega_t(\Omega_t, k)), \forall k \in J).$$

If the choice j involves working, then a wage will also be observed. And in some periods we will also observe child test score realizations. The likelihood contribution of person i in period t (t indexes child age in quarters) is the choice probability times the densities of the wage and test score (if observed) and can be written as

$$(15) \quad L_{it} = \left[\sum_{j \in J} d_t^j \Pr(d_t^j = 1 \mid \Omega_t) \right] \cdot \phi(w_t \mid \Omega_t)^{(f_t + p_t)} \cdot f(S_t \mid \Omega_t)^{I[S_t \text{ available}]}, \\ t = 1, \dots, 20,$$

where $\phi(w_t \mid \Omega_t)$ is the density of the wage w_t conditional on the state space at t and $f(S_t \mid \Omega_t)$ is the density of a given test score S_t given the state at t that includes all prior periods' inputs into the cognitive ability production function. We can then obtain the likelihood contribution over all time periods by taking $L_i = \prod_{t=1,20} L_{it}$. The likelihood function for the sample is the product of these probability statements over people. Equation (15) conditions on the unobserved type of the mother and her child. To obtain the unconditional likelihood contribution for person i , we must take a weighted average of the L_i over all possible types, weighting by the type proportions π_l , which are parameters to be estimated (Heckman and Singer, 1984).

We 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 $t = 1, \dots, 20$ quarters. Instead, the NLSY sample that we use contains individuals for whom employment choices are observed for the entire period ($t = 1-20$) whereas child care choices are observed only for the first three years after the mother gives birth ($t = 1$ to $t = 12$). If we do not observe a woman's child care choice in one period, then we do not fully observe her state space in subsequent periods, because it is not possible to know the value of the cumulative stock of child care use (C_t) with certainty. However it is possible to integrate over unobserved endogenous state variables when forming the likelihood function (see Keane and Wolpin, 2001).³⁸ Given that the number of possible histories increases significantly over time and the estimation can become burdensome, we use semester periods (i.e., half years) instead of

³⁸ For example, the probability of observing choice $\{f_{13}, p_{13}\}$ in $t = 13$ for every possible choice of I_{13}^c (which is not observed) will be given by

$$\Pr(f_{13}, p_{13} \mid w_{13}, \Omega_{13}) = \Pr(f_{13}, p_{13}, I_{13}^c = 0 \mid w_{13}, \Omega_{13}) \cdot \Pr(I_{13}^c = 0 \mid \Omega_{13}) \\ + \Pr(f_{13}, p_{13}, I_{13}^c = 1 \mid w_{13}, \Omega_{13}) \cdot \Pr(I_{13}^c = 1 \mid \Omega_{13}),$$

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

quarters for the fourth and fifth years after the birth of the child. To do this it is only necessary to adjust the discount factor when needed.

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 five-variate integrals. We use a GHK recursive probability simulator (Keane, 1994) of the choice probabilities and form a simulated maximum likelihood estimator.³⁹

4. DATA

The data are taken from the 1979 youth cohort of the 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 her child, i.e., up to four quarters before birth and each quarter interval since the child's birth for a period of five years. For child care, retrospective data were gathered during 1986, 1988, 1992, and 1994–2000 that allows us to construct complete child care histories during each of the first three years of the child's life.

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.

4.1. *Household Inputs and Child Assessments.* Maternal employment is measured in the following way. Women reporting between 75 and 375 hours of work per quarter 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.

Unfortunately, the NLSY does not report the actual number of hours that a child was in child care instead of in the mother's care.⁴⁰ The child care variable available in the NLSY is simply an indicator for whether the mother used child

³⁹ The algorithm uses 25 draws.

⁴⁰ The number of hours the child spends in child care is only available in survey years 1982, 1983, and 1984. However, there is a serious problem of missing data. For example, out of the 529 women in our sample, only 170 would have nonmissing data about hours in the 1982 (note that we would need this information for five years after childbirth and not just one year).

care⁴¹ for at least 10 hours per week during the last month. Using this information we create a dichotomous child care indicator that equals 1 if the answer to this question was yes, 0 otherwise.

We use as measures of the child's cognitive ability the scores on the Peabody Picture Vocabulary Test (PPVT) and the Peabody Individual Achievement Test Reading Recognition subtest (PIAT-R) and Mathematics subtest (PIAT-M).⁴² 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. Finally the PIAT-R measures word recognition and pronunciation ability.⁴³

4.2. *The Sample.* Estimation of the model presented in Section 3 requires a sample of women that live with their husband or coresident male for the first five years after the birth of the child and who do not have an additional child for five years after the birth of the child.⁴⁴ The first condition is required to avoid having to deal with issues related to welfare participation that arise because single mothers are generally a low income group. It has been well documented that welfare participation affects single mother's labor supply decisions. The second condition is required to avoid modeling fertility decisions and to avoid having to model mothers' time allocation among multiple preschool aged children.⁴⁵ Presumably the amount of time that a mother can allocate to an individual child will differ, even conditional on her work and child care decisions, depending on how many children she has. Thus, the effect of child care and maternal employment on child outcomes may differ depending on the number of children.⁴⁶

The final sample consists of 529 mothers and their children.⁴⁷ Of these women, 449 worked at least once during the year prior to giving birth so we have a

⁴¹ Relative or nonrelative, day care center, nursery/preschool, regular school.

⁴² The analysis is based on the "standard" cognitive assessment scores, which are transformations (on an age-specific basis) of the raw scores.

⁴³ In Appendix Table A.2, we present a brief description of these three cognitive ability tests for children in our sample.

⁴⁴ This includes women who have only one child and also women who have more than one child but there is at least a five year period between births.

