Gaps in Early Investments in Children

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Abstract

The human capital profiles of children start to diverge at an early age. Part of this divergence is explained by the differences in the environment that children experience early in their lives. This paper proposes a simple model to quantify the importance of four determinants of early investments: (i) heterogeneity in budget sets; (ii) heterogeneity in preferences; (iii) heterogeneity in the beliefs about the technology of skill formation; and (iv) heterogeneity in human capital at birth. This quantification is important to inform the design of policies that can be implemented should policymakers choose to act to reduce inequality in outcomes. I find that heterogeneity in preferences and beliefs plays an important role in explaining gaps in investments. I discuss possible interpretations of the findings as well as their policy implications.

1 Introduction

Inequalities in economic and social outcomes are fundamentally linked to gaps in skills before individuals start to work (Neal and Johnson, 1996; Carneiro, Heckman, and Masterov, 2005). The data show that policies that intervene late – such as paying a bonus to youth who complete high school or providing tuition subsidies to promote college enrollment – have very limited effects on reducing discrepancies in labor market performance or educational attainment (Cameron and Heckman, 1999; Keane and Wolpin,

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2000). In contrast, an increasing body of evidence shows that boosting early investments in disadvantaged children can substantially improve their performance in many important socio-economic outcomes (e.g., Olds et al, 2002; Campbell et al, 2008; Hoddinott et al, 2008; Heckman et al, 2010; Attanasio et al, 2012; Gertler et al, 2013). This pattern of low returns to late investments and high returns to early ones is consistent with current economic theory, which suggests that (i) early investments produce very basic skills that can be used to acquire other, more advanced ones and (ii) the lower the early investments are, the lower the returns to late investments (and vice-versa; see Cunha and Heckman, 2007).

It has been established that early investments are low in minority and disadvantaged families (e.g., Carneiro, Heckman, and Masterov, 2005; Moon, 2010). However, it is not yet clear why some families choose to invest so little in their children. For example, Cunha (2013) shows that a model in which parents face idiosyncratic fluctuations in income and inter-generational liquidity constraints reproduces the basic facts on parental investments in the human capital of children. Caucutt and Lochner (2012) argue that parents' inability to borrow against their own future income may also lead to sub-optimal early investments in children. A feasible policy prescription emanating from this literature is to subsidize life-cycle investments or supplement family income in order to neutralize the impact of intra- and/or inter-generational credit constraints that presumably play such an important role in determining low levels of investment. In contrast to these theoretical prescriptions, the practical interventions that are shown to have a long-term impact on human capital accumulation are the ones in which investments are delivered "in kind" to the child (e.g., Campbell et al, 2008; Hoddinott et al, 2008; Heckman et al, 2010) or that focus on improving the parent's knowledge in order to provide an enriched environment for his/her child (e.g., Olds et al, 2002; Attanasio et al, 2012; Gertler et al, 2013). In fact, even when cash is tranferred to poor families, it is done so with conditions that the family execute a minimum level of investment in children (e.g., the Progresa Program in Mexico as described in Todd and Wolpin, 2006 and Attanasio, Meghir, and Santiago, 2012). This literature suggests the existence of other reasons why certain families choose to invest so little in their children.

Why would some families invest so little in their children? At its most basic level, economic theory proposes at least four non-mutually exclusive explanations. First, suppose that all children are identical and that parents are the same in every aspect except that they face different budget constraints. Poor parents or parents that who higher prices of investments would thus invest less in their children. Increasing parental income or subsidizing prices of investments would thus increase early investments in children (e.g., Becker and Tomes, 1986; Dahl and Lochner, 2012).

Second, marginal returns to investments and, consequently, levels of investment, may be affected by the characteristics of the child. It is known that differences in ability across children may affect how investments are allocated across and within households (e.g., Behrman, Pollak, and Taubman, 1982; Aizer and Cunha, 2012). Differences in human capital at birth may lead to differential investments by parents, a situation that would at least partly explain gaps.[1]

Third, differences in maternal preferences about two (or more) distinct dimensions of human capital can also explain the observed pattern of investments. For example, Lynd and Lynd (1929, 1937) reported that working-class mothers ranked "strict obedience" as their most important childrearing goal more frequently than higher-SES mothers did. The sociology literature argues that the stronger preferences toward socio-emotional skills by lower-SES mothers reflect those mothers' forecasts for their children choosing occupations in which obedience and conformity have relatively higher returns (Kohn, 1963).

Fourth, maternal subjective beliefs about the technology of skill formation may be correlated with SES. These beliefs partially determine maternal expectations about returns to investments, which, in turn, determine investment choices. If markets are complete and if low SES mothers' beliefs generate low expectations for returns to investments, then low SES mothers will invest too little in their children.

The goal of the paper is to investigate how much of the gaps in early investments is due to differences in the budget constraints that parents face, differences in the child's characteristics, differences in beliefs about the technology of skill formation, and differences in preferences. This quantification matters because the different channels have distinct implications about what public interventions should be implemented to foster human capital formation.

To carry out this research, I propose an economic model of investments in children that incorporates all four mechanisms listed above. I use the model as a guide for the empirical analysis and for the discussion of identification challenges that need to be addressed. In order for the presentation to be as clear as possible, I break the estimation algorithm into three different steps. First, I build on the methodology proposed in Cunha, Elo, and Culhane (2013) to measure parental beliefs about the technology of skill formation. Specifically, Cunha, Elo, and Culhane (2013) show how respondents' answers to a set of questions related to child development are informative about subjective mean about *one* parameter of the technology of skill formation. I build on their study by developing a framework that allows the analyst to recover *subjective distributions* about all parameters of the technology of skill formation. I find that black respondents tend to report lower mean expectations of the parameter that governs the elasticity of child development with

[1] For example, in the mid 1990s, the mean birth-weight for singleton black infants in the U.S. was 3,132 grams, about 277 grams less than the mean birth-weight of 3,409 grams for whites (Martin, MacDorman, and Mathews, 1997).

respect to parental investments. This parameter plays an important role in determining what portion of household resources is allocated to investment in child development.

Second, I measure preferences by engaging respondents in a series of choice experiments. More precisely, I create scenarios of monthly household income and prices of investments. For each income-price scenario, I ask respondents to choose investments from a pre-specified choice-set. As I vary prices and income, I observe choices and beliefs and combine these sources of information to identify the parameters that characterize parents' utility. I find that black parents are more elastic to prices than white parents and that they have a lower valuation on cognitive development.

Third, I use the utility parameters and the beliefs data to simulate a model of parental investments in the human capital of children. I estimate the prices that different races face by matching average investments in the model with average investments in the CNLSY/79. Although black families have lower incomes, I find that they also face a lower price of investments.

The quantification I perform suggests that the gaps in early investments are primarily produced by differences in beliefs and differences in preferences. Roughly speaking, equalizing beliefs would increase the black-white ratio from 78% to close to 84%, and equalizing preferences would eliminate it. In contrast, equalizing budget constraints would increase the ratio to around 81%. Finally, the heterogeneity in human capital at birth plays a minor role in explaining the gaps.

The paper proceeds in the following way. Section 2 documents the racial gaps in early investments across races as implied by the CNLSY/79. Section 3 describes a simple model to quantify the gaps in early investments. Section 4 discusses how to identify and estimate each component of the model. Section 5 presents the data and the results. Section 6 discusses the validity of the findings, offers alternative interpretations, and studies their policy implications.

2 Gaps in Early Investments

In the CNLSY/79 data-set, investment is measured by the household score in the Home Observation for the Measurement of the Environment - Short Form (HOME-SF, Bradley and Caldwell, 1980, 1984). The scores are obtained from the summation of a series of multiple choice items that the interviewer elicits from the respondents. As shown by Cunha, Heckman, and Schennach (2010), it is possible to improve on the procedure by factor analyzing the items. The reason why there is an improvement is that a simple summation of scores ignores the differential informational content of items, while factor analysis does not.

A separate problem that makes interpretation of the results difficult is that the HOME-

Table 1
Heterogeneity in Investments
Dependent Variable: Investments from Birth to Age 2 (HOME Measured in Hours/Year)

	(1)	(2)	(3)	(4)
Mother is white	391.6***	365.5***	333.9***	352.4***
	(18.20)	(21.51)	(23.20)	(23.97)
Mother has high school diploma or at most some college (but no college degree)	148.4***	66.89**	47.69*	43.61
	(22.54)	(26.15)	(27.24)	(27.66)
Mother has at least a 2-year college degree	247.6***	130.7***	78.46**	65.47*
	(26.38)	(32.17)	(35.81)	(36.18)
Standardized human capital of the child at birth[1]	27.45***	28.23***	26.75***	26.02***
	(7.25)	(8.55)	(8.63)	(8.68)
Standardized naturallog of permanent income[2]		81.12***	69.33***	65.20***
		(10.73)	(11.09)	(11.26)
Standardized AFQT score[3]			45.29***	35.56***
			(12.05)	(12.44)
Standardized Rotter locus of control scale[4]				-18.44**
				(9.30)
Standardized Rosenberg self-esteem scale[5]				26.10***
				(9.25)
Constant	1,303***	1,397***	1,432***	1,446***
	(69.59)	(82.50)	(84.95)	(86.47)
Observations	4,001	3,116	3,021	2,937
R-squared	0.416	0.427	0.431	0.439

Standard errors are clustered at the level of the mother. All regressions have dummy variables for: (i) the child's gender, (ii) birth order, (iii) age at the time of measurement of the dependent variable, (iv) year of birth and (v) maternal age at the time of the child's birth.

[1]The human capital of the child at birth is estimated from a factor model in which the measures are the child's weight at birth, length at birth, and weeks of gestation. The latter is used to normalize the scale and location of the factor.

[2]Permanent income is the average family income from the year the child is born to the year the child reaches age 14.

3 The AFQT score is the composite of the scores in Word Knowledge, Paragraph Composition, Arithmetic Reasoning, and Mathematics Knowledge of the ASVAB.

[4]The Rotter locus of control scale measures the extent to which individuals believe that they can control events that affect them. In the NLSY/79, it takes on values between 4 and 16. Low values indicate that individuals tend to believe that they can control the events, while high values suggest that individuals believe that events are beyond their control.

[5]The Rosenberg self-esteem scale measures an individual's self-esteem. In the NLSY/79, it takes on values between 9 and 30. Low values indicate lack of self-esteem.

*** p<0.01, ** p<0.05, * p<0.1

SF score has no metric. To obtain a measure of investment in the metric of time, I proceed in two steps. First, I estimate the distribution of time spent investing in children from the Child Development Supplement of the Panel Study of Income Dynamics - Child Development Supplement (PSID-CDS). The PSID-CDS asks parents to report their children's time diaries for two days of the week (one weekday and one weekend day, both picked randomly). It is possible to use this information to construct a measure of parental investments in hours of interaction with their child per day. I approximate the density of investment time from the PSID-CDS data with a mixture of normal densities. Let $F_X(x)$ denote the distribution of time investment estimated from the PSID-CDS sample. I impose the same distribution on the factor that is extracted from the HOME-SF items from the CNLSY/79.[2] Specifically, let $M_{i,j}$ denote the response of household i for item j in the HOME-SF scale. I assume that the relationship between observed and latent investment $x_i$is given by the following equation:

$$M_{i,j} = b_{0,j} + b_{1,j}x_i + \varepsilon_{i,j}$$

where $\varepsilon_{i,j} \sim N\left(0, \sigma^2_{M,j}\right)$ is a measurement error, and $x_i \sim F_X$ is independent from $\varepsilon_{i,j}$.

