Evaluating the Effects of Child Care Policies on Children's Cognitive Development and Maternal Labor Supply

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To explore the role of child care policies in the development of early cognitive skills, this paper jointly estimates a cognitive achievement production function and a dynamic, discrete choice model of maternal labor supply and child care decisions. Using counterfactuals from the model, I investigate how the design and eligibility for two types of child care policies, Head Start and child care subsidies, affect the formation of cognitive through maternal decisions about work and child care. The results suggest large impacts on cognitive skills from the expansion of Head Start to current non-recipients and the targeting of child care subsidies towards poor, single mothers. (*JEL:* I21, I28, J08, J24)

The formation of cognitive skills has been a source of renewed interested in recent years given the importance of early cognitive skills in predicting later life outcomes (Currie and Thomas, 1999; Chetty et al., 2011) and work suggesting that cognitive skills are formed relatively early in life (Cunha and Heckman, 2007, 2008). Human capital policies for children can take many forms (Almond and Currie, 2011) but one area of focus is the child care decisions of families. The reason for this focus is that children in the U.S. spend on average a substantial fraction of time outside the care of their parents' care, even at young ages, and theories of childhood development emphasize the importance of stimulating environments to foster the development of skills (Case, 1992). Among 9 month old children, for example, 49.7% spent some time in child care and those children were on average 32.25 hours / week in non-parental care.[2] Research consistently finds positive associations between child test score outcomes and the quality of child's environment, whether in the home or the child care setting (Love et al., 1996), so improving child care experiences is seen as a potentially effective means of improving cognitive skills in early childhood.

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[2]Author's calculations, Early Childhood Longitudinal Survey - Birth Cohort (ECLS-B).

In this paper, I study the how two kinds of child care policies, Head Start and child care price subsidies, affect children's child care experiences and their subsequent effects on cognitive skills.[3] Head Start is a free, federally funded preschool program for poor children that aims to "promote school readiness by enhancing the social and cognitive development of children."[4] A randomized controlled trial of Head Start demonstrated that the program has positive effects on cognitive achievement at kindergarten entry that fade-out by 1st grade (Head Start Impact Study, Puma et al., 2005), which has led to calls to cut Head Start funding or to change how Head Start is implemented.[5] In the face of budgetary pressure, understanding who should be eligible for Head Start and how to design Head Start to improve cognitive skills are important questions to answer in order to improve the program's effectiveness.[6]

The second type of policy that I study, child care price subsidies, provided through the Child Care and Development Fund (CCDF), give income eligible working mothers a voucher for child care services. Child care price subsidies are designed primarily to support the labor force participation of women (Adams and Rohacek, 2002) but how to incorporate child development goals into the design of child care subsidies has been an issue at least since the the 1970s (Heckman, 1974). Child care subsidies have an ambiguous impact on child outcomes because the subsidies can simultaneously increase the demand for child care quality, which improves cognitive skills, and incentivize the use of child care, which can lower cognitive skills if the home environment is more productive. Recent reduced form empirical research indicates that subsidies have a harmful effect

[3]Public provision through Head Start and changing the price of child care through subsidies are not the only possible government interventions in the market for child care. Another style of intervention tries to improve child care quality through the regulation of child care providers. Hotz and Xiao (2011) investigate the effects of accreditation regulations and find that they increase child care quality but reduce the number of child care providers. This result suggests that the cognitive skills for children in child care would increase and the cognitive skills of children crowded out of using child care could increase or decrease depending on the quality of their home or of an alternative child care provider not affected by regulation (such as a relative). Previous research suggested that regulations affecting the child-caregiver ratio or teacher qualification would have limited impact of child care quality (Blau, 1997) and no impact on children's skills (Blau, 1999).

[4]For the quote, see the program description at the Office of Head Start http://www.acf.hhs.gov/programs/ohs/.

[5]See the discussion during the recent budget debate: "Cuts to Head Start Show Challenge of Fiscal Restraint" in the NY Times March 10, 2011. http://www.nytimes.com/2011/03/11/us/politics/11headstart.html

[6]See Gibbs et al. (2011) for a discussion about "fade out" and whether fade out perhaps represents catch up. In a Cunha-Heckman production function with complementarities over time, another possibility is that fade out is a result of lack of investment in the post kindergarten period. In this case, Head Start might still be the correct type of intervention but the optimal policy might space investment out over more periods for Head Start eligible children. There is also evidence that Head Start has longer term impacts on noncognitive outcomes (Garces et al., 2002; Ludwig and Miller, 2007; Deming, 2009). To the extent that cognitive impacts are correlated with noncognitive impacts, analyzing the impact of Head Start design and coverage on cognitive outcomes would still be applicable.

on children's cognitive outcomes (Herbst and Tekin, 2010; Hawkinson et al., 2012). An open question is to understand the mechanisms through which child care subsidies affect children's cognitive achievement, to elucidate how child care subsidy policy parameters affect choices and to quantify the trade-offs between impacts on maternal labor supply and cognitive achievement.

To investigate the effects of these two child care policies on cognitive achievement and maternal labor supply, I embed a cognitive achievement production function into a dynamic discrete choice model of child care and maternal labor supply decisions. In each model period (every six months), mothers receive a wage offer and a price-quality offer for child care services. Fathers, when present, contribute to household income. Eligible families have an additional Head Start quality offer in their choice set. The mother makes decisions about whether to stay home, work part-time or work full-time and, for up to two children age 5 or less, whether to use child care part-time, full-time, or not at all. The time spent in child care, the quality of child care and the quality of the home environment are inputs into the value-added cognitive achievement production function. The child's cognitive skills and the mother's labor market experience evolve endogenously and the mother faces trade-offs between consumption, leisure, the cognitive development of her children and the accumulation of labor market experience. Mothers in the model face uncertainty in the form of shocks to wage offers, father's income, the cognitive skills of children, home quality, the price and quality of child care, and preferences for leisure and child care. Marital status and fertility are modeled as stochastic processes.

A dynamic model is a natural setting for examining the impact of alternative child care policies. First, cognitive skills develop over time and the value-added cognitive achievement production function captures the dynamic nature of skill accumulation (Cunha and Heckman, 2007, 2008). Second, female labor market experience also accumulates over time. When making a labor supply decision, the mother weighs not only current consumption and leisure but also the effect of working on future labor market experience and her children's cognitive achievement.[7] On child care policy, Blau (2011) emphasizes "the trade-off faced by policymakers between the goals of improving child well-being and increasing economic self-sufficiency." Heckman (1974) discusses how the evaluation of child care subsidy programs is complicated not only by the fact that subsidies have work requirements but also because different features of the subsidies change who participates and what decisions they make. My modeling approach allows a realistic representation of different child care policy parameters and constraints and of how the design of child care

[7] Lefebvre and Merrigan (2008) provide quasi-experimental evidence that short term child care policies can have exactly these kind of long-term impacts on maternal labor supply.

policies influence program participant outcomes.

This paper contributes to a large literature in child development and education and an emerging literature in economics on child care decisions and their impacts on children. Outside of economics, papers typically focus on measuring the quality of child care environments and regressing child outcomes on child care quality with controls for family characteristics. Then, papers usually assess the impacts on children's skills from improving child care quality. There are two limitations of these papers. First, little attention is paid to the endogeneity of child care choices and sample selection issues. Second, while directly improving child care quality is an interesting thought experiment, it is not, in the language of Pearl (2000), a do-variable for child care policy. Instead, a more realistic set of policies operates through the choice set, prices and the constraints that families face for child care services. Basically, it is difficult to determine which policies could conceivably induce the higher quality choices that these papers consider in their counterfactuals.

Within economics, much more focus is put on the endogeneity of child care decisions and developing a model of the formation of children's skills. Papers have estimated production functions for cognitive achievement taking into account child care decisions (Duncan, 2003; Bernal and Keane, 2010, 2011) and have jointly estimated a behavioral model and a production function (Bernal, 2008; Del Boca et al., 2010).[8] A limitation of these papers from a child development perspective is the lack of focus on child care quality as an input into the production function.[9] Given the large variation and relatively poor quality of child care quality in the U.S. (Lamb, 1998), the intensive use of child care and the importance of a child's environment in theories of child development, the economics papers can be criticized from a child development perspective for not modeling child care

[8] Bernal (2008) is most closely related to my paper. She also models work and child care decisions in the context of a cognitive achievement production function but only considers time in child care as an input and ignores differences in child care quality experiences. This is a result of data limitations in the NLSY-79. She actually suggests incorporating a quality decision as an important extension to her work and as a potential qualification to her work. Interestingly, my results are broadly consistent with her findings but what she attributes to differences in impact by unobserved heterogeneity I find to be driven largely by the quality patterns in the data. This is relevant for policy because if variation in impact is driven by quality choices and not some other unobserved variable (such a mother's ability), then it suggests a direct role for child care policies. My model also extends her framework along several important dimensions by incorporating a Head Start option, a realistic representation in the budget constraint for both child care subsidies and Head Start, an intensive margin for child care and labor supply and the potential for divorce and fertility. Del Boca et al. (2010) model heterogeneity in the choice of time inputs in the home, which is certainly a potentially important source of variation in children's inputs but largely ignores the extensive use of child care and variation in children's child care quality experiences. A synthesis of these various models would be both computationally demanding and would require a kind of data set that, to my knowledge, does not exist.

[9] An important exception is Duncan (2003) who also bridges the economics and child development literatures by considering child care quality inputs in a carefully modeled production function. My paper builds on his work by estimating child care quality inputs in a skill production function jointly with a behavioral model for child care and quality decisions.

quality as input in the production function. My paper incorporates the insights from the child development literature into a behavioral model of child care decisions and serves to bring the economics literature on child development closer to the literature in child development.

To estimate the model, I use data from the ECLS-B, a nationally representative panel of 14,000 children born in the United States in 2001. Children were followed until kindergarten entry and extensive information was collected about the children's home environments, child care environments and scores on cognitive assessments. I define and measure the "quality" of the child's home and child care environments in a way that is consistent with other early childhood research. The data also contain information on the wages and labor force participation decisions of mothers, fathers' income, hours spent in child care, prices paid for child care services, marital status and other characteristics of the child's parents.

I estimate the model parameters using the Method of Simulated Moments (McFadden 1989). I simulate the model and match statistics from the simulated data to statistics from the ECLS-B. Although the model contains multiple children per family, the data only contain information on a single child. To address this limitation, I use an unconditional simulation approach that simulates mothers from their first birth.[10] I integrate over unobserved elements of the statespace and mimic the ECLS-B sample selection procedure by selecting sequences of shocks such that the mother has a birth in the same year that the ECLS-B collected data. I compare predictions of the model about the intra-sibling correlation of cognitive skills and birth order effects on cognitive skills to evidence from external data sets.

Using the estimated model, I first study the effects of Head Start on the cognitive achievement of children. As a model validation exercise, I evaluate Head Start in my model using the design of the Head Start Impact Study (HSIS), a randomized controlled trial of Head Start Puma et al. (2005). The magnitude of the impacts of Head Start on cognitive skills in my model are consistent with those of the HSIS. I also use the model to perform evaluations of changes to Head Start including removing Head Start for two years (an arm that the HSIS did not evaluate) and replacing Head Start with equivalent cash transfers to eligible families. I find that in-kind transfers through Head Start increase cognitive skills at kindergarten entry by 0.13 standard deviations relative to providing parents with the money directly. I then evaluate the effects of expanding Head Start services to current non-eligible recipients.[11] I find that increasing Head Start access improves cog-

[10]This is similar to the approach developed in Keane and Wolpin (2001), which is also used to address problems from missing state variables.

[11]This would be similar to a Scandanavian style child care system in which the care is primarily govern-

nitive achievement because many non-eligible children spend significant amounts of time in low quality child care. In particular, a universal Head Start program increases average cognitive achievement scores by 0.15 standard deviations at kindergarten entry.

I then use the model to study the effects of child care price subsidies on cognitive achievement and maternal labor force participation. In contrast to recent research on child care subsidies, I find that for the typical subsidy-eligible population, child care subsidies have small positive effect on cognitive skills by inducing families to move children from low quality home environments to relatively higher quality child care environments.[12] Six months of an offer of a child care subsidy program increases cognitive achievement scores by .043 standard deviations on average. I then consider changes to the design of the subsidy programs, by changing income eligibility cutoffs, the maximum reimbursement rate and family copayments, and document how these policy parameters affect cognitive skills, maternal labor supply, coverage and cost. I find that the most effective combination of policy parameters to improve cognitive skills targets the program to the very poor, sets the copay to 0 and makes the reimbursement rate generous. I also find that this configuration of program parameters has a large impact on maternal labor force participation, increasing labor supply by 36 percentage points. For the very poor, there do not appear to be trade-offs between labor supply and cognitive achievement goals.

The paper is organized as follows. I present the model in section I and the measurement system for child care and home quality in section II. I discuss the data in section III, the estimation in section IV. In section V, I describe the estimation results, the results in section 9 presents the counterfactual results and section 10 concludes.

I. Model

The model begins when a mother first has a child and ends when she turns 45. Mothers can be married (or not), face the risk of divorce and can have more children as they age. Every 6 months the mother makes a labor force decision and child care arrangement decisions for her children. For her labor supply decision, the mother receives a wage offer that depends on her characteristics and she can either stay home, work part-time or work full-time. For child care, the mother chooses, for each child younger than five, whether they attend child care part-time, full-time or stay at home. I define "child care" as any type of non-parental care and I define "home care" as care given by one of the child's parents in the

ment provided (Lamb et al., 1992).

[12] Interestingly, the policy findings from this paper are consistent with *positive* impacts on child outcomes from an experimental evaluation of a child care subsidy program with conditional employment requirements (Huston et al., 2005).

child's home.[13] In the model, child care varies in both quality and price. Families make a draw from the price/quality distribution for child care services and can choose whether to use child care at that price and quality. Children from eligible families also have the option to attend Head Start, which offers free child care for children from poor families. In the model, mothers face a skill production function with the quality of child care, the time spent in child care, and the quality of the home environment entering as inputs. The child's cognitive skills and the mother's labor market experience evolve endogenously and the mother faces trade-offs between consumption, leisure, the cognitive development of her children and the accumulation of labor market experience. For the remainder of the model section, assume that I have a univariate measures of both home quality and child care quality. After the model section, I discuss how I measure home and child care quality in a way consistent with other early childhood research. To facilitate exposition of the model, I present the model without the specifications and I put the exact specifications in the appendix.