⁴⁵ Both issues, fertility decisions and welfare participation, are undoubtedly very important when trying to understand mothers' employment and child care choices after birth. However, the computational burden implied by the model would be immensely complicated by the introduction of either of these. Bernal and Keane (2008) estimate a quasi-structural version of a similar model using the sample of single mothers in the NLSY. The estimated effect of child care on cognitive outcomes is strikingly similar to the one reported here.

⁴⁶ It is worth noting that essentially all the "reduced form" work in this area has ignored this problem as well (i.e., they do not, in general, account for the fact that effects of maternal work and day care may differ depending on the number of children).

⁴⁷ From the original 10,918 births from NLSY mothers, 2,241 correspond to those who did not have an additional child for five years after the birth of the child. From these, 603 mothers lived with their husband or male coresident during the entire 5-year period after childbirth. Finally, 74 observations have missing test scores data. That means that there are 529 mother/child pairs who satisfy our selection criteria.

TABLE 1
MEAN CHARACTERISTICS OF MOTHERS IN THE SAMPLE

Description	NLSY	Our Sample	<i>t</i> test ^a
Worked within 4 quarters after birth	0.47 (0.004)	0.69 (0.020)	10.23**
Mother's age in years at birth	24.54 (0.052)	24.64 (0.185)	0.66
Mother's education in years at birth year	12.1 (0.026)	12.7 (0.094)	5.49**
Hispanic or Black	0.47 (0.004)	0.31 (0.020)	7.50**
Hourly wage before birth	6.15 (16.60)	6.14 (3.16)	0.00
Obs	3677	449	
Spouse or partner average quarterly income	4315 (4619)	4558 (3094)	0.15
Total number of children of mother	2.83 (0.012)	1.62 (0.031)	21.73**
Father present at birth ^b	0.55 (0.004)	1 —	
Observations	4,814	529	

^a** *t* test for the null hypothesis that means in both samples are equal.

^bBecause of the way in which "our sample" is defined, the father is always present at birth.

** Significant at the 1% level.

pre-childbirth wage measure available for them. For the other 80 women, we must integrate over w_0 (the initial wage) in forming the likelihood. Admittedly, it is not clear whether the results that we report would generalize to other populations of interest, such as the sample of single mothers.⁴⁸

In Table 1 we present mean characteristics of mothers in the sample compared with characteristics of all women in the NLSY. The age of mothers in our sample at childbirth is virtually the same as the average mother in the NLSY, around 24.6. However, mothers in our sample are more educated by about two-thirds of a year. Approximately 31% of the women in our sample are Hispanic or Black, whereas this portion is 47% in the NLSY. Although 46% of women in the NLSY worked at some point during the first year after giving birth, this proportion is equal to 69% in our sample. The hourly wage before childbirth for women in the sample is not statistically different from that of the average woman in the NLSY and is approximately equal to \$6.14 (constant dollars of 1983). The average quarterly income of the spouse or partner was slightly higher in the sample (\$4,558 vs. \$4,315) but the difference is not statistically significant. Finally, women in the sample have on average 1.6 children, whereas women in the NLSY have 2.8 children on average.

Figure 1 displays employment and child care choices after birth of women in the sample. During the first quarter after birth, about 43.5% of mothers stayed at

⁴⁸ In 2000, 68% of children lived in two-parent households in the United States. Hence it is important to understand the behavior of this set of mothers and the effects of these women's choices on children's performance.

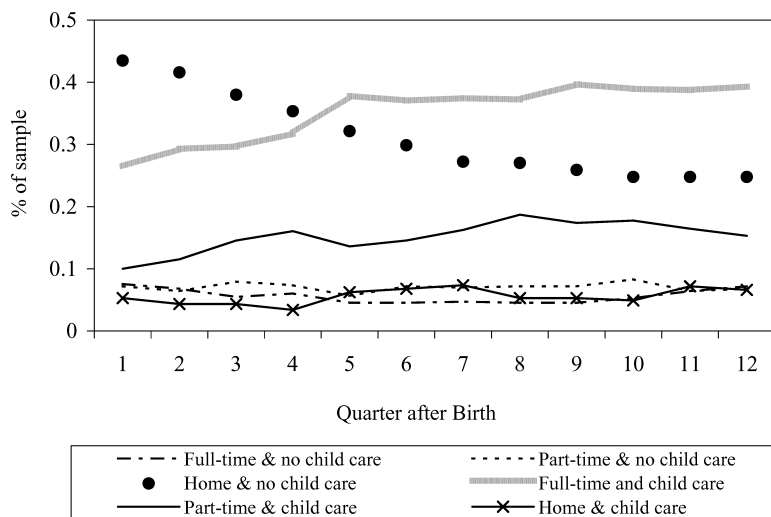


FIGURE 1

CHOICE DISTRIBUTION OF MOTHERS IN THE SAMPLE

home and did not use child care, 36.5% returned to work (full-time or part-time) and used child care, 15% returned to work (full-time or part-time) and reported not having used child care, and the remaining 5% stayed at home and used child care. By the end of the third year after birth, 39% of women were working full-time and used child care and 25% continued to stay at home and did not use child care.

5. ESTIMATION RESULTS

In this section, we present estimates of the structural model presented in Section 3. The estimation procedure involves maximization of the likelihood function given by Equation (15). To do this, we first solve the dynamic programming problem for each individual conditional on a given 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 is fixed at 16. In assessing the model, we consider the reasonableness of the parameter values and the within-sample fit.

5.1. Parameter Estimates. Table 2 reports the estimates of the parameters in the utility function.⁴⁹ These results indicate significant heterogeneity among mothers' types. For example, in regards to tastes for work, one of the types dislikes work almost twice as much as the other type. In particular, although type I mothers' distaste for work (α_2) equals -9.3 , this value is equal to -5.4 in the case of type II women. Interestingly, both mother's education and her race (parameters α_{21} and

⁴⁹ Estimates of the standard errors are obtained directly from the information matrix, which is actually calculated during the maximization algorithm.