The results in Table 1 show large differences in investments between white and black mothers. In all of the regressions shown in Table 1, I add dummies for the child's birth order, the child's year of birth, and maternal age at the time of birth. I divide mothers into three mutually exclusive groups of completed schooling at the time of the birth of the first child. The first group (omitted in the regressions shown in Table 1) is the mothers who are high school dropouts or who have a GED. The second group consists of women who are high school graduates. Some of these mothers may have attended college, but they have not obtained a college degree. The third group consists of mothers who have a two-year college degree or more. Column 1 shows that, controlling for education and the child's human capital at birth, white mothers spend almost 400 hours per year more than black mothers. The gaps in education are also sizeable: Mothers with at least a two-year college degree spend close to 250 hours per year more than mothers of the same race who are high school dropouts.

Column (2) controls for household "permanent income," which is the average household income from the year in which the child is born to the year in which the child turns fourteen years old. When I add this variable to the OLS regression, the black-white gaps in investment falls to 365 hours per year (that is, one hour per day). It is important to note

[2] The factors are identified up to location and scale normalizations. When F is the distribution of a normal random variable, then fixing F or normalizing the mean and variance of the factor distribution is exactly the same thing. To the extent that I don't assume normality, then fixing F is more restrictive then normalizing the mean and variance. The reason why I proceed in this fashion is so that I can use the HOME-SF scores to predict investments in a metric of time.

that the addition of household permanent income makes the education gaps substantially smaller.

In column (3), I add the maternal AFQT score, which is a measure of maternal cognitive skills. In column (4), I also add measures of maternal non-cognitive skills, the mother's scores in the Rotter locus of control and in the Rosenberg self-esteem scales. Interestingly, while the education gaps in column (4) are roughly 75% smaller than those in column (1), the black-white gap is only 10% smaller when the same columns are compared.

In summary, these regressions show that the black-white gap is large and not driven by observable differences across the characteristics of the child or the household. In the next section, I introduce a very simple model of investments in children that I will use as a guide for the remainder of the paper.

3 Model

I describe a one-period model in which the mother decides how much to invest in the human capital of the household's only child. Consider a mother i of race r_i who has income y_i that can be allocated between consumption c_i and child investment x_i. In every period, the mother faces the following budget constraint:

$$c_i + p_r x_i = y_i \tag{1}$$

where p_r stands for the price of investment in terms of consumption and it is allowed to vary by race. Because this is a static problem, I forgo issues about credit constraints that may be important in the determination of investments.

Let c_i and $q_{i,1}$ denote, respectively, household consumption and the quality of the child at the end of the period. The preferences of a mother of race r are represented by:

$$u\left(c_i, q_{i,1}; r_i\right) = \frac{c_i^{1-\lambda_r} - 1}{1-\lambda_r} + \alpha_r \frac{q_{i,1}^{1-\lambda_r} - 1}{1-\lambda_r} \tag{2}$$

The utility function is separable in consumption and child quality. The parameter $\alpha_r \geq 0$ captures how much a mother of race r values child development relative to consumption. The parameter $\lambda_r \geq 0$ denotes the elasticity of substitution between household consumption and child quality. If $\lambda_r = 0$, consumption and child quality are perfect substitutes. As λ_r increases, so does the complementarity between household consumption and child quality.

Following the empirical findings of Cunha, Heckman, and Schennach (2010), I assume that the production function of skills is Cobb-Douglas:[3]

$$\ln q_{i,1} = e^{\psi_i} x_i^{\gamma_i} q_{i,0}^{\rho_i} \tag{3}$$

where $q_{i,1}$ is the child quality at the end of the period. The inputs in the production of skills are (i) the stock of skills at the beginning of the period, $q_{i,0}$, and (ii) parental investments $x_{i,1}$. From the mother's point of view, the maternal productivity ψ_i, the investment share parameter γ_i, and the self productivity parameter ρ_i are random variables. I denote by F_i the subjective distribution of ψ_i, γ_i, and ρ_i, respectively.

Note that the notation in (3) is general enough to allow for the possibility that the technology of skill formation is heterogeneous across households. This has consequences for possible interpretations of the belief data that will be elicited below. In one interpretation, parents are misinformed about the technology they use (i.e., their mean beliefs are biased) or they are not very precise about the characteristics of the technology (i.e., their variance beliefs are large). Another possibility is that they are well informed about the technology they use, but the technology varies considerably from one household to another. These two interpretations can be separately identified if the researcher both observes the beliefs and has data to estimate the technology for each household. Unfortunately, the data I present in Section 5 contain information only about the beliefs, so it is not possible to differentiate between these two possible interpretations.

At the time when the mother makes investment choices, she knows her income y_i, investment prices p_r, the child's initial condition $q_{i,0}$, her preference parameters α_r and λ_r, and her subjective beliefs F_i . Thus, the maternal information set is $\Omega_i = \left(y_i, p_r, q_{i,0}, \alpha_r, \lambda_r, F_i\right)$. The problem of the mother is:

$$V\left(\Omega_i\right) = \max_{x_i} \; E\left[u\left(c_i, q_{i,1}; r\right) \middle| \, \Omega_i, x_i\right] \tag{4}$$

subject to the budget constraint (1) and the technology of skill formation (3). The expectation in (4) is with respect to the subjective beliefs about the technology of skill formation, F_i.

In spite of its simplicity, the model as it is does not have a closed-form solution except for one case. When $\lambda_r = 1$, the preferences are Cobb-Douglas. Then, it can be immediately concluded that investments are determined by the following policy function:

$$x_i = \left(\frac{\alpha_r \mu_{\gamma,i}}{1 + \mu_{\gamma,i}}\right) \frac{y_i}{p_r},$$

[3] Cunha, Heckman, and Schennach (2010) test and cannot reject the Cobb-Douglas formulation when they estimate the process using only cognitive skills (see the results in the online appendix of their paper).

where $\mu_{\gamma,i}$ is the expectation of γ_i. In the Cobb-Douglas case, it is clear that three mechanisms contribute to explain the differences in x_i across households. In particular, this policy function states that investments are an increasing function of "real income" $\left(\frac{y_i}{p_r}\right)$, preferences$(\alpha_r)$, and beliefs $\left(\mu_{\gamma,i}\right)$.

Although the Cobb-Douglas case makes the problem much simpler, it imposes two restrictions that are not interesting from the point of view of the investigation I intend to carry out in this paper. First, the child's human capital at birth $(q_{i,0})$ does not affect investment choices because the implied income and substitution effects exactly cancel each other. Second, it also implies that the higher the mean beliefs, the higher the investment. Neither of these conclusions is robust to variations in λ_r. For this reason, I do not impose the Cobb-Douglas formulation on the data. In the following section, I discuss in detail the identification of the model I have just described.

4 Identification

The identification of the model proposed in Section 3 is challenging because beliefs are not usually measured in data sets in which investments are observed. In this section, I show how the model can be estimated by pooling two data sets, the CNLSY/79 and the the Maternal Knowledge of Infant Development Study (MKIDS), which contain data on beliefs and also on stated choice, that can be used to estimate preferences.[4]

In order to make the argument as clear as possible, I describe the estimation algorithm in three stages. In the first stage, I describe how to recover the beliefs. In the second stage, I use the beliefs data to estimate preferences from the stated-choice data. In the third stage, I take preferences and beliefs as given and simulate investments from the model described in Section 3. Prices are chosen so that simulated moments from the model match the corresponding moments from the CNLSY/79 data.

4.1 Beliefs

4.1.1 The Survey Instrument

As shown in Section 3, a mother's decisions regarding how much to invest in her child depends not on the actual technology in place but rather on the beliefs F_i that she holds about the technology. The research design I describe next allows the analyst to measure beliefs F_i. A more complete description can be found in Cunha, Elo, and Culhane (2013), who also consider other ways to elicit beliefs.

[4] See Cunha, Elo, and Culhane (2013) for a description of the MKIDS data set.

In the MKIDS data set, maternal subjective beliefs are elicited by responding to an adapted version of the Motor-Social Development (MSD) instrument used in the CNLSY/79. In the MSD instrument, mothers answer 15 out of 48 items regarding motor, language, and numeracy development. These items are divided into eight components (parts A through H) that a mother completes contingent on the child's age. All items are dichotomous (scored "no" is equal to zero and "yes" is equal to one) and the total raw score for children of a particular age is obtained by a simple summation (with a range of 0 to 15) of the affirmative responses in the age-appropriate section. The key property of the instrument is that the tasks are described in language easily understood by the mothers and that the tasks are recognizable based on the daily interactions of mothers and their children.

As I now explain, although the questions are similar, they differ in two important details. In the original MSD instrument, a mother provides yes/no answers to questions about child development. For example, one of the items in the MSD scale for children who are twenty-four months old is: "Does your child speak a partial sentence of three words or more?" If the child has already spoken a partial sentence of three words or more, the mother chooses yes; otherwise, she chooses no.

The first difference is that in the MKIDS instrument, which is designed to measure subjective beliefs about the technology of skill formation, the mother is asked: "What do you think is the youngest age and the oldest age at which a child learns to speak a partial sentence of three words or more?" The respondent uses a sliding scale to indicate the age range in which she believes a child will develop these skills.

There is another important difference. Because I am interested in measuring the beliefs with respect to the parameters in the technology of skill formation (3), it is necessary for the respondents to provide answers to the above age-range question for different hypothetical levels of x_i and $q_{i,0}$. For this reason, the survey instrument describes for the expectant mother four different scenarios of investments and the baby's human capital at birth. In the first scenario, the baby's human capital at birth is "high" ($\overline{q}_0$) and the mother chooses a "high" level of investment ($\overline{x}$). In the second scenario, the mother also chooses a "high" level of investment ($\overline{x}$), but the baby's human capital at birth is "low" ($\underline{q_0}$). In the third scenario, the baby's human capital at birth is "high" ($\overline{q}_0$), but the mother chooses a "low" level of investment ($\underline{x}$). Finally, in the fourth scenario, the baby's human capital at birth is "low" ($\underline{q_0}$) and the maternal choice of investment is also low ($\underline{x}$). I emphasize that the levels of the two inputs in the technology of skill formation are invariant across groups of subjects in the survey. So, the variability in the beliefs arises because of the heterogeneity in the age ranges provided by survey respondents.

Before answering the survey questions, the respondents watch a five-minute video that explains in detail the differences between the baby's "high" and "low" human capital at birth. In the instrument, "high" human capital at birth means that the baby is "healthy" at birth, while "low" human capital at birth corresponds to a baby who is "not healthy" at birth. As explained to the mother, a "healthy" baby is one whose gestation lasts nine months, and who weighs eight pounds and is twenty inches long at birth. Conversely, the "not healthy" baby is a baby that is born after seven months of gestation, and who weighs only five pounds and is only eighteen inches long at birth. The "healthy" and "not healthy" babies occupy extremely different positions in the distribution of human capital at birth: the "healthy" baby is around the sixtieth percentile in the distribution, while the "not healthy" baby is around the first percentile.

The video also shows examples of activities that mothers do with the child. With the exception of breastfeeding, all of the activities are part of the Home Observation for the Measurement of Environment – Short Form (HOME-SF) instrument: (a) soothing the baby when he/she is upset; (b) moving the baby's arms and legs around playfully; (c) talking to the baby; (d) playing peek-a-boo with the baby; (e) singing songs with the baby; (f) telling stories to the baby; (g) reading books to the baby; and (h) taking the baby outside to play in the yard, park, or playground. The activities are the same for the "high" and "low" levels of investment. The difference is in the amount of time: in the "high" level, mothers spend more time doing these activities than in the "low" level. In the survey instrument, I say that in the "high" level the mothers spend six hours a day doing these types of activities, while in the "low" level they spend only two hours a day. These figures correspond, respectively, to roughly the 15th and 85th percentile of investments.