A. *Preferences*

The mother's contemporaneous utility function is given by:

$$U(t) = U(C_t^M, h_{L,t}, \theta_t^1, \theta_t^2, h_{cc,t}^1, h_{cc,t}^2, \varepsilon_{L,t}, \varepsilon_{cc,t}; X_t)$$

where her utility at time t depends on her consumption, C_t^M, hours of leisure, $h_{L,t}$, the cognitive skills of child i, θ_t^i, hours of child care for child i, $h_{cc,t}^i$ and shocks to the utility of leisure, $\varepsilon_{L,t}$, and child care use, $\varepsilon_{cc,t}$. The variables X_t enter the model as marginal utility shifters by allowing some parameters to vary by marital status, the number of younger children, the number of older children and the age of the children.

B. *Child Care*

Each period the household receives a price-quality offer for child care services with the

[13] Under this definition, child care encompasses relative care in the child's home, relative care outside the child's home, non-relative care in the child's home, and non-relative care outside the child's home such center based care, Head Start, and preschool. So any care not given by the child's parent would be considered "child care" even if the care occurred in the child's home. For example, a live-in nanny would be considered child care and not home care.

child care quality given by $q_{cc,t}$. I assume the child care quality offers are drawn from:[14]

$$log(q_{cc,t}) \sim N(\mu_{q,cc}, \sigma^2_{q,cc})$$

The price for the child care quality draw is given by the hedonic equation:

$$p_{cc,t} = p(q_{cc,t}, \varepsilon_{p,t})$$

where $\varepsilon_{p,t}$ is a shock to the price offer given a quality draw $q_{cc,t}$. The child can then attend child care of quality $q_{cc,t}$ for $h^i_{cc,t}$ hours at price per hour of $p_{cc,t}$.

C. *Head Start*

Families may be eligible for government provided care in the form of Head Start, which is a federal preschool program for children from poor families. Head Start is free so $p_{HS} = 0$. Let the distribution of Head Start quality be given by:

$$log(q_{HS,t}) \sim N(\mu_{q,HS}, \sigma^2_{q,HS})$$

An eligible child can then attend Head Start that offers child care of quality $q_{HS,t}$.[15] To be eligible for Head Start, the children's age, A^i_t, must be between the ages of 3 and 5 and the family income must be below a federal threshold, I^{HS}, that depends on family size. Because Head Start is rationed I assume that eligible families receive a probabilistic offer of Head Start that depends on a random shock, ε_{HS}. Let H^i_t equal 1 if child i has access to Head Start at time t and zero otherwise:

$$H^i_t = H(A^i_t, Y_t M_t + w_t(1000 - h_{L,t}), \text{Family Size}, \varepsilon_{HS})$$

D. *Home Quality*

Home quality is observed in the data and I model home quality at time t, $q_{hq,t}$, as a function of both observed, X_{hq}, and a permanent unobserved component, ω, as well as a transitory

[14] An important point here is that search for different child care options is not observed in the data. For computational considerations, I only permit one draw from the distribution of price and quality so what I am trying to estimate is the envelope of the offer distribution from some unobserved search process. Then the usual selection issues arise in that I only observe accepted offers from the price-quality distribution. This same issue would come up in a labor supply model without search with only observed wages.

[15] Head Start is a part-time program so I assume that if families choose Head Start but also want to have full-time care that they use their first draw of price and child care quality to provide so-called "wrap around care."

component, $\varepsilon_{hq,t}$:

$$q_{h,t} = q_h(X_{hq,t}, \omega, \varepsilon_{h,t})$$

E. *Cognitive Achievement Production Function*

Cognitive skills evolve endogenously according to the hours spent in child care, the quality of the child care arrangement, the quality of the home environment, the time spent at home and previous skills. The value-added cognitive skill production function is given by:

$$\begin{aligned} &\theta^i_{t+1} = f(\theta^i_t, I^i_t, \omega, \varepsilon^i_{c,t}) && \text{Production Function} \\ &I^i_t = (2000 - h^i_{cc,t})q_{hq,t} + h^i_{cc,t}\tilde{q}^i_{cc,t} && \text{Input} \end{aligned}$$

where $q_{hq,t}$ is the quality of the home environment, $h^i_{cc,t}$ is hours in the child care environment, $\tilde{q}^i_{cc,t}$ is the quality of the child care environment for child i, and $\varepsilon^i_{c,t}$ is child specific shock to cognitive skills. The input is time weighted index for quality hours spent in the home, $(2000 - h^i_{cc,t})q_{h,t}$, and quality hours spent in child care, $h^i_{cc,t}\hat{q}^i_{cc,t}$, where I assume that the child has 2000 hours in a period.[16] The value-added production function captures the cumulative and dynamic nature of cognitive achievement (Cunha and Heckman, 2007, 2008). Current skills build on past skills through the parameter $\gamma_{1,c}$ so that lagged inputs can affect the formation of current skills.

F. *Wages and Income*

For married couples, the household enters the period knowing the father's education, E_f, and experience, $X_{f,t}$. The household draws an income shock $\varepsilon_{I,t}$ and forms current period income. Similarly, the household draws a wage shock, $\varepsilon_{w,t}$ and uses the mother's education, E_m, and experience, $X_{m,t}$, to form the current wage offer. The income and wage functions are:

$$\begin{aligned} w_t &= w(black, E_m, X_{m,t}, \omega, \varepsilon_{w,t}) \\ I_t &= I(black, E_f, X_{f,t}, \omega, \varepsilon_{I,t}) \end{aligned}$$

I allow being black to directly affect the wage offer and I also have added a household specific permanent component, ω, for the mother's wage and for the father's income. I assume that the father works full time so that his experience evolves deterministically.

[16]If children are awake for 80 hours per week times 26 weeks (6 months) this is approximately 2000 hours.

The mother's experience evolves according to her labor supply decision. The transition of the stocks of experience is given by: Put Eckstein and Wolpin (1989) in here somewhere

$$X_{m,t+1} = X_{m,t} + \frac{1000 - h_{L,t}}{2000}$$
$$X_{f,t+1} = X_{f,t} + .5$$

G. *Child Care Subsidies*

A typical government funded child care subsidy has three features: (1) a copay that is a percentage of family income, (2) a rate ceiling; the subsidy pays the entire price if the price is less than the rate ceiling. If the price is greater than the rate ceiling then the family pays the difference between the price and the rate ceiling for each hour of child care, and (3) an income cutoff that determines eligibility. Define the following terms:

$$\text{copay} = \psi(I_t M_t + w_t(1000 - h_{L,t}))$$
$$\text{rate ceiling} = rc$$
$$\text{income eligibility cutoff} = \bar{\mathrm{I}}^{\mathrm{s}}$$

where ψ is the percentage of income that is a copay. For a given number of hours, $h_{cc,t}$, instead of paying, $p_{cc,t}h_{cc,t}$, the cost under the subsidy program is:

$$C_t^s = 0\, h_{cc,t}\, 1_{\{p_{cc,t} \leq rc\}} + 1_{\{p_{cc,t} > rc\}}[p_{cc,t} - rc]h_{cc,t} + \psi(I_t M_t + w_t(1000 - h_{L,t}))$$

Families always pay the copay and pay zero marginal price per hour if the price of child care is less than the rate ceiling and positive marginal price ($p_{cc,t} - rc$) if the price is greater than the rate ceiling. The subsidy program has an interesting feature that subsidy eligible mothers may not always elect to use the subsidy. This can occur if the copay is large enough to outweigh the fall in marginal price of child care from the subsidy. This would particularly apply to families with low prices for child care or those having relatively higher incomes.[17] Let S_t be 1 if the family uses the subsidy, 0 otherwise:

$$S_t = 1_{\{h_{L,t} < 1000\}} 1_{\{I_t M_t + w_t(1000 - h_{L,t}) < \bar{\mathrm{I}}^{\mathrm{s}}\}} 1_{\{C_t^s < p_{cc,t} h_{cc,t}\}}$$

[17] The standard explanation for the lack of take up of CCDF subsidies is unfamiliarity with or difficulty navigating the program requirements (Herbst, 2008). This analysis shows that there are structural features of the program that reduces participation. Explicitly modeling the subsidy system also reveals a *Catch-22*-esque feature in that mothers need to work to be eligible but working may put family income above the income eligibility cutoff, thus making the family ineligible. This feature can also obviously reduce participation.

which captures the three main features of the program: (1) mothers must work so that hours of leisure is less than full time, $h_{L,t} < 1000$, (2) family income,$I_t M_t + w_t(1000 - h_{L,t}$, must be below an income threshold, $\bar{\mathrm{I}}^{\mathrm{S}}$ and (3) the cost under the subsidy, C_t^s, must be less than the family would pay without the subsidy, $p_{cc,t} h_{cc,t}$.

H. *Fertility and Divorce*

In the model, the probability of a new child is given by $\pi_b = \pi_b(X_t^b \phi^b)$, which depends on observable characteristics X_t^b and is parameterized by ϕ^b. I do not permit mothers to have more than two children less than five years of age.[18] The probability of divorce is given by $\pi_d^t = \pi_d(X_t^d \phi^d)$, which depends on observable characteristics X_t^d and is parameterized by ϕ^d. I do not permit women with young children to remarry or to cohabit with a non-biological father.[19] Both the fertility and divorce probabilities are estimated using logit probability specifications.

I. *Shocks and State Space*

Before making labor force and child care decisions, the mother makes a child care quality and price draw, $q_{cc,t}$ and $p_{cc,t}$, a Head Start quality draw, $q_{HS,t}$, and a shock to Head Start availability to form H_t^i. The household also draws shocks to cognitive skills for each young child i in the house, $\varepsilon_{c,t}^i$, to home quality, $\varepsilon_{q_h,t}$, to the utility of leisure for the mother, $\varepsilon_{L,t}$, to the utility of using child care, $\varepsilon_{cc,t}$, to the mother's wage offer, $\varepsilon_{w,t}$, and to income, $\varepsilon_{I,t}$. Collecting the shocks in a vector $\vec{\varepsilon}_t$ and define the state space at time t:

$$\Omega_t = \{X_{f,t}, E_f, M_t, black, X_{h,t}, E_h, h_{L,t-1}^1, \theta_{c,t}^1, A_t^1, H_t^1, h_{cc,t-1}^1,$$
$$\theta_{c,t}^2, A_t^2, H_t^2, h_{cc,t-1}^2, \theta_{c,t}^T, O_t, q_{cc,t}, p_{cc,t}, q_{HS,t}, \vec{\varepsilon}_t\}$$

Let the nonstochastic part of the state space be $\bar{\Omega}_t$.

J. *Choices*

The mother makes decisions about her hours of leisure and the child care hours for each child younger than age 5. Let $h_{L,t}$ be a discrete variable that equals 0 if the mother stays

[18]HERE ABOUT NUMBER OF WOMEN WITH MORE THAN THREE CHILDREN UNDER AGE 5

[19]This selection criterion reduces the sample by 9%. I also define a "father" as the child's biological father and being "married" in the model conflates cohabitation and marriage. Divorce then refers to the child's biological father exiting the household. Women who are "divorced" in the initial state space may have never been married or may have been cohabiting and then the father left before the child was 6 months old. Finally, there is a small group where the biological father is not in the house at baseline but later lives in the house. I exclude this group from the sample and I lose a further 5%. Evidently women with young children are unlikely to remarry. See Table 4 for a complete list of sample selection criteria.

at home in period t, 500 if she works part time and 1000 if she works full time.[20] Hours of child care for child i, $h^i_{cc,t}$, can also equal either 0, 500 or 1000. For a family with Head Start in their choice set for child i, let D^i_{HS} equal 1 if child i attends Head Start and 0 otherwise. In addition to the three labor supply choices, a household with two children can have up to five child care choices for each child (home, part-time child care, full-time child care, part-time Head Start or full-time Head Start) for a total of up to 75 choices. Household with less children and who are not Head Start eligible have a smaller choice set.

G. *Budget Constraint*

The budget constraint is straightforward on the revenue side: the father's income I_t enters if marital status, M_t equals 1, and the mother's wage, w_t, multiplies her hours of work $1000 - h_{L,t}$. On the cost side, both Head Start and child care subsidies shift the marginal and fixed cost of child care expenditures for each child. The programs can affect child care costs independently or potentially interact.

$$
\begin{aligned}
I_t M_t + w_t(1000 - h_{L,t}) = C_t + \sum_{i=1}^{K_t} \Big[& p_{cc,t} h^i_{cc,t} \underbrace{(1 - H^i_t D^i_{HS,t})(1 - S^i_t)}_{\text{No Head Start, No subsidies}} \\
& [1(p_{cc,t} > rc)[p_{cc,t} - rc] h^i_{cc,t} + \psi(I_t M_t + w_t(1000 - h_{L,t}))] \underbrace{(1 - H^i_t D^i_{HS,t}) S^i_t}_{\text{Subsidies only}} \\
& + 500 p_{cc,t} 1\{h^i_{cc,t} = 1000\} \underbrace{H^i_t D^i_{HS,t}(1 - S^i_t)}_{\text{Head Start only}} \\
& + [1(p_{cc,t} > rc)[p_{cc,t} - rc]500 + \psi(I_t M_t + w_t(1000 - h_{L,t}))] 1\{h^i_{cc,t} = 1000\} \underbrace{H^i_t D^i_{HS,t} S^i_t}_{\text{Head Start and subsidies}} \Big]
\end{aligned}
$$

I assume that mothers receive a share of family consumption that depends on family size and marital status according to:

$$
C^M_t = \frac{C_t}{1 + 0.7M_t + 0.5O_t + 0.5K_t}
$$

In addition, I assume single mothers receive a minimal amount of consumption, C_{min}, which is a parameter to be estimated, and is intended to capture other government transfer not modeled here.[21]

[20] Because each period corresponds to 6 months, I assume that mothers working full-time work 40 hours per week times 24 weeks = 960 hours. I round to 1000 hours for full-time work and set 500 hours as part-time work.

[21] Few models of female labor supply with endogenous experience incorporate savings because of com-

K. *Mother's Problem*

At each period a, the mother makes labor supply and child care decisions to maximize the expected present value of remaining lifetime utility:

$$\mathrm{E}\left[\sum_{t=a}^{A} \beta^{t-a} U(t) | \Omega_a\right]$$

subject to the within period budget constraint. The expectation is formed over the distribution of the value function with respect to the controlled stochastic process generated by the optimal decision rule.

L. *Terminal Value*

For the terminal value function, the woman needs to keep track of the cognitive skills for all of her children. At age 45, the woman then attaches a utility value to the total stock of age five cognitive skills of all her children. Define $\theta_{c,t}^T$ as the total cognitive skills for all of the children in the house at time t. The stock of cognitive skills increases when children turn 5 according to:

$$\theta_{c,t}^T = \theta_{c,t-1}^T + \theta_{c,t}^1 1\{A_t^1 > 5\} + \theta_{c,t}^1 1\{A_t^2 > 5\}$$

The horizon is finite. At period T, assumed to be 45 years of age, the woman faces a terminal value function that depends on the state space. I assume:

$$V_{T+1} = A_c \theta_{c,t}^T + A_e X_{f,T+1}$$

where A_c and A_e are parameters to be estimated.

