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Maternal Input Choices and Child Cognitive Development

Testing for Reverse Causality

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Maternal Input Choices and Child Cognitive Development: Testing for Reverse Causality

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Abstract

I assess whether the results of child achievement tests affect maternal employment and the child-care choices of mothers with prekindergarten children. To test this hypothesis, I first incorporate into Bernal and Keane's (2010) model the mother's imperfect knowledge of the child's cognitive ability endowment and possible mechanisms through which the mother may learn the child's endowment. Then, I use a quasi-structural approach to form approximations to the mother's employment and child-care decision rules and jointly estimate them with the child cognitive development production function and wage equation. Using a sample of single mothers from the NLSY79, I find evidence that maternal employment and child-care decisions are sensitive to past achievement scores. In particular, a mother whose child has taken the Peabody Picture Vocabulary Test before entering kindergarten and whose child's standardized test score is above a certain threshold intends to use child care more and work more part-time hours immediately after observing the child's performance on the achievement test.

(JEL: C23, J13, J22)

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[2] All errors are mine.

1. INTRODUCTION

In the literature, the effect of maternal input choices and children's cognitive development has been widely explored using a variety of estimation strategies, such as OLS with extended controls (Baydar and Brooks-Gunn, 1991; Vandell and Ramanan, 1992; Parcel and Menaghan, 1990; Blau, 1999; Han et al., 2001; Ruhm, 2004; Duncan, 2003), fixed-effect estimators (James-Burdumy, 2005; Blau, 1999), instrumental variables (Blau and Grossberg, 1992; Blau, 1999; James-Burdumy, 2005), and, finally, more structured approaches (Bernal, 2008; Bernal and Keane, 2010). However, the literature lacks studies that explore reverse causality between maternal input choices and children's cognitive development. In other words, not enough attention in the literature has been paid to the question of whether a mother engages in any compensatory behavior after observing the performance of her child on an achievement test. This study tries to fill this gap in the literature.

In the real world, the reverse causality issue between maternal input choices and child cognitive development may arise if the mother does not perfectly observe her child's cognitive ability endowment in the first couple of years of the child's life. A potential signal that the mother uses to update her belief about the child's true endowment level is the child's performance on achievement tests in later ages. If the mother's understanding of the child's cognitive ability endowment via achievement tests is the true mechanism, then the data should provide ample support that poor or good performance on the achievement test leads to immediate changes in input choices. The latter would suggest that the mother is involved in compensatory behavior. Otherwise, if the learning is not a part of the decision-making process, then results on the achievement test do not provide any valuable information to the mother, and she stays unresponsive to the child's test scores.

To test whether a mother is involved in any compensatory behavior after observing her child's performance on achievement tests, I first incorporate asymmetric information and learning into Bernal and Keane's (2010) model. The theoretical model allows establishing direct relationships between maternal input choices (employment and child care) and past cognitive development outcomes. The latter is measured by the child's performance on the Peabody Picture Vocabulary Test (PPVT). In a similar fashion as Bernal and Keane (2010), instead of estimating the full structural model, I utilize a quasi-structural approach by forming approximations to the mother's employment and child-care decision rules and jointly estimating them with the child's cognitive development function and the mother's wage equation. I estimate this mixed discrete-continuous model with endogenous variables in each equation using the simulated maximum likelihood technique.[3]

Using a sample of single mothers from the NLSY79,[4] I find ample evidence that maternal employment and child-care decisions are sensitive to past achievement scores. In particular, a mother whose child has taken the PPVT before entering kindergarten and whose child's standardized test score is above a certain threshold intends to use child care more and work more part-time hours immediately after observing her child's good performance on the achievement test. This implies that mothers counteract children's positive results on the test by spending less time with their children and increasing working hours.

[3] Bernal and Keane (2010) use the simulated maximum likelihood method with the GHK algorithm.
[4] I use the same sample of single mothers used by Bernal and Keane (2010), who generously provided the full data for my empirical exercise.

This paper is structured as follows. The next section extends the theoretical model of Bernal and Keane (2010), Section 3 derives the empirical specification of the test and discusses the method of estimation, and Section 4 discusses the data. The main empirical results are discussed in Section 5, and Section 6 offers conclusions.

2. THEORETICAL MODEL

In the model, a single woman makes sequential choices about work and child care in each period. In this context, a *period* is one quarter. Similar to Bernal and Keane (2010), I allow for three employment options (part-time, full-time, and not working), two welfare participation options (participating and not participating), and two child-care options (informal child care, including parental child care, and formal child care). Welfare participation implies a single mother's choice to receive cash assistance to finance any formal child care from the Temporary Assistance for Needy Families (TANF) program. The eligibility criteria for TANF cash assistance differ by state *s* and time *t*, which helps identify the effect of child care and employment on the child's cognitive development, as in Bernal and Keane (2010). Thus, the choice set is given by

$$J = \{(h_t, g_t, I_t^C); h_t = 0,1,2; g_t = 0,1; I_t^C = 0,1\} \qquad (1)$$

$$h_t = \begin{cases} 0\text{ - not to work} \\ 1\text{ - part-time} \\ 2\text{ - full-time;} \end{cases} \quad g_t = \begin{cases} 0\text{ - not in TANF} \\ 1\text{ - in TANF;} \end{cases} \quad I_t^c = \begin{cases} 0\text{ - parental care} \\ 1\text{ - formal child care;} \end{cases}$$

and the choice indicator is

$$d_t^j = I[\text{alternative j} \in \text{J}_{\text{st}} \text{ is chosen in period t}]. \qquad (2)$$

The current-period utility function, given the choice of option *j,* similar to Bernal and Keane (2010) is

$$U_t^j = \frac{1}{\alpha_1} c_t^{\alpha_1} + \alpha_2 h_t + \alpha_3 \tilde{A}_t + \alpha_4 g_t + \alpha_5 I_t^C + \varepsilon_t^j, \qquad (3)$$

where α_1 is the coefficient of the risk aversion for consumption, α_2 is the disutility from work, α_3 is the utility from the child's cognitive ability, α_4 is the disutility from welfare participation, and α_5 is the non-pecuniary cost associated with child-care use. There are two major differences with Bernal and Keane (2010). First, in the case of learning, a woman does not perfectly observe the child's cognitive ability at period *t,* and she has only a subjective measure of it, given by $\tilde{A}_t$. Second, the mother gets utility from $\tilde{A}_t$ according to the CRRA function with the parameter $\lambda = 1$.[5]

In Equation 3, c_t is per-period consumption, which is a function of wage income, non-wage income, cash assistance from the TANF, and the cost of child care:

$$c_t = 250 w_t h_t + y_t + g_t B\left(w_t, h_t, y_t, D_t, R_{st}\right) - cc\left(w_t, h_t, y_t, D_t, \theta_t\right) I_t^c, \qquad (4)$$

where w_t is the per-hour wage rate; *B* is the amount of cash assistance received from the TANF, which is a function of the woman's labor income and non-labor income (y_t), the TANF experience (D_t), measured in months and time- and state-specific welfare rules (R_{st}); *cc* is the child-care cost, which is a function of labor and non-labor income, the TANF experience, and time- and state-specific CCDF rules (θ_t).

