

Eliciting Maternal Subjective Expectations about the Technology of Cognitive Skill Formation¹

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Abstract

In this paper, we formulate a model of early childhood development in which mothers have subjective expectations about the technology of skill formation. The model is useful for understanding how maternal knowledge about child development affects the maternal choices of investments in the human capital of children. Unfortunately, the model is not identified from data that are usually available to econometricians. To solve this problem, we conducted a study where mothers were interviewed to elicit maternal expectations about the technology of skill formation. We interviewed a sample of socioeconomically disadvantaged African-American women. Our estimates suggest that if we equate beliefs with the objective estimates of the technology of skill formation, investments would increase by approximately 10%.

Key words: Cognitive skills, parental expectations, investments

JEL Code: A12

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1 Introduction

In a pioneering study, Hart and Risley (1995) documented the differences in how much parents talked to their babies. Children whose families were on welfare heard about 600 words per hour. In contrast, children of parents with professional occupations heard over twice as many words in the same amount of time. Hart and Risley (1995) also showed that the better the early language environment at home (as measured by the number of words or conversational turns), the better the language development of children, the higher their IQ, and the better they did in school.

Why do some parents talk more to their children than other parents do? Research by Rowe (2008) argued that the gaps in the language environment exist because poor, uneducated mothers do not know about the role it plays in determining the language and cognitive development of their children. Rowe's finding suggested that there may be heterogeneity in beliefs about the technology of skill formation and that investments may be partially driven by these beliefs.

In other settings, research has demonstrated that expectations about returns matter for investments in human capital. Attanasio and Kauffman (2009) showed that the higher the subjective expectations of the returns from schooling, the more likely the decision to invest in education. In his study in the Dominican Republic, Jensen (2010) found that students hold *subjective* expectations of returns from schooling that imply extreme underestimation of the *objective* returns from schooling. More important, for the purposes of the current paper, Jensen showed that individuals react to new information: Students in randomly selected schools who were given information about the higher measured returns completed on average 0.20–0.35 more years of school over the next four years than those who were not.

Recent literature provides evidence that expectations about the technology of skill formation can be changed by public information campaigns. Aizer and Stroud (2010), for example, tracked the smoking habits of educated and uneducated pregnant women before and after the release of the 1964 Surgeon General's Report on Smoking and Health. Before the release of the report, educated and uneducated pregnant women smoked at roughly the

same rates. After the report, the smoking habits of educated women decreased immediately, creating a ten-percentage-point gap in pregnancy smoking rates between educated and uneducated women. Therefore, heterogeneity in beliefs and in investments in human capital may be driven by information campaigns that have differential effectiveness across diverse socio-economic groups.

Motivated by this research, we have formulated a model of early childhood development in which mothers have subjective expectations about the technology of skill formation. The model is useful for understanding how maternal knowledge affects investments in the human capital of children. Unfortunately, the model is not identified from data that are usually available to econometricians. If we only observe investments and measures of human capital, it is impossible to decompose heterogeneity in expectations from heterogeneity in preferences (Manski, 2004).

To solve this identification problem, we created a survey instrument to elicit maternal expectations about the technology of skill formation. In summary, in this survey we created scenarios of “high” and “low” levels of investments or human capital at birth. For each scenario of investment and human capital at birth, we asked a set of questions that allowed us to estimate the expected human capital at age two years. By comparing the answers across scenarios, we were able to estimate maternal subjective expectations about the technology of skill formation.

We interviewed a sample of socioeconomically disadvantaged, pregnant African-American women. We found that the subjective expectation about the elasticity of child development with respect to investments depends on the child’s human capital at birth. If the child’s human capital at birth is at the 25th percentile, the median parent believes the elasticity is 28.5%. For a child at the 30th percentile in the distribution of human capital, the median parent believes the elasticity is 30%. In comparison, when we estimated the technology of skill formation from the Children of the National Longitudinal Survey of Youth (CNLSY)/79 data, also using the Motor Social development (MSD) scale, we found that the elasticity can be as high as 45%.

We used the model and our data to answer the following question: Consider the median mother in our survey. What would happen to investments and child development if we implemented a policy that moved her subjective expectation to the objective estimates that we obtained from the CNLSY/79 data? According to our estimates, investments would go up by 10%, and the stocks of cognitive skills at age 24 months would increase by 4.5%.

This paper is organized as follows. In Section 2, we introduce our model of investment in human capital of children. Section 3 describes the identification and estimation of the model, including the methodology for estimating maternal subjective expectations about the technology of skill formation. We present the estimation results in Section 4. In Section 5, we quantify the importance of beliefs in determining investments. We compare the results from our model simulation with policies that potentially affect maternal beliefs.

2 Model

2.1 The Technology of Skill Formation

Let $q_{i,0}$ and $q_{i,1}$ denote, respectively, the stocks of human capital of child i at birth and at 24 months.¹ Let x_i denote the flow of maternal investments in the human capital of child i during the first 24 months of the child's life. Let v_i denote shocks to the development process. We assume that the technology of skill formation is “approximately” Cobb-Douglas:

$$\ln q_{i,1} = \psi_0 + \psi_1 \ln q_{i,0} + \psi_2 \ln x_i + \psi_3 \ln q_{i,0} \ln x_i + v_i. \quad (1)$$

Previous research showed that the technology of cognitive skill formation, seen in Equation (1), follows a Cobb-Douglas specification.² However, the goal of this paper is to elicit maternal beliefs about the technology of skill formation. Thus, we aim to measure parental expectations about the parameter vector ψ and, in particular, we want to test if mothers believe that the technology is described by the Cobb-Douglas function. The parameterization in Equation (1) is particularly convenient to make progress on these

¹ In the empirical application below, we measure $q_{i,0}$ by birth weight, birth length, and gestation length. We measure $q_{1,i}$ by developmental tests around the time the child is 24 months old.

² See Cunha, Heckman, and Schennach (2010).

questions. To see why, let \mathcal{H}_i denote the mother's information set. According to the technology function denoted in Equation (1), it follows that:

$$E(\ln q_{i,1} | q_0, x, \mathcal{H}_i) = \mu_{i,\psi,0} + \mu_{i,\psi,1} \ln q_0 + \mu_{i,\psi,2} \ln x + \mu_{i,\psi,3} \ln q_0 \times \ln x \quad (2)$$

where $\mu_{i,\psi,j} = E(\psi_j | q_0, x, \mathcal{H}_i)$. Under specification (1), we can investigate, for example, if mother i believes that the technology is Cobb-Douglas by testing the hypothesis that $\mu_{i,\psi,3} = 0$.