M. *Unobserved Heterogeneity*

Finally, the distribution of unobserved heterogeneity is $f(\omega)$ where I assume that $f(\cdot)$ follows a discrete distribution with K support points. The support points are sometimes called "types." This treatment of unobserved heterogeneity follows Heckman and Singer (1984). Recall that there is unobserved heterogeneity over income, wages, home quality and cognitive skills. Because the unobserved heterogeneity also determines the initial conditions through a process not modeled here, I allow the probability of being a particular

putational considerations. In this model, single mothers who do not work do not have a source of non-labor income, which is impossible with log or CRRA utility over consumption. Some authors, such as Eckstein and Wolpin (1989), have utility linear in consumption so that zero or even negative consumption is not computationally problematic.

type to be a function of the initial conditions. In the estimation, I assume that there are K = 2 types.

N. *Solution Method*

The model is solved backward from the last period. Given the state space, I draw from the distribution of shocks and calculate the optimal choice. I repeat this process and take the average over the optimal values. This simulated integration gives the expected maximum value at that particular state space point. I then pick a different state space point and repeat the simulated integration. The resulting function is known in the literature as the EMAX function. Instead of calculating the EMAX at every point in the state space, I use an approximation method developed by Keane and Wolpin (1994). First, I randomly select a subset of the state space points and calculate the EMAX at each point in the randomly drawn subset. Second, I use a polynomial approximation to the EMAX function and use the predicted value to "fill-in" any state space point where I did not calculate the EMAX. For the evolution of marriage and number of children, I use exact integration because I assume a closed form for the probabilities.

II. Measuring Child Care and Home Quality

The quality of an environment, either in the home or in a child care setting, is intended to capture the amount of stimulation that children receive in that environment.[22] Stimulation can come in the form of developmentally appropriate materials, whether the caregiver encourages the child and the kinds of activities that the classroom or child does during their time in child care, such as reading books or singing songs.[23] In the child care literature, researchers make a distinction between structural and process measures of quality.[24] Structural measures include the student-caregiver ratio and the qualifications of the caregiver. Improved structural measures are thought to increase the likely of high quality care but do not guarantee improved care quality. On the other hand, process measures capture what actually occurs in the child care environment and are the actual "quality" of the child care environment.

One commonly used measure of child care quality is the Early Childhood Environment Rating Scale (ECERS). The ECERS asks questions about the routines that occur in

[22]The word quality is typically used in reference to child care settings. The quality of home environment might be called the HOME score (in refernence to a particular scale) or home inputs. I use quality to define the amount of measured stimulation in any environment whether home or child care. The point of my paper is that the foregone alternative of making a child care choice is often the quality of the home environment.

[23]See Love et al. (1996), Caldwell and Bradley (1984) for discussions and definitions.

[24]See Vandell and Wolfe (2000).

the classroom, the use of language by the caregiver toward the child, whether there is time for motor activities, whether the child engages in creative activities such as music or art, observer impressions of the "tone of interaction" and many others. Other scales, such as the Global Rating Scale, attempt to measure whether the relationship between the care provider and the child is "positive" by assessing how the caregiver speaks to the child, whether they enjoy the child, etc.[25] Although the scales have some overlap, there does not seem to be complete uniformity in questions that related to quality. In general, measures of child care "quality" can then be any variable that measures materials in the care environment and whether the interactions between child and caregivers are "stimulating."

Analogous to issue of measuring child care quality is the issue of measuring home quality. A commonly used measure is the Home Observation for the Measurement of the Environment (HOME). The HOME scale is based on direct observation and interviewer questions of the parent. The questions vary by the age of the child. Some subscales that span multiple ages are questions related to the learning environment, parental responsivity, and learning materials.[26] The HOME scale includes questions about whether the parent spontaneously spoke to the child, verbal responses to the child, whether the parent provided toys to the child and whether the interviewer felt the play environment was safe. The goal is capture whether the child lives in a stimulating environment both from the mother and from items that the family might buy.[27] Caldwell and Bradley (1984) argue that the HOME scale is consistent with "Piagetian notions about the development of sensorimotor and preoperational thinking."

An advantage of using the ECERS and HOME scales is that these scales have both been extensively used and validated in the literature. A disadvantage is the weighting of the scale items is essentially arbitrary. Cunha and Heckman (2008) state "[t]he constructed indices often have an ad hoc quality about them and may be poor proxies for the true combination of inputs that enter the technology." In my data, I have measures from the HOME scale and from the ECERS scale. However, a limitation is the data contain only a subset of questions from the HOME scale and the ECERS was collected only for a small subset of children. The data also contain additional questions that could be considered inputs and I risk losing information by focusing only on the HOME and ECERS scale. Table 2 have a

[25] Lamb (1998) has a discussion of child care quality with examples of difference scales that measure quality and the different areas that the scales measure.

[26] See the Home Observation for Measurement of the Environment (HOME) Inventory at

[27] Bernal and Keane (2010) make a distinction between time and goods inputs, which I do not follow. Todd and Wolpin (2007) also discuss how the HOME scale conflates time and goods inputs and also combines items that could logically be considered inputs with items that instead seem to be proxies for inputs. Instead my approach is closer to Cunha and Heckman (2008), who model the inputs into the production function as a latent variable.

list of information in the data that I use to form the measure of the home environment and table 3 has a comparable list of questions that I use the form the child care quality measure. The home quality measures are a mix of direct observation and self-reports by the parents. The child care quality measures are reported by the child care providers. Similar to the existing scales, I choose to combine all of the information on inputs into a single variable for the home environment and a single variable for the child care environment. Specifically, for the measurements of home and child care quality and for each round, I use principle components analysis (PCA) to collapse the data into an index and I treat the predicted component as data, where the component is chosen to explain the maximize amount of variance in the measures of home and child care quality. Although using PCA does not address the criticism that the weights are arbitrary, PCA captures a component that explains the maximum amount of variance in the data and allows me to expand my sample and to incorporate all input information in the data. Moreover, given that questions vary across existing scales, it seems that there is no consensus on which measures should be used to capture the quality of children's experiences.[28]

III. Data

I estimate the model using data from the Early Childhood Longitudinal Study - Birth Cohort (ECLS-B). The ECLS-B is a nationally representative panel of 14,000 children born in 2001. Researchers followed the children from birth until kindergarten entry and collected detailed information about their family background, home environment, maternal work decisions, maternal wages, family income, child care usage and cognitive achievement outcomes. Child care providers were given questionnaires that asked detailed information about the care environment, care activities, qualifications and questions designed to elicit information about their attitudes towards child care. Families were also asked questions about the kinds of activities the child engaged in and the materials and toys the child had access to. Selected summary statistics for the data used in the analysis is given in table 1. The measures used in the principal-components analysis for the child care and home environment quality are given in tables 2 and 3.

The ECLS-B consists of five rounds of data collection. The researchers visited the children when they were approximately 9 months, 2 years, 4 years and 5 years with a follow-up round for delayed kindergarten entrants. I use the first four rounds.[29] Two issues complicate taking the model to the data. First, the spacing between rounds is irregular. Second, there is a large amount of variability in assessment age at each round. For

[28]See Layzer and Goodson (2006) for a discussion about the difficulties in defining and measuring child care quality and relating child care quality to child outcomes.

[29]The fifth round of data collection is for the subset of children who are delayed kindergarten entrants.

example, in the 9 month round, the children actually ranged in age from 6 months to 18 months. Because of these features of the data set, I instead organize the data into 6 month bins with bins at 6 - 12 months, 12 - 18 months, 18 - 24 months, etc. For each round I will see some children in each age bin and I will see each child four times (ignoring attrition). I treat the observations between rounds when I do not see the child as missing data. Because the amount of missing data is large, I do not estimate the model by maximum likelihood. Instead I use the method of simulated moments where I simulate different paths and form statistics for the children when I observe them. The estimation procedure is described in more detail below.

For the cognitive achievement measures, the ECLS-B contains the Bayley Short Form-Research Edition (BSF-R) at the 9 month and 2 year waves. The BSF-R uses a subset of the Bayley Scales for Infant Development, 2nd Edition (BSID-II), which is a assessment that places infants in various situations and scores their responses. The BSF-R can be given to children from 2 to 30 months. The assessment contains both a mental and a motor score. I use the mental score for my analysis. Examples situations from the BSF-R include ringing bells and checking whether the child turns their head in response and whether the child vocalizes at least once during the interview. Each situation contains a series of activities that are age and developmentally appropriate. The assessor checks the child's responses in order to locate their basal and ceiling levels. For the ECLS-B, the interviewers gave children a core assessment and moved downward to the basal set for children for whom the core set was too difficult. The ceiling set was used for children who got the core set perfectly. Instead of reporting the BSF-R score, researchers used Item Response Theory (IRT) to predict a scale score on the BSID-II, which is what is reported in the data file. The data also contain a norm referenced T-score.

For cognitive achievement at older ages, the ECLS-B administered math and early reading tests. The math and reading tests were adaptive tests derived from well-known early childhood assessments. To encourage cross-study comparisons, the ECLS-B used questions previously developed for the ECLS-K, the Head Start Impact Study and the Family and Child Experiences Study. In addition, questions were added from the Peabody Picture Vocabulary Test (PPVT, various forms), the Test of Early Mathematics Ability-3 (TEMA-3), the Preschool Comprehensive Test of Phonological and Print Processing (Pre-CTOPPP) and the PreLAS 2000.[30] Again, the ECLS-B contain scale scores and T-scores for both the math and early reading tests. I use the scale scores. To combine information, I simply average the math and early reading scores. Finally, because test scores do not have

[30]For additional information on the cogntive assessments see "The ECLS-B Direct Assessment Choosing the Appropriate Score for Analysis" http://nces.ed.gov/ecls/pdf/birth/ChoosingScores.pdf

a metric, I standardize the scale scores by age.

IV. Estimation

The model has 73 parameters that I estimate using the method of simulated moments. The basic idea is to match statistics from simulated data generated from the model to corresponding statistics in the data. The procedure works as follows. Given a set of parameter values, I solve the model by iterating backward from the terminal value. I then use each woman's initial conditions to draw her type from the discrete distribution of types. Given the model solution, her type and the initial conditions, I then simulate a path of endogenous variables for each woman in the data set. I repeat this procedure five times to create five "clones" of each person in the data set. I calculate statistics from the simulated data using only the rounds where I actually observe the families. The estimation procedure iterates between the model solution and objective function, which is a weighted distance between statistics computed from the data and corresponding statistics computed from the simulated data. I weight the moment difference by the inverse of the variance of each data moment.

There are two complications in the estimation. The first estimation issue is that the model has multiple children per family but I only observe one child per family in the ECLS-B . It is important to consider multiple children in the estimation because restricting the sample to families with one realized child could bias the estimation if families perceive that they will have more children even if they actually do not end up having more children. I am able to identify the model with multiple children through assumptions about the mother's utility over cognitive skills and through the estimation procedure. I assume that the children's skills enter linearly and additively separably in the utility function so that mothers care about efficiency when making decisions.[31] Then because I use unconditional simulations from the initial conditions, I never have to calculate conditional choice probabilities for unobserved state space elements such as the cognitive skills of other children in the family. Although my assumptions about the mother's utility function is not testable because I never observe the cognitive skills of other children in family, the model does have implications for how sibling's cognitive achievement scores are correlated.[32] In the estimation results section I present simulated evidence from the model about the intra-sibling correlation in cognitive skills and birth order effects on cognitive achievement, which I compare to other studies to give an idea about the model's predictions. I

[31] Even when multiple children are observed estimates of the efficiency vs. equity trade-offs have produced different results. See the discussion and papers cited in Behrman (1997). Recently Cunha and Aizar FIND.

[32] The ECLS-B does have information on twins, which I do not use in the estimation, but this could be another potential avenue to check the modeling assumptions.

also plan to explore the robustness of my conclusions in future work by using a CES aggregator of the children's cognitive skills for different assumptions about the value of the complementary parameter.

The second estimation issue is that the ECLS-B is not a random sample of children but a sample of children born in 2001. However, I assume that the model begins when the mother first has a child, which could be in or before 2001. In order for the mother to be selected in the ECLS-B, she must have a sequence of shocks such that she has a birth in 2001. I mimic the ECLS-B sample selection procedure by only keeping sequences of shocks with a birth in 2001.

A. *Objective Function*

Suppose θ is the vector of parameters to estimate. Let K_i be an M x 1 vector function of the data for family i. The method of simulated moments estimator is given by:

$$\hat{\theta}_{msm} = \underset{\theta}{\text{argmin}}\ \psi(\theta)$$

with:

$$\begin{aligned}
&\psi(\theta) = \\
&[\frac{1}{N}\sum_{i=1}^{N}[K_i - \frac{1}{S}\sum_{s=1}^{S} k_i(u_i^s;\theta,\omega_i^s|u_i^s \in \text{ECLSB})]]W^{-1} \\
&[\frac{1}{N}\sum_{i=1}^{N}[K_i - \frac{1}{S}\sum_{s=1}^{S} k_i(u_i^s;\theta,\omega_i^s|u_i^s \in \text{ECLSB})]]
\end{aligned}$$

K_i : M x 1 vector function of the data for family i

$k_i(u_i^s;\theta,\omega_i^s)$: M x 1 vector function of the simulated data for family i given draw u_i^s and permanent component ω_i^s

W^{-1} : weighting matrix

The simulated integration over the shocks u_i^s also includes integrating out the unobserved heterogeneity ω_i^s, which I draw from the discrete distribution given family i's initial conditions. The conditioning statement $u_i^s \in$ ECLSB captures that the sequence of shocks must be such that the mother has a birth in 2001 in order to have been selected into the ECLS-B. For the weighting matrix W, I use the inverse of the diagonal variance matrix of the data moments.