Besides the above budget constraint, the mother is also constrained by other two functions: wage equation and the child's cognitive ability production function. The mother's wage at period *t* is a function of observed and unobserved characteristics:

[5] Bernal and Keane (2010) specify that the mother gets utility from the child's ability in the form of $\alpha_3 \left(\frac{A_t^\lambda - 1}{\lambda} \right)$

$$\ln w_t(\mu_w) = \mu_w + \theta_1 age + \theta_2 age^2 + \theta_3 educ + \theta_4 AFQT + \theta_5 race - \\ - \delta t + \varphi_1 E_t + \varphi_2 f_{t-1} + \varphi_3 p_{t-1} + \varphi_4 E_t educ + \varphi_5 \tau_{st} + \nu_{wt}. \quad (5)$$

Bernal and Keane (2010) use self-explanatory variable names as shown in Equation 5, with exception of τ_{st}, which stands for local market conditions; δ, a stigma effect of non-employment after childbirth; E_t, the cumulative experience after childbirth, such as $E_t = \sum_{\tau=0}^{t-1} h_\tau$; and *f* and *p*, which are the lagged indicators of full-time and part-time employment. Finally, there are two stochastic terms in the wage equation: μ_w, unobserved heterogeneity in the mothers' skill endowment, and ν_{wt}, the measurement error.

The child's cognitive ability production function is given by

$$\ln A_t(\mu_s) = \ln A_0(\mu_s) + \gamma_{12}\hat{T}_t + \gamma_{13}\hat{C}_t + \gamma_{14}\ln \hat{G}_t + \eta_{st}, \quad (6)$$

where A_0 is the initial level of child's cognitive ability and μ_s is the unobserved heterogeneity in the child's endowment of mental capacity which positively correlates with μ_w:

$$\ln A_0(\mu_s) = \mu_s + \gamma_1 educ + \gamma_2 race + \gamma_3 AFQT + \gamma_4 age + \gamma_5 age^2 + \\ + \gamma_6 I\left[age < 18\right] + \gamma_7 I\left[age > 33\right] + \gamma_{10} BW + \gamma_{11} gender = X\gamma + \mu_s. \quad (7)$$

$\hat{T}_t$ is the cumulative input of maternal time through period *t*:

$$T_{it} = T - C_{it}. \quad (8)$$

T_{it} is maternal time spent with the child in period *t*, *T* is the total available time, and C_{it} is the total child-care time in period *t*.

$\hat{G}_t$ is the cumulative input of goods:

$$\ln \hat{G}_t = q_0 + q_1 X + q_2 \mu_s + q_3 \hat{C}_t + q_4 \ln \hat{I}_t(W, H; R) + q_5 t + \varepsilon_j^g, \tag{9}$$

where $\hat{I}_t$ is the cumulative income, which is a function of wage (*W*), working hours (*H*) and welfare rules (*R*), and ε_{it}^g is the mother's idiosyncratic tastes for investment in the form of goods.

Finally, η_{st} is the shock to the child's development path in Equation 6.

By substituting Equations 7, 8, and 9 into Equation 6, and after simple algebraic rearrangements, the child cognitive production function is given by

$$\begin{aligned}\ln A_t(\mu_s) = (\gamma_{12} T + \gamma_{14} q_5) t + (\gamma_{13} - \gamma_{12} + \gamma_{14} q_3) \hat{C}_t + \gamma_{14} q_0 + X(\gamma + \gamma_{14} q_1) + \\ + \gamma_{14} q_4 \ln \hat{I}_i(W, H; R)) + (1 + \gamma_{14} q_2) \mu_{si} + \gamma_{14} \varepsilon_j^g + \eta_{st}.\end{aligned} \tag{10}$$

The final version of the cognitive development production function can be written in the following way:

$$\ln A_t(\mu_s) = \beta_0 + \beta_1 t + \beta_2 \hat{C}_t + \beta_3 \ln \hat{I}_t + X\beta_4 + \hat{\mu}_s + \hat{\varepsilon}_j^g + \eta_{st}. \tag{11}$$

It should be noted that for welfare rules (R_{st}) and local demand conditions (τ_{st}) to be valid instruments for estimating the cognitive development production function, both variables must be uncorrelated with both $\hat{\mu}_s$ and $\hat{\varepsilon}_t^g$.

In reality, econometricians do not observe the actual cognitive ability of children, but surveys provide information on children's performance on achievement tests. If I denote S_t as the test score at period *t*, then it is a function of actual cognitive ability and some measurement error, η_{st}:

$$\ln(S_t) = \ln(A_t(\mu_s)) + \eta_{st}. \tag{12}$$

So far, I have closely followed Bernal and Keane's (2010) model. The next stage is to incorporate the asymmetric information into their model. Under the assumption of imperfect information, the mother does not directly observe the child's cognitive ability at period *t* because she does not observe μ_s perfectly. Suppose μ_s can have two values, such that

$$\mu_s = \begin{cases} 1 \text{ high endowment} \\ 0 \text{ low endowment} \end{cases}$$

Then, in each period, the mother forms belief q_t that her child has the high endowment of mental capacity; as a result of asymmetric information, she observes only the subjective measure of the child's cognitive ability at period *t,* which can be written in the following way:

$$\tilde{A}_t = \pi_t \ln A_t(\mu_s = 1) + (1 - \pi_t) \ln A_t(\mu_s = 0). \quad (13)$$

The probability that the child has a high endowment of mental capacity can be computed using Bayes' rule:

$$\begin{aligned} \pi_t = P(\mu_s = 1 \mid S^t, C^t) &= \frac{P(\mu_s = 1) P(S^t \mid \mu_s = 1, C^t)}{P(S^t \mid C^t)} = \\ &= \frac{P(\mu_s = 1) P(S^{t-1} \mid \mu_s = 1, C^{t-1}) P(S_{t-1} \mid \mu_s = 1, C_{t-1})}{P(S^{t-1} \mid C^{t-1}) P(S_{t-1} \mid C_{t-1})} = \\ &= \frac{P(S_{t-1} \mid \mu_s = 1, C_{t-1})}{P(S_{t-1} \mid C_{t-1})} \pi_{t-1}, \end{aligned} \quad (14)$$

where $C^t = C_1, ..., C_{t-1}$ is the experience history and $S^t = S_1, ..., S_{t-1}$ is the test score history.