I now discuss how to transform the answer to the question asked in our instrument – "What do you think is the youngest age and the oldest age at which a child learns to do [an MSD task]?" – into a measurement of the subjective beliefs of child development at age twenty-four months. In order to do so, I break the problem into three steps. In the first step, I transform the age range into the probability that a child will learn a given MSD task by twenty-four months. In the second step, I transform this probability into an estimate of the child's skill for each scenario and for each MSD item. In the third step, I use these estimates of child skills to estimate a measurement-error model from which I recover beliefs F_i.

4.1.2 Transforming Age Ranges into Probabilities

Without loss of generality, consider the scenario in which both the human capital at birth and investments are "high." For this scenario, suppose that the survey respondent states that the youngest and oldest age at which a child will learn how to speak partial sentences of three words or more is $\underline{a}$ and $\overline{a}$ months, respectively. My interpretation of the answer is that the respondent believes that the probability that the child will be able to speak a partial sentence of three words or more before age $\underline{a}$ is a number Δ_0 (arbitrarily) close to zero and the probability after age $\overline{a}$ months is a number Δ_1 (arbitrarily) close to one. To infer the respondent's subjective probability that the child will learn how to speak partial sentences by twenty-four months, I need to somehow construct how the probability varies with age. Suppose, for example, that the relationship between probability and age is logistic. That is, let $pr_{i,j,k}(a)$ denote the maternal subjective expectation that the child i will be able to do MSD item j (e.g., "speak a partial sentence of three words or more") under hypothetical scenario k by age a months. Under the logistic assumption, this probability is linked to the child's age according to the following parametric specification:

$$\ln \frac{pr_{i,j,k}(a)}{1 - pr_{i,j,k}(a)} = r_{i,j,k,0} + r_{i,j,k,1}a. \tag{5}$$

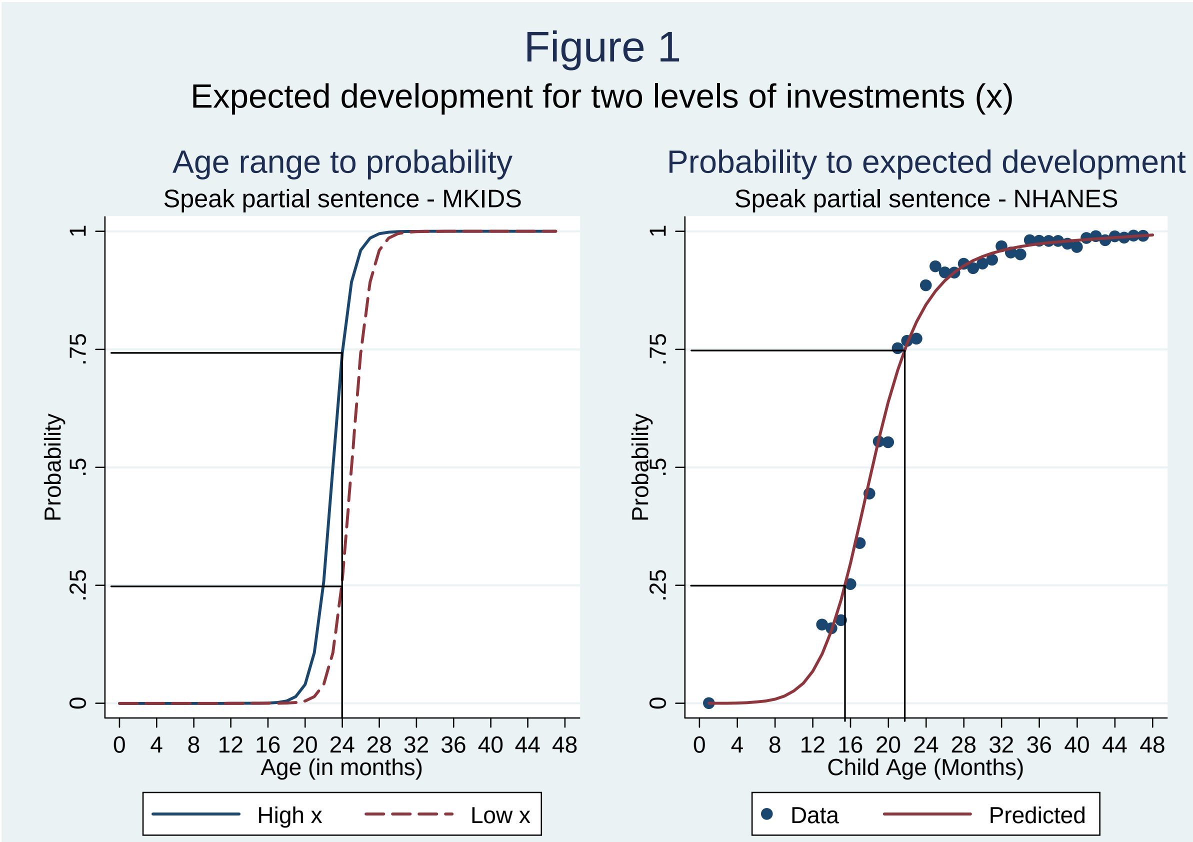
Given Δ_0 and Δ_1, the parameters $r_{i,j,k,0}$ and $r_{i,j,k,1}$ are just identified from the data provided by the survey respondent. Given the knowledge of the parameters $r_{i,j,k,0}$ and $r_{i,j,k,1}$, I can invert the logistic function (5) to predict the probability at twenty-four months:

$$pr_{i,j,k}(24) = \frac{\exp\left\{r_{i,j,k,0} + r_{i,j,k,1}24\right\}}{1 + \exp\left\{r_{i,j,k,0} + r_{i,j,k,1}24\right\}}.$$

For concreteness, Figure 1 (left panel) illustrates this algorithm for two different scenarios of investments. In both scenarios, the baby's human capital at birth is "high." When investment is "high," suppose that a respondent states that the youngest and oldest ages are eighteen and twenty-eight months, respectively. If I choose $\Delta_0 = 0.005$ and $\Delta_1 = 0.995$, then the interpolation under the logistic assumption implies that the probability at twenty-four months is around 0.75 (Figure 1, left panel, solid curve). For comparison, when investment is "low," suppose that the same respondent reports that the lowest and highest ages are twenty and thirty months, respectively. Using the same values for Δ_0 and Δ_1, the higher age range implies a lower probability of learning how to "speak a partial sentence of three words or more" at twenty-four months of around 0.25 (Figure 1, left panel, dashed curve).

4.1.3 Transforming Probabilities into Development

To derive an error-ridden measure of maternal expectation of development at age twenty-four months, $q_{i,j,k}$, from the probability obtained in the previous step, $pr_{i,j,k}(24)$, I explore the information from the National Health and Nutrition Examination Survey (NHANES) data set. An important feature of the MSD instrument is that its items are asked about children who are at very different ages. For example, the MSD item "speak a partial



sentence of three words or more" is asked about children who are between 13 and 47 months. This large variation in age makes it possible to estimate the fraction of children who can perform the same task at each age a, a quantity that I denote by $\chi_{j,a}$. I can then estimate how this probability evolves with age by adopting the following "flexible" logistic specification:

$$\ln \frac{\chi_{j,a}}{1-\chi_{j,a}} = g_j\left(a\right) + \nu_{j,a}$$

where $g_j\left(a\right)$ is monotonically increasing in a and $\nu_{j,a}$ is an error term that is orthogonal to age a. For illustration purposes, Figure 1 (right panel) shows the data and the resulting logistic prediction for the MSD item "speak a partial sentence of three words or more." Clearly, the function $g_j\left(a\right)$ provides a very good fit of the data.

The interpretation of the function $g_j\left(a\right)$ is straightforward: If I had 100 children who are a months old, I would expect $100 \times \frac{\exp\left\{g_j(a)\right\}}{1+\exp\left\{g_j(a)\right\}}$ of them to be able to "speak a partial sentence of three words or more." Conversely, consider a group of 100 children, all of whom have the same unknown age. Suppose that a fraction pr of children in this group could "speak a partial sentence of three words or more." Would it be possible to estimate the age of this group of children from the information above? The answer is yes! Given the monotonicity of the function $g_j\left(a\right)$, I can invert it to obtain an estimate of the age of the children in the group. The estimator would be

$$\hat{a} = g_j^{-1}\left[\ln \frac{pr}{1-pr}\right]. \tag{6}$$

It turns out that when I use the probability $pr_{i,j,k}(24)$ derived in subsection 4.1.2 in the right-hand side of (6) above, I obtain in the left-hand side of (6) the error-ridden measure of maternal expectations of child development at twenty-four months, $q_{i,j,k}$. That is, $q_{i,j,k} = g_j^{-1}\left[\ln \frac{pr_{i,j,k}(24)}{1-pr_{i,j,k}(24)}\right]$. Importantly, the higher the subjective probability that the mother reports for a given item j and scenario k, the higher the corresponding quality $q_{i,j,k}$. Figure 2 illustrates the mechanics of the argument. Again, consider the hypothetical survey respondent in subsection 4.1.2. As discussed above, her answers imply probabilities around 0.75 and 0.25 for the "high" and "low" investment scenarios, respectively. As shown in Figure 1 (right panel), 25% of the children who are about sixteen months old and 75% of the children who are about twenty-two months old have already learned "how to speak a partial sentence of three words or more." Thus, when investment is "high," the mother expects the 24-month-old child to have the skills of the typical 22-month-old child; when investment is "low," she expects the 24-month-old child to attain the development level of a typical 16-month-old child.

4.1.4 Estimating Beliefs

For each respondent i and MSD item j I have the following system:

$$\ln q_{i,j,k} = \psi_i + \rho_i \ln q_{0,k} + \gamma_i \ln x_k + \zeta_{i,j,k}, \qquad k = 1,2,3,4. \tag{7}$$

where k indexes the scenarios of investments and human capital at birth. In principle, I could estimate the parameters ψ_i, ρ_i, and γ_i by running a simple OLS regression in (7). Let $\hat{\psi}_{i,j}$, $\hat{\rho}_{i,j}$, and $\hat{\gamma}_{i,j}$ denote the OLS estimates implied by the responses to MSD item j. I would then estimate individual means by using the familiar expressions:

$$\mu_{\psi,i} = \tfrac{1}{J}\textstyle\sum_{j=1}^{J} \hat{\psi}_{i,j}, \quad \mu_{\rho,i} = \tfrac{1}{J}\textstyle\sum_{j=1}^{J} \hat{\rho}_{i,j}, \quad \mu_{\gamma,i} = \tfrac{1}{J}\textstyle\sum_{j=1}^{J} \hat{\gamma}_{i,j}\ .$$

Given means, I estimate variances in the following fashion:

$$\sigma^2_{\psi,i} = \tfrac{1}{J-1}\textstyle\sum_{j=1}^{J}\left(\hat{\psi}_{i,j}-\mu_{\psi,i}\right)^2, \quad \sigma^2_{\rho,i} = \tfrac{1}{J-1}\textstyle\sum_{j=1}^{J}\left(\hat{\rho}_{i,j}-\mu_{\rho,i}\right)^2, \quad \sigma^2_{\gamma,i} = \tfrac{1}{J-1}\textstyle\sum_{j=1}^{J}\left(\hat{\gamma}_{i,j}-\mu_{\gamma,i}\right)^2\ .$$

If I ignore the fact that part of the variability in $\hat{\psi}_{i,j}$, $\hat{\rho}_{i,j}$, and $\hat{\gamma}_{i,j}$ is due to measurement error and assume that ψ_i, ρ_i, and γ_i are independent and normally distributed, the above strategy would be sufficient to recover beliefs. Instead, I pursue a different approach that allows for measurement error and does not impose normality. It is easy to see that equation (7) is a factor model in which ψ_i, ρ_i, and γ_i are the factors with corresponding factor loadings "1," " $\ln q_{0,k}$," and " $\ln x_k$." The term $\zeta_{i,j,k}$ is the uniqueness, which I assume is normally distributed and independent from the factors ψ_i, ρ_i, and γ_i. Identification of the model follows from the analysis in Schennach (2004).