B. *Standard Errors*

To simplify notation let $\mu(\theta) = \frac{1}{S}\sum_{s=1}^{S} k_i(u_i^s;\theta,\omega_i^s|u_i^s \in \text{ECLSB})$ be the vector of simulated moments given the parameter vector θ. Taking the derivative of the objective function with respect to θ yields the following first order conditions:

$$\left.\frac{\partial\mu}{\partial\theta}\right|_{\hat{\theta}_N}^{\prime} W^{-1}[\frac{1}{N}\sum_{i=1}^{N}[K_i - \mu(\theta_N)] = 0$$

A Taylor expansion around $\mu(\theta_0)$ gives:

$$\mu(\theta_N) = \mu(\theta_0) + \left.\frac{\partial\mu}{\partial\theta}\right|_{\theta_*}(\theta_N - \theta_0)$$

for some θ_* between θ_0 and θ_N. Plugging the Taylor expansion into the first order condition, premultiplying and rearranging gives:

$$\sqrt{N}(\theta_N - \theta_0) = \left(\left.\frac{\partial\mu}{\partial\theta}\right|_{\hat{\theta}_N}^{\prime} W^{-1}\left.\frac{\partial\mu}{\partial\theta}\right|_{\theta_*}\right)^{-1}\left(\left.\frac{\partial\mu}{\partial\theta}\right|_{\hat{\theta}_N}^{\prime} W^{-1}\left[\frac{1}{\sqrt{N}}\sum_{i=1}^{N}[K_i - \mu(\theta_0)]\right]\right)$$

Applying a Central Limit Theorem gives the following variance-covariance matrix for the limiting distribution:

$$\left(\left.\frac{\partial\mu}{\partial\theta}\right|_{\hat{\theta}_N}^{\prime} W^{-1}\left.\frac{\partial\mu}{\partial\theta}\right|_{\theta_*}\right)^{-1}\left(\left.\frac{\partial\mu}{\partial\theta}\right|_{\hat{\theta}_N}^{\prime} W^{-1}V[K-\mu(\theta_0)]W^{-1}\left.\frac{\partial\mu}{\partial\theta}\right|_{\hat{\theta}_N}\right)\left(\left.\frac{\partial\mu}{\partial\theta}\right|_{\hat{\theta}_N}^{\prime} W^{-1}\left.\frac{\partial\mu}{\partial\theta}\right|_{\theta_*}\right)^{-1}$$

I then approximate $\left.\frac{\partial\mu}{\partial\theta}\right|_{\hat{\theta}_N}$ using the matrix of numerical partial derivatives calculated at the optimal parameter value and $V[K-\mu(\theta_0)]$ is approximated by the variance-covariance of the moments at the optimal parameter value.

C. *Moments*

To estimate the model, I use 622 moments in the estimation.[33] I use the means of the endogenous variables (cognitive skills, labor force hours, child care use, home quality, chosen child care quality) conditional on the exogenous variables (black, maternal education, maternal age, father's education, father's experience, marital status, and number of children). I also match the variance of the endogenous variables and the correlation between data rounds. In addition, I match the distribution of work and child care decisions, the transition of work decisions, and the transition of child care decisions.

[33]See the material for the online appendix for a complete list.

V. Estimation Results

A. *Parameters Estimates*

The parameter estimates and associated standard errors are displayed in Table C.1 in Appendix C. The parameters of the cognitive achievement production function play an important role in tracing out the impact of different policy counterfactuals on the cognitive skills of children. The parameters suggest that cognitive skills are persistent ($\gamma_{1,c} = 0.79$), a child's environment is an important determinant of skills ($\gamma_{3,c} = 0.43$) and that home environments are on average more productive than child care environments in producing cognitive skills ($\alpha = 0.59$). These parameter estimates are important for the counterfactuals because the persistence in the production of cognitive skills causes inputs in one period to affect future cognitive achievement through the value-added achievement production function.

Besides these parameters, the type distribution parameter on being black is insignificant although being black is significant determinant of wage and income offers. This is an important result because it suggests that observed differences by race in marriage rates, education levels, wage and income offers and their effects on choices can explain the black-white achievement gap.[34] Other parameters have intuitive and obvious signs and magnitudes.

Some of the features of the estimates are difficult to understand without simulating the model. In Table C.2, I compute wage elasticities, intra-sibling correlation in cognitive skills and birth order effects on cognitive skills. Computing the elasticities on data simulated from the model at the final parameter estimates, the intensive labor supply elasticity is 0.89 and the extensive labor supply elasticity is 0.88, which are consistent with previously high estimated wage elasticities for women.[35] Comparing cognitive skills among siblings, I find 0.48 for the intra-sibling correlation in cogntive achievement test scores, which is very close to the 0.5 intra-sibling correlation for IQ scores among siblings reported in Scarr (1992).

I find evidence for both spurious and genuine birth order effects in the simulated data. In Table C.2, without conditioning on the number of children, the results show that later born children have lower cognitive achievement test scores on average, which is consistent with reported findings on birth order. However, conditioning on the number of children, the effect of birth order on cognitive achievement diminishes, which is consistent with the

[34] This is consistent with Fryer Jr and Levitt (2004) who document that the black-white achievement gap at kindergarten entry in the ECLS-K shrinks dramatically with a few controls.

[35] See the discussion and papers cited in Keane and Wolpin (2010).

theory that mothers with larger families have lower observed or unobserved determinants of their children's cognitive achievement.[36] However, even conditioning on number of children, the later born children still have lower scores on average. The model can generate such birth order effects through the budget constraint if mothers choose lower and more affordable child care quality when faced with more children of child care age. Or, when the number of children increases, low quality home environment mothers could select to be stay at home and not use child care, which would result in a higher dose of low quality home care for later born children.

B. *Model Fit*

The model fit is displayed in Tables C.3 - C.12 in Appendix C. The model captures well all the main features of the data (Table C.3). There are gaps in cognitive achievement test scores by race, mother's marital status and maternal education (Table C.4). Home quality is higher on average for white children with married parents and mothers with higher education (Table C.9). Child care quality also displays the patterns observed in the data with blacks and children of single parents having, on average, better child care experiences than white children and children with married parents (Table C.6). This reflects the role of Head Start and the higher likelihood of more disadvantaged children being eligible for Head Start. The lower home quality of these groups also increases the marginal productivity of child care quality, which provides an additional incentive for them to accept higher quality child care draws. On the other hand, the lower wages draws of single and black mothers mitigates their ability to pay for child care quality.

The model also captures the U-shape for child care quality as maternal education increases. To the extent that maternal education proxies for socioeconomic status, the child care quality experiences for middle-income children are often the worst because their families are not poor enough to quality for subsidized care but higher quality care is more expensive. Another interesting feature is that quality does not increase dramatically for higher education mothers, which is strange given the apparent productivity of higher quality care.[37] Such a pattern could reflect poor consumer knowledge of the quality of child care experiences Walker (1991) or perhaps the mothers have limited knowledge of the cognitive achievement production function.[38] The model also picks up the patterns of child

[36] Rodgers et al. (2000) discuss how most birth order studies use cross-sectional data and that the findings disappear with controls for family size.

[37] Blau and Hagy (1998) document a similar pattern for the demand for structural measures of quality. Their result is perhaps not as surprising given the lack of productivity of structural measures of quality (Blau, 1999) and the weak relation between structural measures and process measures (Blau, 1997).

[38] Bernal (2008) discusses the assumption that the mothers know the functional form for the production of cognitive achievement.

care use with small differences in black/white and married/single usage patterns. White mothers have higher wage offers (as a result of higher education and experience), which increases their likelihood to work, but they also are more likely to be married, which increases their demand for leisure through non-labor (husband's) income effects. The higher home quality of married/white mothers gives an additional incentive to stay home because of higher productivity of their inputs in creating cognitive skills. The model also captures different labor force patterns by maternal characteristics (Table C.10), the distribution of decision (Table C.11) and the transition of work and child care decisions (Table C.11).

In Figure F.4, F.5 and F.6, I document several patterns that the model captures even though these moments were not used explicitly in the estimation. It is noteworthy that the model can capture these patterns because it suggests that the within sample fit for some important moments not used in the estimation is reasonable. First, Figures F.4 and F.5 show the emergence of the test score gap by maternal education and by race. The model captures the small initial gaps in test scores by race and maternal education that open up early and persist as the children age.[39] Second, Figure F.6 plots the average child care quality by race and child's age. Although the data are noisy, the interesting feature of this pattern is that the higher average child care quality for black children occurs only after around age 3. The model captures through the availability of Head Start when the children turn age 3. Black children are disproportionately eligible for Head Start because of lower average family income so that beginning at age 3 their mothers receive higher average child care quality offers, which pushes up the average child care quality for blacks and the model generates a similar pattern to that observed in the data.

VI. Counterfactuals

The main goal of the paper is to evaluate the role of two kinds of child care policies, Head Start and child care subsidies, and their effects on (a) children's cognitive achievement and (b) maternal labor force participation. For cognitive skills, I discuss how different policies affect the amount of child care used and the quality of child care chosen. I also document the per capita and total cost associated with different interventions and the effect of policies on closing gaps in cognitive achievement by race.

A. *Head Start*

The results from the Head Start counterfactuals are displayed in Tables D.1 to D.3 in Appendix D. As a model validation exercise, I first use the model to evaluate Head Start using the same design as the Head Start Impact Study (HSIS), a randomized controlled

[39] Fryer Jr and Levitt (2006) also document the small test score gap at the 9 month round in the ECLS-B.

trial of Head Start. The HSIS consisted of two interventions; a group of 4 year olds who were randomized to receive Head Start or not (HSIS 4 year olds) and a group of 3 year olds who were randomized into a treatment group and a delayed treatment control group that could apply again for Head Start at age 4 (HSIS 3 year olds). In Table D.1, I report the effect sizes for two arms of the HSIS computed in my estimated model and from the report of the HSIS.[40] I report two kinds of estimates of the program's effect. The first, the Intent to Treat estimate, is the average change in the outcome for all eligibles. The second estimate is the Treatment on the Treated, which is the average change in the outcome only for children that use the program.

The intent to treat estimate for the HSIS 4 year olds design is 0.06 in my model and 0.12 in the HSIS study. For the same design, the Treatment on the Treated estimate is 0.12 in my simulations and 0.17 in the HSIS. Using the HSIS 3 year olds design, I find an effect size of 0.07 in my simulations and the HSIS reports 0.05 for the Intent to Treat estimate. The Treatment on the Treated estimate is 0.13 versus 0.06 in the HSIS. Although the HSIS was conducted on a different cohort of children, with a sample of oversubscribed Head Start centers and could not prevent treatment crossovers to other Head Start centers, the effect sizes simulated in my model and reported in HSIS are of a similar magnitude, which provides evidence of the validity of my model.[41]

I next use the model to consider three types policies: removing Head Start completely (an arm that the HSIS did not evaluate), replacing Head Start with cash transfers to eligible families and expanding Head Start services to current non-eligibles. Table D.2 displays the results from these counterfactual experiments. I report Intent to Treat estimates for the effect of the different interventions on Head Start eligibles, where Head Start eligibility can change depending on the income cutoff. The first row illustrates that removing Head Start lowers cognitive achievement scores by -0.15 standard deviations at kindergarten entry. Removing Head Start has only a moderate impact on changing maternal labor force participation. This is not surprising given that Head Start imposes no work requirement as a condition of participation. The second row considers the effect of not only removing

[40]The effect sizes from the HSIS were computed as follows: for the reading domain outcomes, I averaged across the effect sizes for all of the reading outcomes. For the math domain, I averaged across the effect sizes for all of the math outcomes. I then averaged the separate math and reading effect sizes, which most closely approximates my treatment of the data in the ECLS-B. The Treatment on the Treated impacts were derived from the Intent to Treat impacts in the HSIS using the Bloom adjustment.

[41]Todd and Wolpin (2006) use experimental data to validate a structurally estimated economic model. They estimate their model using data from from an experimental evaluation of PROGRESA, a conditional cash transfer program in Mexico. They limit their estimation sample to data in the control group and use the estimated model to predict the experimental impacts of PROGRESA. The difference in my case is that I estimate the model using a completely different data set and only mimic the design of the experiment for the model validation. However, the spirit of the exercise is the same.

Head Start but giving Head Start eligible families a cash transfer of the per student spending on Head Start per six months ($3,610). The idea is to test whether in kind transfers are a better method of achieving the aims of Head Start through parents making better decisions when provided the money directly. The results indicate that, compared to providing Head Start, providing transfers lowers cognitive achievement scores (-0.13 SD). The cash transfer also has a large negative effect on maternal labor supply (-10 percentage points) so to the extent that maternal labor supply is a policy objective these unconditional transfers do not encourage labor supply.

Table D.2 rows 3 to 6 gradually expand Head Start by increasing the Head Start income eligibility cutoff. The Intent to Treat estimates increases monotonically in the income cutoff for a maximum of 0.21 SD impact on cognitive achievement at kindergarten entry. This finding suggests that even for higher income children there substantial gains to be had in their cognitive achievement scores at kindergarten entry.[42] One reason for this is that children from higher income families tend to spend more time in child care and the child care quality data presented in the data section show that child care quality experiences of these children are not particularly high. Providing a relatively higher quality Head Start option increases the cognitive skills of non-eligibles because of their extensive use of low quality child care.

Finally, in Table D.3, I consider the effect of the previously described counterfactuals on closing the black-white (BW) achievement gap. The first column shows that without Head Start the BW achievement gap would be 9% larger at kindergarten entry. Head Start has a fairly substantial effect of narrowing the BW achievement gap. This finding reflects both the relative productivity of Head Start compared to other forms of child care and the differential access to Head Start by black children, because of family income eligibility cutoffs. The cash transfer in place of Head Start increases the black-white achievement gap; the gap would be 3.96% higher with cash transfers in place of Head Start. Increasing the eligibility cutoff at first lowers the gap but gradually increases the gap as more and more higher income children benefit from Head Start services. With universal Head Start, the BW achievement gap would actually be 12.11% larger. This result shows that closing the BW achievement gap can be a paradoxical goal; there are policies that benefit all children yet would increase differences between blacks and whites at kindergarten entry.

B. *Child Care Subsidies*

The results from the child care subsidies counterfactuals are presented in Tables D.4 to D.6 in Appendix D. As discussed previously, I estimate the model without the child care

[42]This result is consistent with Gormley et al. (2005).

subsidy program and then introduce the program into the model with the policy parameters calibrated to national averages. In Table D.4, I report the effect on cognitive achievement of the calibrated subsidy program; I find that 6 months of exposure increases cognitive achievement scores by 0.034 standard deviations. The child care subsidies also have a large impact on labor force participation; increasing the labor supply by 18 percentage points.[43] Another interesting feature of the simulations is that the subsidy take-up, defined as the percentage of eligible families that use the subsidy, is 40.8 percent, which implies that a substantial fraction of the low take-up of subsidies can be explained by the labor supply decisions of mothers and not using the subsidies for low price child care providers.[44]

I next vary each subsidy policy parameter holding the other two policy parameters constant at their calibrated values. The idea is to describe how changing the policy parameter affects the cognitive skills of children, the labor supply of mothers, the program coverage and the cost per child. In the first block in Table D.4, I gradually increase the copay from 0 percent to 30 percent. The Intent to Treat estimated effect on cognitive skills gradually falls. Although child care quality could increase as the copay increases (by discouraging subsidy recipients from accepting low price child care offers), the effect on cognitive skills seems to diminish. This result is partly driven by lower take-up of the subsidy as the copay increases (falling from 62.9% to 10.4%). The cost per child falls and the total cost of the child care subsidy program (relative to the simulated cost of the baseline child care subsidy program) also falls from 1.87 to 0.11 times the total cost of the baseline program. The total cost subtracts out the copayments from the families so the decrease in total cost is driven both by less program participation and by offsetting receipts from higher parental copayments.