2.2 Preferences and Budget Constraint

We assume that preferences are represented by the following utility function:

$$U(c_i, q_{i,1}, x_i) = \ln c_i + \alpha_{i,1} \ln q_{i,1} + \alpha_{i,2} \ln x_i \quad (3)$$

The utility function denoted in Equation (3) is Cobb-Douglas, and it has three arguments. Under our assumptions, parents care about consumption (c_i), about child development, and about investments directly. Direct preference for investment is not usually present in most models of human capital formation, but here it is important to include it because we want to allow for investments to be determined by a component other than the one mediated by maternal beliefs. As we will demonstrate below, the Cobb-Douglas preferences are convenient because it allows us to focus on investigating the importance of mean beliefs, so it is not necessary to elicit beliefs about higher-order moments.

Let y_i denote household income, which we assume is exogenously determined in the model. The budget constraint reads:

$$c_i + px_i = y_i \quad (4)$$

2.3 Optimal Investment

Optimal parental investment is the one that maximizes utility—Equation (3)—subject to the perceived technology of skill formation—Equation (2)—and the budget constraint—Equation (4). It is easy to show that the policy function for investment is:

$$x_i^* = \left[\frac{\alpha_{i,1}(\mu_{i,\psi,2} + \mu_{i,\psi,3} \ln q_0) + \alpha_{i,2}}{\alpha_{i,1}(\mu_{i,\psi,2} + \mu_{i,\psi,3} \ln q_0) + \alpha_{i,2} + 1} \right] \left(\frac{y_i}{p} \right) \quad (5)$$

Typically, econometricians observe the vector $D_i = (q_{0,i}, q_{1,i}, x_i, y_i, p)$. As explained in Manski (2004), the major identification issue that arises when D_i is the only data available is that one cannot separately identify heterogeneity in preferences (captured in Equation [5] by $\alpha_{i,1}$ and $\alpha_{i,2}$) from heterogeneity in beliefs (represented in Equation [5] by $\mu_{i,\psi,2}$, and $\mu_{i,\psi,3}$). In the context of this simple model, the main contribution of our research was to develop and implement a methodology to elicit $\mu_{i,\psi}$. Clearly, to the extent that investments are partly determined by these beliefs, these variables are interesting by themselves. More important, if we add $\mu_{i,\psi}$ to the data D_i , we are able to separately identify heterogeneity in preferences from heterogeneity in beliefs.

3 Identification and Estimation of the Model

In this section, we start by presenting the MSD scale, which played a major role in the development of the elicitation questionnaire. Then, we present the survey questionnaire items that were used to elicit expectations. We show how to transform maternal answers to these items into maternal expectations about child development (the left-hand side variable in Equation [2]). The next step shows how to use maternal expectations data to recover expectations about the parameters of the technology of skill formation. Finally, we show our procedure to identify the parameters of the utility function.

3.1 The Motor Social Development Scale

The MSD scale played an important role in our analysis, so we briefly explain it in this section. This scale was used in the CNSLY/1979 and in the National Health and Nutrition Examination Study 1988 (NHANES). 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. Part A is appropriate for infants aged zero through three months, and the most advanced section, Part H, is addressed to children between the ages of 22 and 47 months. 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 0 to 15) of the affirmative responses in the age-appropriate section. Because the age

at which children learn how to do given tasks varies considerably across children, one MSD item may be present in many of the parts of the instrument. 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. Thus, this particular item is a member of parts E, F, G, and H of the MSD instrument.

Two key properties of the MSD instrument that make it appealing to our goal is that the tasks are described in language easily understood by the mothers, and the tasks are recognizable based on the daily interactions of mothers and their children. In fact, this is one important reason why we took the MSD instrument as a starting point in the development of the questionnaire to elicit maternal expectations.

Another important reason to start from the MSD instrument is that we ensure that comparability is maintained. The set of items used to elicit maternal subjective expectations about child development is the same one used to measure actual child development in the objective estimation of the technology of skill formation, Equation (5), that we employ in Section 4.

In both the CNLSY/79 and the NHANES dataset, child development is estimated by counting the number of answers that are equal to “yes.” This particular feature was somewhat problematic for our goals, and, as will become clearer below, it was necessary to estimate an Item Response Theory (IRT) model so that we could transform maternal answers to the survey instrument into expectations about child development. Thus, we next introduce the IRT model that was the base of our study.

Let the variable a_i denote the child i ’s age at the time of the measurement of skills in the NHANES dataset. Let θ_i denote the child i ’s development relative to other children in the same age group. For example, $\theta_i = 0$ if child i ’s development is typical for his or her age; $\theta_i > 0$ if child i is advanced for the age; and $\theta_i < 0$ if child i has developmental delays relative to children in his or her age group. The variable θ_i is a latent factor whose distribution we aim to estimate with the IRT model. For each child i and MSD item j , define the latent variable $d_{i,j}^*$ according to the following specification:

$$d_{i,j}^* = b_{j,0} + b_{j,1} \left(\ln a_i + \frac{b_{j,2}}{b_{j,1}} \theta_i \right) + \eta_{i,j} \quad (6)$$

We do not observe the variable $d_{i,j}^*$. We observe, however, that the binary variable $d_{i,j}$ is equal to one whenever $d_{i,j}^* \geq 0$ and equal to zero otherwise.

In the IRT model of Equation (6), the parameters $b_{j,0}$ are smaller for the harder items. The parameter $b_{j,1}$ describes how fast performance in task j improves as age increases. The parameter $b_{j,2}$ denotes the informational content of item j with respect to child development. The higher the value of $b_{j,2}$, the more information item j contains about child development θ_i .

Let Φ denote the cumulative distribution function (CDF) of a normal random variable with mean zero and variance one. If we assume that the idiosyncratic component $\eta_{i,j} \sim N(0,1)$, it follows that the probability that child i can perform MSD task j is equal to:

$$Pr(d_{i,j} = 1 | a_i, \theta_i) = 1 - \Phi \left[-b_{j,0} - b_{j,1} \left(\ln a_i + \frac{b_{j,2}}{b_{j,1}} \theta_i \right) \right] \quad (7)$$

IRT models are, in fact, factor models in which the dependent variables take on discrete values. As in other factor models, we need to make two normalizations: one for the location and the other for the scale of θ_i . Thus, we restrict the mean of θ_i to be equal to zero, and we set $b_{2,j} = 1$ for one of the MSD items. In our empirical analysis, we assume that the distribution of the factor θ_i is equal to a mixture of two normal CDFs.

Equation (7) plays a major role in our analysis for two reasons. First, it allows us to estimate the actual natural logarithm of child development, which we then use to estimate the parameter vector ψ in the right-hand side of Equation (4).

Second, it allows us to translate answers from the questionnaire designed to elicit maternal expectations about (the natural logarithm of) child development. This information allows us to recover maternal expectations about the parameters of the technology of skill formation (the vector μ_ψ in the right-hand side of Equation [5]). By comparing the

parameter vector ψ that we estimate with the maternal beliefs μ_ψ , we are able to estimate if mothers have biased or unbiased expectations about the technology of skill formation.