In practical terms, I approximate the subjective beliefs F_i with a discrete approximation with N given support points. Thus, the contribution of individual i to the log-likelihood is:

$$l_i = \sum_{n=1}^{N} \pi_n \prod_{j=1}^{J} \prod_{k=1}^{4} \phi \left(\ln q_{i,j,k}, \psi_{i,n} + \rho_{i,n} \ln q_{0,k} + \gamma_{i,n} \ln x_k, \sigma^2_{\zeta,j,k} \right)$$

where ϕ denotes the pdf of a normal random variable and $\sigma^2_{\zeta,j,k}$ is the variance of $\zeta_{i,j,k}$. Let $\pi = (\pi_n)$ and $\sigma^2_\zeta = \left[\left(\sigma^2_{\zeta,j,k} \right)_{k=1}^{4} \right]_{j=1}^{J}$. The optimization problem is to solve:

$$\left(\sigma^2_\zeta, \pi \right) = \arg\max \sum_{i=1}^{I} l_i. \tag{8}$$

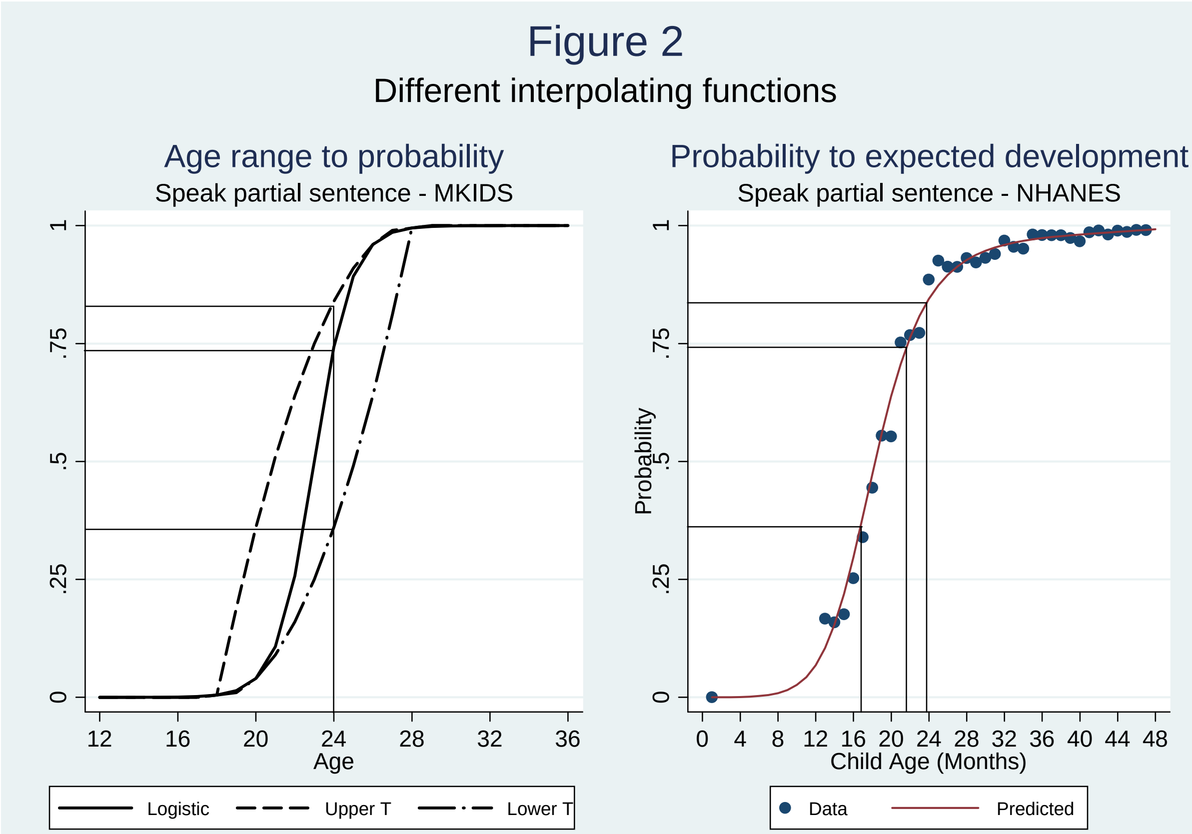
Given estimated parameters, I can estimate individual beliefs by:

$$\hat{\pi}_{i,l} = \frac{\pi_l \prod_{j=1}^{J} \prod_{k=1}^{4} \phi \left(\ln q_{i,j,k}, \psi_{i,l} + \rho_{i,l} \ln q_{0,k} + \gamma_{i,l} \ln x_k, \hat{\sigma}^2_{\zeta,j,k} \right)}{\sum_{n=1}^{N} \pi_n \prod_{j=1}^{J} \prod_{k=1}^{4} \phi \left(\ln q_{i,j,k}, \psi_{i,n} + \rho_{i,n} \ln q_{0,k} + \gamma_{i,n} \ln x_k, \sigma^2_{\zeta,j,k} \right)}. \tag{9}$$

for $l = 1, ..., N$ and $i = 1, ..., I$. Given probabilities $\hat{\pi}_{i,l}$ for each individual, I can compute moments such as means and variances.

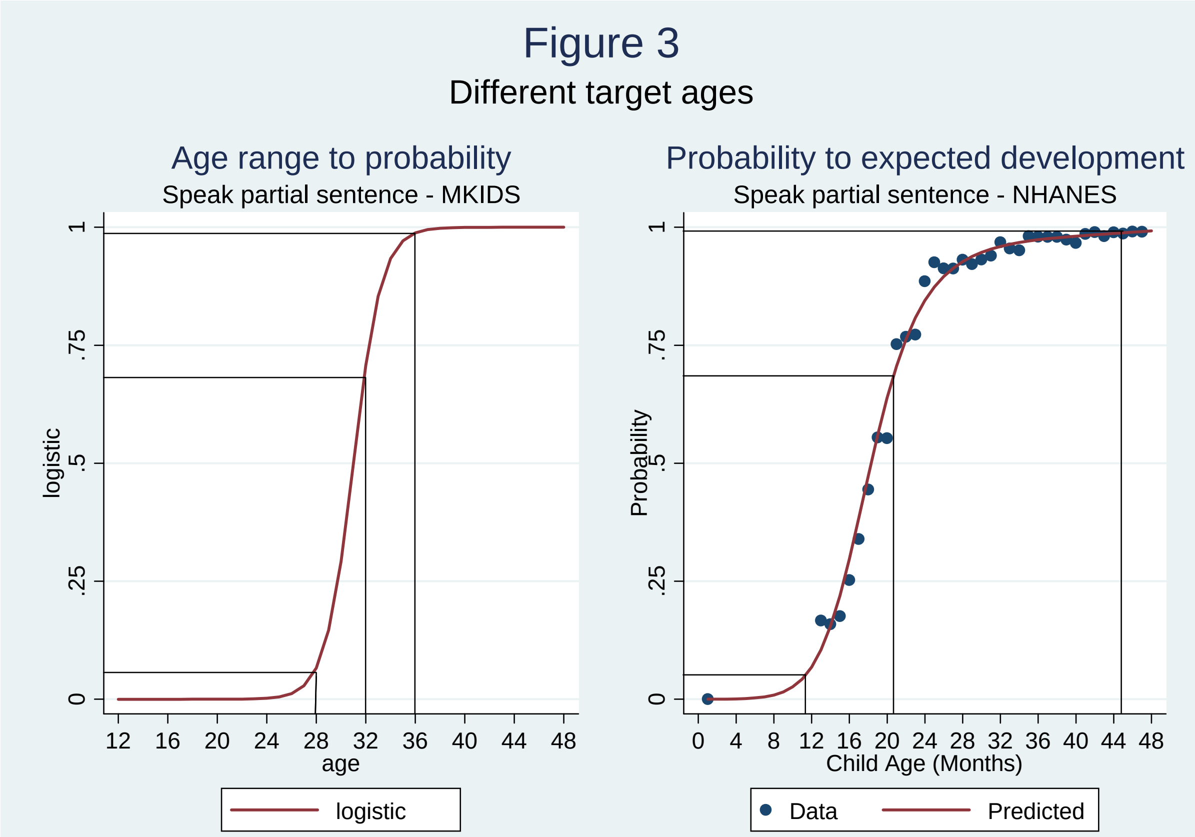
4.1.5 Alternative Interpolating Functions and Target Ages

Clearly, the logistic function is only one (of infinitely many) possible way to interpolate between the youngest and oldest ages provided by the respondent. It is thus important to consider a few alternatives that are informative about the range of values that beliefs can take. Consider the scenario in which q_0 and x are "high" and suppose that the survey respondent states that the youngest and oldest age at which a child will learn how to speak partial sentences of three words or more is $\underline{a}$ and $\overline{a}$ months, respectively. Then, I envelop the logistic distribution between $\underline{a}$ and $\overline{a}$ by defining the following two triangular distributions. The "upper" triangular distribution is the one in which the mode is set arbitrarily close to $\underline{a}$, while the "lower" triangular distribution is the one in which the mode is set arbitrarily close to $\overline{a}$. Figure 2 plots the logistic as well as the upper and lower triangular distributions for a hypothetical respondent who provides $\underline{a} = 18$ and



$\bar{a} = 28$ months. Let $F_{UT}(a)$, $F_{LT}(a)$, and $F_{LOG}(a)$ denote, respectively, the upper triangular, lower triangular, and logistic distribution. Note that for any $a \in [\underline{a}, \bar{a}]$ I have $F_{LT}(a) \leq F_{LOG}(a) \leq F_{UT}(a)$. For example, if $\underline{a} = 18$ and $\bar{a} = 28$, then $F_{LT}(24) \simeq 0.36$, $F_{LOG}(24) \simeq 0.75$, and $F_{UT}(24) \simeq 0.84$. These probabilities, in turn, translate into expected developmental levels of approximately seventeen, twenty-two, and twenty-four months, respectively. In the empirical results in Section 5, I report not only the beliefs implied by the logistic interpolation but also the ones generated by using the "upper" and "lower" triangular interpolating functions.

It is known that parents tend to overestimate the age at which children achieve developmental milestones (e.g., Epstein, 1979; Ninio, 1988). For example, suppose that in the scenario in which both q_0 and x are "high," the mother reports that $\underline{a} = 25$ and $\bar{a} = 38$ and for the scenario in which q_0 is "high," but x is "low," she reports that $\underline{a} = 27$ and $\bar{a} = 40$. In this case, the probabilities for both scenarios at age twenty-four months would be equal to the lower bound Δ_0. Because of this fact, $q_{i,j,k} = g_j^{-1}\left[\ln \frac{\Delta_0}{1-\Delta_0}\right]$ and it would follow that the subjective expected return would be zero. In order to evaluate the importance of overestimation of the age at which children attain the developmental milestones used in the survey, I also consider three other target ages: twenty-eight, thirty-two, and thirty-six months. Figure 3 illustrates the argument for the example in which the respondent states that $\underline{a} = 25$ and $\bar{a} = 38$. In this case, the logistic interpolation at age twenty-four months



(not shown in Figure 3) implies a probability of 0.002. In contrast, the probability is 0.065, 0.71, and 0.99 when the target ages are twenty-eight, thirty-two, and thirty-six months, respectively. In the empirical results that I report in Section 5, I consider all possible combinations of the three different interpolating functions with the four possible target ages.