Increasing the rate ceiling from \$0 to \$20 while holding the other parameters constant, both the intent to treat parameter on cognitive skills and maternal labor force participation increase as the rate ceiling increases. Cognitive skills increase because more children participate and because mothers can accept higher price/quality child care offers, which also increases the impact on cognitive achievement. Labor force participation increases because the size of the transfer increases. However, at a rate ceiling of \$20, both the cost per child, \$9,223, and the total relative cost of the program, 3.7 times the baseline subsidy program, increase substantially.

[43]This is consistent with the effect of child care costs on maternal employment estimated in Blau and Robins (1988), Connelly (1992) and Ribar (1992).

[44]Herbst or someone else on low take up? Other authors have invoked a lack of awareness of child care subsidies or difficulty navigating the requirements of the program to explain the low take up of potentially eligible mothers. However, my analysis suggests that a substational fraction of the low take-up can be explained the structure of the program and relatively higher income families or families with very low cost child care providers optimally electing not to use the program.

Finally, I vary the income cutoff from $5,000 to $30,000 and the intent to treat on cognitive achievement falls as the income cutoff increases. Higher income families use the subsidy but the mothers were likely already working and using child care so the child's cognitive skills do not change, which causes the intent to treat parameter to decrease. The final row of Table D.6 examines the effect of a targeted program to very poor mothers (household income less than $10,000 per year) and offers a subsidy with a generous rate ceiling ($20 / hour) and 0% copay. The results show that this targeted intervention both increases cognitive achievement scores (0.144 SD) and maternal labor supply (0.36 percentage points). Especially for the very poor there do not appear to be trade-offs between encouraging maternal labor supply and improving cognitive achievement.

In Table D.5, I explore more in depth how subsidy policy parameters change the quality of care chosen. The columns supertitled eligibles show the difference in average child care quality between subsidy users and non-users. For example, in the program calibrated to national averages, subsidy users had average quality of 0.06 SD and eligible non-users had average quality of -.02 SD. However, the Δ Quality column reports that the change in quality is 0 for the subsidy program, which means that the children who are induced to enter child care by the subsidy have no better or worse child care quality experiences than average. The subsidy generates the differences in quality because low-price/low-quality child care users opt not to use the subsidy and high-price/high-quality child care users elect to use the subsidy. The subsidy basically segments the mothers into users and non-users by the price of child care they would have used anyways. The subsidy is capable of improving cognitive achievement primarily by encouraging mothers with low quality home environment to use child care so that their children spend less time at home. In this model, the conclusion is that to improve cognitive achievement the subsidies should be targeted toward children with low quality home environments but that the ability to design the subsidies to improve child care quality experiences is limited.

In Table D.6, I examine the effect of child care subsidies on the black-white (BW) achievement gap. Unlike the Head Start example, I consider the impact on the BW achievement gap average across all periods. The estimated impact is the ability of a particular configuration of policy parameters to decrease (or increase) the achievement gap. The first result is that the child care subsidy program has a very small impact on the BW achievement gap; increasing the gap by 0.4 percent. I then vary the copay, the rate ceiling and the income cutoffs. The effects are generally small and range from positive to negative depending on whether the parameter configuration induces changes more from black or white mothers. The child care subsidy program targeted to mothers with less than $10,000 annual income decreases the achievement gap by 1.4 percent. The effect on cognitive skills for this intervention is large and evidently primarily benefits black children but the coverage is low so the effect on the black-white gap is relatively small.

VII. Conclusions

In this paper, I explore the effects of two kinds of child care policies, Head Start and child care price subsidies, on the cognitive achievement of children and maternal labor supply. I first use the estimated model to examine the effects of the existing Head Start program on participants. I find that Head Start is effective at increasing cognitive achievement (0.21 SD) and when I mimic the design of a randomized evaluation of Head Start I find similar sized impacts. Replacing Head Start with cash transfers has a sizable negative impact on cognitive achievement (-0.13 SD). Expanding Head Start services increases cognitive achievement at kindergarten entry (0.21 SD for a universal program), primarily because many non-eligible children spend significant amounts of time in low quality child care.

Child care subsidies, as typically designed, do not have negative impacts on cognitive achievement. Six months of exposure to a child care subsidy program increases cognitive achievement by 0.043 standard deviations. Child care subsidy policy parameters do have an important role in increasing cognitive achievement but the effect comes through which children participate in child care and not through the child care quality choices. A generous child care subsidy program targeted to very poor households (less than $10,000 annual income) both increases children's cognitive achievement scores and increases labor force participation of mothers. For the some families, there are no trade-offs between improving cognitive skills and increasing labor force participation.

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Appendix A: Data

Table A.1: Descriptive Statistics

Child care participation	47.1%
Labor force participation women	57.1%
Average hourly wage ($)	21.37
Average income ($)	28,350
Average price child care / hour ($)	4.93
Average number of years of education	
Wives	14.37
Husbands	14.46
Average number of years work experience at baseline	
Wives	7.01
Husbands	13.07
Age at first birth	27.55
Average number of children	2.04
Percent married	94.5%
Percent black	7.4%
Sample size	3,000

Notes: Income is over 6 month for married men only. Marriage includes cohabitation. Sample size rounded to nearest 50 per NCES requirements.

Table A.2: Home Quality Measurements

	Round 1		Round 2		Round 3		Round 4	
	N = 4350		N = 3800		N = 4200		N = 3200	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Caregiver spoke spontaneously to child?[1]	0.94	0.25	0.98	0.15	.	.	.	.
Caregiver responded verbally child?[1]	0.86	0.34	0.97	0.17	.	.	.	.
Caregiver caressed/kissed/hugged child?[1]	0.95	0.21	0.95	0.21	.	.	.	.
Caregiver provided toys to child?[1]	0.84	0.37	0.84	0.37	.	.	.	.
Caregiver interfered with child's actions?[1]	0.79	0.41	0.77	0.42	.	.	.	.
Caregiver kept child in view?[1]	0.98	0.15	0.95	0.21	.	.	.	.
Play environment was safe?[1]	0.97	0.16	0.99	0.11	.	.	.	.
Read books to child?[2]	2.85	1.01	3.29	0.84	3.23	0.81	3.21	0.81
Tell stories to child?[2]	2.55	1.12	2.70	1.03	2.71	0.92	2.58	0.89
Sings songs with child?[2]	3.64	0.70	3.60	0.69	3.28	0.84	3.05	0.92
Talk to your child about books you read to them?[2]	.	.	.	.	.	.	2.99	0.87
Take on errands?[2]	3.35	0.88	3.38	0.81	.	.	.	.
Play peek-a-boo?[3]	5.00	1.14	.	.	.	.	.	.
Tickle/blow on belly/move playfully?[3]	5.78	0.58	.	.	.	.	.	.
Walk/yard/park/playground?[3]	4.15	1.35	.	.	3.48	0.99	.	.
Number soft toys	.	.	25.34	29.00	.	.	.	.
Number push/pull toys	.	.	12.54	20.52	.	.	.	.
Number books	.	.	58.68	52.25	90.32	102.25	103.55	115.67
Number records/tapes/CDs	.	.	12.85	18.96	.	.	.	.
Visit zoo, aquarium, or petting farm?[1]	.	.	0.31	0.46	.	.	.	.
Visited art gallery, museum, or historical site?[1]	.	.	0.15	0.36	.	.	.	.
Visited library?[1]	.	.	0.31	0.46	0.43	0.50	0.46	0.50
Play chasing games?[3]	.	.	3.77	1.04	.	.	.	.
Play with games or toys indoors?[3]	.	.	4.35	0.84	.	.	.	.
Go to a restaurant or out to eat?[3]	.	.	2.18	0.76	.	.	.	.
Affection by hugging, kissing or holding?[4]	.	.	4.86	0.39	4.77	0.50	.	.
Easygoing and relaxed with my child?[4]	.	.	4.13	0.82	3.93	0.78	.	.
Don't have the energy to make my child behave?[4]	.	.	3.42	1.14	3.48	1.03	.	.
Trouble stick to rules?[4]	.	.	3.73	1.12	3.73	1.08	.	.
Hours TV?	.	.	2.94	8.37	2.12	2.09	1.96	1.97
Number of days family eats dinner together	.	.	5.96	1.76	5.60	1.77	0.00	0.00
Organized athletic activities?[1]	.	.	.	.	0.37	0.48	0.51	0.50
Dance lessons?[1]	.	.	.	.	0.15	0.36	0.19	0.39
Music lessons?[1]	.	.	.	.	0.07	0.26	0.08	0.28
Drama lessons?[1]	.	.	.	.	0.01	0.12	0.02	0.15
Art classes?[1]	.	.	.	.	0.09	0.29	0.10	0.30
Organized performing arts?[1]	.	.	.	.	0.17	0.37	0.22	0.42
Craft classes or lessons?[1]	.	.	.	.	0.12	0.33	0.13	0.34
Play together with toys for building?[1]	.	.	.	.	0.38	0.49	.	.
Computer?[1]	.	.	.	.	0.66	0.47	0.74	0.44

Notes: '·' indicates the question was not asked in that particular round.
Responses were coded as follows:
[1]No = 0 , Yes = 1
[2]Number times per week: not at all = 1, once or twice = 2, 3 to 6 times = 3, every day = 4
[3]How often per month: more than once a day = 1, about once a day = 2, few times a week = 3, few times a month = 4, rarely = 5, not at all = 6
[4]Sounds like me? exactly like = 1, very much like = 2, somewhat like = 3, not much like = 4, not at all like = 5

Table A.3: Child Care Quality Measurements

	Round 2 N = 1650		Round 3 N = 2900		Round 4 N = 700	
	Mean	SD	Mean	SD	Mean	SD
Number books	54.50	89.26	110.89	169.35	111.58	164.06
Number records/tapes/CDs	17.53	25.54	.	.	.	.
Number soft toys	21.53	24.27	.	.	.	.
Number push/pull toys	10.70	16.96	.	.	.	.
How often talk to child?[1]	3.60	0.60	.	.	.	.
Hours of TV?	.	.	0.47	1.00	4.74	19.79
How often read books to child?[2]	3.50	0.83	6.34	4.69	5.86	3.86
How often tell stories to child?[2]	3.06	1.09	4.24	3.63	4.18	3.28
How often sing songs to child?[2]	3.60	0.76	7.10	6.87	6.46	6.99
Ask questions about story?[3]	0.91	1.44	3.21	0.85	.	.
Play chasing games?[4]	2.85	1.41	.	.	.	.
Computer?	.	.	1.39	0.49	1.34	0.47
Play games/puzzles?	.	.	4.26	3.33	4.11	2.95
Build something?	.	.	3.55	2.99	3.46	2.72
Walk to yard/park/playground?[4]	2.14	1.21	.	.	.	.
Visit zoo, aquarium, or petting farm?[5]	0.12	0.32	.	.	.	.
Visited art gallery, museum, or historical site?[5]	0.06	0.23	.	.	.	.
Visited library?[5]	0.14	0.35	.	.	.	.
Reading area?[5]	.	.	0.75	0.43	0.79	0.41
Listening center?[5]	.	.	0.53	0.50	0.62	0.49
Writing center?[5]	.	.	0.71	0.45	0.78	0.42
Pocket board?[5]	.	.	0.62	0.49	.	.
Math area?[5]	.	.	0.73	0.45	0.75	0.43
Blocks?[5]	.	.	0.75	0.43	0.78	0.41
Puzzle area?[5]	.	.	0.63	0.48	0.79	0.41
Water area?[5]	.	.	0.70	0.46	0.65	0.48
Drama area?[5]	.	.	0.74	0.44	0.74	0.44
Art area?[5]	.	.	0.52	0.50	0.78	0.42
Private area?[5]	.	.	4.13	1.29	.	.
Work on learning names of letters?[6]	.	.	3.46	1.60	4.43	1.01
Practice writing the letters of the alphabet?[6]	.	.	3.95	1.36	3.93	1.21
Discuss new words?[6]	.	.	3.61	1.47	4.24	1.07
Tell stories to a caregiver/teacher/provider?[6]	.	.	4.00	1.38	3.74	1.29
Work on phonics or phonemics?[6]	.	.	4.13	1.29	4.02	1.30
Listen to stories and see print?[6]	.	.	2.18	2.10	4.25	1.15
Listen to stories and don't see print?[6]	.	.	3.10	1.50	2.90	1.72
Retell stories?[6]	.	.	3.44	1.77	3.32	1.27
Learn about conventions of print?[6]	.	.	3.90	1.55	3.86	1.41
Write own name?[6]	.	.	3.00	1.64	4.44	1.05
Learn about rhyming words and word families?[6]	.	.	4.58	0.89	3.28	1.33
Count out loud?[6]	.	.	3.84	1.39	4.75	0.68
Work with geometric manipulatives?[6]	.	.	3.51	1.64	3.88	1.24
Work with counting manipulatives?[6]	.	.	3.19	1.56	3.86	1.29
Play math-related games?[6]	.	.	2.45	1.80	3.46	1.31
Music for math concepts?[6]	.	.	2.21	1.77	2.78	1.46
Creative movement for math concepts?[6]	.	.	2.41	1.68	2.49	1.43
Work with measuring instruments? [6]	.	.	3.79	1.84	2.67	1.35
Calendar activities?[6]	.	.	2.20	1.97	4.30	1.34
Telling time activites?[6]	.	.	3.83	1.38	2.88	1.65
Engage with shapes and patterns?[6]	.	.	.	.	4.08	1.15

Notes: '.' indicates the question was not asked in that particular round.
[1]Typical day: 1 = Almost never, 2 = sometimes, 3 = Often, 4 = Always
[2]Number times per week: 1 = Not at all, 2 = once or twice, 3 = 3 to 6 times, 4 = Every day
[3]almost never = 1, sometimes = 2, often = 3, always = 4
[4]more than once a day = 1, about once a day = 2, few times a week = 3, few times a month = 4, rarely = 5, not at all = 6
[5]No = 0 , Yes = 1
[6]never = 0, once a month = 1, 2 or 3 times per month = 2, 1 or 2 a week = 3, 3 or 4 times a week = 4, everyday = 5

Table A.4: Sample Selection Criteria

	N	% of baseline sample
Baseline sample	10,700	100%
Exclusion criteria		
Half/step siblings in house	3,250	30.3%
Age birth less than 20, greater than 40	2,750	25.7%
More than two children less than age 5	2,250	21%
Child has a twin	1,650	15.4%
Subsidy recipient	1,250	11.7%
Families with step-fathers, non-biological father figures	950	8.9%
Biological father exits/re-enters household	600	5.6%
Drop American Indian/Alaskan Natives	300	2.8%
Union of exclusion criteria	7,700	72%
Estimation Sample	3,000	28%

Notes: Per NCES requirements, sample sizes are rounded to the nearest 50. The ECLS-B originally sampled 14,000 birth certificates but only 10,700 entered the first wave of the study. This table presents the effect of the sample selection criteria on the size of the baseline study entrants.