3.2 Eliciting Maternal Beliefs

In order to elicit maternal subjective expectations of child development, we adapted the MSD instrument used in the CNLSY/79. As we now explain, although the questions are similar, they differ in two important details. The first difference relates to how questions are formulated. The second difference is because the elicitation of subjective expectations requires the creation of hypothetical scenarios of investments and human capital at birth. Parents answer each question for every such hypothetical scenario.

Without loss of generality, we base our discussion of these differences on the following item for the MSD scale for children who are 24 months old: “Does your child speak a partial sentence of three words or more?”

3.2.1 Question Wording

Because the purpose of our study was to elicit expectations (and not measure child development), it was necessary for us to reformulate questions in our instrument. In this paper, we analyze the answers from two types of questions:

1. *How likely is it that a baby will learn how to say a partial sentence with three words or more by age two years?*
2. *What do you think is the youngest age and the oldest age a baby learns to speak a partial sentence of three words or more?”*

In the first type of question, the respondent uses a sliding scale to indicate the likelihood by age two years that the child will learn how to say a partial sentence. This type of question is more closely related to how the literature in economics elicits subjective expectation (see summary of this literature in Manski, 2004), so it is relatively straightforward to transform answers to measures of expectations about the natural log of child development.

In the second type of question, the respondent uses a sliding range scale to indicate the youngest and oldest ages.³ The second question is more in line with how the literature in child development measures parental knowledge about child development (see Epstein, 1979; Ninio, 1988). This type of question requires additional steps in order to be able to transform answers into measures of expectations.

3.2.2 Scenarios of Human Capital at Birth and Investments

The second difference in our instrument, with comparison to the usual MSD instrument, is because the respondents in our study provided answers to the two types of questions described in Section 3.2.1 for different levels of human capital at birth and investments.

More specifically, our survey instrument described to the expectant mother four different hypothetical scenarios of investments and the baby's human capital at birth. In the first scenario, the baby's human capital at birth is “high” (\bar{q}_0), and the mother chooses a “high” level of investment (\bar{x}). In the second scenario, the mother also chooses a “high” level of investment (\bar{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,” but the mother chooses a “low” level of investment (\underline{x}). Finally, in the fourth scenario, both the baby's human capital at birth and investments are low.

These scenarios were concretely defined in a five-minute video that the respondents watched before answering any questions. In the video, we designated “high” human capital as the one in which the baby's gestation lasted nine months, the baby weighed eight pounds at birth, and the baby was 20 inches long at birth. In contrast, the “low” level of initial human capital corresponds to a baby whose gestation was only seven months long, weighed only five pounds at birth, and was only 18 inches long at birth. The “high” and “low” scenarios occupy extremely different positions in the distribution of human capital at birth: the “high” human capital is around the 60th percentile in the distribution, while the “low” human capital is around the 1st percentile.

³ The design of the survey instrument was influenced by Delavande, Giné, and McKenzie (2011), who showed that individuals report more accurately when their answers are represented with visual instruments.

The same video also showed 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 (see Bradley and Caldwell 1980, 1984) : (a) soothing the baby when the baby 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” level of investments. The difference is in the amount of time. 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 95th and 15th percentile of investments.⁴

3.2.3 Estimating Expectations Using “How likely” Questions

We now discuss how we transform the answer to the questions asked in our instrument into measurements of the subjective expectation of child development at age 24 months. This expectation is conditional on three objects: the maternal information set \mathcal{H}_i , the level of human capital at birth, and the flow of investment given to the respondent through the scenarios described above (see Equation [2]).

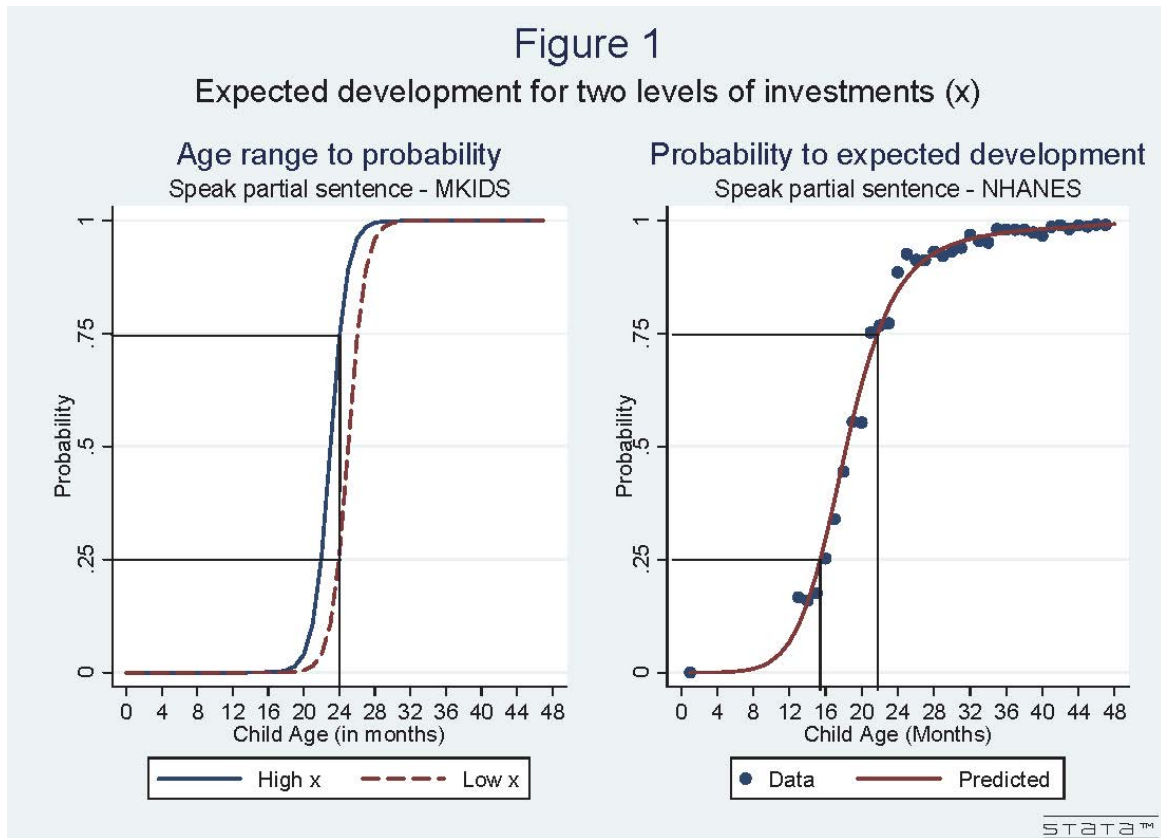
Let $p_{i,j,k}^L$ denote the likelihood reported by respondent i that a child will learn MSD item j by age 24 months if human capital at birth and investments are at the levels determined in scenario k . We explore the IRT model to derive an error-ridden measure of maternal expectation of the natural log of development at age 24 months, $\ln q_{i,j,k}^L$, from the reported probability $p_{i,j,k}^L$. To do so, we invert Equation (7) and solve for θ_i :

$$\ln q_{i,j,k}^L \equiv \left(\ln 24 + \frac{b_{2,j}}{b_{1,j}} \theta_{i,j,k}^L \right) = - \left[\frac{b_{j,0} + \Phi^{-1}(1 - p_{i,j,k}^L)}{b_{j,1}} \right] \quad (8)$$