4.2 Preferences

The beliefs $F_i = (\widehat{\pi}_{i,n})_{n=1}^{N}$ obtained in Section 4.1 are an input in the estimation of the preference parameters α_r and λ_r. For this part of the analysis, I explore the data from s series of choice experiments with the MKIDS participants. In all of the experiments, the respondents are told to assume that the child's human capital at birth is "high." The study subject is presented with a series of nine hypothetical scenarios of monthly income and prices of investments that arise from distinct combinations of monthly income, taking values in the set $\mathcal{Y} = \{\$1,500; \$2,500; \$3,500\}$, and prices of investment goods, itself an element in the set $\mathcal{P} = \{\$30; \$45; \$60\}$. In each one of these scenarios, the expectant mother picks what she considers the optimal alternative in a pre-specified choice set.

In order to explain to the respondent that investments are costly, a three-minute video explains that the more time the mother interacts with her child, the more money she has to spend every month on educational goods, such as children's books and educational toys. The concept is illustrated with the following examples:

> "If [the mother] spends two hours a day interacting with the child, she needs to buy two books and two educational toys per month... But if she spends three hours a day, she needs to buy three books and three educational toys per month... and so on."

For each combination of prices and income, the respondents are asked the following question:

> "Suppose that your household income is \$$y$ per month and that for each hour per day that the mother spends interacting with the child she has to spend \$$p$ per month on educational goods. Consider the following four options..."

The four options represent different levels of investments, measured in hours of interaction per day, in the individual's choice set $\mathcal{X} = \{2, 3, 4, 5\}$. Let $v(x_{i,m,n}, p_m, y_n)$ denote the utility of choosing $x_{i,m,n}$ when the choice-experiment scenario is defined by $(p_m, y_n) \in P \times \mathcal{Y}$. Then:

$$v(x_{i,m,n}, p_m, y_n, \overline{q}_0) = E_{F_i}\left[\left.\frac{(y_n - p_m x_{i,m,n})^{1-\lambda_r} - 1}{1-\lambda_r} + \alpha_r \frac{\left(e^{\psi_i} x_{i,m,n}^{\gamma_i} \overline{q}_0^{\rho_i}\right)^{1-\lambda_r} - 1}{1-\lambda_r}\right| y_n, p_m, x_{i,m,n}, \overline{q}_0\right] \quad (10)$$

The expectation in (10) is taken with respect to the beliefs F_i and conditional on the state variables that determine each one of the nine scenarios described to the respondent. The underlying assumption is that the reported choice is the solution to the problem:

$$V(p_m, y_n, \overline{q}_0) = \max_{x \in \mathcal{X}} \{v(x, p_m, y_n, \overline{q}_0) + \xi_{i,h,m,n}\},$$

where the shock $\xi_{i,h,m,n}$ is an error term that is, by construction, uncorrelated with the exogenously chosen prices π_m and income y_n. The respondent reports choice x^* if, and only if:

$$\xi_{i,x,m,n} - \xi_{i,x^*,m,n} \leq v(x^*, p_m, y_n, \overline{q}_0) - v(x, p_m, y_n, \overline{q}_0)$$

for all $x \in \mathcal{X}$ and $x \neq x^*$. If we assume that $\xi_{i,x,m,n}$ follows an extreme value distribution, then without loss of generality, the probability that a respondent chooses $x^* = 2$ is given by:

$$\Pr(x^* = 2 | p_m, y_n, \overline{q}_0) = \frac{e^{v(2, p_m, y_n, \overline{q}_0)}}{\sum_{x \in \mathcal{X}} e^{v(x, p_m, y_n, \overline{q}_0)}}.$$

Note that this is the probability for one combination of prices and income. The contribution of an individual to the likelihood is, thus:

$$L_i = \prod_{p_m \in P} \prod_{y_n \in Y} \left\{ \prod_{x \in \mathcal{X}} \Pr\left(x^* = x \,|\, p_m, y_n, \overline{q}_0 \right)^{\mathbf{1}(x^*=x)} \right\}$$

The likelihood is maximized with respect to the utility function parameters.

4.3 Prices of Investments

In this section, I show how to estimate the investment prices p_r that mothers of race r face. In order to do so, I use the beliefs F_i and preference parameters α_r and λ_r. Intuitively, prices are estimated by matching the average investments of parents of race r from the CNLSY/79 data with the average investments of parents of the same race r simulated from the model presented in Section 3.

More specifically, I start by drawing a simulated individual s from the MKIDS data set. In practical terms, a simulated individual in MKIDS is the vector $(y_s, F_s, \alpha_r, \lambda_r)$. The income variable is directly observed in the data, the beliefs are the ones recovered in Section 4.2, and the preference parameters are estimated in Section 4.3. In order to solve the model, I need to know all of the variables in the vector Ω_s, but the MKIDS does not report information on $q_{s,0}$ because the respondents were pregnant at the time of choice. To solve this problem, I draw $q_{s,0}$ from $G_{Q_0|r}$ which is the CNLSY/79 distribution of q_0 conditional on race r. Given the vector Ω_s, I solve the following problem for simulated individual s:

$$x_s^* = \arg\max_{x_s \in \mathbb{R}_+} \left\{ \frac{(y_s - p_r x_s)^{1-\lambda_r} - 1}{1-\lambda_r} + \alpha_r \sum_{l=1}^{N} \widehat{\pi}_{s,l} \frac{\left(e^{\psi_s} x_s^{\gamma_s} q_{s,0}^{\rho_s} \right)^{1-\lambda_r} - 1}{1-\lambda_r} \right\}$$

Let S_r denote the number of simulated individuals of race r and define:

$$\widehat{x}_r = \frac{1}{S_r} \sum_{s=1}^{S_r} 1\left(r_s = r\right) x_s^*.$$

Let $\overline{x}_r$ denote the average investment of parents of race r in the CNLSY/79. Then, the estimated prices are the solution to:

$$p^* = \{p_r^*\}_{r=1}^{R} \min_{\pi} \sum_{r=1}^{R} \left(\widehat{x}_r - \overline{x}_r\right)^2.$$

Table 2
Demographic Characteristics

	Overall (N = 224)		Black (N = 158)		White (N = 66)	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Age	25	6	23	5	29	6
Household Income	2733	2284	1951	1381	4604	2871
Education	Fraction		Fraction		Fraction	
Dropout or GED	15.2		17.7		9.1	
High school graduate	33.9		42.4		13.6	
Some college, no degree	22.8		27.9		10.6	
Two-year college degree	4.9		4.4		6.1	
Four-year college degree or above	23.2		7.6		60.6	
Type of Medical Insurance						
Private	31.7		16.5		68.2	
Medicaid	60.7		73.4		30.3	
Other	7.6		10.1		1.5	
Marital Status						
Single	60.2		73.4		28.8	
Married or cohabiting	38.8		25.3		71.2	
Separated or divorced	1.0		1.3		0.0	

5 Results

5.1 Data

I start by describing the Maternal Knowledge of Infant Development Study (MKIDS) data. The sample is recruited from four prenatal clinics affiliated with a university hospital in Philadelphia, PA. Eligibility criteria include women who were currently pregnant, at least 18 years of age, English-speaking, and had at most only one previous live birth.

The recruitment procedures consisted of the following: every week, clinic staff released to the study coordinator a list of the date, time, and location of prenatal appointments of potentially eligible study participants. Once a potential participant registered at the clinic, the interviewer approached her to explain the study and screen for eligibility. If eligible, the participant was asked to provide written informed consent. Over 1,300 subjects were approached, of whom 539 were deemed eligible. Of these women, 535 agreed to participate. Subjects who completed the entire survey received $25 for their participation. The interview was conducted in a private office at the prenatal clinic while the respondents waited for their prenatal care visit.

The analysis in this paper focuses on the 224 black and white participants who were assigned the instrument with the questions on beliefs and choice experiments. Table 2 shows the demographic characteristics of the sample. The study participants are young:

On average, the typical black participant is twenty-three years old and the white subjects are six years older. There are large differences in educational attainment across races: sixty percent of blacks are, at most, high-school graduates, while sixty percent of whites have at least a two-year college degree. The inequality between blacks and whites also shows up in resources: the typical household income of black participants is around $2,000 per month, which is less than fifty percent of the monthly household income of white participants. Another indication of the prevalence of poverty in the black sample is that seventy-three percent of the respondents are on Medicaid and the corresponding figure for whites is thirty percent. Finally, there is a large difference in marital status by race: over seventy percent of blacks are single; in contrast, over seventy percent of whites are married.

5.2 Estimated Beliefs

Before discussing racial differences in summary statistics for the beliefs, I present "raw" features of maternal answers. Table 3 presents the average natural logarithm of child development for each one of the four scenarios. To remind the reader, respondents provide the youngest and oldest age for each MSD item and scenario. I then transform the age information into probabilities which, in turn, I transform into corresponding levels of child development. This is done for each respondent, each MSD item, and each scenario. To construct the figures in Table 3, I first take the average child development across all MSD items for a given respondent and a given scenario. Then, I take the average across individuals within a race for a given scenario. Table 3 shows that the averages in Scenarios "1" and "2" obtained from white respondents are higher than the ones provided by black respondents. Most of the differences in Scenarios "3" and "4" are not large enough to be statistically significant.

To understand the results about beliefs I am going to report below, it is useful to analyze in more detail the numbers reported in Table 3. The beliefs about γ_i are identified by comparing answers from Scenario "1" with the ones from Scenario "3" or Scenario "2" to Scenario "4." For example, consider the numbers reported for the logistic interpolation at twenty-four months. If we take the typical black parent and give equal weight to all scenarios, then mean beliefs about γ_i for the typical black parent would be:

$$\mu_{\gamma,i}^{Black} = \frac{1}{2}\left(\frac{2.92 - 2.66}{\ln 6 - \ln 2}\right) + \frac{1}{2}\left(\frac{2.77 - 2.50}{\ln 6 - \ln 2}\right) = 0.2412,$$

while for the white mother it would be:

$$\mu_{\gamma,i}^{White} = \frac{1}{2}\left(\frac{3.15 - 2.78}{\ln 6 - \ln 2}\right) + \frac{1}{2}\left(\frac{3.01 - 2.59}{\ln 6 - \ln 2}\right) = 0.3595.$$

Table 3

Median log child development across all MSD items, by race

	Scenario 1			Scenario 2			Scenario 3			Scenario 4		
	Black	White	Diff.	Black	White	Diff.	Black	White	Diff.	Black	White	Diff.
Logistic at 24 months	2.42	2.54	*	2.32	2.36		2.23	2.28		2.17	2.14	
Logistic at 28 months	2.76	2.94	**	2.61	2.76	**	2.50	2.58		2.36	2.39	
Logistic at 32 months	3.06	3.28	***	2.89	3.13	***	2.78	2.90		2.59	2.69	
Logistic at 36 months	3.28	3.55	***	3.15	3.45	***	3.04	3.21	**	2.84	2.98	*
Lower triangular at 24 months	2.39	2.50	*	2.29	2.33		2.20	2.25		2.15	2.12	
Lower triangular at 28 months	2.66	2.82	**	2.52	2.64	**	2.41	2.50		2.30	2.32	
Lower triangular at 32 months	2.92	3.15	***	2.77	3.01	***	2.66	2.78	*	2.50	2.59	
Lower triangular at 36 months	3.22	3.48	***	3.07	3.38	***	2.97	3.14	**	2.76	2.93	**
Upper triangular at 24 months	2.49	2.62	**	2.38	2.45		2.28	2.34		2.22	2.19	
Upper triangular at 28 months	2.93	3.10	**	2.73	2.91	***	2.62	2.70		2.45	2.50	
Upper triangular at 32 months	3.18	3.42	***	3.03	3.30	***	2.92	3.06	*	2.72	2.84	
Upper triangular at 36 months	3.33	3.60	***	3.20	3.52	***	3.10	3.29	**	2.89	3.07	**

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: In scenario 1, the child is "healthy" at birth and the mother spends 6 hours/day interacting with the child. In scenario 2, the child is "not healthy" at birth and the mother spends 6 hours/day interacting with the child. In scenario 3, the child is "healthy" at birth and the mother spends 2 hours/day interacting with the child. Finally, in scenario 4, the child is "not healthy" at birth and the mother spends 2 hours/day interacting with the child. A "healthy" child is one whose gestation lasts 9 months, and who weighs 8 pounds and is 20 inches long at birth. A "not healthy" child is the whose gestation lasts 7 months, and who weighs 5 pounds and is 18 inches long at birth.