TABLE 2
UTILITY FUNCTION

Parameter	Estimate	Std. Errors
Consumption (α_1)	0.36	0.01
Mother's education on taste for work (α_{21})	-0.27	0.04
Mother's race on taste for work (α_{22})	-0.37	0.28
Disutility from work (α_2) Type I	-9.30	0.53
Disutility from work (α_2) Type II	-5.41	0.58
Utility from child's ability (α_3)	0.00	0.02
Ability function (λ)	0.46	0.20
Mother's education in taste for child care (α_{41})	-0.02	0.02
Mother's race in taste for child care (α_{42})	0.39	0.12
Utility from child care (α_4) Type I	-0.27	0.24
Utility from child care (α_4) Type II	7.92	1.15
Cost of no child care if working (α_5)	-4.67	0.08
Cost of initiating child care (α_6)	-5.08	0.03
Extra cost of using child care in qtr 1 (α_7)	-0.26	0.16
Extra cost of using child care during 1st year (α_8)	-1.20	0.06
Child care cost (cc)	156.8	70.8

α_{22}) decrease the disutility from work. To have a clearer interpretation of some of these parameters, we express them in terms of consumption units. Average consumption per quarter is \$6,350. For example, working full time during a given period reduces consumption by \$919 for women type I (high disutility from work) and \$535 for type II women (low disutility from work). In addition, in Table 5 we show that approximately 43% of the mothers in the sample correspond to type II (low disutility from work).

Women are quite different in their tastes for child care. Although one of the types derives disutility from child care ($\alpha_4 = -.271$), the other type derives a high utility from using child care in any given period ($\alpha_4 = 7.92$).⁵⁰ Race significantly increases the utility derived from using child care⁵¹ whereas education is not significantly associated with tastes for child care (parameters α_{41} and α_{42} , respectively). The disutility from using child care for women type I is equivalent to -\$27 whereas the utility of using child care in the case of women type II is approximately \$783.

The cost to a parent of working without using child care is \$462 (-4.66 in utility units). The cost of initiating child care (if never used before) is about \$502. The extra cost associated with using child care during the first quarter after birth is \$26 and the extra cost of using child care before the child is one year old is approximately \$119. Finally, the cost of child care per quarter is estimated to be \$156 (dollars of 1983), which corresponds approximately to \$324 in 2007. Although this amount may seem small, it is important to remember that this estimation averages over various types of child care, which can have very different qualities and prices, including child care provided by relatives (which is in most cases free).

⁵⁰ According to the results presented in Table 5 only 23% of women in the sample correspond to type II (high utility from using child care).

⁵¹ Race is a dummy variable that equals 1 for nonwhites.

TABLE 3
WAGE EQUATION

Parameter	Estimate	Std. Errors
Wage Equation		
Depreciation rate (δ)	-0.003	0.000
Experience (ϕ_1)	0.007	0.002
Previous full-time exp (ϕ_2)	0.047	0.004
Previous part-time exp (ϕ_3)	0.028	0.002
Experience*Education (ϕ_4)	0.000	0.000
Local unemployment rate ($\phi_{5,1}$)	0.000	0.000
Local wage 20 percentile ($\phi_{5,2}$)	0.007	0.001
Local employment in services ($\phi_{5,3}$)	0.030	0.017
Measurement error (σ_ϵ^2)	0.342	0.000
Initial Wage Equation		
Age (β_1)	0.063	0.000
Age ² (β_2)	0.000	0.000
Education (β_3)	0.024	0.001
Race (β_4)	-0.031	0.002
AFQT score (β_5)	0.000	0.000
Skill endowment type I (μ_{ol})	-0.237	0.012
Skill endowment type II (μ_{oh})	-0.092	0.013

Finally, the λ (the parameter in the CRRA function in child's cognitive ability) turned out to be less than 1. This implies that mothers get diminishing marginal utility from child ability and will therefore have an incentive to engage in behaviors that compensate children with relatively low initial ability endowments. It is worth noting that some of the parameters in the utility function are imprecisely estimated, for example, the effect of mother's race on her taste for work and the effect of mother's education on her taste for child care. However, most of the parameters are statistically significant and we can still produce meaningful simulations of policy experiments.

Table 3 shows the estimates of the wage equation parameters. The experience effect on wages indicates that wages increase by 0.7% with each additional quarter of experience, which is in line with previous estimates implying that each additional year of experience increases wages by roughly 4% (see Moffit, 1984; Blau and Kahn, 2000). The depreciation rate is equivalent to 0.3% per quarter. In addition, the estimates of the initial wage equation ($\ln w_0$) indicate that maternal age at childbirth, education, and AFQT score significantly increase wages whereas race is significantly associated with lower wages prior to giving birth. Finally, the estimates indicate that there is significant heterogeneity in terms of the unobserved component of the mother's skill endowment (μ_o). High ability mothers (type I) are almost three times more skilled than low ability mothers. In addition, in Table 5 we show that high ability mothers represent approximately 57% of the sample.

The estimation results for the cognitive ability equation are displayed in Table 4. All inputs turn out to have the expected sign, and most of them are statistically significant. Estimates of γ_1 to γ_6 have the expected signs. The positive coefficient on education implies that better educated mothers have a better technology for

TABLE 4
COGNITIVE ABILITY PRODUCTION FUNCTION

Parameter	Estimate	Std. Errors
Mother's skill type (γ_1)	0.057	0.092
Mother's education (γ_2)	0.006	0.002
Child's race (γ_3)	-0.111	0.011
Mother's AFQT score (γ_4)	0.002	0.000
Father's education (γ_5)	0.002	0.002
Child's birthweight (γ_6)	0.000	0.000
Mother's too young dummy (γ_7)	-0.011	0.017
Mother's too old dummy (γ_8)	-0.137	0.037
Child's gender (γ_9)	-0.010	0.008
Cognitive ability Type I	4.175	0.095
Cognitive ability Type II	4.323	0.096
Child's age (γ_{14})	0.015	0.004
Log cumulative household income (γ_{11})	0.000	0.007
Experience (γ_9)	0.078	0.020
Child care usage (γ_{10})	0.021	0.012
Experience * $\ln A_o$ (γ_{12})	-0.018	0.005
Child care usage * $\ln A_o$ (γ_{13})	-0.005	0.002