The algorithm described above can be easily explained graphically. For illustration purposes, Figure 1 (right panel) shows the data and the resulting prediction from the IRT

⁴ For a subset of the respondents, we provided alternative definitions of these hypothetical scenarios. As a result, we investigated the sensitivity of answers with respect to variations in how scenarios are framed.

model for the MSD item “speak a partial sentence of three words or more.” The algorithm above simply transforms the probability into the equivalent age. Building on the example shown in Figure 1, suppose that the mother believes that there is a 75% chance that the child will learn how to speak a partial sentence by age two years when investment is “high.” According to the IRT model, this statement means that the mother believes that at age 24 months, $\ln \hat{q}_{i,j,k}^L = \ln 22$.



Importantly, the lower the subjective probability that the mother reports for a given item j , the lower the corresponding expectation about the natural log of child development at age 24 months. Again, we refer to Figure 1 for a visual explanation of the mechanics of the algorithm. Suppose that for the “low” investment scenario, the mother believes that there is a 25% chance that the child will learn how to speak a partial sentence with three words or more by age 24 months. As shown in Figure 1, this statement means that the mother

believes that at age 24 months the natural log of child development is such that $\ln \hat{q}_{i,j,k}^L = \ln 16$.

The final step is to normalize the units according to the discussion in Section 2.1. In order to do so, note that $\ln q_{i,j,k}^L = \ln \hat{q}_{i,j,k}^L - \ln \bar{q}_1$, where \bar{q}_1 is as defined in Section 2.1.

3.2.4 Estimating Expectations Using Age-Range Questions

For the MSD item j and scenario k , suppose that the survey respondent i states that the youngest and oldest age at which a child will learn how to speak partial sentences of three words or more is $\underline{a}_{i,j,k}$ and $\bar{a}_{i,j,k}$ months, respectively. Our 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 $\underline{a}_{i,j,k}$ is a number Δ_0 (arbitrarily) close to zero, and the probability after age $\bar{a}_{i,j,k}$ 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 age 24 months, we need to somehow construct how the probability varies with age. To do so, we show how the age-range data can be used to estimate a respondent i specific IRT model along with the parameterization used in Equation (6). To do so, let $\tilde{d}_{i,j,k}^*$ denote the latent variable that is determined according to:

$$\tilde{d}_{i,j,k}^* = \tilde{b}_{i,j,k,0} + \tilde{b}_{i,j,k,1} \ln a_{i,j,k} + \tilde{\eta}_{i,j,k} \quad (9)$$

where the shock $\tilde{\eta}_{i,j,k}$ is normally distributed with mean zero and variance one. Similar to the model described in Section 2.2, let $\tilde{d}_{i,j,k}$ denote the binary variable that takes the value one if $\tilde{d}_{i,j,k}^* \geq 0$ and zero, otherwise.

Note the parallelism between the IRT model described by Equation (6) and its counterpart represented in Equation (9). The parameters $\tilde{b}_{i,j,k,0}$ and $\tilde{b}_{i,j,k,1}$ in Equation (9) have the same interpretations to the parameters $b_{j,0}$ and $b_{j,1}$ in Equation (6).

However, there are two important differences between the models in Equations (6) and (9). First, the IRT model in Equation (9) describes maternal beliefs about typical development if investment and human capital at birth are defined according to scenario k . Because it

reflects typical from the point of view of the mother, the factor θ_i in Equation (6) is set to zero in Equation (9). In addition, because the IRT model is specific for scenario k , the parameters in (9) are indexed by k .

Second, the model represented in Equation (6) is fitted using actual developmental data from the NHANES study, while the one in (9) uses respondent i age-range data collected in our study.

If we combine the model in Equation (9) with the age ranges provided by the respondent, we conclude that, according to the respondent i , the probability that the child will learn how to do MSD task j in scenario k by age $\underline{a}_{i,j,k}$ is:

$$\Delta_0 = 1 - \Phi[-\tilde{b}_{i,j,k,0} - \tilde{b}_{i,j,k,1} \ln \underline{a}_{i,j,k}]. \quad (10a)$$

Analogously, the probability that the child will learn how to do MSD task j in scenario k by age $\bar{a}_{i,j,k}$ is

$$\Delta_1 = 1 - \Phi[-\tilde{b}_{i,j,k,0} - \tilde{b}_{i,j,k,1} \ln \bar{a}_{i,j,k}]. \quad (10b)$$

If we manipulate the system of Equations (10a) and (10b), we conclude that for arbitrary j and k , the following equalities hold:

$$\tilde{b}_{i,j,k,1} = \frac{\Phi^{-1}(1 - \Delta_0) - \Phi^{-1}(1 - \Delta_1)}{\ln \bar{a}_{i,j,k} - \ln \underline{a}_{i,j,k}} \quad \tilde{b}_{i,j,k,0} = \frac{\Phi^{-1}(1 - \Delta_1) \ln \underline{a}_{i,j,k} - \Phi^{-1}(1 - \Delta_0) \ln \bar{a}_{i,j,k}}{\ln \bar{a}_{i,j,k} - \ln \underline{a}_{i,j,k}}$$

Having estimated the parameters in the IRT model as perceived by respondent i , the next step in the algorithm is to estimate the probability that the child will learn how to say a partial sentence with three words or more by age 24 months. According to individual-specific IRT model, this probability is $p_{i,j,k}^A$ and defined according to:

$$p_{i,j,k}^A = 1 - \Phi[-\tilde{b}_{i,j,k,0} - \tilde{b}_{i,j,k,1} \ln 24].$$

We use this estimate of the probability, together with the IRT model defined in Equation (6), to derive an error-ridden measure of maternal expectation of the natural log of development at age 24 months, $\ln q_{i,j,k}^A$, from the implied probability $p_{i,j,k}^A$. To do so, we invert Equation (7) and solve for $\theta_{i,j,k}^A$:

$$\ln \hat{q}_{i,j,k}^A = \ln 24 + \frac{\tilde{b}_{i,j,2}}{\tilde{b}_{i,j,1}} \theta_{i,j,k}^A = - \left[\frac{b_{j,0} + \Phi^{-1}(1-p_{i,j,k}^A)}{\tilde{b}_{i,j,1}} \right]. \quad (11)$$

3.2.5 Accounting for Measurement Error

Note that $\ln q_{i,j,k}^L$ and $\ln q_{i,j,k}^A$ are two error-ridden measures of maternal expectations about the natural log of child development. We assume that:

$$\ln q_{i,j,k}^L = R_{i,j} \delta_L + E(\ln q_{i,1} | q_0, x, \mathcal{H}_i) + \epsilon_{i,j,k}^L,$$

$$\ln q_{i,j,k}^A = R_{i,j} \delta_A + E(\ln q_{i,1} | q_0, x, \mathcal{H}_i) + \epsilon_{i,j,k}^A.$$

The vector $R_{i,j}$ captures heterogeneity across individuals, MSD items, or the type of question asked. In this sense, the measurement error model that we use in this paper allows for the error-ridden measures $\ln q_{i,j,k}^L$ and $\ln q_{i,j,k}^A$ to be biased indicators of the latent variable of interest, $E(\ln q_{i,1} | q_0, x, \mathcal{H}_i)$.