Finally, applying the total probability law to Equation 14, the probability that the child has a high endowment of mental capacity is

$$\pi_t = \frac{P(S_{t-1} \mid \mu_s = 1, C_{t-1})}{\pi_{t-1} P(S_{t-1} \mid \mu_s = 1, C_{t-1}) + (1 - \pi_{t-1}) P(S_{t-1} \mid \mu_s = 0, C_{t-1})} \pi_{t-1}. \quad (15)$$

The vector of observed endogenous state variables at the beginning of t has seven elements:

$$s_t = (S_{t-1}, h_{t-1}, E_t, \hat{C}_t, D_t, I^C_{t-1}, \pi_{t-1}). \qquad (16)$$

There are also a number of state variables that evolve exogenously, such as the child's cognitive endowment of mental capacity, gender, birth weight, mother's endowment of skills, age, education, race, AFQT score, state-specific welfare policy rules, child-care subsidy parameters, and local labor market conditions. In the next section, I derive quasi-structural approximations of employment and child-care decision rules, the child cognitive production function, and the wage equation implied by this structural model. According to theory, the decision rules for employment and child care should be functions of all the state variables. In that case, the only difference from Bernal and Keane's (2010) empirical model would be the inclusion of the lagged test score in both the employment and child-care equations. The statistical significance of the lagged test score parameter in both equations would suggest the existence of the reverse causality issue. Otherwise, the empirical model will be exactly the same as in the case of perfect information.

3. EMPIRICAL MODEL

Using the above structural model, I derive the approximation of the employment decision rule, which has the following multinomial specification:

$$\begin{aligned}\ln\frac{\Pr[h_t = j]}{\Pr[h_t = 0]} = {} & \beta_{0,j} + \beta_{1,j} age + \beta_{2,j} age^2 + \beta_{3,j} educ + \beta_{4,j} race + \\ & + \beta_{5,j} AFQT + \beta_{6,j} t + \beta_{7,j}\tau_{st} + \beta_{8,j} BW + \beta_{9,j} gender + \\ & + \beta_{10,j} I[age < 20] + \beta_{11,j} I[age < 33] + \beta_{12,j} I[t = 1] + \beta_{13,j} I[t < 5] + \\ & + \beta_{14,j} R_{st} + \beta_{15,j}\theta_{st} + \beta_{16,j}\ln S_{t-1} + \beta_{17,j} I[S_{t-1} \neq 0] + \mu_j,\end{aligned} \qquad (17)$$

where *j* is equal to 1 if the mother works part-time, 2 if she works full-time, and 0 if she does not work in period *t*. The employment and child-care decisions are not only functions of the lagged test score, but also they depend on whether the child took the test in the previous period. In Section 4, I discuss the main rationale behind the inclusion of the lagged test indicator in the empirical specification.

The approximation of the child-care decision rule can be given by the logit equation

$$\begin{aligned}\ln\frac{\Pr[I_t^C=1]}{\Pr[I_t^C=0]} &= \beta_{35}+\beta_{36}age+\beta_{37}age^2+\beta_{38}educ+\beta_{39}race+\\ &+\beta_{40}AFQT+\beta_{41}t+\beta_{42}\tau_{st}+\beta_{43}BW+\beta_{44}gender+\\ &+\beta_{45}I[age<20]+\beta_{46}I[age<33]+\beta_{47}I[t=1]+\beta_{48}I[t<5]+\\ &+\beta_{49}R_{st}+\beta_{50}\theta_{st}+\beta_{51}\ln S_{t-1}+\beta_{52}I[S_{t-1}\neq 0]+\mu_3.\end{aligned} \tag{18}$$

Finally I do not need to approximate anything in the cognitive development production function and wage equation; in the empirical model, they have the same forms as in the structural model:

$$\begin{aligned}\ln S_t &= \beta_{53}+\beta_{54}AFQT+\beta_{55}educ+\beta_{56}race+\beta_{57}age+\beta_{58}age^2\\ &+\beta_{59}I[age<20]+\beta_{60}I[age<33]+\beta_{61}gender+\beta_{62}BW+:\\ &+\beta_{63}\hat{C}_t+\beta_{64}\hat{I}_t+\beta_{65}t+\mu_4+\nu_{1t}\end{aligned} \tag{19}$$

$$\begin{aligned}\ln w_t &= \beta_{75}+\beta_{76}educ+\beta_{77}age+\beta_{78}age^2+\beta_{79}race+\beta_{80}AFQT+\beta_{81}\tau_{st}+\\ &+\beta_{82}t+\beta_{83}E_t+\mu_5+\nu_{2t}.\end{aligned} \tag{20}$$

Now, using the above empirical model implied by the structural model, I can formulate the main hypothesis of this study. *There will be evidence of reverse causality either if* β_{16} *has an effect on the part-time employment decision, or if* β_{33} *has an effect on the full-time employment decision, or if* β_{51} *has an effect on the child-care decision.*

I assume that the permanent error components $[\mu_1, \mu_2, \mu_3, \mu_4, \mu_5]$ in the above equations are jointly normally distributed, while time-varying transitory components $[v_{1t,} v_{2t}]$ of the cognitive production function and wage equation are independent normal. Next, I specify both covariance matrices for the permanent and transitory error components.

$$\Sigma_\mu = \begin{vmatrix} \sigma_{\mu 11} & & & & \\ \sigma_{\mu 21} & \sigma_{\mu 22} & & & \\ \sigma_{\mu 31} & \sigma_{\mu 32} & \sigma_{\mu 33} & & \\ \sigma_{\mu 41} & \sigma_{\mu 42} & \sigma_{\mu 34} & \sigma_{\mu 44} & \\ \sigma_{\mu 51} & \sigma_{\mu 52} & \sigma_{\mu 35} & \sigma_{\mu 45} & \sigma_{\mu 55} \end{vmatrix} \tag{21}$$

$$\Sigma_v = \begin{vmatrix} \sigma_{v1} \\ \sigma_{v2} \end{vmatrix} \tag{22}$$

The contribution of individual *i* to the likelihood function is

$$\begin{aligned} L_i(\theta) = \int_\mu \prod_{t=1}^{T} \ & \Pr[I_t^C = 1 \mid \mu_3]^{I_t^C} (1 - \Pr[I_t^C = 1 \mid \mu_3])^{1-I_t^C} \times \\ & \times \prod_{j=0}^{2} \Pr[h_t = j \mid \mu_j]^{I[h_t = j]} \frac{1}{\sigma_{v1}} \varphi\left(\frac{\ln S_t - \ln \hat{S}_t}{\sigma_{v1}} \mid \mu_4 \right) \times \\ & \times \frac{1}{\sigma_{v2}} \varphi\left(\frac{\ln w_t - \ln \hat{w}_t}{\sigma_{v2}} \mid \mu_5 \right) f(\mu) d\mu. \end{aligned} \tag{23}$$

To solve the above multidimensional integral, I use a simulation-based technique. First, I take five draws (the number of draws corresponds to the number of equations in the model) from a standard normal density using a random number generator. Then, I multiply the vector of these standard normal draws by the Cholesky decomposition of the covariance matrix in Equation 21. The result of the multiplication is a vector of draws from a normal density with variance Σ_μ. Then, I use the vector of draws to compute the likelihood contribution of individual *i*. I repeat the previous steps 50 times and average the individual's likelihood contribution. The log-likelihood function is a sum of the logs of all individuals' averaged likelihood contributions:

$$L(\theta) = \sum_{i=1}^{N} \log L_i(\theta). \tag{24}$$

I use the BFGS method to optimize the above log-likelihood function using an object-oriented matrix programming language, *Ox*. Finally, I compute standard errors using the White-Huber estimator.

$$\text{cov}_\theta \hat{\theta} = [-L''(\theta)]^{-1}[L'(\theta)' L'(\theta)][-L''(\theta)]^{-1}, \tag{25}$$

where $L'(\theta) = \frac{\partial L(\theta)}{\partial \theta}$ and $L''(\theta) = \frac{\partial^2 L(\theta)}{\partial \theta^2}$.