TABLE 5
ESTIMATED TYPE PROPORTIONS

Parameter	Estimate	Std. Errors
Low disutility from work $\pi_{\alpha 2l}$	0.572	(0.098)
High disutility from work $\pi_{\alpha 2h}$	0.428	(...)
Low utility from child care $\pi_{\alpha 4l}$	0.772	(0.265)
High utility from child care $\pi_{\alpha 4h}$	0.228	(...)
Child's low ability types $\pi_{\omega l}$	0.439	(0.091)
Child's high ability types $\pi_{\omega h}$	0.561	(...)
Mother's low ability type $\pi_{\mu h}$	0.428	(0.065)
Mother's high ability type $\pi_{\mu l}$	0.572	(...)
Discount factor	0.981	(0.347)

Note that type proportions should add to one, which implies that one of the type probabilities is obtained as the residual; thus we do not report standard errors in this case.

transferring human capital to their children. Interestingly, once we condition on maternal education, father's education is not significantly associated with child's achievement. The results indicate that being a teenage mother is not significantly associated with lower child's cognitive outcomes.⁵² However, being older than 33 does significantly reduce child's cognitive achievements. These results also indicate significant heterogeneity among children's ability types. Type II children's

⁵² Lopez (2003) and Geronimus et al. (1994), show that differences in test scores of children of young mothers with respect to scores of children of older mothers seem to disappear once family background characteristics are controlled for.

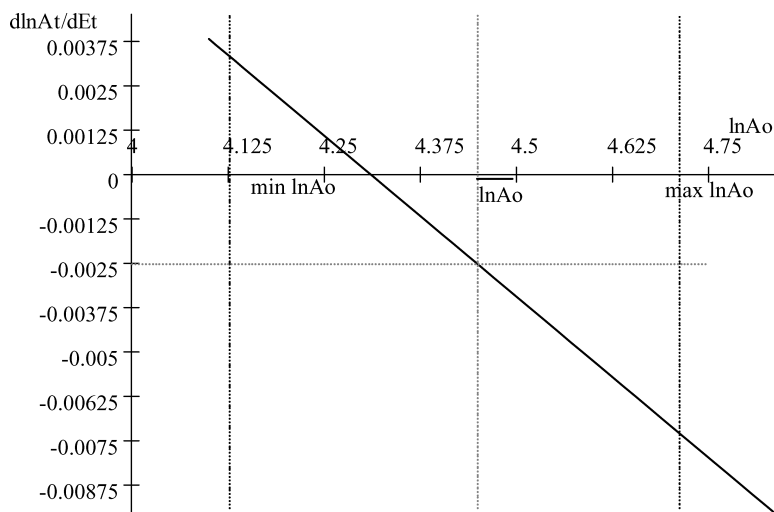


FIGURE 2

EFFECT OF MATERNAL EMPLOYMENT ON COGNITIVE ABILITY: $d \ln S_t/dE_t = 0.078 - 0.018 \ln A_0$

unobserved ability endowment is 15% higher than type II children's (4.32 vs. 4.17).⁵³

Given that the cognitive ability production function contains interaction terms (inputs interacted with initial ability $\ln A_0$) the total effect of maternal employment on child's cognitive achievement is given by $d \ln A_t/dE_t = 0.078 - 0.018 \ln A_0$. Figure 2 plots this equation, i.e., the effect of mother's working experience on the child's cognitive ability as a function of the child's ability endowment ($\ln A_0$). We are only interested in the relevant range of $\ln A_0$ that, given the estimated parameters, is between 4.12 (min $\ln A_0$ in the sample) and 4.71 (max $\ln A_0$ in the sample), i.e., the region between the vertical lines. This means that the net effect of maternal employment on the child's cognitive ability ranges from 0.33% to -0.7% per quarter. In addition, the slope is negative ($\gamma_{11} < 0$), which means there is a higher technological return on time spent with high ability children. In other words, the effect of maternal employment could actually be positive in the case of very low ability children,⁵⁴ but it is significantly negative in the case of high ability children. In particular, the total effect of maternal employment on child's ability evaluated at the average initial ability endowment ($\ln A_0$) is -0.25%. The later estimate has a standard error of .10, and hence a *t*-stat of -2.41. This implies that an additional year of mother's work experience is associated with a 1% reduction in child's test scores (equivalent to 0.07 standard deviations).

The estimates are consistent with the case that mothers provide a more stimulating environment than the average alternative day care provider, and that this

⁵³ Increasing the number of types did not improve the fit of the model.

⁵⁴ This could be associated with the fact that low ability children might be best served by specialized care.

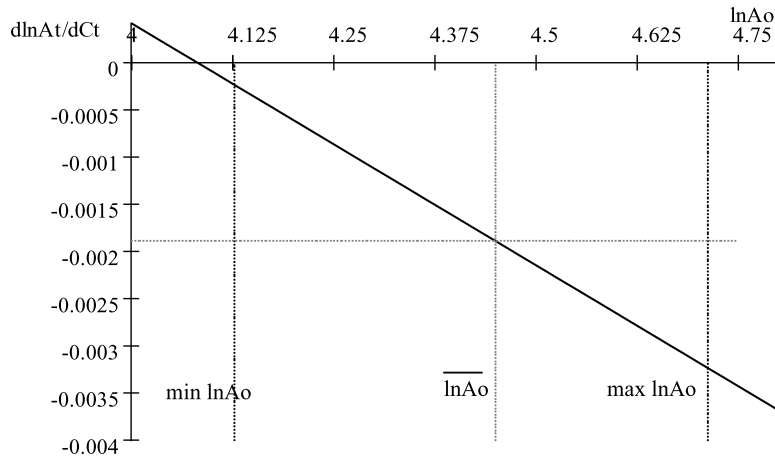


FIGURE 3

EFFECT OF CHILD CARE USE ON COGNITIVE ABILITY: $d \ln S_t / d C_t = 0.021 - 0.005 \ln A_0$

effect is stronger for higher ability children.⁵⁵ However, 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.