Let $\ln z_k = 0.5(\ln q_{0,k} - \ln x_k)^2$ and use Equation (5) to arrive at the following model:

$$\ln q_{i,j,k}^L = R_{i,j} \delta_L + \mu_{\psi,i,0} + \mu_{\psi,i,1} \ln q_{0,k} + \mu_{\psi,i,2} \ln x_k + \mu_{\psi,i,3} \ln z_k + \epsilon_{i,j,k}^L \quad (12a)$$

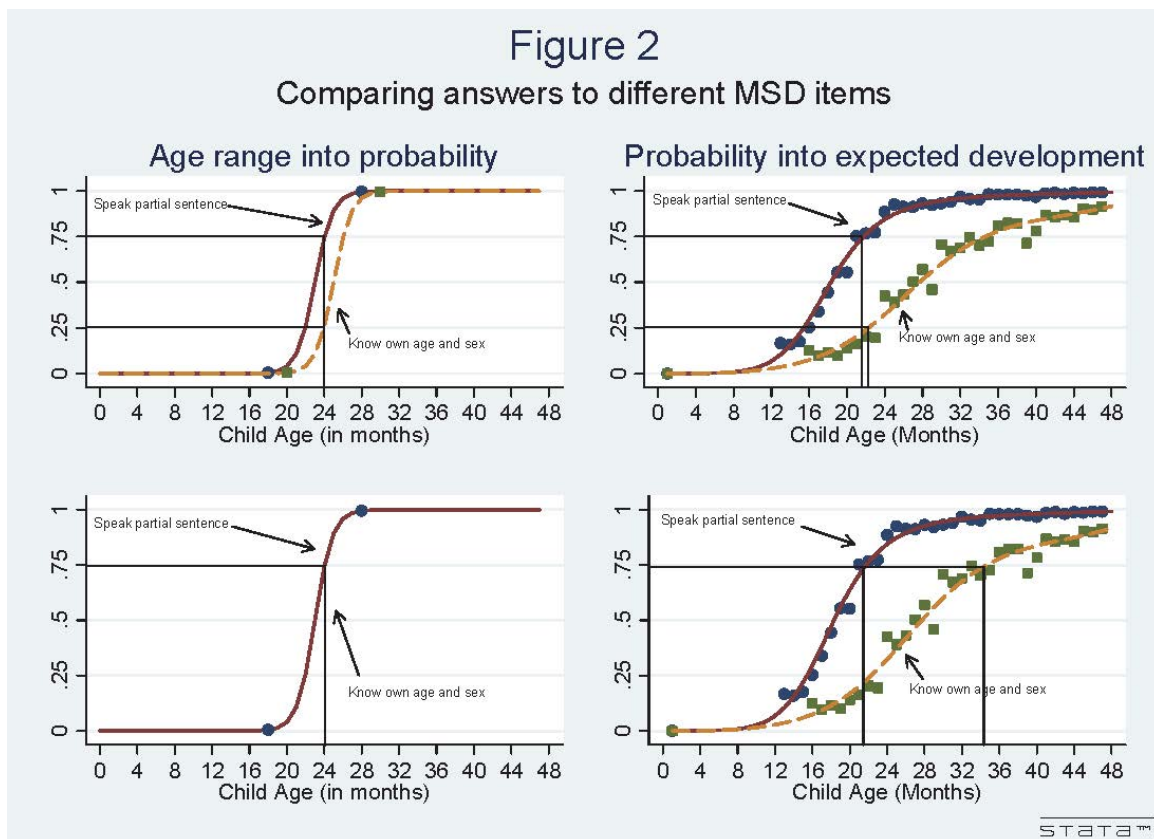
$$\ln q_{i,j,k}^A = R_{i,j} \delta_A + \mu_{\psi,i,0} + \mu_{\psi,i,1} \ln q_{0,k} + \mu_{\psi,i,2} \ln x_k + \mu_{\psi,i,3} \ln z_k + \epsilon_{i,j,k}^A \quad (12b)$$

Equations (12a) and (12b) constitute a linear factor model in which $\mu_{\psi,i} = (\mu_{\psi,i,0}, \mu_{\psi,i,1}, \mu_{\psi,i,2}, \mu_{\psi,i,3})$ are the factors, $\epsilon_{i,j,k} = (\epsilon_{i,j,k}^L, \epsilon_{i,j,k}^A)$ are the measurement errors, and $\lambda_k = (1, \ln q_{0,k}, \ln x_k, \ln z_k)$ are the factor loadings. Interestingly, note that λ_k is known and fully determined by the description of the scenarios of investments and human capital at birth. The fact that the factor loadings are known reduces the estimation of the model in Equations (12a) and (12b) to the estimation of the distribution of $\mu_{\psi,i}$ and the distribution of $\epsilon_{i,j,k}$.

Thus, it would be possible to estimate the model using only one item of the MSD scale. However, if we have multiple items, we can investigate how the respondents' answers vary across MSD items for a fixed scenario of human capital at birth and investments. For example, the top right panel in Figure 2 shows, for each age, the fraction of children who

can “speak a partial sentence of three words or more” (solid curve). Also shown in the same top right panel in Figure 2 is the fraction of children who “know own sex and age” (dashed curve). Clearly, at each age, there are children who can speak a partial sentence of three words or more but who do not know their own sex and age. This fact indicates that the latter is a more difficult item than the former.

If the respondents understand the survey instrument, we would expect them to assign a lower probability or higher age ranges to items that are more difficult. This is the case depicted in the top left panel of Figure 2. Fixing the scenario in which the baby’s health at birth is “good” and investments are “high,” this hypothetical respondent provided answers that imply a high probability of “speak[ing] a partial sentence” but a low probability of “know[ing] own age and sex.” As a result, once we transform the probability into measures of expected development, the two different measures are quite close in a quantitative sense (top right panel).



It is also possible that respondents report similar probabilities or age ranges for the same scenario across different items. Such a possibility is depicted at the bottom half of Figure 2. In that case, we would see measures of expected development that vary widely from easier to more difficult items. If the results indicate such constancy of age ranges, we would be worried about the possibility that respondents do not understand the instrument very well.