4. DATA

I use the sample of single mothers drawn from the NLSY79. The sample consists of quarterly information on maternal employment and child-care use. The number of mother-child pairs in the sample is 1,464, or 29,280 person/time observations. Each mother-child pair is observed for 20 quarters (five years). Table 1 provides descriptive statistics and definitions for all variables used in the empirical testing of reverse causality between maternal inputs and child cognitive development. The average single mother in the sample is more than 23 years old, has less than 12 years of education, earns \$5.26 per hour, and has \$10,818 of non-labor income per quarter. Almost 40 percent of single mothers worked at least one quarter, and 50 percent of single mothers placed their children in formal care before the child entered kindergarten.

In this study, I use the log of standardized scores of the Peabody Picture Vocabulary Test (PPVT) as the dependent variable in the child cognitive development production function. To most accurately determine the effect of test scores on maternal employment and child-care decisions, the PPVT must be administered within the first 20 quarters of the child's life. After the child enters kindergarten, roughly at age 5, the mother's choice problem changes fundamentally, and child care is no longer relevant (Bernal and Keane, 2010). Within the targeted age range, I observe PPVT test scores only for 878 children in the sample. For the rest of the children (586), PPVT scores are also observable; however, the age of these children at the time the PPVT was administered is outside of the targeted age range. Though Bernal and Keane (2010) use those test scores in their analysis, along with other test scores, such as the PIAT-Math and PIAT-Reading, any test score from a child above age 5 is practically useless in this study.

The PPVT was first introduced by Dune and Dune in 1981. The test measures an individual's receptive vocabulary for Standard American English and, at the same time, provides a quick estimate of verbal ability and scholastic aptitude. Children born to NLSY79 female respondents were surveyed biannually beginning in 1986. In 1986, 1992, and 1994, the survey's first "PPVT-eligible age" was 36 months and above; in the rest of the surveys, the first "PPVT-eligible age" was 48–60 months. The eligibility of children for the PPVT in the NLSY is based on children's "PPVT age" measured in months, which can be slightly different from their calendar ages. In creating a PPVT month-of-age variable, a child's age is rounded up to the next month if the child is more than 15 days through a given month as of the survey date. For example, two children who were born in the same year could be given the PPVT at different ages due to disparities in the months when the children were assessed (in most cases, the survey month and the assessment month coincide) or the months in which the children were born. Therefore, all NLSY children naturally are selected into two groups by age based on when the PPVT was taken for first time. The first group includes children who took the PPVT for the first time before entering kindergarten. The second group includes children who were first assessed on cognitive development after entering kindergarten. Therefore, I include in the approximations of the employment and child-care decision rules both the lagged log of the standardized PPVT score and the lagged indicator of whether a child has taken the PPVT at the previous period. This allows me to compare how maternal employment and child-care decisions are affected by the PPVT across the two groups and within the first group.

The assessment itself consists of 175 vocabulary items of generally increasing difficulty. During the test, a child is shown four pictures from which he or she chooses the one that best describes a particular word's meaning. The mother, in most cases, is in the same room, so she can observe her child's performance on the test. When the child correctly identifies eight consecutive items, the "basal" score is established. Further, if the child incorrectly identifies six of eight consecutive items, the "ceiling" score is established. A child's raw score is determined by adding the number of correct responses between the basal and ceiling to the basal score. The NLSY sample has been normalized against a national population with a mean of 100 and standard deviation of 15. Table 1 demonstrates that the average child in the sample scores roughly 80 points, which is well below the national average.

In a dynamic model, the important source of identification is the sufficient transition rate of agents across states (employment and child care). Table 2a demonstrates that there is considerable transition among those who worked part-time in period t to full-time employment in period t+1 (32.55 percent) and to non-employment (25.32 percent). However, there is significant persistence among the non-employed (89.45 percent) and moderate persistence among full-timers (77.47 percent). Not surprisingly, as soon as a child is in formal child care, the likelihood of changing the state is very small—only 6.54 percent (Table 2b). Similarly, in the case of parental care, the likelihood of changing the state is also not substantial (10.96 percent). Finally, the important feature of Table 2c is that the data confirm the restriction of the theoretical model in which the set of options that allow a single mother to work and at the same time not use any formal child care are excluded. A small fraction of single mothers worked part-time and used parental child care in period *t*; however, in next period, all of them transitioned to the non-employment state.

5. RESULTS

In this section, results from difference-in-difference and quasi-structural approaches are presented and discussed.

5.1 Difference-in-difference approach

First, I demonstrate some evidence that mothers' employment and child-care decisions are affected by test results using a difference-in-difference approach. This approach is based on information about mothers' employment and child-care decisions before and after the test at age *a*. As the control group, I use mothers whose children did not take the achievement test at age *a*, and the treatment group comprises mothers whose children took the test. I use only information about maternal inputs at age *a–1* "before" and *a* "after," so each mother has only two observations in the regression, where *d* is an indicator of "after," *T* is an indicator of treatment group, and *S* is a normalized test score:

$$y_i = \alpha_0 + \alpha_1 d_i + \alpha_2 T_i + \alpha_3 T_i d_i + \alpha_4 S_i + \varepsilon_i. \qquad (27)$$

Table 3 shows the results of the difference-in-difference analysis. It is important to note that I break down the sample of mother-child pairs into four subsamples by child age (13–14, 15–16, 17–18, and 19–20 quarters). For example, the first subsample includes only the mother-child pairs in which the child took the test at age 13–14 quarters and did not take the test at the same age. Similarly, every other subsample comprises the mother-child pairs in which the child took the test and did not take it at a given age. The mother-child pairs in which the child took the test in earlier ages are excluded from the subsequent subsamples. I perform the difference-in-difference analysis separately for each subsample.

For this analysis, I choose the four most interesting outcomes. Among them, three outcomes are measured discretely (e.g., whether the mother worked at all, worked full-time, or used child care) and one outcome is measured continuously (e.g., weekly working hours) Furthermore, I estimate a variety of specifications of the above regression equation. The first specification is a baseline specification exactly as in Equation 27. Then, in the next specification, I add welfare characteristics, assuming that they may correlate with the test score. It should be noted that I use exactly the same welfare characteristics in the quasi-structural model for the purpose of identification (theoretical exclusion restrictions). In the third specification, I add the set of variables that control for labor-market conditions, such as the state unemployment rate, the state average wage at the 20th percentile, and the state employment rate in services. Finally, in the last specification, in addition to the previously discussed factors, I include the set of variables that control for maternal and child characteristics.