Similarly, the total effect of child care use on the child's cognitive ability is given by $d \ln A_t / d C_t = 0.021 - 0.005 \ln A_0$. This expression 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 $\ln A_0$ ranges from -0.02% to -0.32% per quarter. The net effect evaluated at the average of $\ln A_0$ is -0.19% . This estimate has a standard error of .11, and hence a t -stat of -1.67 . This means that an additional year of child care use is associated with a reduction of approximately 0.8% in child's test scores (equivalent to 0.05 standard deviations). 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.

In sum, the total effect of an additional quarter of maternal working experience and child care use on children's test scores is -0.44% .⁵⁶ This estimate has a standard error of .13, and hence a t -stat of -3.32 . This means that having a mother that works full-time and uses child care during one whole year (within the first

⁵⁵ We 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.

⁵⁶ The first column in Table 7 shows the results from running the cognitive ability Equation (1) by OLS using the same sample of women. The total effect of maternal employment and child care use on children's outcomes is around -0.12% per quarter.

five years after the birth of the child) is associated with a reduction in test scores of approximately 1.8% (which is equivalent to 0.13 standard deviations).

Finally, the estimated effect of household income since the birth of the child is quantitatively small and statistically insignificant (see Table 4), given controls for mother's education and mother's AFQT scores. This is consistent with a view that permanent income is significant in determining parental investment in children and hence the children's achievement, whereas transitory income is not.⁵⁷ However, we do not attempt to disentangle the role of (i) genetic transmission of parental ability from (ii) the impact of household permanent income on investment in children.

5.2. 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. 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.⁵⁸ Finally, predicted period-by-period transitions, predicted wages by mother's education and age, as well as predicted log average scores by age and by characteristics of the mother (figures not shown) fit the data quite closely.

5.3. 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 (since the parameter γ_{11} turned out to be negative) but women derive higher marginal utility from spending time with lower ability children (given that $\lambda < 1$). Because these two effects go in opposite directions, whether mothers engage in compensating behaviors such that they spend more time (or use less child care) with low ability children is an empirical issue that we now turn to discuss.

Table 6 shows the proportion of mothers of low ability endowment children who work (per period) compared to the proportion of mothers of high ability endowment children who do. 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, 2.7 percentage points (5%) less women work and 1 percentage points less women use child care. The same is true for every period after birth. This pattern implies that mothers of low ability children compensate them by spending

⁵⁷ This finding is reminiscent of the findings by Keane and Wolpin (2001) and Cameron and Heckman (1998) to the effect that transitory fluctuations in parental income have little effect on college attendance decisions by youth. In addition, it is consistent with findings by Blau (1999) and Carneiro and Heckman (2002) according to which permanent household income is significant in determining investments in children whereas transitory income is not.

⁵⁸ χ^2 goodness-of-fit test statistics (not reported) confirm the graphical results, with the fit being rejected in very few periods.