Appendix B: Functional Forms

Utility:

$$
\begin{aligned}
&U(C_t + C_{min}(1-M_t), \theta^1_{c,t}, \theta^2_{c,t}, h_{L,t}, h^1_{cc,t}, h^2_{cc,t}, \varepsilon_{L,t}, \varepsilon_{cc,t}) = && \\
&\frac{(C_t + C_{min}(1-M_t))^{1-\gamma}}{1-\gamma} + && \text{Consumption} \\
&(\phi^{L,0}_{\mathbf{K},\mathbf{O},\mathbf{M}} + \phi^{L,1} h_{L,t} + \varepsilon_{L,t}) h_{L,t} + \phi^{L,2} |h_{L,t} - h_{L,t-1}| + \phi^{L,3} 1_{\{h_{L,t} \neq 0\}} + && \text{Leisure} \\
&\sum_{i=1}^{2} (\phi^{cc,0}_{\mathbf{A},\mathbf{q}} + \varepsilon_{cc,t}) h^i_{cc,t} + \phi^{cc,1} |h^i_{cc,t} - h^i_{cc,t-1}| + \phi^{cc,2}_{\mathbf{M}} (h_{w,t} - h^i_{cc,t}) 1_{\{h_{w,t} > h^i_{cc,t}\}} && \text{Hours of Care} \\
&\sum_{i=1}^{2} \phi_c \theta^i_{c,t} && \text{Cognitive Skills}
\end{aligned}
$$

Utility parameter heterogeneity:

$$
\begin{aligned}
\phi^{L,0}_{\mathbf{K},\mathbf{O},\mathbf{M}} &= \phi^{L,0}_0 + \phi^{L,0}_1 K_t + \phi^{L,0}_2 O_t + \phi^{L,0}_3 M_t \\
\phi^{cc,0}_{\mathbf{A},\mathbf{q}} &= \phi^{cc,0}_0 + \phi^{cc,0}_1 A^i_t + \phi^{cc,0}_2 q_{cc,t} \\
\phi^{cc,2}_{\mathbf{M}} &= \phi^{cc,2}_0 + \phi^{cc,2}_1 M_t
\end{aligned}
$$

Hedonic pricing equation:

$$
p_{cc,t} = (\gamma^p_0 + \gamma^p_1 q_{cc,t} + \varepsilon_{p,t}) 1\{\gamma^p_0 + \gamma^p_1 q_{cc,t} + \varepsilon_{p,t} > 0\}
$$

Head Start eligibility:

$$
\begin{aligned}
&H^i_t = 1\{\varepsilon_{HS} \leq \gamma_{HS}\} 1\{A^i_t \in [3,5]\} 1\{I_t M_t + w_t(1000 - h_{L,t}) < \mathrm{I}^{HS}(1 + M_t + K_t + O_t)\} \\
&\varepsilon_{HS} \sim U[0,1]
\end{aligned}
$$

Home quality:

$$log(q_{h,t}) = \mu_{qh} + \varepsilon_{qh,t}$$

Production Function:

$$\theta^i_{c,t+1} = (\gamma_{0,c} + \mu_c)(\theta^i_{c,t})^{\gamma_{1,c}}(I^i_t)^{\gamma_{3,c}} e^{\varepsilon^i_{c,t}} \qquad \text{Production Function}$$

$$I^i_t = (2000 - h^i_{cc,t})q_{h,t} + h^i_{cc,t}\bar{q}^i_{cc,t} \qquad \text{Input}$$

Chosen Child Care Quality:

$$\bar{q}^i_{cc,t} = q_{cc,t}(1 - H^i_t D^i_{HS,t}) + q_{HS,t}1\{h^i_{cc,t} = 500\}H^i_t D^i_{HS,t} + (.5q_{HS,t} + .5q_{cc,t})1\{h^i_{cc,t} = 1000\}H^i_t D^i_{HS,t}$$

$$\bar{q}^i_{cc,t} = q_{cc,t}(1 - H^i_t D^i_{HS,t}) + q_{HS,t}1\{h^i_{cc,t} = 500\}H^i_t D^i_{HS,t} + (.5q_{HS,t} + .5q_{cc,t})1\{h^i_{cc,t} = 1000\}H^i_t D^i_{HS,t}$$

Wage offer function:

$$log(w_t) = \gamma^w_0 + \gamma^w_1 black + \gamma^w_2 E_w + \gamma^w_3 X_{w,t} + \gamma^w_4 X^2_{w,t} + \mu_w + \varepsilon_{w,t}$$

Husband's income:

$$log(I_t) = \gamma^h_0 + \gamma^h_1 black + \gamma^h_2 E_h + \gamma^h_3 X_{h,t} + \gamma^h_4 X^2_{h,t} + \mu_I + \varepsilon_{I,t}$$

Probability of a birth:

$$P(K_{t+1} = K_t + 1 | X^b_t) = \frac{1}{1 + exp(-X^b_t \phi^b)}$$

$$P(K_{t+1} = K_t + 1 | X^b_t, K_t = 2) = 0$$

$$X^b_t \phi^b = \phi^b_0 + \phi^b_1 E_w + \phi^b_2 X_{w,t} M_t + \phi^b_3 E_h M_t + \phi^b_4 X_{h,t} + \phi^b_5 black + \phi^b_6 K_t + \phi^b_7 O_t + \phi^b_8 t + \phi^b_9 M_t$$

Evolution of age, younger and older children:

$$
\begin{aligned}
&A^i_{t+1} = A^i_t + .5\\
&O_{t+1} = O_t + 1\{A^1_t > 5\} + 1\{A^2_t > 5\}\\
&K_{t+1} = K_t - 1\{A^1_t > 5\} - 1\{A^2_t > 5\} + 1\{\varepsilon_b \leq P(K_{t+1} = K_t + 1|X^b_t)\}\\
&\varepsilon_b \sim U(0,1)
\end{aligned}
$$

Probability of a divorce:

$$
\begin{aligned}
&P(M_{t+1} = 0|M_t = 1, X^d_t) = \frac{1}{1 + exp(X^d_t \phi^d)}\\
&P(M_{t+1} = 1|M_t = 0) = 0\\
&X^d_t \phi^d = \phi^d_0 + \phi^d_1 E_w + \phi^d_2 E_h + \phi^d_3 X_{h,t} + \phi^d_4 black + \phi^d_5 K_t + \phi^d_6 O_t + \phi^d_7 t
\end{aligned}
$$

Evolution of marriage:

$$
\begin{aligned}
&M_{t+1} = M_t - 1\{\varepsilon_d \leq P(M_{t+1} = 0|M_t, X^d_t)\}\\
&\varepsilon_d \sim U(0,1)
\end{aligned}
$$

State space:

$$
\begin{aligned}
\Omega_t =&\{X_{f,t}, E_f, X_{m,t}, E_m, black, h_{L,t-1}, h^1_{cc,t-1}, h^2_{cc,t-1}, A^1_t, A^2_t, O_t,\\
&M_t, \theta^1_{c,t}\theta^2_{c,t}, \theta^T_{c,t}, q_{cc,t}, p_{cc,t}, q_{HS,t}, H^1_t, H^2_t, \varepsilon^1_{c,t}, \varepsilon^2_{c,t}, \varepsilon_{qh,t}, \varepsilon_{L,t}, \varepsilon_{cc,t}, \varepsilon_{w,t}, \varepsilon_{I,t}\}
\end{aligned}
$$

Unobserved heterogeneity:

$$
\begin{aligned}
&Pr(type = 1|Z_0) = \frac{1}{1 + exp(Z_0 \beta_{type})}\\
&Pr(type = 2|Z_0) = 1 - Pr(type = 1|Z_0)
\end{aligned}
$$

with

$$Z_0\beta_{type} = \beta_{0,type} + \beta_{1,type} black + \beta_{2,type} M_0 + \beta_{3,type} E_h M_0 + \beta_{4,type} X_{h,0} M_0 + \beta_{5,type} E_w + \beta_{6,type} t_0$$

Appendix C: Parameters and Model Fit

Table C.1: Parameter Estimates

Description	Parameter	Estimate	Standard Error
Utility			
CRRA	γ	0.952 *	0.051
Utility cognitive skills	ϕ_c	0.015	0.05
Utility leisure	ϕ^{L0}	0.002	0.022
Diminishing returns to leisure	ϕ^{L1}	-0.24	0.215
Leisure X younger children	ϕ_1^{L0}	0.013	0.191
Leisure X older children	ϕ_2^{L0}	0.008	0.096
Leisure X marital status	ϕ_3^{L0}	0.007	0.088
Switching costs leisure	ϕ^{L2}	-1.8 *	0.879
Fixed cost of working	ϕ^{L3}	-0.014	0.098
Variance leisure shock	σ_L^2	2.991	1.759
Utility child care	ϕ_0^{cc0}	-0.882 *	0.226
Utility child care X child age	ϕ_1^{cc0}	0.021	0.032
Utility child care X quality	ϕ_2^{cc0}	0.002	0.043
Switching costs child care	ϕ^{cc1}	-0.583 *	0.226
Disutility work and no care	ϕ_0^{cc2}	-1.713 *	0.449
Disutility work and no care X divorced	ϕ_1^{cc2}	-0.324	0.612
Variance child care utility shock	σ_{cc}^2	2.55 *	1.212
Continuation value cognitive skills	A_c	2.046	2.055
Continuation value mother experience	A_w	0.003	0.071
Discount factor	β	0.9 *	0.095
% transfered to wife	τ_0	0.991	1
% transfered to wife X black	τ_1	0.957	0.99
Cognitive achievement production function			
Intecept type 0	$\gamma_{0,\text{type }0}^c$	0.053	0.032
Intercept type 1	$\gamma_{0,\text{type }1}^c$	0.01	0.012
Value-added	γ_1^c	0.792 *	0.107
Share parameter	α	0.586	0.392
Scale parameter	γ_3^c	0.428 *	0.089

Variance of cognitive skill shock	σ_c^2	0	0.008
Child care quality offer distribution			
Mean quality	μ_{ccq}	0.051	0.146
Variance quality	σ_{ccq}^2	0.65 *	0.166
Hedonic equation			
Hedonic intercept	γ_0^p	4.091 *	0.999
Hedonic quality	γ_1^p	0.257	0.562
Hedonic shock variance	σ_p^2	15.35 *	2.893
Head Start			
Mean HS quality	μ_{HSq}	0.697	0.623
Variance HS quality	σ_{HSq}^2	0.16	0.229
Probability Head Start Offer	γ_{HS}	0.744	0.699
Home quality			
Intercept type 0	$\phi_{qh,\text{type 0}}$	-0.856 *	0.367
Intercept type 1	$\phi_{qh,\text{type 1}}$	1.087 *	0.375
Variance home quality shock	$\sigma_{q_h}^2$	0.808	0.423
Wage offer equation			
Intercept type 0	$\gamma_{0,\text{type 0}}^w$	0.001	0.018
Intercept type 1	$\gamma_{0,\text{type 1}}^w$	0.555	0.309
Black	γ_1^w	-0.034	0.355
Returns to education	γ_2^w	0.127 *	0.019
Variance wage shock	σ_w^2	0.049	0.084
Income equation			
Intercept type 0	$\gamma_{0,\text{type 0}}^h$	7.315 *	0.687
Intercept type 1	$\gamma_{0,\text{type 1}}^h$	0.86	0.502
Black	γ_1^h	-0.169	0.472
Returns to education	γ_2^h	0.109 *	0.042
Returns to experience	γ_3^h	0.113 *	0.041
Diminishing returns to experience	γ_4^h	-0.004 *	0.001
Variance income shock	σ_I^2	0.009	0.023
Divorce logit			
Intercept	ϕ_0^d	-3.776	6.549

Mother education	ϕ_1^d	-0.034	0.11
Black	ϕ_2^d	0.098	0.528
Mother age	ϕ_3^d	0.034	0.051
Father education	ϕ_4^d	-0.332	0.579
Father experience	ϕ_5^d	-0.014	0.069
Number younger kids	ϕ_6^d	0.595	1.035
Number older kids	ϕ_7^d	0.713	0.569
Fertility logit			
Intercept	ϕ_0^b	-1.524 *	0.349
Mother education	ϕ_1^b	-0.001	0.006
Black	ϕ_2^b	-0.043	0.561
Mother age	ϕ_3^b	-0.008	0.012
Father education X marital status	ϕ_4^b	0.001	0.008
Number of younger kids	ϕ_5^b	0.001	0.011
Number of older kids	ϕ_6^b	-0.154	0.134
Type probability			
Intercept	β_{0type}	-2.75 *	1.166
Black	β_{1type}	-0.037	8.54
Mother education	β_{2type}	0.136	0.115
Mother age at first birth	β_{3type}	0.05	0.071
Initial marital status	β_{4type}	0.32	0.673
Father education X marital status	β_{5type}	0.059	0.076
Father initial experience X marital status	β_{6type}	-0.048	0.072

Notes: * indicates statistically significant at the 5% level. There are 73 parameters.

Table C.2: Ancillary Statistics

Elasticities				
Wage Elasticity of Labor Supply (intensive)	0.92			
Wage Elasticity of Labor Supply (extensive)	0.88			
Cognitive skills				
Intra-sibling correlation in cognitive skills	0.49			
Average cognitive skills by birth order:				
		Family size		
Birth order	Unconditional	1	2	3
First born	-0.02	0.17	0.2	-0.1
Second born	-0.07	-	0.15	-0.15
Third born	-0.2	-	-	-0.2

Notes: The wage elasiticty considers the average change in labor force participation given a 5% increase in the wage in every period for every woman. The estimate elasticity is uncompensated.