Table 3 provides substantial evidence that mothers may be involved in compensatory behavior after observing the child's test score. I only discuss the estimates in the last four rows of Table 3 because I believe that this specification includes almost all variables suggested by the theoretical model. The signs of the estimates suggest that a high test score is associated with a higher probability of working at all, working full-time hours, and using child-care. In addition, the signs of the estimates also suggest that the high test score is associated with longer working hours.

Note that evidence provided by the difference-in-difference approach is substantial, but it is weak. The main reason is that this approach does not account for selection into employment and child care by unobserved factors, such as the child's cognitive ability endowment and the mother's taste for investment of goods. For example, the mother of the child with high endowment of cognitive ability may work more than the mother of a less-endowed child. Therefore, the quasi-structural approach, which in the employment and child-care equations accounts for more complicated relationships between the test score, the child's endowment, and the mother's taste for investment in goods, should provide stronger evidence of whether mothers engage in any compensatory behaviors.

5.2 Quasi-structural approach

I have already explained that there would be evidence of reverse causality between maternal inputs and a child's cognitive development if the set of parameters $(\beta_{16}, \beta_{33}, \beta_{51})$ differs from zero in the quasi-structural model. The first rows of Tables 4 through 6 provide estimates for the above set of parameters. Although it is not the main objective of the study, I also show that the endogeneity issue actually affects the points of estimates. I do this by presenting the results of the restricted version[6] of the quasi-structural model assuming orthogonal relationships between the test score and unobserved factors. The first three columns in Tables 4 through 6 report the estimates if such restrictions are imposed in the model. Then, I show the results of the non-restricted

[6] The off-diagonal and diagonal elements of the covariance-variance matrix in Equation 21 are set to zero. This assumption breaks down the empirical model into four separate, independent regressions.

version of the empirical model suggested by the theoretical model. The last three columns in Table 4- through 6 report the estimates without restrictions.

It should be noted that, regardless of whether restrictions on the covariance-variance matrix have been imposed, the results suggest that mothers make their employment and child-care decision immediately after the achievement test, albeit the points of estimates differ significantly across the versions of the model. The magnitude of the effects of the test score significantly decreases when the orthogonal condition between the test score and unobserved factors is not imposed. If the test score and the mother's taste for investment in goods are positively correlated and the higher test score leads to an increase in the likelihood of employment and child-care use, then upwardly biased estimates in the restricted version of the quasi-structural model come as no surprise.

Using the estimates from the non-restricted version of the quasi-structural model, I compute that mothers increase (decrease) the use of formal child care if the test score is above (below) 56 points. Moreover, mothers are more (less) likely to work part-time if the test score is above (below) 70 points. Finally, the effect of the test score on full-time employment is statistically insignificant when the orthogonal condition between the test score and unobserved factors is not imposed.

Combining all these facts from my empirical model, I can articulate that, first, mothers who had not worked before the test started gradually entering the labor force and working part-time hours after receiving a positive signal about the child's cognitive ability endowment. Second, it is likely that a significant fraction of the above mothers started using formal child care after the test. Third, some mothers who used formal child care before the achievement test started working part-time after receiving the positive signal.

A number of common patterns can be observed in the part-time and full-time employment and child-care equations. In particular, maternal employment and child-care use increases with the mother's education and AFQT score. After controlling for unobserved heterogeneity, I could not find any evidence that mothers of black children worked more or used more child care. There is also no evidence that mothers of boys tended to work more or use more child care than mothers of girls. Finally, I could not find any evidence that the child's birth weight significantly affected the mother's employment or child-care decisions.

I do not discuss any findings regarding the child cognitive development production function and wage equation here, because the estimates from these equations do not provide any additional support or opposition to the main objective of this study. Furthermore, I do not discuss the estimates of unobserved heterogeneity or the transitory error covariance-variance matrices. However, for those who might be interested in those estimates, I report them separately in the appendix.

6. CONCLUSION

Using a sample of single mothers from the NLSY79, I find evidence that maternal employment and child-care decisions are sensitive to past achievement test results. In particular, a mother whose child has taken the PPVT before entering kindergarten and whose child's standardized test score is above 56 points tends to increase her use of child care. Furthermore, she tends to work more part-time hours immediately after the test if the standardize test score is above 70 points. These findings imply that mothers counteract children's good results on the test by spending less time with their children and further increasing their working hours.

The results of the empirical test of reverse causality between maternal inputs and child cognitive ability unravel the important issue of what a mother knows about her child's cognitive ability endowment and when she learns about it. Eventually, performance on an achievement test may serve as a good signal for the mother in terms of her child's cognitive ability endowment. The more quickly she draws the correct expectation about the child's cognitive ability endowment, the sooner she can find more effective ways to accommodate her child based on his or her unobserved innate ability. This study implicitly proposes that a universal achievement test among prekindergarten children may positively affect child cognitive development through improved maternal input choices.

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Table 1. Descriptive statistics and variable definitions

Variable	Description	Mean (Std)
Child and mother characteristics		
RAB	Age of mother at child's birth	23.167 (4.598)
MEDUC	Mother's education	11.230 (1.878)
RACE	Child's race (1 if black/Hispanic and 0 otherwise)	0.824 (0.380)
CHBW	Child's birth weight (ounces)	111.96 (22.089)
CHSEX	Child's gender (1 if male and 0 if female)	0.495 (0.499)
MAFQT	Mother's AFQT score	18.935 (18.419)
MISMAFQT	I[AFQT score missing]	0.029 (0.167)
MWA	Hourly wage after childbirth if working	5.114 (2.362)
INCOME	Household income, by period, after childbirth	10.818 (23.590)
Policy variables		
PRBEN	Real AFDC/TANF maximum benefits, calculated by the state (dollars)	300.185 (149.503)
EXDWRS	Experience in welfare participation	5.323 (3.871)
TLI	Dummy for whether state *s* has a time limit in place in period *t*	0.016 (0.127)
TL_LENGTH	Length of time limit in state *s* in period *t*	45.564 (15.616)
ELAPSED_TL	Time in months elapsed since the implementation of the time limit	2.091 (5.057)
TL_HIT	Dummy variable indicating whether a woman would have hit the time limit	0.001 (0.026)
REMAIN_TL_ELIG	Minimum potential remaining length of a woman's time limit	36.924 (16.682)
DWR	Dummy for whether state *s* had a work requirement in place in period *t*	0.026 (0.159)
WR_LENGTH	Length (in months) of work requirement limit in state *s* in period *t*	14.492 (10.156)
ELAPSED_WR	Time in months elapsed since the implementation of the work requirement	9.449 (8.777)
AGE_EXEM	Age of youngest child below which the mother will be exempted from work requirement in state *s* at time *t*	20.787 (30.223)
EXEMP	Age of youngest child below which the mother will be exempted from work requirement in state *s* at time *t*	2.038 (9.949)
WR_HIT	Indicator for whether a woman could be subject to a work requirement	0.009 (0.098)
FLAD_DIS	Flat amount of earnings disregarded in calculating the	34.513 (25.038)