By analogy, parental beliefs about ρ_i are identified by contrasting answers between Scenarios "1" and "2" or Scenarios "3" and "4." Again, the figures in Table 3 suggest that the mean beliefs about ρ_i for the typical black parent is:

$$\mu_{\rho,i}^{Black} = \frac{1}{2}\left(\frac{2.92-2.77}{\ln 9.10-\ln 7.34}\right)+\frac{1}{2}\left(\frac{2.66-2.50}{\ln 9.10-\ln 7.34}\right) = 0.7211,$$

while for the typical white mother it is:

$$\mu_{\rho,i}^{White} = \frac{1}{2}\left(\frac{3.15-3.01}{\ln 9.10-\ln 7.34}\right)+\frac{1}{2}\left(\frac{2.78-2.59}{\ln 9.10-\ln 7.34}\right) = 0.7677.$$

Finally, the beliefs about ψ_i affect the "residual" level across all four scenarios of investments and human capital at birth.[5]

I approximate the respondent's beliefs by estimating a discrete probability density function for the random variables ψ_i, ρ_i, and γ_i. One advantage of using the discrete approximation is that I don't have to make parametric assumptions about the distribution of beliefs. Let $K_\psi = \left\{k_n^\psi\right\}_{n=1}^{N_\psi}$,$K_\gamma = \left\{k_n^\gamma\right\}_{n=1}^{N_\gamma}$, and $K_\rho = \left\{k_n^\rho\right\}_{n=1}^{N_\rho}$ denote, respectively, the support of ψ_i, ρ_i, and γ_i. The larger the number of points in the support, the more accurate the discrete approximation will be. On the other hand, the larger the number of points, the more costly the computational aspects of the problem. I assume that $N_\psi = 15$, $N_\gamma = N_\rho = 21$ and that the points in the support are equidistant. Given the chosen number of points, an unrestricted density function would contain over 6,600 parameters which is computationally not feasible to estimate given the small number of observations in the MKIDS data set. For this reason, I assume that the random variables are independent. This assumption substantially reduces the number of parameters to be estimated.

As explained in Section 4.1.4, the likelihood function (8) is maximized with respect to the parameter vector $\left(\pi, \sigma_\zeta^2\right)$. Given the estimated parameter $\widehat{\pi}$, I estimate individual belief parameters $\widehat{\pi}_i$ through equation (9). Given these individual belief parameters, I can estimate individual mean and standard deviations for each individual. For example, the mean and the standard deviation of γ, respectively denoted by $\mu_{\gamma,i}$ and $\sigma_{\gamma,i}$, implied by the beliefs of individual i are given by:

$$\mu_{\gamma,i} = \sum_{n=1}^{N_\gamma} \pi_{i,n}^\gamma k_n^\gamma$$

$$\sigma_{\gamma,i} = \sqrt{\sum_{n=1}^{N_\gamma} \pi_{i,n}^\gamma \left(k_n^\gamma - \mu_{\gamma,i}\right)^2}$$

Table 4 shows the median (by race) of the mean (μ_i) and standard deviation (σ_i) of the

[5] The comparison is not direct because Table 3 reports average levels of child development by scenario, while Table 4 reports median belifs.

Table 4

Black and White Differences in Means and Standard Deviation of

	Mean of γ			Mean of ψ			Mean of ρ		
	Black	White	Difference	Black	White	Difference	Black	White	Difference
Logistic 24 months	0.153	0.205	0.052 **	1.365	1.320	-0.045 **	0.357	0.378	0.021
Logistic 28 months	0.193	0.242	0.049 ***	1.586	1.587	0.001	0.470	0.510	0.040
Logistic 32 months	0.209	0.239	0.030 *	1.582	1.646	0.064	0.612	0.649	0.037
Logistic 36 months	0.247	0.278	0.031 *	1.709	1.869	0.160 ***	0.690	0.711	0.021 *
Lower triangular 24 months	0.189	0.198	0.009 ***	1.358	1.320	-0.039 *	0.399	0.421	0.022
Lower triangular 28 months	0.170	0.232	0.062 ***	1.559	1.541	-0.018	0.411	0.448	0.037
Lower triangular 32 months	0.223	0.267	0.044 **	1.559	1.622	0.063	0.558	0.588	0.030 ***
Lower triangular 36 months	0.227	0.256	0.029 *	1.152	1.177	0.025	0.282	0.271	-0.011
Upper triangular 24 months	0.164	0.171	0.007 **	1.401	1.365	-0.036	0.459	0.484	0.025 *
Upper triangular 28 months	0.189	0.264	0.075 ***	1.030	1.016	-0.014	0.295	0.309	0.014
Upper triangular 32 months	0.249	0.278	0.029	1.017	1.029	0.012	0.288	0.278	-0.010
Upper triangular 36 months	0.169	0.237	0.068 ***	1.145	1.176	0.031	0.296	0.282	-0.014
	Standard Deviation of γ			Standard Deviation of ψ			Standard Deviation of ρ		
	Black	White	Difference	Black	White	Difference	Black	White	Difference
Logistic 24 months	0.043	0.063	0.021 ***	0.015	0.023	0.008	0.009	0.017	0.008
Logistic 28 months	0.058	0.086	0.028 **	0.063	0.086	0.022	0.045	0.054	0.009
Logistic 32 months	0.060	0.095	0.035 ***	0.156	0.194	0.038 **	0.079	0.094	0.015 *
Logistic 36 months	0.052	0.055	0.003	0.199	0.190	-0.009	0.088	0.082	-0.006
Lower triangular 24 months	0.038	0.057	0.019 **	0.014	0.022	0.008	0.008	0.014	0.006
Lower triangular 28 months	0.060	0.090	0.030 ***	0.053	0.083	0.030	0.038	0.053	0.015 *
Lower triangular 32 months	0.052	0.055	0.003	0.172	0.199	0.027	0.086	0.099	0.014
Lower triangular 36 months	0.027	0.026	0.000	0.071	0.044	-0.027 *	0.069	0.069	0.000
Upper triangular 24 months	0.038	0.043	0.005	0.024	0.044	0.019	0.018	0.034	0.016 **
Upper triangular 28 months	0.025	0.035	0.010	0.053	0.061	0.008	0.008	0.007	0.000
Upper triangular 32 months	0.033	0.036	0.003	0.059	0.051	-0.008	0.004	0.006	0.002
Upper triangular 36 months	0.026	0.039	0.013	0.085	0.060	-0.025	0.007	0.009	0.002

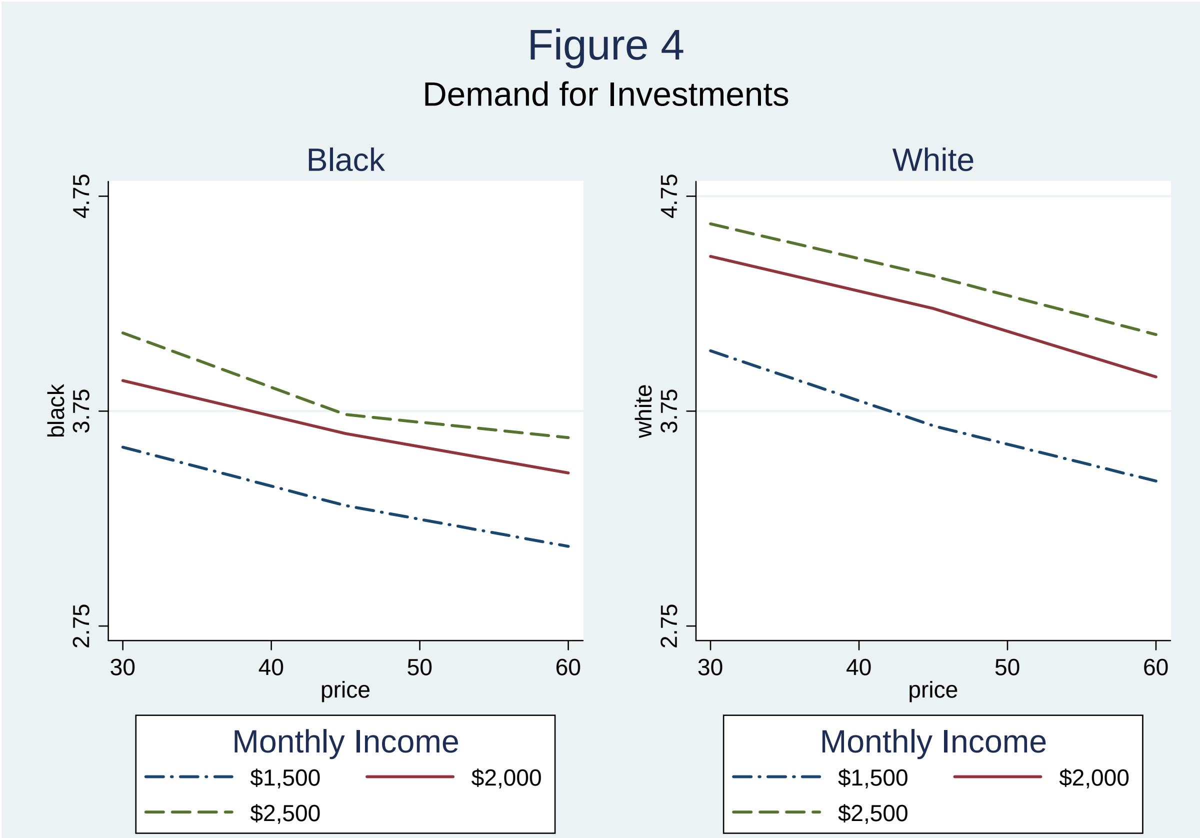
*** p<0.01, ** p<0.05, * p<0.1

beliefs about ψ_i, ρ_i, and γ_i. I present the results for all twelve possible combinations of interpolating functions (logistic, lower triangular, and upper triangular) and target ages (twenty-four, twenty-eight, thirty-two, and thirty-six months). As anticipated from the discussion about Table 3, the conclusion from Table 4 is suggestive that black parents have lower mean and standard error beliefs about the parameter γ than white parents. When I use the logistic function to interpolate and take twenty-four months as the target age, the mean beliefs for black and white parents are 0.153 and 0.205, respectively. As shown in Table 4, the different interpolating and target ages produce very diffierent mean beliefs. In fact, the estimated mean beliefs for black parents vary from 0.153 to 0.249. For white parents, the range of values for mean beliefs is 0.171 and 0.278. For both black and white parents, the lower and higher values are generated by the upper triangular at twenty-four months and at thirty-two months, respectively. It is important to note that the white parents' mean beliefs are higher than the black parents' in all of the twelve models that I estimated. In eight of them, the differences are statistically significant at the five percent level.

Table 4 also shows the mean of the standard deviation by race. For example, according to the model with logistic interpolation and target age twenty-four months, the typical black parent and the typical white parent have a standard deviation of 0.043 and 0.062. So, the black parent has lower mean and lower uncertainty about γ_i. In the context of the model that I use in this paper, the lower standard error implies lower parental uncertainty about the returns to investments in children and, consequently, may be a force toward higher levels of investment in black children. [6]The evidence about racial differences in parental uncertainty is not as strong as in the case of the mean beliefs: Only five out of the twelve models generate differences that are statistically significant. The remaining models generate differences that tend to be small and not very important in an economic sense.