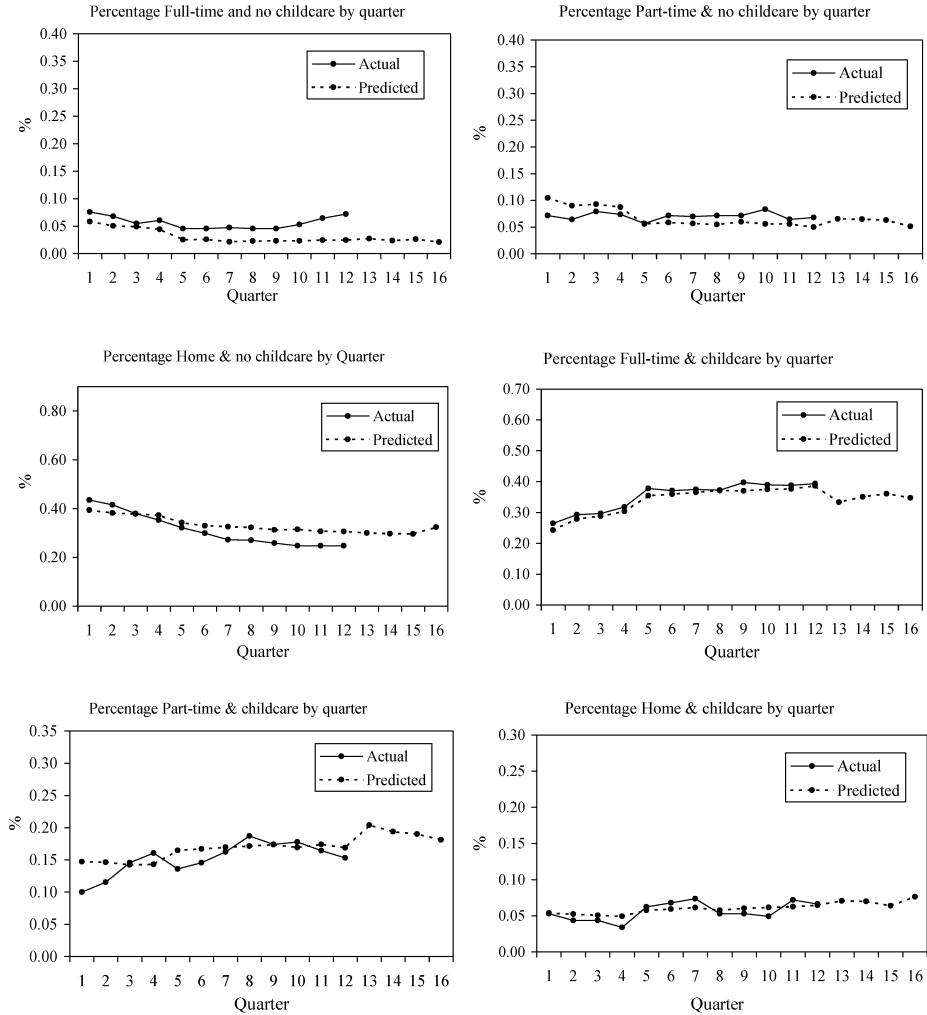


FIGURE 4

MODEL FIT TO CHOICE DISTRIBUTIONS

more time with them, in spite of the higher technological return of investing in high ability children. Note that this result contradicts the assumptions required by the family fixed effects model because it implies that mothers make decisions based upon the individual characteristics of each child.

In Table 7, we present OLS estimates of the score equation. The first column uses actual data from the sample of 529 women used in the structural estimation. According to these results, one additional quarter of maternal employment and child care use is significantly associated with a reduction of -0.12% in children's achievement. Recall that the estimated effect from the structural model is -0.44% ,

TABLE 6
MOTHER'S CHOICES BY CHILD'S ABILITY ENDOWMENT
(% OF WOMEN CHOOSING EACH ALTERNATIVE)

Quarter after birth	Work			Child Care		
	Mothers of			Mothers of		
	Low Ability Child	High Ability Child	Difference	Low Ability Child	High Ability Child	Difference
1	54.40	57.16	2.76	45.13	45.99	0.86
2	56.74	60.97	4.23	49.16	49.90	0.75
3	57.58	62.60	5.01	49.91	50.67	0.76
4	57.58	60.88	3.29	49.63	50.86	1.23
5	60.11	64.22	4.11	57.02	60.50	3.47
6	61.05	66.41	5.36	59.27	61.64	2.37
7	62.08	65.36	3.28	58.80	62.79	3.98
8	62.17	64.60	2.43	60.11	62.21	2.10
16	61.52	66.41	4.90	61.61	63.84	2.23

Based on a simulation of 8,000 individuals.

which means that OLS estimates of the maternal employment and child care use on children's achievement are indeed upwardly biased as expected. That is, once we correct for the endogeneity problem, the effect significantly declines relative to the OLS estimates. In addition, household cumulative income turns out to be positive and significant. However, the effect is quantitatively very small. In particular, a 1% increase in household income is associated with an increase of 0.009% in children's test scores.

Column (2) shows the same OLS estimation using simulated data generated by the model and the estimated parameter vector. Interestingly, results from the estimation on simulated data turn out to be very close to the OLS estimation on actual data.⁵⁹ These results indicate that the effect of an additional quarter of maternal employment and child care use is around -0.18% . This means that the model is in fact generating the same endogeneity bias present in the data and it goes in the expected direction.

Finally, column (3) shows OLS estimates using simulated data again but we condition on both mother's types and children's types (which are known in the simulation). In other words, we can assign ω -types and μ_0 -types and include these as additional controls in the regression. We observe that once we control for unobserved types, the effect of maternal employment and child care use is significantly larger. In particular, an additional quarter of maternal work experience and child care use is associated with a 0.24% reduction in children's achievements. That means that once we partially control for the sources of endogeneity we significantly reduce the bias.

⁵⁹ These regressions are based on a simulation of 8,000 individuals whereas the actual data contains 529 observations. The fact that the size of the simulated data is bigger can be the reason that some coefficients turn out to be significant whereas they were insignificant when estimated on actual data.

TABLE 7
OLS ESTIMATION OF THE TEST SCORE EQUATION

	Actual data (1)	Simulated Data	
		(2)	(3)
Work experience + child care use	−0.0012 (0.0006)*	−0.0018 (0.0001)**	−0.0024 (0.0008)**
Log(Cumulative Income)	0.0096 (0.0053)*	0.0090 (0.0029)**	0.0006 (0.0022)
Gender	0.0108 (0.0078)	−0.0027 (0.0022)	−0.0044 (0.0016)
Birthweight	0.0001 (0.0002)	0.0002 (0.0001)**	0.0003 (0.0001)**
Mother's education	−0.0014 (0.0027)	0.0101 (0.0007)**	0.0054 (0.0005)**
Mother's AFQT	0.0014 (0.0002)**	0.0012 (0.0001)**	0.0019 (0.0004)**
I[age < 18]	−0.0187 (0.0189)	−0.0003 (0.0069)**	−0.0262 (0.0052)**
I[age ≥ 33]	−0.0696 (0.0302)**	−0.1021 (0.0087)**	−0.1077 (0.0065)**
Race	−0.0663 (0.0093)**	−0.0877 (0.0025)**	−0.0935 (0.0019)**
Father's education	0.0098 (0.0020)**	0.0016 (0.0005)**	0.0011 (0.0004)**
Child's age	0.0164 (0.0066)**	0.0182 (0.0026)**	0.0210 (0.0015)**
PPVT dummy	−0.0943 (0.0134)**	−0.0921 (0.0047)**	−0.0741 (0.0035)**
MATH dummy	−0.0602 (0.0097)**	−0.0508 (0.0030)**	−0.0344 (0.0022)**
Constant	4.4605 (0.0413)**	4.3478 (0.0306)**	
Mother type 1 + Child type 1			4.3853 (0.0233)**
Mother type 1 + Child type 2			4.3769 (0.0230)**
Mother type 2 + Child type 1			4.5065 (0.0232)**
Mother type 2 + Child type 2			4.5017 (0.0230)**
R^2	0.241	0.253	0.414

(1) OLS estimated with actual data.

(2) OLS estimated with simulated data.

(3) OLS estimated with simulated data but assigning mother-child types.

Standard errors reported do not take into account the estimation error on the model parameters.