	benefit amount	
PERC_DIS	Benefit reduction rate	0.055 (0.134)
ENFORCE	Child support enforcement expenditure in state *s* at year *t* per single mother	0.135 (0.096)
EITC	EITC phase in rate constructed from both federal- and state-level data	0.145 (0.072)
CHILCARE	CCDF expenditure per single mother in state *s* at time *t*	0.046 (0.100)
Labor market conditions		
UNRATE	Unemployment rate in state *s* in period *t*	8.043 (3.203)
SWAGE	Hourly wage rate at the 20^{th} percentile	4.435 (0.957)
SERV	% employed in services	0.398 (0.075)
Employment and care outcomes		
PWORK	Part-time work	0.154 (0.362)
FWORK	Full-time work	0.243 (0.429)
CHCARE	Child care	0.500 (0.500)
Child Cognitive Outcomes		
PPVT (878 test scores)	Peabody Picture Vocabulary Test	79.801 (15.662)

Table 2. Employment and child care transition rates

a)

		Employment at *t+1* Not working	Part-time	Full-time	Total
Employment at *t*	Not working	89.45	7.73	2.81	100
	Part-time	25.32	42.13	32.55	100
	Full-time	4.76	17.76	77.47	100
	Total	62.1	14.62	23.28	100

b)

		Child care at *t+1* Parental	Formal	Total
Child care at *t*	Parental	89.04	10.96	100
	Formal	6.54	93.46	100
	Total	48.45	51.55	100

c)

			Employment at *t+1*						**Total**
			Not working		Part-time		Full-time		
			Par.	Form.	Par.	Form.	Par.	Form.	
Employment at *t*	Not working	Parental	89.00	2.75	0.05	6.13	0.00	2.06	100
		Formal	5.58	75.32	0.00	13.49	0.00	5.61	100
	Part-time	Parental	66.67	33.33	0.00	0.00	0.00	0.00	100
		Formal	14.13	11.04	0.00	42.21	0.00	32.62	100
	Full-time	Parental	0.00	0.00	0.00	0.00	0.00	0.00	0
		Formal	2.46	2.30	0.00	17.76	0.00	77.47	100
Total			48.42	13.68	0.03	14.59	0.00	23.28	100

Table 3. Effect of test score on maternal and child-care decisions by child's age, difference-in-difference approach

	Working hours		Work (any)		Work (full-time)		Child care	
	Est.	St.Err.	Est.	St.Err.	Est.	St.Err.	Est.	St.Err.
Age of child	No additional control							
13–14 quarters[1]	0.0492	0.0085	0.0014	0.0002	0.0012	0.0002	0.0016	0.0002
15–16 quarters[2]	0.0473	0.0094	0.001	0.0003	0.0011	0.0002	0.001	0.0003
17–18 quarters[3]	0.0458	0.0118	0.001	0.0003	0.0011	0.0003	0.001	0.0003
19–20 quarters[4]	0.1499	0.037	0.0058	0.0001	0.0037	0.0009	0.0061	0.001
Age of child	+ welfare							
13–14 quarters[1]	0.0379	0.0091	0.0012	0.0003	0.0009	0.0002	0.0014	0.0003
15–16 quarters[2]	0.0361	0.0096	0.0008	0.0003	0.0009	0.0002	0.0011	0.0003
17–18 quarters[3]	0.0367	0.0118	0.0008	0.0003	0.0009	0.0003	0.0009	0.0003
19–20 quarters[4]	0.1622	0.0359	0.0060	0.001	0.0041	0.0009	0.0060	0.001
Age of child	+ welfare + labor market							
13–14 quarters[1]	0.0388	0.0091	0.0013	0.0003	0.0010	0.0002	0.0014	0.0003
15–16 quarters[2]	0.0365	0.0097	0.0008	0.0027	0.0009	0.0002	0.0011	0.0002
17–18 quarters[3]	0.0371	0.0118	0.0009	0.0003	0.0009	0.0003	0.0009	0.0003
19–20 quarters[4]	0.1544	0.0359	0.0058	0.001	0.0039	0.0009	0.0058	0.001
Age of child	+ maternal and child + welfare + labor market							
13–14 quarters[1]	0.0197	0.0089	0.0007	0.0002	0.0005	0.0002	0.0008	0.0002
15–16 quarters[2]	0.0231	0.0094	0.0005	0.0003	0.0006	0.0002	0.0007	0.0003
17–18 quarters[3]	0.0253	0.0115	0.0006	0.0003	0.0006	0.0003	0.0007	0.0003
19–20 quarters[4]	0.0787	0.0361	0.0034	0.001	0.0020	0.0009	0.0030	0.001

Note: The table provides the estimates and standard errors of a_4 from model $y_i = a_0+a_1 d2_i+a_2 T_i+a_3 T_i d2_i+a_4 S_i+e_i$, where $d2$ is an indicator of period 2, T is an indicator of treatment group, and S is a normalized test score with mean of 100 and standard deviation of 15.

Welfare parameters: TANF benefits amount, state work limit length, state flat earning disregard, state percent earnings disregard, state child support enforcement amount, computed individual Earned Income Tax Credit, and state Child Care and Development Fund per child.

Local labor conditions and cycles: state unemployment rate, state average wage 20th percentile, and percent employment in services.

Maternal and child characteristics: mother's age at child's birth, mother's age at child's birth squared, whether mother was less than 20 years old at child's birth, whether mother was more than 33 years old at child's birth, maternal education at child's birth, race, child's birth weight, child's sex, mother's AFQT test score, and whether AFQT test was missed.