Table C.3: Basic Statistics

	Data	**Model**
Average Cognitive Skills	0.00	**0.01**
Average Home Quality	1.38	**1.44**
Average Child Care Quality	1.41	**1.45**
Average Price Child Care / Hour ($)	4.39	**4.47**
Percent Full Time Child Care	0.33	**0.34**
Percent Part Time Child Care	0.14	**0.10**
% in Head Start	0.04	**0.02**
Average Head Start Quality	2.30	**2.27**
Percent Full Time Labor	0.44	**0.44**
Percent Part Time Labor	0.09	**0.12**
Average Female Wage ($)	21.76	**23.03**
Average Husband Income ($)	28,767	**29,156**
% Labor Force Participation	0.57	**0.56**
% Child Care Participation	0.46	**0.44**
% Married	0.95	**0.95**
Average Number Younger Children	1.53	**1.53**
Average Number Older Children	0.39	**0.39**

MODEL FIT: **Cognitive Skills**

Table C.4: Average Cognitive Skills By Household Characteristics

	Data	**Model**
Married	0.02	**0.03**
Single	-0.39	**-0.39**
White	0.10	**0.03**
Black	-0.32	**-0.21**
Mother less than H.S.	-0.43	**-0.37**
Mother H.S.	-0.28	**-0.18**
Mother Some college	-0.10	**-0.04**
Mother College+	0.26	**0.19**
Standard deviation	1.00	**0.94**

MODEL FIT: **Child Care Participation**

Table C.5: % in Child Care By Household Characteristics

	Data	**Model**
Married	0.45	**0.44**
Single	0.59	**0.37**
White	0.47	**0.44**
Black	0.53	**0.43**
Mother less than H.S.	0.27	**0.24**
Mother H.S.	0.41	**0.33**
Mother Some college	0.44	**0.41**
Mother College+	0.54	**0.54**

MODEL FIT: **Child Care Quality**

Table C.6: Average Child Care Quality By Household Characteristics

	Data	**Model**
Married	1.40	**1.44**
Single	1.50	**1.52**
White	1.39	**1.44**
Black	1.65	**1.45**
Mother less than H.S.	1.48	**1.54**
Mother H.S.	1.46	**1.49**
Mother Some college	1.28	**1.41**
Mother College+	1.46	**1.45**

MODEL FIT: **Child Care Price**

Table C.7: Average Child Care Price By Household Characteristics

Married	4.46	**4.51**
Single	2.92	**3.52**
White	4.61	**4.49**
Black	3.77	**4.20**
Mother less than H.S.	2.49	**3.64**
Mother H.S.	3.10	**4.11**
Mother Some college	3.73	**4.48**
Mother College+	5.11	**4.62**

MODEL FIT: **Head Start C.8**

Table C.8: Head Start Participation By Household Characteristics

	Data	**Model**
Average Head Start Quality	2.30	**2.27**
SD Quality	0.99	**1.00**
Married	0.04	**0.02**
Single	0.11	**0.16**
White	0.03	**0.02**
Black	0.09	**0.06**
Mother less than H.S.	0.10	**0.11**
Mother H.S.	0.08	**0.05**
Mother Some college	0.05	**0.01**
Mother College+	0.01	**0.00**

MODEL FIT: **Home Quality**

Table C.9: Average Home Quality By Household Characteristics

	Data	**Model**
Married	1.40	**1.46**
Single	1.03	**1.18**
White	1.50	**1.45**
Black	1.09	**1.31**
Mother less than H.S.	0.74	**1.12**
Mother H.S.	1.10	**1.22**
Mother Some college	1.33	**1.38**
Mother College+	1.65	**1.64**

MODEL FIT: **Labor Force Participation**

Table C.10: % in Labor Force By Household Characteristics

	Data	**Model**
Married	0.57	**0.56**
Single	0.59	**0.56**
White	0.58	**0.56**
Black	0.64	**0.60**
Mother less than H.S.	0.36	**0.38**
Mother H.S.	0.50	**0.46**
Mother Some college	0.59	**0.53**
Mother College+	0.63	**0.66**

MODEL FIT: **Distribution and Transition of Decisions**

Table C.11

Distribution of Care/Work Decisions: Data, **Model**

	Round T		
Round T	No Work	Part-Time Work	Full-Time Work
No Child Care	0.38 , **0.41**	0.04 , **0.04**	0.11 , **0.11**
Part-Time Child Care	0.05 , **0.01**	0.03 , **0.07**	0.05 , **0.02**
Full-Time Child Care	0.03 , **0.02**	0.00 , **0.01**	0.27 , **0.31**

Child Care Transition Between Rounds: Data, **Model**

	Round T		
Round T-1	No Care	Part-Time Care	Full-Time Care
No Child Care	0.67 , **0.67**	0.16 , **0.09**	0.17 , **0.24**
Part-Time Child Care	0.28 , **0.26**	0.33 , **0.47**	0.39 , **0.27**
Full-Time Child Care	0.20 , **0.25**	0.09 , **0.06**	0.71 , **0.69**

Work Transition Between Rounds: Data, **Model**

	Round T		
Round T-1	No Work	Part-Time Work	Full-Time Work
No Work	0.78 , **0.75**	0.07 , **0.09**	0.15 , **0.16**
Part-Time Work	0.26 , **0.03**	0.39 , **0.73**	0.35 , **0.24**
Full-Time Work	0.13 , **0.02**	0.05 , **0.02**	0.82 , **0.96**

MODEL FIT: **Wages**

Table C.12

Average Wage By Mother's Characteristics

	Data	**Model**
Married	22.17	**23.35**
Single	13.82	**16.44**
White	23.66	**23.32**
Black	17.21	**19.14**
Mother less than H.S.	9.31	**9.13**
Mother H.S.	12.45	**12.66**
Mother Some college	16.94	**17.3**
Mother College+	29.14	**30.41**

MODEL FIT: **Income**

Table C.13

Average Income By Father's Characteristics

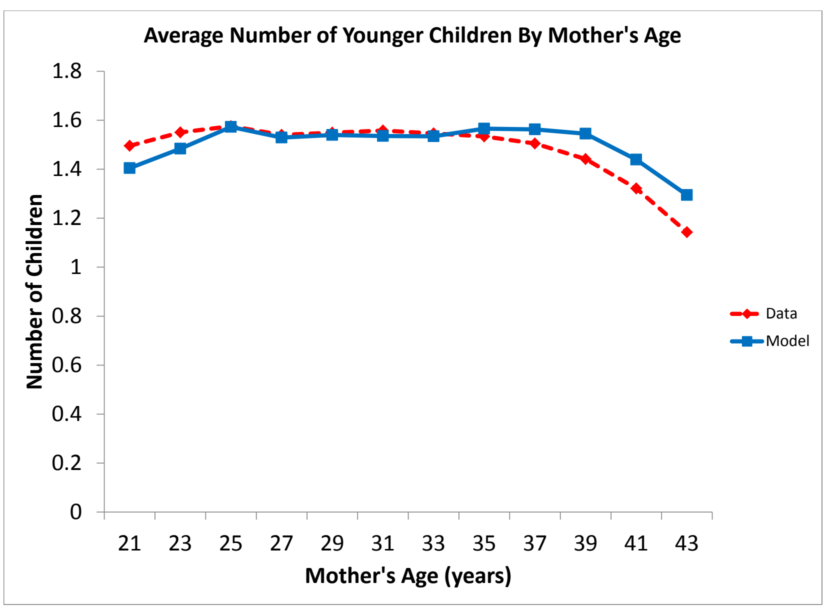
	Data	**Model**
White	31,890	**29,815**
Black	21,064	**19,728**
Father less than H.S.	12,128	**11,003**
Father H.S.	18,978	**17,370**
Father Some college	23,697	**23,919**
Father College+	39,430	**41,568**
Father Experience 0-5	18,732	**25,030**
Father Experience 5-10	24,979	**31,687**
Father Experience 10-15	31,662	**36,692**
Father Experience 15-20	31,721	**33,012**
Father Experience 20-25	26,227	**24,995**
Father Experience 25+	21,636	**10,154**

MODEL FIT: **Number of Younger Children**

Table C.14

Average Number of Younger Children By Household Characteristics

	Data	**Model**
Married	1.53	**1.53**
Single	1.47	**1.50**
White	1.54	**1.53**
Black	1.48	**1.54**
Mother less than H.S.	1.47	**1.54**
Mother H.S.	1.52	**1.54**
Mother Some college	1.54	**1.53**
Mother College+	1.53	**1.53**

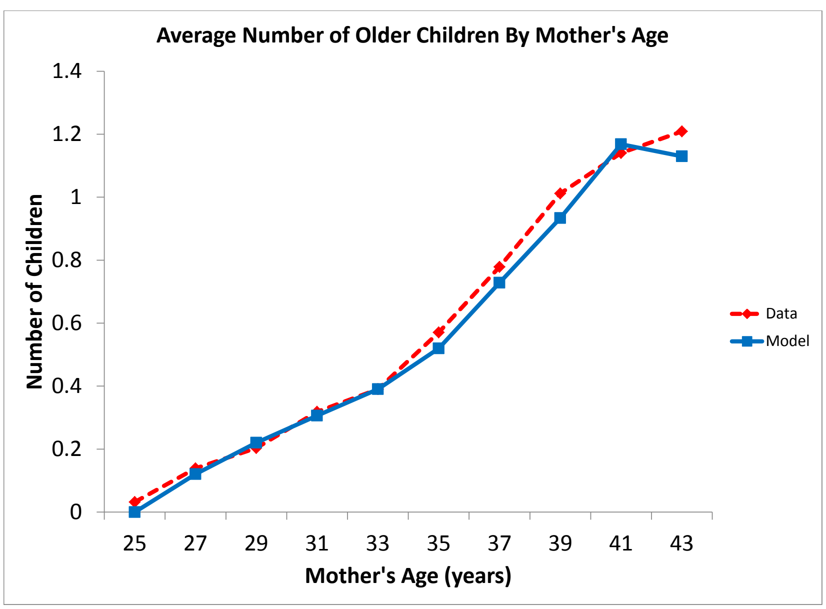


MODEL FIT: **Number of Older Children**

Table C.15

Average Number of Older Children By Household Characteristics

	Data	**Model**
Married	0.38	**0.36**
Single	0.62	**0.93**
White	0.34	**0.37**
Black	0.63	**0.57**
Mother less than H.S.	0.60	**0.57**
Mother H.S.	0.49	**0.49**
Mother Some college	0.44	**0.43**
Mother College+	0.27	**0.28**