3.3 Eliciting Preferences

Typically, preference parameters are estimated by using revealed preference data. Unfortunately, this is not possible in our case because we do not observe investments. To estimate $\alpha_{i,1}$ and $\alpha_{i,2}$, we follow a different route. Our approach is to elicit the preference parameter by stated-choice data. In our survey, we first told the respondent to assume that the baby's human capital at birth is "high." We then presented the respondent with nine hypothetical scenarios of monthly income and prices of investments. These nine hypothetical scenarios are the combination of three levels of monthly income (\$1500, \$2000, and \$2500) and three levels for the price of investment goods (\$30, \$45, and \$60).

In order to link investment to time (i.e., the age of the child), we prepared a three-minute video in which we explained to the respondent 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 purpose of this exercise was to explain to the respondent that investments are costly.⁵ We illustrated the concept by giving 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, we presented the respondents with the following instructions: "Suppose that your household income is \$y per month and that for

⁵ We have implicitly assumed that the production function for investment goods is Leontief in maternal time and investment goods (such as children books). Obviously, this need not be the case.

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: two, three, four, or five hours per day interacting with a child. For example, if the mother i chooses $x_{i,m,n}$ hours per day when the price is $\$p_m$ and income is $\$y_n$ then her monthly expenditure is $\$p_m x_{i,m,n}$, and the share of income allocated to investment is $s_{i,m,n} = \frac{\$p_m x_{i,m,n}}{\y_n} . Note that variability in the share $s_{i,m,n}$ across respondents i arises strictly because of variability in choices $x_{i,m,n}$ (all respondents face the same set of prices and incomes).

The manipulation of Equation (5), together with the definition of $s_{i,m,n}$, allows us to conclude that:

$$\frac{s_{i,m,n}}{1-s_{i,m,n}} = \alpha_{i,1}(\mu_{i,\psi,2} + \mu_{i,\psi,3} \ln q_0) + \alpha_{i,2} + \epsilon_{i,m,n}. \quad (13)$$

Equation (13) suggests a factor model in which $\frac{s_{i,m,n}}{1-s_{i,m,n}}$ is the measurement associated with two latent factors ($\alpha_{i,1}$ and $\alpha_{i,2}$) with corresponding factor loadings ($\mu_{i,\psi,2} + \mu_{i,\psi,3} \ln q_0$) and one, respectively. The $\epsilon_{i,m,n}$ is a mean-zero error term.

4 Results

In this section, we describe the empirical results from our analysis of the Maternal Knowledge of Infant Development Survey (MKIDS) and the Philadelphia Human Development (PHD) Study. Appendix A contains a detailed explanation about procedures and features of each one of these two studies.

4.1 The Data

The analysis in this paper focuses on a very homogenous group of 777 participants. All of the respondents were black. The participants in both studies tended to be young (about 80% of them were at most 25 years old) and had little schooling (18% of the respondents were high school dropouts or have received a GED, 43% had a high school diploma, and 39% had some post-secondary schooling, but only about 5% of them have completed a college diploma). The sample was economically disadvantaged. The median income was

below \$20,000 per year, which is about the second decile in the US distribution of household income.⁶ Finally, the vast majority of the respondents were single. Appendix Table A1 presents additional information on demographic characteristics of respondents.

The data collected in each study was different. This is because the MKIDS and PHD studies have different purposes. MKIDS was a pilot study and, because of budget constraints, data collection was limited to one interview during the participant's pregnancy. MKIDS' main goal was to develop a questionnaire to elicit maternal beliefs about the technology of skill formation. Therefore, the MKIDS' dataset contains considerable experimentation about the way to formulate questions and define scenarios.

In contrast, the PHD study was longitudinal and followed the mother up to the point in which the child turns two years old. The PHD study measured parental investments around the time that the children were one year old as well as assessed child development and re-elicited beliefs around the time that the children were two years old. Its main goals were to test if beliefs predict investments and the extent to which parents update beliefs. For this reason, the study adopted a standardized set of questions and definition of scenarios based on the knowledge acquired by the study team with the MKIDS study.

The first difference in these two studies relate to the types of elicitation questions used in each study. As shown in Table 1, 233 out of the 323 black participants in the MKIDS study answered only the questions formulated as age ranges. About 70 participants were asked both types of questions, and only 20 participants were asked the probability (i.e., "how likely") questions. In contrast, in the PHD study, all participants were asked both sets of questions.

The second difference relates to the number of MSD items used in the elicitation procedures. As shown in Table 1, the MKIDS participants provided answers regarding 15 different MSD items, but in this paper, we focus only on the eight items that measure cognitive development.⁷ In comparison, the PHD participants answered questions

⁶ For comparison, in 2010 the black median household income was \$33,460. The median household income in our survey was roughly half that amount.

⁷ The remaining seven items measure motor development.

Table 1						
Comparison of Datasets						
Number of observations	MKIDS		PHD		Total	
	323		454		777	
	N	%	N	%	N	%
Type of Elicitation Method						
Only probability	20	6.2	0	0.0	20	2.6
Only age ranges	233	72.1	0	0.0	233	30.0
Both methods	70	21.7	454	100.0	524	67.4
MSD Items						
Wearing wet pants bothers child	323	100.0	0	0.0	323	41.6
Speak partial sentence	323	100.0	454	100.0	777	100.0
Say first and last name	323	100.0	454	100.0	777	100.0
Count 3 objects correctly	323	100.0	454	100.0	777	100.0
Know own age and sex	323	100.0	454	100.0	777	100.0
Says the names of 4 colors	323	100.0	0	0.0	323	41.6
Count out loud up to 10	323	100.0	0	0.0	323	41.6
Draw picture of man/woman	323	100.0	0	0.0	323	41.6
Hypothetical scenarios						
Baseline	158	48.9	454	100.0	612	78.8
Alternative scenario #1	42	13.0	0	0.0	42	5.4
Alternative scenario #2	91	28.2	0	0.0	91	11.7
Alternative scenario #3	32	9.9	0	0.0	32	4.1
Stated choice data						
Hypothetical scenarios for prices of investment and income	158	48.9	0	0.0	158	20.3

regarding only four MSD items, but they did so for two different methods of elicitation. The combination of variation of MSD items and different elicitation methods provides additional ways to handle measurement error in elicitation of beliefs.

The third difference is in the definition of the hypothetical scenarios. For approximately half of the MKIDS participants—and for all of the PHD participants—the baseline hypothetical scenarios were defined as described in Section 3.2.2. The other half of MKIDS participants received one of three alternative definitions of the hypothetical

scenarios.⁸ Appendix Table A2 provides a summary of the definitions used in the different scenarios presented to study participants.