[1] Sample size is 2,918 x time

[2] Sample size is 2,576 x time

[3] Sample size is 2,204 x time

[4] Sample size is 1,708 x time

Table 4. Child care

	Without heterogeneity			With heterogeneity		
Variable	Coeff.	St.Err.	t-stat.	Coeff.	St.Err.	t-stat.
Lagged test	1.033	0.349	2.960	0.888	0.420	2.120
I[test=1]	–4.225	1.481	–2.850	–3.574	1.783	–2.000
Lagged child care	5.297	0.089	59.540	5.006	0.138	36.400
Lagged full-time	0.562	0.128	4.410	–0.181	0.179	–1.020
Lagged part-time	–1.102	0.099	–11.100	–1.648	0.138	–12.000
Time	–0.105	0.040	–2.650	–0.009	0.061	–0.143
I[child's age<5]	0.183	0.090	2.040	–0.029	0.089	–0.322
Welfare benefits	–0.271	0.032	–8.470	–0.374	0.060	–6.290
Welfare participation experience	0.063	0.045	1.410	0.148	0.067	2.220
I[any time or work limit]	–0.226	0.406	–0.560	–0.665	0.601	–1.110
Length of time limit	0.103	0.121	0.850	0.001	0.184	0.004
I[time or work limit might hit]	0.507	0.392	1.300	0.465	0.573	0.811
Remaining month of TL eligibility	–0.108	0.112	–0.960	–0.032	0.175	–0.180
Remaining categorical eligibility	–0.162	0.033	–4.850	–0.221	0.056	–3.950
Work limit length	0.132	0.068	1.950	0.178	0.089	2.010
Age of youngest child exemption	0.050	0.057	0.880	0.023	0.044	0.518
Number of WR exemptions	–0.116	0.068	–1.720	–0.061	0.103	–0.598
Flat earnings disregard	–0.067	0.032	–2.110	–0.094	0.054	–1.740
Percent earnings disregard	–0.038	0.031	–1.220	–0.010	0.045	–0.214
State child support enforcement	0.063	0.039	1.610	0.043	0.063	0.679
EITC	0.086	0.059	1.470	0.114	0.120	0.951
CCDF	–0.093	0.054	–1.730	–0.186	0.085	–2.190
State unemployment rate	–0.140	0.028	–4.910	–0.172	0.040	–4.350
Average wage 20th percentile	0.038	0.047	0.810	0.094	0.082	1.150
% employment in services	–0.030	0.033	–0.890	–0.011	0.064	–0.168
Mother's age at child's birth	–1.128	0.452	–2.490	–1.890	1.067	–1.770
Mother's age at child's birth squared	0.973	0.451	2.160	1.723	1.070	1.610
I[mother's age<20]	0.019	0.111	0.170	0.080	0.242	0.332
I[mother's age>32]	0.049	0.208	0.230	–0.326	0.511	–0.639
Mother's education	0.368	0.031	12.000	0.629	0.078	8.100
Child's race (I[black=1])	–0.190	0.070	–2.710	–0.126	0.170	–0.743
Child's birth weight	0.052	0.026	2.050	–0.003	0.056	–0.051
Child's sex (I[male=1])	–0.035	0.049	–0.710	–0.065	0.117	–0.556
Mother's AFQT score	0.280	0.031	9.190	0.446	0.059	7.550
Mother's AFQT score missing	0.598	0.130	4.610	0.826	0.322	2.570
Constant	–2.035	0.077	–26.560	–1.570	0.189	–8.320

Note: The dependent variable is 0 for parental care and 1 for formal care. The "without heterogeneity" specification is estimated in STATA using the "mlogit" command. The "with heterogeneity" specification allows for unobserved heterogeneity to be normally distributed across employment and child-care decisions, the cognitive development production function, and the wage equation.

Table 5. Part-time

Variable	Without heterogeneity Coeff.	St.Err.	t-stat.	With heterogeneity Coeff.	St.Err.	t-stat.
Lagged test	0.987	0.390	2.530	0.836	0.456	1.840
I[test=1]	–4.191	1.682	–2.490	–3.555	1.959	–1.810
Lagged child care	0.620	0.068	9.050	–0.057	0.100	–0.568
Lagged full-time	3.250	0.093	34.780	3.028	0.123	24.600
Lagged part-time	3.125	0.069	45.060	2.974	0.090	33.100
Time	0.004	0.040	0.090	0.082	0.061	1.350
I[child's age<5]	0.296	0.089	3.340	0.139	0.088	1.580
Welfare benefits	–0.282	0.033	–8.540	–0.367	0.056	–6.540
Welfare participation experience	0.032	0.043	0.750	0.074	0.061	1.210
I[any time or work limit]	0.077	0.353	0.220	–0.155	0.523	–0.296
Length of time limit	–0.031	0.112	–0.280	–0.154	0.185	–0.834
I[time or work limit might hit]	0.457	0.363	1.260	0.528	0.585	0.902
Remaining month of TL eligibility	0.002	0.104	0.020	0.091	0.165	0.551
Remaining categorical eligibility	–0.190	0.034	–5.510	–0.264	0.054	–4.910
Work limit length	0.042	0.054	0.770	0.080	0.071	1.130
Age of youngest child exemption	0.040	0.031	1.310	0.025	0.035	0.708
Number of WR exemptions	–0.062	0.049	–1.280	–0.022	0.083	–0.267
Flat earnings disregard	–0.082	0.031	–2.620	–0.100	0.051	–1.940
Percent earnings disregard	–0.007	0.030	–0.220	0.015	0.045	0.336
State child support enforcement	0.135	0.037	3.610	0.124	0.058	2.130
EITC	0.071	0.059	1.220	0.082	0.112	0.735
CCDF	–0.110	0.052	–2.110	–0.163	0.079	–2.070
State unemployment rate	–0.120	0.027	–4.470	–0.152	0.037	–4.120
Average wage 20th percentile	–0.031	0.047	–0.660	0.002	0.078	0.026
% employment in services	–0.009	0.032	–0.290	0.003	0.055	0.047
Mother's age at child's birth	–0.983	0.417	–2.360	–2.072	1.011	–2.050
Mother's age at child's birth squared	0.857	0.415	2.060	1.932	1.015	1.900
I[mother's age<20]	0.059	0.101	0.580	0.062	0.227	0.274
I[mother's age>32]	0.117	0.187	0.620	–0.355	0.479	–0.741
Mother's education	0.237	0.030	7.790	0.479	0.071	6.760
Child's race (I[black=1])	–0.083	0.067	–1.240	–0.020	0.155	–0.128
Child's birth weight	0.062	0.024	2.600	0.021	0.053	0.401
Child's sex (I[male=1])	–0.078	0.047	–1.670	–0.087	0.110	–0.793
Mother's AFQT score	0.210	0.028	7.630	0.382	0.056	6.780
Mother's AFQT score missing	0.057	0.137	0.420	0.122	0.277	0.442
Constant	–2.742	0.079	–34.860	–2.312	0.178	–13.000

Note: The dependent variable is 0 for not working, 1 for working part-time, and 2 for working full-time. The "without heterogeneity" specification is estimated in STATA using the "mlogit" command. The "with heterogeneity" specification allows unobserved heterogeneity to be normally distributed across employment and child-care decisions, the cognitive development production function, and the wage equation.