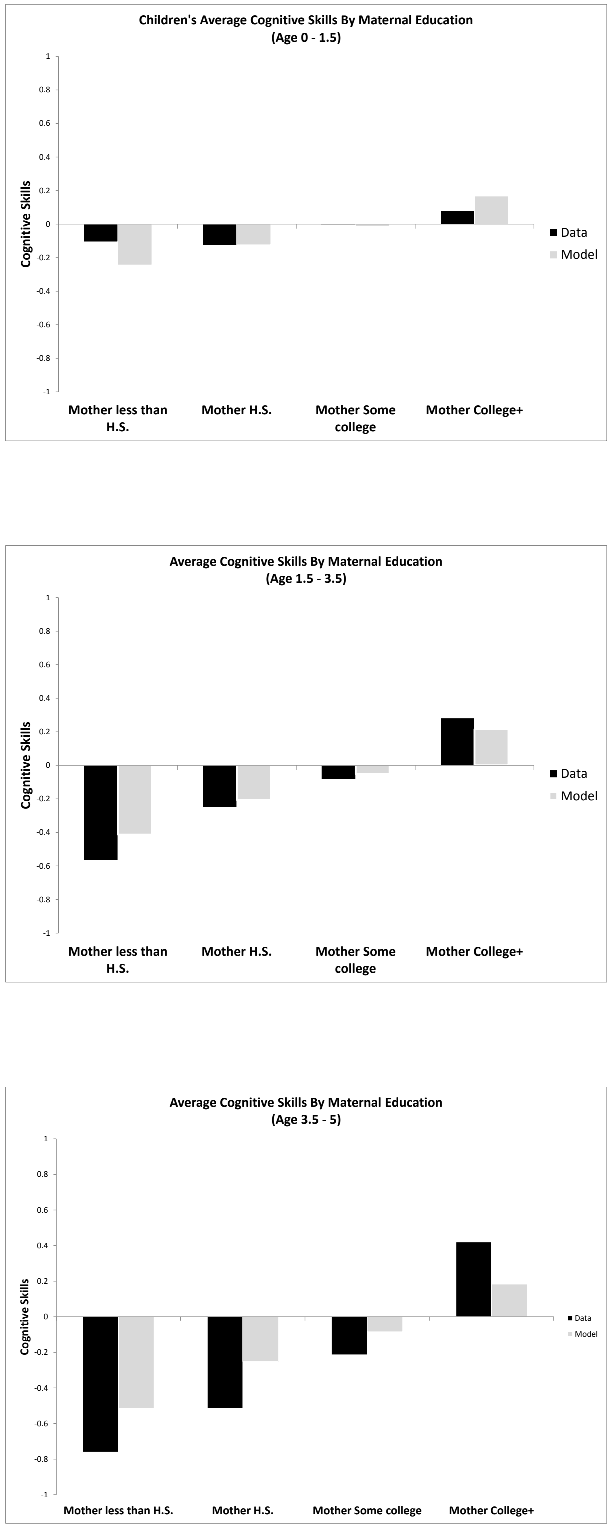
MODEL FIT: **Marriage**

Table C.16

Percent Married By Household Characteristics

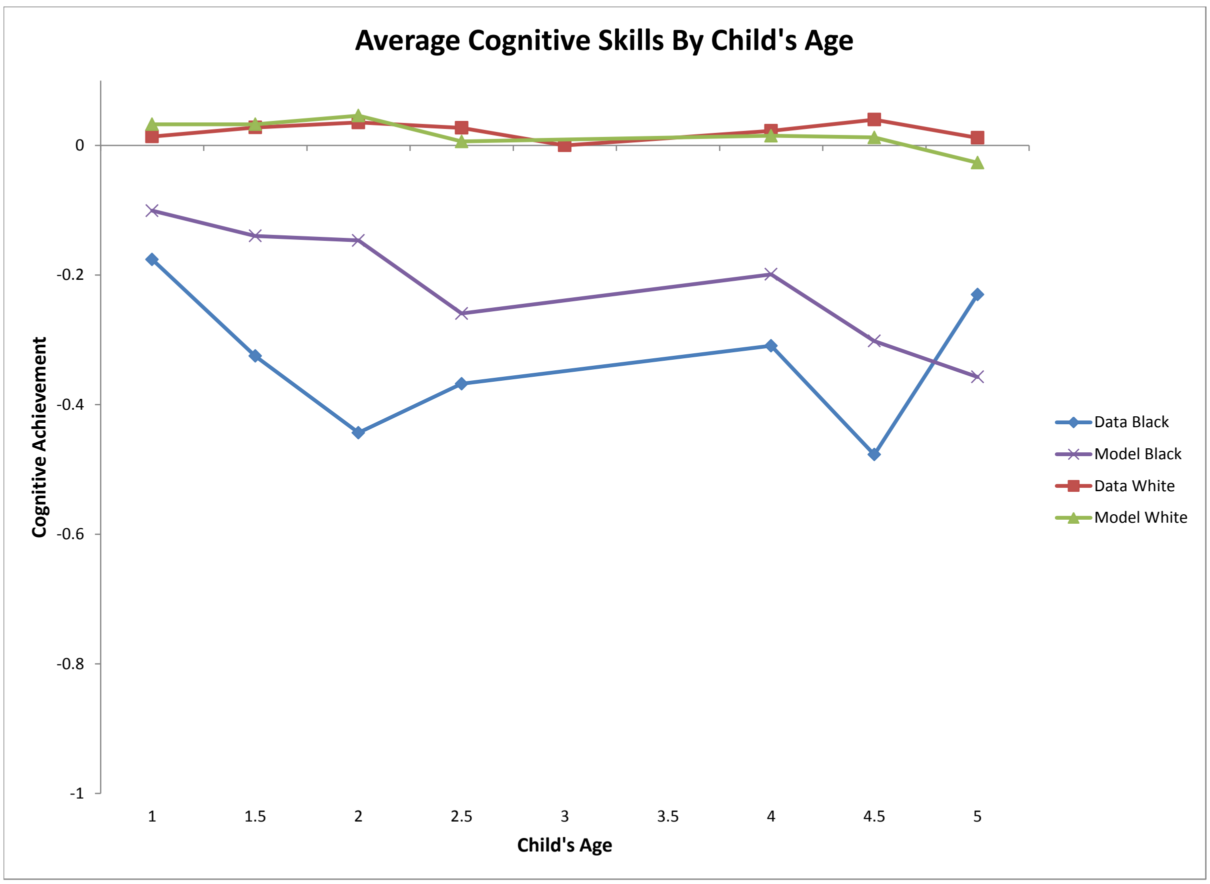
	Data	**Model**
White	0.97	**0.97**
Black	0.72	**0.73**
Mother less than H.S.	0.88	**0.86**
Mother H.S.	0.91	**0.92**
Mother Some college	0.94	**0.94**
Mother College+	0.99	**0.99**

Figure C.1



Children's Average Cognitive Skills By Maternal Education
(Age 0 - 1.5)
Cognitive Skills
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
Data
Model
Mother less than H.S.
Mother H.S.
Mother Some college
Mother College+
Average Cognitive Skills By Maternal Education
(Age 1.5 - 3.5)
Cognitive Skills
Data
Model
Mother less than H.S.
Mother H.S.
Mother Some college
Mother College+
Average Cognitive Skills By Maternal Education
(Age 3.5 - 5)
Cognitive Skills
Data
Model
Mother less than H.S.
Mother H.S.
Mother Some college
Mother College+

Figure C.2


Average Cognitive Skills By Child's Age
Cognitive Achievement
0
-0.2
-0.4
-0.6
-0.8
-1
1
1.5
2
2.5
3
3.5
4
4.5
5
Child's Age
Data Black
Model Black
Data White
Model White

Appendix D: Counterfactuals

Table D.1: Head Start Impact Study (HSIS) Model Validation

	Intent to Treat		**Treatment on the Treated**	
	Model Δ Cognitive	HSIS Δ Cognitive	Model Δ Cognitive	HSIS Δ Cognitive
Design				
HSIS 4 year olds	0.06	0.12	0.12	0.17
HSIS 3 year olds	0.07	0.05	0.13	0.06

Notes: Δ Cognitive reports change in cognitive achievement at kindergarten entry for the model simulations (Model) and from impacts reported in the Head Start Impact Study (HSIS). The two columns supertitled Intent to Treat report the average change in cognitive achievement at kindergarten entry of being Head Start eligible (in the model) and the average change in cognitive skills at kindergarten entry for children who were offered Head Start services (in the HSIS). The two columns supertitled Treatment on the Treated report the average change in cognitive achievement at kindergarten entry of using Head Start (in the model) and the Bloom adjusted Intent to Treat estimate (in the HSIS). The column label Design refers to the two arms of randomization in the HSIS. The 4 year old cohort was a group of children randomized to receive Head Start or not at 4 years old. The 3 year old cohort consisted of a treatment and a delayed treatment control starting at 4 years old. I implement these design features in the model simulations by removing Head Start from the choice set for 4 year olds in the control counterfactual for the HS Impact Study 4 year olds design and by removing Head Start from the choice set of 3 year olds in the control counterfactual for the HS Impact Study 3 year olds design.

Table D.2: Head Start Counterfactuals

Intent to Treat

	Δ Cognitive	Δ LFP	Take-Up	Coverage	Total Cost
Counterfactuals					
1. Remove Head Start	-0.15	-0.03	-	-	1
2. Remove Head Start: Cash Transfer $3,610	-0.13	-0.10	100%	1.2%	3.7
3. Increase Head Start Income Cutoff: +$10,000	0.13	0.02	42.8%	4.1%	3.4
4. Increase Head Start Income Cutoff: +$20,000	0.16	0.03	47.9%	6.9%	5.8
5. Increase Head Start Income Cutoff: +$40,000	0.18	0.02	50.1%	11.5%	9.6
6. Increase Head Start Income Cutoff: +$80,000	0.21	0.02	55.6%	17.7%	14.9

Notes: Δ Cognitive and Δ LFP are the average differences across treatment and baseline in cognitive skills and labor force participation for the Head Start eligible population (Intent to Treat). Take-Up is the percentage using Head Start among eligibles and Coverage is usage in the population. Cost per child is the average cost per child per year, which I set to $\$7,220$. The Head Start cash transfer is a six-month transfer that is half of the yearly cost per child in Head Start ($\$7,220$). Total Cost is the total cost per year for the different Head Start program configurations relative to the total simulated cost of the baseline Head Start program.

Table D.3: Head Start Counterfactuals

	IT Δ Cognitive	**TT** Δ Cognitive	**TE** Δ Cognitive	Total Relative Cost	TE / Total Relative Cost
1. Remove Head Start	-0.15	-0.29	-0.0027	1	-0.0027
2. Remove Head Start: Cash Transfer $3,610	-0.13	-0.13	-0.0105	3.7	-0.0028
3. Increase Head Start Income Cutoff: +$10,000	0.13	0.21	0.0114	3.43	0.0033
4. Increase Head Start Income Cutoff: +$20,000	0.16	0.25	0.0209	5.81	0.0036
5. Increase Head Start Income Cutoff: +$40,000	0.18	0.26	0.033	9.69	0.0034
6. Increase Head Start Income Cutoff: +$80,000	0.21	0.28	0.0504	14.91	0.0034

Notes: The three Δ Cognitive columns report the average differences across treatment and baseline in cognitive achievement for different subsets of children. Intent to Treat is the average change for all eligibles regardless of whether the child uses Head Start. Treatment on the Treated is the average change for eligible Head Start users in the treatment. Total Effect is the average change in cognitive skills across all children in model regardless of Head Start eligiblity or use. Total Cost is the total cost per year for the different Head Start program configurations relative to the total simulated cost of the baseline Head Start program. TE / Total Relative Cost is ratio of total effect to total relative relative cost.

IT: Intent to Treat
TT: Treatment on the Treated
TE: Total Effect

Table D.4: The Effect of Head Start Policies on the Black-White (BW) Achievement Gap

	BW Achievement Gap	%Δ in BW Achievement Gap
Baseline gap at kindergarten entry	-0.296	
Head Start Counterfactuals		
1. Remove Head Start	-0.324	-9.66
2. Remove Head Start: Cash Transfer $3610	-0.307	-3.95
3. Increase Head Start Income Cutoff: +$10000	-0.27	8.51
4. Increase Head Start Income Cutoff: +$20,000	-0.267	9.78
5. Increase Head Start Income Cutoff: +$40,000	-0.284	3.82
6. Increase Head Start Income Cutoff: Universal	-0.331	-12.11

Notes: The Head Start counterfactuals are relative to closing the black-white achievement gap at kindergarten entry. The column %Δ in BW Achievement Gap reports the percent change in the counterfactual black-white achievement gap relative to the simulated baseline black-white achievement gap for the Head Start counterfactuals.

Table D.5: Subsidy Counterfactuals

			Intent to Treat					
Income Cutoff	Rate Ceiling	Copay	Δ Cognitive	Δ LFP	Take-Up	Coverage	Cost Per Child ($)	Total Cost
$ 15,000	$ 3.9	9%	0.037	0.11	40.8 %	3.1 %	4,104	1
Vary Copay								
$ 15,000	$ 3.9	0%	0.063	0.17	62.9 %	5.2 %	4,586	1.87
$ 15,000	$ 3.9	10%	0.037	0.1	39.6 %	3 %	3,960	0.93
$ 15,000	$ 3.9	20%	0.023	0.06	23.6 %	1.7 %	2,757	0.36
$ 15,000	$ 3.9	30%	0.016	0.04	10.4 %	0.7 %	1,854	0.11
Vary Rate Ceiling								
$ 15,000	$ 1	9%	0.002	0.01	6.3 %	0.4 %	376	0.01
$ 15,000	$ 5	9%	0.045	0.14	44.9 %	3.5 %	5,353	1.49
$ 15,000	$ 10	9%	0.082	0.2	55.3 %	4.8 %	8,283	3.13
$ 15,000	$ 20	9%	0.086	0.23	56.3 %	5.1 %	9,223	3.7
Vary Income Cutoff								
$ 5,000	$ 3.9	9%	0.094	0.22	29.6 %	0.3 %	4,085	0.08
$ 10,000	$ 3.9	9%	0.052	0.14	34 %	1.2 %	4,228	0.39
$ 15,000	$ 3.9	9%	0.037	0.11	40.8 %	3.1 %	4,104	1
$ 30,000	$ 3.9	9%	0.027	0.09	43.8 %	9.5 %	3,510	2.6
Targeted to Very Poor								
$ 5,000	$ 20	0%	0.144	0.36	65.6 %	0.8 %	8,323	0.49

The child care subsidy policy parameters are calibrated to averages across state level policy parameters. I use $15,000 for the income cutoff, $3.90 for the rate ceiling and 9% for the copay. Δ Cognitive and Δ LFP are the average differences across treatment and baseline in cognitive skills and labor force participation for the subsidy eligible population regardless of subsidy use (Intent to Treat). Take-Up is the percentage using subsidies among the subsidy eligible population and Coverage is the percentage using subsidies in the population. Cost per child is the average subsidy payment per child per year net of copayments paid by the family. The total cost is the total cost per year net of copayments and scaled relative to the total simulated cost of the baseline subsidy program.

Table D.6: Subsidy Counterfactuals

Income Cutoff	Rate Ceiling	Copay	Intent to Treat Δ Cognitive	Δ Quality	Δ CCP	Eligibles Quality: Users	Quality: Non-Users	Home Quality	% Switchers
$ 15,000	$ 3.9	9 %	0.037	0	0.15	0.06	-0.02	-0.7	29.5
Vary Copay									
$ 15,000	$ 3.9	0 %	0.063	0.01	0.24	0.05	-	-0.7	40.5
$ 15,000	$ 3.9	10 %	0.037	0.01	0.14	0.06	-0.02	-0.7	28.4
$ 15,000	$ 3.9	20 %	0.023	0	0.08	0.06	0.02	-0.7	17.8
$ 15,000	$ 3.9	30 %	0.016	0	0.05	0.03	0.03	-0.7	10.4
Vary Rate Ceiling									
$ 15,000	$ 1	9 %	0.002	0	0.01	-0.04	0.05	-0.7	2.4
$ 15,000	$ 5	9 %	0.045	0.01	0.19	0.06	-0.03	-0.7	35.7
$ 15,000	$ 10	9 %	0.082	0.02	0.3	0.08	-0.02	-0.7	50.1
$ 15,000	$ 20	9 %	0.086	0.01	0.32	0.07	-0.02	-0.7	52
Vary Income Cutoff									
$ 5,000	$ 3.9	9 %	0.094	0.02	0.26	0.04	-0.08	-0.8	35.5
$ 10,000	$ 3.9	9 %	0.052	-0.01	0.19	0.06	0	-0.7	31.7
$ 15,000	$ 3.9	9 %	0.037	0	0.15	0.06	-0.02	-0.7	29.5
$ 30,000	$ 3.9	9 %	0.027	0	0.1	0.07	-0.01	-0.7	21.7

The child care subsidy policy parameters are calibrated to averages across state level policy parameters. I use $15,000 for the income cutoff, $3.90 for the rate ceiling and 9% for the copay. Δ Cognitive, Δ Quality and Δ CCP are the average differences across treatment and baseline in cognitive skills, child care quality and child care participation for the subsidy eligible population (Intent to Treat). The two columns supertitled Eligibles shows the average quality for eligible subsidy users and eligible subsidy non-users. Home Quality reports the average home quality for the subsidy eligible population. % Switchers reports the percentage of children for whom the parents use the subsidy and make a different child care choice relative to baseline.

Table D.7:
The Effect of Child Care Subsidies on the Black-White (BW) Achievement Gap

			BW Achievement Gap	%Δ in BW Achievement Gap
Baseline gap across all periods			-0.2078	
Income Cutoff	Rate Ceiling	Copay		
\$15000	\$3.9	9%	-0.2086	-0.4
Vary Copay				
\$15,000	\$3.9	0%	-0.2102	-1.2
\$15,000	\$3.9	10%	-0.2068	0.5
\$15,000	\$3.9	20%	-0.2064	0.6
\$15,00	\$3.9	30%	-0.2069	0.4
Vary Rate Ceiling				
\$15,000	\$1	9%	-0.2083	-0.3
\$15,000	\$5	9%	-0.2108	-1.4
\$15,000	\$10	9%	-0.2052	1.3
\$15,000	\$20	9%	-0.2062	0.8
Vary Income Cutoff				
\$5,000	\$3.9	9%	-0.2062	0.8
\$10,000	\$3.9	9%	-0.2071	0.4
\$15,000	\$3.9	9%	-0.2086	-0.4
\$30,000	\$3.9	9%	-0.2087	-0.4
Targeted to Very Poor				
\$5,000	\$20	0%	-0.2042	1.7

Notes: The subsidy counterfactuals are relative to closing the black-white achievement gap averaged across all periods. The difference between the two numbers reflects the gradual opening of the black-white achievement gap. In the column %Δ in BW Achievement Gap, I report the percent change in the counterfactual black-white achievement gap relative to the simulated baseline black-white achievement gap for subsidy counterfactuals.