6. POLICY EXPERIMENTS

In this section, we evaluate the effect of various policies on women's choice distributions and children's average test scores.

TABLE 8
THE EFFECT OF A 35% CHILD CARE SUBSIDY ON AVERAGE TEST
SCORES (PERCENTAGE DIFFERENCE IN TEST SCORES WITH RESPECT
TO THE BASELINE)

Test and child's age	% change in avg. test scores
PPVT age 3	-1.07
PPVT age 4	-1.87
PPVT age 5	-0.24
MATH age 5	-1.19
MATH age 6	-0.94
READ age 5	-0.82
READ age 6	-0.23

Based on a simulation of 8000 individuals.

6.1. *Child Care Subsidy.* The first experiment involves a 35% child care subsidy. In particular, the parameter cc is reduced from its estimated value of \$156.8 to \$102. As expected, the percentage of women choosing alternatives that include child care increases with respect to the baseline case. On average, there is an increase of 4 percentage points per period in the number of women that now choose to use child care (choice distribution not shown).

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 more. On the other hand, there is an income effect given 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 childbirth by approximately 1 percentage point, which implies that the substitution effect dominates.

Table 8 displays the percentage difference in average log scores by ability type in the 35% 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 at all ages. This reduction ranges from 0.23% to 1.8% depending on the test and the age of the child. 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.⁶⁰

6.2. *Maternity Leave Policy.* In this section, we analyze a maternity leave policy according to which there is no wage penalty for time out of the labor market after giving birth. In particular, we do this by setting the wage depreciation rate δ at 0. This means that if a woman did not work for a few periods after giving

⁶⁰ One can calculate the mother's mean expected present value of lifetime utility at $t = 1$ and observe that it increases on average 0.3% once the child care subsidy is introduced.

birth, her re-employment wage is drawn from the same wage distribution she had before giving birth.⁶¹

Once the wage depreciation rate is set at 0 a higher percentage of women choose to work full-time relative to the baseline case, whereas less choose to either stay at home or work part-time (choice distribution not shown). For example, in period 4 the total percentage of women choosing to work increases by 6 percentage points, and the proportion of mothers choosing to use child care raises by 5 percentage points.

Intuitively, women are still getting zero wages during the time they are away from the labor market after childbirth but the opportunity cost of staying at home has now increased relative to the baseline scenario. Forgone 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 terms of forgone 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. The reduction in average test scores with respect to the baseline case ranges from 0.1% to 1% depending on the test and the age of the child. Mothers' mean expected present value of lifetime utility at time $t = 1$ is increased by 0.6% with respect to the benchmark case. It is difficult to assess whether this type of policy is effective or not given the fact that although it increases women's lifetime utility, it decreases children's test scores.

6.3. 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.⁶² In this case, fewer women choose alternatives that include work and more women decide to stay at home with their children (choice distributions are not shown).

Table 9 reports 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 reduction in the proportion of women working (full-time and part-time) of 3.8 percentage points and a reduction in the proportion of women using child

⁶¹ An alternative way to model the maternity leave policy would be to allow for the possibility of paid benefits during a given leave period. However, in this case the state space would have to be altered to account for the new state variable. In the United States the law requires only that employers hold the mother's job for 12 weeks after giving birth but does not mandate paid benefits during this time. Hence it seems reasonable to model this policy as one in which women are not penalized in the sense that their wage after childbirth is not reduced depending on the time they spent out of the labor market after giving birth.

⁶² 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 \$6000 for the third child. Parents in Japan get a \$70 allowance a month for the first two children until they enter pre-school. Also, a per-child tax deduction as those that have been implemented in the United States would be analogous to this type of bonus.

TABLE 9
THE EFFECT OF A \$250 BABY BONUS ON EMPLOYMENT AND CHILD CARE CHOICES
(% OF PEOPLE WHO CHOOSE EACH ALTERNATIVE)

	Baseline	Baby Bonus	Change (percentage points)
Full-time and no child care	4.41	3.83	-0.58
Part-time and no child care	8.75	6.85	-1.89
Home and no child care	37.32	41.97	4.65
Full-time and child care	30.32	27.41	-2.91
Part-time and child care	14.29	15.83	1.54
Home and child care	4.91	4.11	-0.80
Work	57.77	53.92	-3.85
Child care	49.53	47.35	-2.17

Based on a simulation of 8000 individuals.

Child care distributions reported correspond to the fourth quarter after childbirth.

care of almost 2 percentage points. The same pattern can be observed for almost every period after childbirth until the end of the fifth year. As a consequence of the change in input choices (maternal time and child care time), average scores increase for all tests and all ages. On average, the increase in test scores ranges from 0.1% to 0.8% 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 1.2%.

7. CONCLUSIONS

In this article we focus on the labor supply and child care decisions of women immediately following childbirth, to evaluate the effects of mothers' decisions on their children's cognitive development. In particular, we are interested in assessing the impact of maternal employment, child care, and household income on children's outcomes. 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.⁶³ However, the question of what determines children's cognitive achievement in general, and the role of parental time and goods inputs in particular, remains largely unresolved. In this article, we use data from the National Longitudinal Survey of Youth to assess the impact of home inputs (maternal employment, day care time inputs, and household income) on Peabody Picture Vocabulary Tests scores and Peabody Individual Achievement Test scores (Math and Reading Sections) of children ages 3–6.

The key issue dealt with in the article is the potential endogeneity of home inputs in the child's cognitive ability production function that arises as a result of

⁶³ Currie and Thomas (2001) 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.

the existence of unobserved characteristics of both mothers and children. 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. Estimation of a structural model of women's employment and child care choices jointly with a cognitive ability production function is suggested as an alternative way of implementing a correction mechanism for this endogeneity problem. Most importantly, estimation of the structural model allows us to explore the effects of counterfactual policy experiments on women's choices and children's outcomes that we would not be able to do with the ability production function alone.