The fourth and final difference in the datasets relates to the fact that the MKIDS study contained elicitation of stated-choice data. As shown in Section 3.3, this information allows us to estimate the preference parameters that are necessary to quantitatively evaluate the impact of policies that affect parental beliefs. Due to time constraints, it was not possible to collect this data for the PHD study. On the other hand, the PHD study contained data on investments, so it is possible to estimate preference parameters using revealed preference data.

4.2 Subjective Expectations About the Technology of Skill Formation

Before we report our findings about maternal expectations, we briefly describe raw features of the data. Table 2 organizes MSD items in ascending order of difficulty. Thus, the first item is “child lets someone know that wearing wet diapers bothers him/her” which almost all children can do by the age of two years. The last item is “draw a picture of a man/woman with at least two parts of the body besides a head,” which only 2% of the children are able to do by the time that they are 24 months.

Several important features of the elicitation data arise from this table. The probabilities reported by respondents vary in ways that are consistent with basic assumptions of the technology of skill formation. *Ceteris paribus*, the higher the stock of human capital at birth, or the flow of investment, the higher the probability that a baby will learn the MSD tasks used in the elicitation exercise. This feature of the data is true for both elicitation methods.

However, there are two important differences between the elicitation method that relies on mothers reporting probabilities and the one in which the mothers report age ranges. The first difference relates to how the elicited probabilities correlate with the difficulty of the MSD items. The probabilities derived from answers to the “how likely” questions are uncorrelated with the difficulty of the MSD item. In fact, the likelihood reported by

⁸ Appendix Table A2 provides a summary of the definitions used in the different scenarios presented to study participants.

mothers for any given MSD item is around 80% for Scenario 1, 60% for Scenario 2, 66% for Scenario 3, and 49% for Scenario 4.

Table 2												
Basic Features of Raw Data												
MSD Items ranked in ascending order of difficulty		NHANES	Probability Scenarios				Age ranges Scenarios					
Rank	Item Description		Obs.	1	2	3	4	Obs.	1	2	3	4
1	Child lets someone know that wearing wet pants bothers him/her.	0.99	90	0.78 (0.24)	0.55 (0.27)	0.70 (0.27)	0.51 (0.26)	303	0.64 (0.33)	0.55 (0.36)	0.50 (0.36)	0.43 (0.37)
2	Child speaks a partial sentence of 3 words or more.	0.72	544	0.81 (0.18)	0.63 (0.22)	0.61 (0.20)	0.45 (0.20)	757	0.60 (0.36)	0.44 (0.38)	0.42 (0.38)	0.31 (0.36)
3	Child counts 3 objects correctly.	0.39	544	0.84 (0.18)	0.67 (0.22)	0.62 (0.20)	0.47 (0.20)	757	0.41 (0.38)	0.32 (0.36)	0.26 (0.33)	0.19 (0.30)
4	Child knows own age and sex.	0.31	544	0.83 (0.19)	0.66 (0.23)	0.62 (0.21)	0.47 (0.21)	757	0.33 (0.36)	0.26 (0.33)	0.23 (0.31)	0.17 (0.29)
5	Child says first and last name together without someone's help.	0.26	544	0.80 (0.20)	0.64 (0.22)	0.60 (0.21)	0.46 (0.21)	757	0.31 (0.36)	0.24 (0.33)	0.22 (0.31)	0.17 (0.29)
6	Child says the names of at least 4 colors.	0.20	90	0.81 (0.23)	0.59 (0.28)	0.74 (0.22)	0.56 (0.27)	303	0.26 (0.31)	0.22 (0.29)	0.19 (0.28)	0.16 (0.26)
7	Child counts out loud up to 10.	0.07	90	0.80 (0.20)	0.58 (0.27)	0.75 (0.19)	0.53 (0.27)	303	0.24 (0.30)	0.20 (0.28)	0.19 (0.28)	0.16 (0.27)
8	Child draws a picture of a man/woman, 2 parts besides head.	0.02	90	0.71 (0.25)	0.51 (0.28)	0.67 (0.21)	0.48 (0.26)	303	0.15 (0.26)	0.15 (0.26)	0.14 (0.26)	0.13 (0.25)

Note: Standard errors in parentheses.

This issue can be illustrated by focusing on two MSD items. The first is “speak a partial sentence with three words or more” and the second is “say first and last name.” According to the NHANES dataset, by age 24 months, 72% of the children will have already spoken a partial sentence with three words or more, but only 26% of them will have already said their first and last names. This difference indicates that “say first and last name” is more difficult for a two-year-old child than “speak partial sentence.”

When mothers are asked the likelihood that children will be able to do these tasks by age two years, their answers for a given scenario are about the same for both items. For example, the typical mother states that, for both items, the probability is around 80% and 45% in Scenarios 1 and 4, respectively. This suggests that mothers believe that these two items have about the same difficulty level, which contradicts the evidence from the NHANES dataset.

This issue exists, but is arguably far less serious, when mothers are asked to report age ranges. With respect to the two MSD items highlighted above, the transformation of age ranges into probabilities imply that in Scenario 1, 60% of children will know how to speak a partial sentence, but only 31% will say first and last name. Thus, the elicitation according to the age-range methodology suggests that “say first and last name” is more difficult than “speak partial sentence,” which is consistent with the NHANES dataset.⁹

The second difference refers to the fact that both methods produce very different estimates of probabilities, and neither of them are consistent with the probabilities observed in the NHANES dataset. The issue is more serious for the easiest and hardest MSD items. For example, 99% of children will have learned the easiest MSD item (“let someone know that wearing wet pants/diapers bothers child”). No elicitation method comes close to this figure, even for the best scenarios of human capital at birth and investment. The same conclusion can be reached for the hardest MSD items (“count out loud up to 10” and “draw a picture of a man/woman”). Although very few children are able to do these tasks by age 24 months, none of the methods suggest probabilities that are near what is observed in the data, even when we only consider the worst scenarios of human capital at birth and investments. This conclusion partly explains why the PHD study discarded the easiest and hardest MSD items and only used those items for which the age-range elicitation method performs reasonably well in levels.¹⁰

⁹ It is possible to summarize the discussion above with simple OLS regressions in which the dependent variables are average probabilities specific for each elicitation method and scenario, reported in Table 2, and the independent variables are a constant and the MSD-item difficulty rank. It turns out that the coefficients on item difficulty are near zero and statistically insignificant for the probabilities generated by “how likely” questions. At the same time, the same coefficients are statistically significant for the age-range questions. We then do the same analysis using the average objective probabilities from the NHANES dataset. In this case, the coefficient of difficulty rank is also negative and statistically significant. This evidence suggests that the elicitation method that relies on mothers reporting age ranges produces a correlation pattern between item difficulty and probabilities that are closer to the ones observed in the NHANES dataset.

¹⁰ It is important to keep in mind that the elicitation method that uses “how likely” questions can perform better than the age-range questions when it comes to predicting investments. For this reason, the PhD study asked participants both types of questions.