Perhaps surprisingly, I find no difference across races for mean and standard beliefs about ψ_i or ρ_i. The mean beliefs about ρ_i are higher for white parents, but the differences are small and in only two cases statistically significant. All in all, both black parents and white parents differ in terms of their beliefs about the parameter γ, which dictates the elasticity of child development with respect to parental investments.

[6] However, in a model with learning as in Badev and Cunha (2012), early parental investments in children not only increase the child's stock of human capital but also provide a source of learning about the technology of skill formation parameters. The incentive to invest to learn about the parameters is stronger the higher the uncertainty that parents face. So, in the learning model, the higher uncertainty that white parents face may be a force toward higher investments in white children.



5.3 Estimated Preference Parameters

Before presenting the point estimates of the preference parameters, I show some features of the raw data from the choice experiment described in Section 4.2. Figure 4 plots the demand for invesments for each race and level of income. Note that the demand curves are well behaved: the quantity of investment demanded by parents decreases as the price of investment increases. Also, an increase in income moves the demand curve upward, which proves that investments and child development are normal goods for both black and white parents. Another clear feature of the data is that there are racial differences in the demand for investments: holding constant prices and income, the demand curve of white respondents is at a higher level than the corresponding one for the black respondents (compare the left and right panels of Figure 4).

Table 5 reports the estimated preference parameters for each of the twelve interpolating function and target age combinations. The parameter α, which describes how parents value child development relative to consumption, is particularly sensitive to the choice of beliefs. For black parents, the lower and upper bounds for the parameter α are 2.1955 and 3.4872, respectively. For white parents, the same bounds are 3.5874 and 6.3315. The racial differences are statistically significant and, as I will show below, they account for a significant fraction of the differences in investments between black and white parents.

The parameter λ captures the elasticity of substitution between child development and consumption. The lower λ, the higher the elasticity of substitution between consumption and child development. Again, the estimated elasticity parameter depends on the interpolation and the target age used for the estimation of beliefs, but in general I find that λ is lower for blacks. As Table 5 shows, the estimated value of λ for blacks is between 0.3985 and 0.5801, while the same paratemer for whites is between 0.4959 and 0.8447.

5.4 Estimated Prices of Investments

As explained in Section 4.3, in order to estimate investment prices, I use the beliefs and preference parameters to simulate the model and compare average investments by race as predicted by the model with the corresponding quantity to the CNLSY/79 data. In both the model and the data, investment is measured in a metric of time. Table 5 presents the results. I find large differences in prices of investments. While the point estimates for prices of investments faced by blacks are between \$1.97 and \$2.90 per hour of investment, the corresponding interval for whites is \$4.47 and \$5.07 per hour of investment. These large differences in price result from the fact that the differences in investments are too small given the large differences in preferences, beliefs, and income. For the small differences in investments to be rationalized by these large differences in the "state variables," it is necessary for whites to face a higher price of investment than blacks. If investments are intensive in time, then these differences in prices can be justified on the grounds that they partially capture the discrepancies in opportunity cost of time, which is higher for individuals with higher educational attainment and potential experience.

5.5 Gaps in Investments: Quantification of the Roles of Four Determinants

I use the model and the estimates reported above to investigate how the four determinants affect gaps in investments documented in Section 2. The results can be read from Table 6. The "Baseline" row shows the model's prediction of investments for both black and white parents. This is the moment I target to estimate the prices in Section 4.3.

The row "Equalizing Beliefs" simulates a policy that equalized the distribution of beliefs across races. Suppose that parent i is black and let F_i denote her beliefs. I then randomly draw a white parent j whose beliefs are F_j. The figures in the row "Equalizing Beliefs" are obtained by computing investments of the parent i if her beliefs were F_j, but all other state variables were the same as in the baseline case. This simulation is done for every possible combination of interpolating function and target age. As shown in Table 6, a policy that equalized beliefs would move average investment among black parents from 1,497 to at least 1,512 and at most 1,884 hours per year. If I average across twelve

Table 5

Preference Parameters and Investment Prices by Race

	α		λ		Prices	
	Black	White	Black	White	Black	White
Logistic 24 Months	2.5797	4.2739	0.5801	0.5801	2.8361	4.9773
	0.0921	0.1699	0.0268	0.0268	0.0072	0.0119
Logistic 28 Months	2.8085	4.5859	0.4708	0.6554	2.5596	4.7939
	0.0779	0.2249	0.0231	0.0871	0.0077	0.0133
Logistic 32 Months	3.3371	5.2227	0.4613	0.8447	2.5989	4.8913
	0.0941	0.2748	0.0226	0.0944	0.0072	0.0123
Logistic 36 Months	3.4872	4.1974	0.3985	0.6047	2.9011	4.9653
	0.1177	0.1995	0.0271	0.0754	0.0084	0.0142
Lower Triangular 24 Months	2.7398	5.1675	0.4881	0.5499	2.6253	5.0332
	0.1005	0.1861	0.0281	0.0700	0.0081	0.0137
Lower Triangular 28 Months	3.0402	6.3315	0.4793	0.9077	2.5363	5.0777
	0.0909	1.5803	0.0243	0.1897	0.0075	0.0125
Lower Triangular 32 Months	2.8726	4.2113	0.4490	0.6412	2.5783	4.8899
	0.0794	0.1980	0.0239	0.0888	0.0086	0.0143
Lower Triangular 36 Months	2.8534	3.9433	0.4098	0.5685	1.9691	4.4746
	0.0912	0.1654	0.0294	0.0854	0.0059	0.0100
Upper Triangular 24 Months	3.2524	5.6888	0.4700	0.6649	2.6077	4.8835
	0.0993	0.2392	0.0236	0.0752	0.0080	0.0139
Upper Triangular 28 Months	2.2933	3.9110	0.5542	0.5542	2.8342	4.9465
	0.0729	0.1371	0.0239	0.0239	0.0069	0.0117
Upper Triangular 32 Months	2.3180	3.5874	0.4959	0.4959	2.8179	5.0728
	0.0715	0.1191	0.0240	0.0240	0.0080	0.0130
Upper Triangular 36 Months	2.1955	3.7254	0.5592	0.5592	2.7983	4.9606
	0.0763	0.1439	0.0265	0.0265	0.0073	0.0121

possibilities, the investments among black parents would be around 1,603 hours per year and the black-white ratio in investments would be around 84%.

In comparison, consider a policy that equalized preferences across races but maintained everything else unchanged. If such a policy were implemented, then investments among black parents would increase to at least 1,784 and at most 2,517 hours per year. Again, taking averages across all possible combinations of interpolating functions and target ages, the investments by black parents would increase to 2,084 hours per year. This policy would reverse the gap in investments across races.

The row "Equalizing Budget Constraints" shows the results of equalizing prices and the distribution of income. That is, suppose that parent i is black and let y_i denote her household income. I then randomly draw a white parent j whose household income is y_j. In order to equalize the budget constraints, I also need to equalize prices, so I set the price of investments of the black parents equal to the price of investments of the white parents. Taking averages across all interpolating functions and target ages, the results show that investments would increase to around 1,545 hours per year and, as a result, the black-white ratio would increase to around 81%.

Finally, the last row "Equalizing Human Capital at Birth" investigates the impact of equalizing the distribution of the child's initial stock of human capital on parental investments. Specifically, suppose that parent i is black and let $q_{0,i}$ denote her child's human capital at birth. I then randomly draw a white parent j whose child's human capital at birth is $q_{0,j}$. I then simulate the investment of the black parent if her child had been born with human capital $q_{0,j}$. As Table 6 shows, the impact on investments would be minimal: investments would increase by about one hour per year.

Interestingly, the simulation of the policies above assume that all black parents would "adopt" the beliefs of white parents. Clearly, this need not be the case because parental utility may be lower when they are assigned the beliefs of a white parent than their own beliefs. In order to investigate if this is the case, I compute the utility of a black parent in the baseline case and the utility of the same parent when her beliefs are randomly drawn from the white distribution. I assume that a black parent voluntarily adopts the beliefs drawn from the white distribution if such beliefs maximize parental utility. Table 7 displays the results of this analysis. For most combinations of interpolating functions and target ages, I find that around fifty-five percent of black parents would adopt the beliefs drawn from the white distribution. Interestingly, as shown in Column 2, only a minority of parents who choose to stick to their beliefs do so in spite of the fact that the child's development would be higher with the beliefs drawn from the white distribution. As a result, under voluntary adoption, the policy that informed parents about beliefs would increase black investments to at least 1593 and at most 1882 hours per year.

Table 6

Decomposing Gaps in Investments

Investments: HOME-SF in a metric of hours/year

	Logistic											
	24 Months			28 Months			32 Months			36 Months		
	Black	White	Ratio	Black	White	Ratio	Black	White	Ratio	Black	White	Ratio
Baseline	1497	1908	0.785	1497	1908	0.785	1497	1908	0.785	1497	1908	0.785
Equalizing Beliefs	1627	1908	0.853	1615	1908	0.846	1594	1908	0.836	1595	1908	0.836
Equalizing Preferences	1866	1908	0.978	2204	1908	1.155	2434	1908	1.276	2075	1908	1.087
Equalizing Budget Constraints	1643	1908	0.861	1575	1908	0.825	1535	1908	0.804	1704	1908	0.893
Equalizing Human Capital at Birth	1497	1908	0.785	1500	1908	0.786	1498	1908	0.785	1499	1908	0.786
	Lower Triangular											
	24 Months			28 Months			32 Months			36 Months		
	Black	White	Ratio	Black	White	Ratio	Black	White	Ratio	Black	White	Ratio
Baseline	1497	1908	0.785	1497	1908	0.785	1497	1908	0.785	1497	1908	0.785
Equalizing Beliefs	1514	1908	0.794	1632	1908	0.855	1602	1908	0.840	1578	1908	0.827
Equalizing Preferences	2055	1908	1.077	2517	1908	1.319	2185	1908	1.145	1784	1908	0.935
Equalizing Budget Constraints	1461	1908	0.766	1384	1908	0.725	1522	1908	0.798	1404	1908	0.736
Equalizing Human Capital at Birth	1499	1908	0.786	1496	1908	0.784	1497	1908	0.785	1499	1908	0.786
	Upper Triangular											
	24 Months			28 Months			32 Months			36 Months		
	Black	White	Ratio	Black	White	Ratio	Black	White	Ratio	Black	White	Ratio
Baseline	1497	1908	0.785	1497	1908	0.785	1497	1908	0.785	1497	1908	0.785
Equalizing Beliefs	1512	1908	0.792	1844	1908	0.966	1560	1908	0.817	1639	1908	0.859
Equalizing Preferences	2223	1908	1.165	1911	1908	1.001	1863	1908	0.976	1896	1908	0.994
Equalizing Budget Constraints	1546	1908	0.810	1665	1908	0.873	1560	1908	0.818	1627	1908	0.853
Equalizing Human Capital at Birth	1498	1908	0.785	1496	1908	0.784	1500.3	1908	0.786	1499	1908	0.785

Table 7
Investment Gaps When Adoption of Beliefs Is Voluntary

	Fraction who adopt new beliefs[1]	Fraction who do not adopt even though children would receive higher investments[2]	Average investments if adoption of beliefs is voluntary	B/W ratio when adoption is voluntary
Logistic 24 Months	57.6	12.3	1752	0.92
Logistic 28 Months	54.9	10.3	1658	0.87
Logistic 32 Months	56.6	19.7	1683	0.88
Logistic 36 Months	56.6	10.4	1668	0.87
Lower Triangular 24 Months	52.4	7.7	1593	0.83
Lower Triangular 28 Months	54.0	8.3	1681	0.88
Lower Triangular 32 Months	55.2	14.7	1707	0.89
Lower Triangular 36 Months	85.4	9.7	1882	0.99
Upper Triangular 24 Months	50.5	12.0	1608	0.84
Upper Triangular 28 Months	56.3	12.1	1705	0.89
Upper Triangular 32 Months	55.5	11.9	1726	0.90
Upper Triangular 36 Months	54.0	12.9	1718	0.90

[1]Let V(F) denote the utility in the baseline case and let V(F') denote the utility when beliefs F' are drawn from the distribution of white respondents. Individuals adopt new beliefs if the new beliefs maximize utility, i.e., if V(F') > V(F).