Table 6. Full-time

	Without heterogeneity			With heterogeneity		
Variable	Coeff.	St.Err.	t-stat.	Coeff.	St.Err.	t-stat.
Lagged test	0.767	0.375	2.050	0.576	0.454	1.270
I[test=1]	–3.074	1.618	–1.900	–2.257	1.958	–1.150
Lagged child care	0.843	0.106	7.950	0.191	0.140	1.370
Lagged full-time	5.886	0.105	55.910	5.443	0.154	35.400
Lagged part-time	3.132	0.094	33.150	2.935	0.119	24.600
Time	–0.128	0.048	–2.690	–0.036	0.069	–0.517
I[child's age<5]	0.593	0.111	5.330	0.410	0.104	3.920
Welfare benefits	–0.382	0.040	–9.510	–0.514	0.071	–7.250
Welfare participation experience	–0.007	0.046	–0.150	0.046	0.073	0.627
I[any time or work limit]	0.310	0.346	0.900	0.125	0.585	0.213
Length of time limit	0.103	0.117	0.880	–0.046	0.216	–0.215
I[time or work limit might hit]	0.287	0.350	0.820	0.354	0.464	0.762
Remaining month of TL eligibility	–0.141	0.112	–1.260	–0.035	0.203	–0.173
Remaining categorical eligibility	–0.300	0.040	–7.480	–0.365	0.066	–5.530
Work limit length	–0.008	0.054	–0.150	0.045	0.082	0.547
Age of youngest child exemption	0.063	0.029	2.200	0.042	0.043	0.979
Number of WR exemptions	–0.023	0.051	–0.460	0.015	0.094	0.162
Flat earnings disregard	–0.027	0.032	–0.840	–0.024	0.054	–0.447
Percent earnings disregard	–0.031	0.034	–0.910	–0.028	0.055	–0.515
State child support enforcement	0.103	0.043	2.390	0.088	0.073	1.200
EITC	–0.052	0.064	–0.820	–0.048	0.122	–0.391
CCDF	–0.062	0.056	–1.090	–0.075	0.087	–0.866
State unemployment rate	–0.152	0.031	–4.860	–0.213	0.049	–4.340
Average wage 20th percentile	0.021	0.054	0.380	0.031	0.096	0.320
% employment in services	–0.020	0.035	–0.560	–0.041	0.074	–0.557
Mother's age at child's birth	–0.090	0.496	–0.180	–1.444	1.139	–1.270
Mother's age at child's birth squared	0.182	0.487	0.370	1.492	1.150	1.300
I[mother's age<20]	0.112	0.123	0.920	–0.007	0.264	–0.025
I[mother's age>32]	–0.002	0.203	–0.010	–0.620	0.558	–1.110
Mother's education	0.401	0.036	11.140	0.670	0.103	6.540
Child's race (I[black=1])	–0.160	0.080	–1.980	–0.018	0.186	–0.098
Child's birth weight	0.034	0.028	1.200	–0.002	0.062	–0.038
Child's sex (I[male=1])	–0.067	0.055	–1.230	–0.110	0.134	–0.820
Mother's AFQT score	0.175	0.032	5.460	0.427	0.069	6.230
Mother's AFQT score missing	–0.132	0.183	–0.720	–0.107	0.424	–0.253
Constant	–3.902	0.104	–37.360	–3.565	0.211	–16.900

Note: The dependent variable is 0 for not working, 1 for working part-time, and 2 for working full-time. The "without heterogeneity" specification is estimated in STATA using the "mlogit" command. The "with heterogeneity" specification allows unobserved heterogeneity to be normally distributed across employment and child-care decisions, the cognitive development production function, and the wage equation.

APPENDIX

Wage equation

	Without heterogeneity			With heterogeneity		
Variable	Coeff.	St.Err.	t-stat.	Coeff.	St.Err.	t-stat.
Quarters since birth	–0.065	0.006	–11.570	–0.019	0.021	–0.880
State unemployment rate	0.038	0.004	10.030	0.000	0.009	0.034
Average wage 20th percentile	0.010	0.004	2.440	0.044	0.019	2.320
% employment in services	0.048	0.006	8.600	–0.017	0.013	–1.240
Mother's age at child's birth	–0.008	0.036	–0.210	0.260	0.150	1.740
Mother's age at child's birth squared	0.021	0.036	0.580	–0.215	0.152	–1.410
Postpartum work experience	0.088	0.005	17.170	0.041	0.019	2.100
Mother's education	0.064	0.005	12.810	0.013	0.033	0.377
Mother's race (I[black=1])	0.071	0.011	6.320	0.243	0.033	7.330
Mother's AFQT score	0.079	0.004	19.330	0.148	0.012	12.600
Mother's AFQT score missing	0.228	0.034	6.620	0.345	0.043	8.080
Lagged full-time	0.113	0.012	9.520	0.045	0.010	4.560
Lagged part-time	0.005	0.012	0.420	0.011	0.009	1.290
Constant	1.303	0.014	96.230	1.191	0.028	41.900

Cognitive ability production function

	Without Heterogeneity			With Heterogeneity		
Variable	Coeff.	St.Err.	t-stat.	Coeff.	St.Err.	t-stat.
Time	–0.143	0.019	–7.400	–0.142	0.019	–7.400
Child's birth weight	0.001	0.010	0.110	0.001	0.010	0.118
Child's sex (I[male=1])	–0.049	0.017	–2.820	–0.048	0.017	–2.840
Mother's age at child's birth	0.062	0.168	0.370	0.064	0.167	0.385
Mother's age at child's birth squared	–0.074	0.161	–0.460	–0.076	0.160	–0.478
I[mother's age<20]	0.052	0.040	1.320	0.052	0.039	1.330
I[mother's age>32]	0.073	0.060	1.210	0.077	0.060	1.280
Mother's education	0.052	0.013	4.160	0.052	0.012	4.180
Child's race (I[Black=1])	–0.188	0.024	–7.740	–0.187	0.024	–7.760
Log of household income	0.023	0.008	2.780	0.023	0.008	2.810
Mother's AFQT score	0.034	0.010	3.440	0.034	0.010	3.430
Mother's AFQT score missing	0.151	0.055	2.760	0.156	0.054	2.870
Child care experience	0.022	0.009	2.370	0.023	0.009	2.490
Constant	4.595	0.029	158.330	4.592	0.029	160.000

Covariance-variance matrix

Variable	Coeff.	St.Err.	t-stat.
varA(Child care)	1.829	0.104	5.800
covA(Child care,Cogn. p.f.)	0.000	0.046	0.009
covA(Child care,Wage)	0.000	(fixed)	
covA(Child care,Part-time)	1.000	1.742	2.520
covA(Child care,Full-time)	0.947	0.166	10.800
varA(Cogn. p.f.)	0.000	1.492	5.210
covA(Cogn. p.f.,Wage)	–0.025	0.048	0.523
covA(Cogn. p.f.,Part-time)	0.000	(fixed)	
covA(Cogn. p.f.,Full-time)	–0.120	0.104	1.160
varA(Wage)	0.191	0.131	12.600
covA(Wage,Part-time)	0.000	(fixed)	
covA(Wage,Full-time)	0.218	0.052	4.240
varA(Part-time)	1.417	0.112	3.110
covA(Part-time,Full-time)	0.947	0.163	11.000
covA(Full-time,Full-time)	2.257	0.146	5.560
varE(Cogn. p.f.)	0.062	0.089	31.200
varE(Wage)	0.049	0.066	45.500

Note: The diagonal elements of unobserved heterogeneity matrix were retransformed by the exponential function, and off-diagonal elements were retransformed by the hyperbolic tangent function. The elements of the transitory error matrix were retransformed by exponential function