Results suggest that the effects of maternal employment and child care during the first five years of life of the child are rather sizable. In fact, an additional year of full-time work is associated with a reduction of about 1% in test scores, and an additional year of child care use is associated with a reduction of approximately 0.8% in children's achievement. This means that having a full-time working mother that uses child care during an entire year (within the first five years after the birth of the child) is associated with a 1.8% (0.13 standard deviations) reduction in ability test scores. Furthermore, we find that this effect is stronger for high ability 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. However, we also find that mothers get diminishing marginal utility from child ability, and will therefore have an incentive to compensate children with relatively low initial ability endowments. We find that the latter effect is big enough to counteract the former.

In addition, the estimated effect of household income since the birth of the child is quantitatively small and statistically insignificant, given controls for mother's education and mother's AFQT scores. This is consistent with a view that permanent income is significant in determining parental investment in children, and hence the children's achievement, whereas transitory income is not. But we make no attempt to disentangle the extent to which the mother's education and AFQT coefficients reflect genetic transmission of maternal ability to the child vs. the impact of household permanent income on investment in children.

The results of the policy experiments suggest that both child care subsidies and maternity leave entitlements can be detrimental for pre-school aged children's cognitive outcomes, 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 high utility from child care to choose alternatives that include child care. This has a negative effect on children's average scores.

On the other hand, by setting the wage depreciation at zero, in other words, eliminating the wage penalty that a woman would incur depending on the number

of periods she was away from the labor market after giving birth, children are made worse off. Intuitively, given the fact that women do not receive a wage (or a portion of it) while away from the labor market and forgone 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 forgone 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 children's average scores.

Finally, the effect of a \$250 quarterly baby bonus after the birth of a child and until he/she goes to primary school at age 5 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 1.2% and on the other hand average scores of children increase by about 0.5%. The increase in household's income provides an incentive for women to work less and stay at home with their children at the same time that it acts as a disincentive for child care use. Therefore, the net effect is to increase children's cognitive ability as well as mothers' utility.

We do not claim that the estimated effects and the results of the policy experiments reported here can be generalizable. As a matter of fact, we have used a restricted sample of women in the NLSY to estimate the model. In particular, we have used mothers that are married and women that do not have an additional child during the five year period following childbirth. Hence, the results should only be thought as applicable to this specific subset of women.⁶⁴

In this article, we have assumed that there is a homogeneous type of child care. An interesting extension of the model would be to 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 sizable 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, the results could be sensitive to changes in the assumptions about what the mother knows about her child. One could allow, for example, the child's unobserved ability endowment (ω_k) to be a composite of two components, one of which is observed by the mother. It is difficult to predict in which direction the results would change but it is plausible to think that this could describe parents' behavior better.

⁶⁴ Bernal and Keane (2008) estimate a quasi-structural version of a model very similar to the one presented in this article using the sample of single mothers in the NLSY. In addition, Bernal and Keane (2007) use a set of welfare rules and local demand conditions as instrumental variables to estimate a cognitive ability production function using the same sample of single mothers (NLSY). The estimated effects of child care use on children's cognitive outcomes in both papers are strikingly similar to the ones reported here for the sample of married women.

APPENDIX

TABLE A.1
WORKING PROBABILITIES BY THE END OF THE 5-YEAR PERIOD

	Full-time	Part-time
Age at end of period	-0.103 (0.06)**	-0.173 (0.05)**
Education at end of period	0.077 (0.11)	0.184 (0.09)*
Race of mother	-0.740 (0.41)*	-0.576 (0.34)*
Accumulated experience during the period	0.200 (0.05)**	0.047 (0.04)
I[worked previous period]	6.986 (0.73)**	2.846 (0.52)**
I[worked full-time before childbirth]	-0.481 (0.65)	0.072 (0.48)
I[worked part-time before childbirth]	0.189 (0.59)	0.332 (0.42)
Average husband's income	9.0E - 05 (0.00)	-1.1E - 05 (0.00)
Constant	-2.148 (1.54)	1.141 (1.12)
Estimation	Logit	
No. of observations	529	
Pseudo- R^2	0.46	

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.

TABLE A.2
COGNITIVE ABILITY TESTS IN OUR NLSY SAMPLE
DESCRIPTIVE STATISTICS

Child's Age	PPVT			PIAT - Math		PIAT-Reading	
	3	4	5	5	6	5	6
Sample ($N = 529$)	95.65 (17.33)	97.58 (16.81)	101.44 (18.20)	102.56 (15.23)	103.40 (12.02)	112.99 (14.80)	105.18 (11.15)
Nonwhites	82.81 (18.50)	86.87 (17.51)	93.00 (16.70)	97.03 (14.39)	99.46 (11.93)	109.73 (15.24)	103.34 (11.04)
Whites	100.26 (14.40)	102.86 (13.71)	105.57 (17.53)	104.50 (15.08)	105.71 (11.50)	114.14 (14.51)	106.28 (11.10)
Maternal education (12 yrs+)	96.02 (17.92)	98.96 (16.01)	102.36 (18.65)	103.32 (15.16)	104.33 (11.98)	114.29 (14.51)	105.98 (11.39)
Maternal education (<12 yrs)	92.81 (11.90)	88.15 (19.33)	95.81 (14.21)	97.55 (14.97)	98.33 (11.10)	104.37 (14.00)	100.63 (8.42)
Male	94.78 (17.38)	97.35 (18.89)	101.64 (17.66)	101.59 (16.19)	103.56 (13.23)	111.74 (16.26)	105.27 (11.92)
Female	96.49 (17.37)	97.81 (14.53)	101.23 (18.84)	103.49 (14.25)	103.23 (10.57)	114.18 (13.22)	105.09 (10.31)

PPVT: Peabody Picture Vocabulary Test.

PIAT: Peabody Individual Achievement Test.

Standard errors in parentheses.

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