[2]Let V(F) denote the utility in the baseline case and let V(F') denote the utility when beliefs F' are drawn from the distribution of white respondents. Let x(F) denote investments in the baseline case and x(F') denote investments when beliefs F' are drawn from the distribution of white respondents. This column reports the share of individuals who do not adopt new beliefs (i.e., V(F') ≤ V(F)) even though investments in their children would be higher with new beliefs (i.e., x(F') > x(F)).

6 Discussion

The evidence presented so far suggests that beliefs and preferences should not be ignored when trying to understand gaps in investments. It is important to keep in mind that the results above are obtained from a small, non-representative sample and that there are large differences in the socio-demographic characteristics of black and white parents. So, it is possible that the differences I report are not due to differences in race but to differences in other demographic characteristics. With this fact in mind, I discuss the validity of the findings with respect to beliefs and preferences and offer possible alternative interpretations.

An important assumption in the paper is that the beliefs elicited in the MKIDS data ultimately influence investment in children. Unfortunately, there is no information on investments in the MKIDS data set. Nevertheless, I try to evaluate the informational content of the beliefs data by answering two related questions. First, is the elicitation methodology proposed in Cunha, Elo, and Culhane (2013) really measuring beliefs about the technology of skill formation? If so, is there any reason to think that parental beliefs do partially determine investments?

In their original study, Cunha, Elo, and Culhane (2013) investigated the validity of their elicitation methodology by analyzing how an individual's responses varied across items. The basic idea is that there should be a specific pattern of predictability in answers across MSD items within a scenario of investment. The pattern relates to the fact that the MSD items vary in difficulty. For example, at any age a, there are more children who "can speak a partial sentence with three words or more" than who "know the names of at least four colors." Cunha, Elo, and Culhane (2013) reason that, if respondents understand well the questions about beliefs, the age ranges they provide should be higher for "know the names of at least four colors" and lower for "speak partial sentence," holding constant the scenario of investments and human capital at birth. As the authors show in their analysis of the MKIDS data set, this is precisely what happens in their data.

The answer to the second question is difficult because it is necessary to obtain data on beliefs and investments to establish that these variables are at least correlated. Recent work in child development and pediatrics offers suggestive evidence not only that beliefs and investments are correlated but also that changes in beliefs lead to changes in investments. The evidence I describe next relates to the work by Hart and Risley (1995), who measured the language environment children were exposed to up to age 36 months. In their pathbreaking study, Hart and Risley documented that the child of welfare parents heard about 600 words per hour, while the child of professional parents heard almost twice as many words in the same amount of time. Not surprisingly, the children of professional parents exhibited superior language development throughout the period of the study. The Hart and Risley results were recently reproduced by Rowe (2008), whose aim was to understand why some parents spoke so little to their children. According to her data, poor and uneducated women were simply unaware that it was important to talk to their babies. This is persuasive evidence that beliefs about the technology of skill formation are correlated with investment choices.

Suskind and Leffel (2013) conducted a small-scale intervention to improve parental knowledge about the importance of talking to young children. The intervention, known as the "Thirty Million Words Project," is based on three components. The first component communicates to parents the scientific evidence on how the early language environment experienced by children affects children's brain development. The second component provides parents with suggestions on how to easily and very cheaply improve the language environment at home. The third component supplies parents with information about the quality of the language environment at their home and encourages them to reach for higher levels of hourly word counts and daily conversational turns. As a result of the intervention, the parents in the treatment group increased the amount of conversation turns per hour by around fifty percent and the children's language development (measured in number of vocalizations per hour) also increased by fifty percent. This is persuasive evidence that beliefs have a causal effect on parental investments.[7]

Another potential interpretation of the Suskind and Leffel (2013) findings is that the intervention allows parents to adopt a more efficient technology of skill formation. As discussed above, this is also a possible interpretation of the model presented in Section 2. As I now show, there is reason to suspect that heterogeneity in technology adoption is prevalent and that different technologies may affect different dimensions of human capital more or less efficiently. It is perhaps easier to recognize alternative technologies when the observation relates to a culture that is very distinct from the typical Western societies. For this reason, I illustrate this issue by exploring studies on the anthropology of child development.[8] A particularly informative case is that of the !Kung San of the Kalahari desert. As documented by Lee (1979, 1984) and Shostak (1981), in the early 1960s the San were transitioning from hunters and gatherers to a society of permanent settlers. In spite of this fact, Lee (1984) argues that the San still kept some of their culture and traditions during this transition and that the observation of their parenting behavior was informative about how early humans reared their children. According to Konner (1977), San parents believe that motor skills, such as sitting, standing, and walking, must be taught and children should be encouraged to practice these skills. San parents act on this belief by investing time and effort in making sure that their babies are physically developed early on. As a consequence of this training, San children perform better in motor-coordination and motor-cognition tests because they are physically more developed and are able to concentrate harder than their Western peers (Konner, 1973).[9] Clearly, a possible interpretation of this finding is that San children are genetically predisposed to learn motor skills from an early age. However, there is experimental evidence that it is possible to accelerate motor development in typical Western children by engaging in similar exercises to the types to which San children are exposed from since an early age (Zelazo et al, 1972).

In contrast, consider the Ache of Paraguay who live in forests in which children can fall prey to jaguars, poisonous snakes, or other dangers. Researchers conjecture that Ache parents act to postpone motor development in order to protect the child: if the child cannot walk, he or she will not venture onto dangerous grounds by himself or herself (e.g., Kaplan and Dove, 1987; Hill and Hurtado, 1996). One way that motor development can be slowed down is by maintaining children in a horizontal position, something that Ache parents do by making sure that their babies ride in slings early on and are carried piggyback by fathers at later ages. As a result of these actions, Ache children walk nine

[7] In terms of the technology parameter γ_i, this finding suggests that the elasticity of language development with respect to investments is one.

[8] A survey of this literature can be found in Small (1999).

[9] The same finding is confirmed with a different group of children. Leiderman et al (1973) show that Kikuyu babies in East Africa also do better in motor and cognitive tests than Western babies.

months later than American children (Kaplan and Dove, 1987). Clearly, as children age, they become heavier and the act of carrying them piggyback could cause (some of the members of) the group to move too slowly. So, when Ache children are five years old, they are supposed to start walking on their own two feet, but given the underdevelopment of their muscles it is not suprising that this transition presents a major crisis for them (Hill and Hurtado, 1996).

Another interesting case studied by anthropologists are the Gusii in the African highlands (see LeVine et al, 1994). The Gusii society is organized in such a way that each household is a semi-autarkic economic unit in which individual members cooperate in growing crops, herding animals, and sometimes providing income by doing work outside the household. For the Gusii, children are economic assets because from an early age they are able to help in the field or tend livestock or care for other children. In this system of clear interdependence of the household members, the Gusii children are reared to be obedient and able to contribute to the subsistence of this economic unit. According to Gusii beliefs, children who are praised or who receive too much attention become disobedient and selfish. As a result, Gusii parents avoid talking to children and actually treat them as low status members who should learn by observing the older members of the group.

The above discussion aims to illustrate two things. First, it may be challenging to separate heterogeneity in parental beliefs from heterogeneity in technology adoption. For example, the San have adopted a technology of skill formation that is efficient in producing motor skills but may not be as efficient in producing numeracy skills. In their recent past, this technology produced skills that were valued by the San who were constantly moving.[10] In contrast, the Ache parents apparently adopted a technology in which motor skills are developed very slowly.[11] If I were to elicit beliefs about the technology of motor skill formation, it could be the case that San parents would have "higher" mean beliefs about the elasticity of motor development with respect to investment than Ache parents. Needless to say, their answers could perfectly constitute an unbiased estimate of the technology choices they have made.

This leads to the second observation. As the examples above show, the technology of skill formation that parents choose promotes optimal development of the skills that maximize "success" in the dimensions valued by the parents and the society in which they live. So, even if we had a version of the Thirty Million Words intervention targeted

[10] Another interesting fact about the San is that they practice on-demand breastfeeding until the child is around four years old. Because this type of breastfeeding inhibits ovulation, the typical San woman has a child around every four years. If mobility is important, it is probably optimal to avoid having another child until the previous one has already learned how to move by himself or herself (Konner, 1973).

[11] In contrast, Ache children have an advanced understanding of basic botanic and animal tracking, which will prove to be useful once they become adults (Kaplan and Dove, 1987).

toward Gusii mothers, it is possible that the same intervention would not change Gusii parental behavior simply because the intervention promotes the development of skills that Gusii mothers believe could disrupt the organization and the success of their economic unit.

In essence, the success of an intervention that changes beliefs, such as the Thirty Million Word intervention in the United States, is possible if (i) the proposed intervention offers knowledge about a more "effective" technology; (ii) the technology promotes the development of skills that are valued by parents; and (iii) the intervention provides parents with clear directives about how to put this knowledge into practice.

I now turn to a discussion of the findings related to heterogeneity in preferences. As discussed in the introduction, the work by Lynd and Lynd (1929, 1937) suggests that there is heterogeneity in how parents value different skills. In their original study almost eighty-five years ago, they registered that working-class mothers ranked "strict obedience" as their most important goal more frequently than higher-SES mothers did. Harwood (1992) found that, when asked to describe how they would like their toddlers to behave if left with a stranger in a doctor's waiting room, lower-SES mothers rated proper demeanor as more important than did higher-SES mothers. This finding has been confirmed in other contexts as well (e.g., Alwin, 1984; Luster, Rhoades, and Haas, 1989; Pearlin and Kohn, 1966; Tudge et al, 2000; Wright and Wright, 1976). So, the evidence presented in Section 5 that black and white parents have different preferences over cognitive skills should not be literally interpreted as black parents have a lower valuation of their children's human capital. In other words, the findings here are not inconsistent with black and white parents placing different valuation over different dimensions of human capital.

More important, a small modification of the model presented in Section 3 suggests a different interpretation of the findings about preferences: black parents may have a lower valuation of the labor-market returns to human capital. To see what I mean, suppose that parental utility depents on the child's future lifetime utility, which is ultimately determined by the child's income, which, in turn, is a function of the child's human capital: $y_i = h_i^{\beta}$. The parameter β dictates the labor-market returns to investments in human capital. I denote by $\mu_{\beta,i}$ the mean expectation of parent i with respect to the parameter β. Suppose that preferences are represented by the log utility and assume that parents can only transfer resources via investments in human capital. Then, parental investment is given by:

$$x_i = \frac{\alpha_r \left(\mu_{\beta,i} + \mu_{\gamma,i}\right)}{1 + \alpha_r \left(\mu_{\beta,i} + \mu_{\gamma,i}\right)} \frac{y_i}{p_r}.$$

This simple variation of the model in Section 3 shows that the allocation of household income to investments in children depends not only on the beliefs about the technology of skill formation but also on the beliefs about the child's human capital returns in the labor market. Although the current study accounts for the former, it does not account for the latter. Yet, there is evidence to suggest that poor parents in developing countries have low expectations about the returns to human capital investments (Attanasio and Kaufman, 2009). This informational interpretation of the findings related to preferences offers yet another policy channel to affect human capital investments in children.

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