Table 3 displays the summary statistics of the subjective expectations with respect to ψ . This table presents the results when we assume that $\Delta_0 = 10\%$ and $\Delta_1 = 90\%$.¹¹ The typical and median woman believes that the intercept term (the parameter $\mu_{\psi,0}$ in Equation [5]) is 0.115 and 0.108, respectively. There is enormous variability in the beliefs, as the variance is 0.035 (which implies a coefficient of variation of 1.62) and the interquartile range is 0.252, which is about twice the mean value.

Table 3					
Maternal Beliefs about the Technology of Skill Formation					
	25th percentile	Median	75th percentile	Mean	Variance
$\mu_{\psi,0}$	-0.015 (0.009)	0.101 (0.008)	0.236 (0.009)	0.115 (0.007)	0.035 (0.002)
$\mu_{\psi,1}$	0.077 (0.011)	0.296 (0.016)	0.554 (0.022)	0.365 (0.016)	0.204 (0.026)
$\mu_{\psi,2}$	0.065 (0.006)	0.166 (0.007)	0.285 (0.010)	0.192 (0.008)	0.046 (0.005)
$\mu_{\psi,3}$	-0.008 (0.007)	0.094 (0.010)	0.335 (0.024)	0.190 (0.020)	0.320 (0.051)

Note: Standard errors in parentheses.

The parameter $\mu_{\psi,1}$ represents maternal beliefs about the coefficient on human capital at birth. Above 90% of survey respondents believe that the higher the human capital at birth, the higher the human capital at age two years. However, there is considerable heterogeneity in beliefs even in this very homogenous sample. While the median mother believes that $\mu_{\psi,1}$ is about 30%, the mother at the 25th percentile believes this figure is about four times smaller. In contrast, the mother at the 75th percentile holds expectations about $\mu_{\psi,1}$ that are almost twice as large as the median mother's expectations.

According to the model presented in Section 2, an important parameter to drive maternal behavior with respect to investment is the parameter $\mu_{\psi,2}$. Approximately 10% of the

¹¹ Table 3 shows point estimates and their standard errors, which are quite small. For this reason, we do not discuss our findings about standard errors.

sample believes that this parameter takes on negative values. In other words, they believe that investments hurt the chances that children will acquire new skills.¹² Again, heterogeneity in beliefs is important. The mean of maternal beliefs is about 19% and the variance is about 5%. These two figures suggest a coefficient of variation around 1.11.

The parameter $\mu_{\psi,3}$ is the term that captures deviations from the Cobb-Douglas function. About 70% of respondents believe that the technology of skill formation has more complementarity between human capital at birth and investments than the one implied by Cobb-Douglas parameterization. This finding has important consequences for how maternal investments respond to the child's human capital at birth. Again, the heterogeneity in beliefs is important for this parameter as well. While the mother at the 25th percentile believes that the production function is Cobb-Douglas, the median mother believes $\mu_{\psi,3}$ is around 10%, and the 75th-percentile mother's expectations are 33%.

For completeness, Panels B and C in Appendix Table A3 report how these beliefs vary as we change the values for the parameters Δ_0 and Δ_1 . As can be easily seen, the distribution of beliefs changes very little as we change the values of the parameters Δ_0 and Δ_1 . Thus, we forego discussion about this issue. For the remainder of this paper, we focus our analysis on the case in which $\Delta_0 = 10\%$ and $\Delta_1 = 90\%$ because this generates the best fit of the data, as indicated by the values of the log likelihood reported in that table.

It is possible that beliefs about the technology of skill formation vary with respect to different definitions of what constitutes “low” versus “high” levels of investments or human capital at birth. Next, we analyze the results from the experimentation about framing scenarios of investments and human capital at birth.

Before we proceed, it is important to remark that all of the data in the baseline scenario were collected via the computer-assisted personal interviewing (CAPI) technique in which

¹² Interestingly, the HOME-SF contains one item that reads as follows: “Some parents spend time teaching their children new skills while other parents believe children learn best on their own. Which most closely describes your attitude?” Approximately 7% of the black mothers report that the statement that “children learn best on their own” best describes their beliefs.

an interviewer asked the study participants the questions and entered the answers in the electronic survey instrument.

In contrast, all of the data in the alternative scenarios was collected via audio computer-assisted self-interview (ACASI). In this technique, the questionnaire is self-administered, and the computer displays each question and its answer alternatives while presenting a prerecorded interviewer's voice that reads these to the respondent, who listens privately through headphones. Researchers interested in eliciting information about sensitive information (e.g., sexual behavior) worry about face-to-face interviewing methods because it may induce study participants to report what is socially desirable (Waruru, Nduati, and Tylleskar, 2005). In our context, one could be worried that respondents who hold very low expectations would report higher beliefs because they understand that this is a more socially desirable answer.

As shown in Appendix Table A2, the main difference between the baseline scenario and the alternative scenario #1 is the technique of the interview. In particular, note that while there are very small differences in the definition of the scenarios for human capital at birth, there are no differences in the definition of the scenarios for investments. As a result, we argue that differences in beliefs between baseline and alternative scenario #1—if they exist—are probably due to differences in interviewing techniques.

Table 4 presents the analysis of the sensitivity of beliefs with respect to the definitions of scenarios and interviewing techniques. To be sure, we restrict the analysis to the MKIDS sample, as this form of experimentation was restricted to this particular study. Moreover, we show the results generated under the assumption that $\Delta_0 = 10\%$ and $\Delta_1 = 90\%$, but the qualitative conclusions are invariant to the values taken by these two parameters.

To construct Table 4, we estimated a seemingly unrelated regression model (SURE, see Zellner, 1962) in which the dependent variables were the beliefs about the parameters $\mu_{\psi,l}$ for $l = 0,1,2,3$, and the regressors were an intercept and a dummy variable for each alternative description of the scenarios for investments. Therefore, the coefficients on these dummy variables capture differences in beliefs relative to baseline.

Table 4					
Alternative Definition of Scenarios and Maternal Beliefs					
Regressors	Dependent variables				F-Test
	$\mu_{\psi,0}$	$\mu_{\psi,1}$	$\mu_{\psi,2}$	$\mu_{\psi,3}$	(p-value)
Intercept (baseline)	0.018 (0.017)	0.147 (0.043)	0.112 (0.022)	0.070 (0.062)	- -
Dummy for alternative scenario #1	0.067 (0.037)	-0.027 (0.094)	-0.032 (0.048)	-0.081 (0.136)	1.080 (0.364)
Dummy for alternative scenario #2	0.280 (0.028)	0.469 (0.071)	0.175 (0.037)	0.424 (0.103)	33.910 (0.000)
Dummy for alternative scenario #3	0.206 (0.041)	0.027 (0.104)	0.051 (0.054)	0.091 (0.152)	6.750 (0.000)

Note: Standard errors in parentheses, except in the F-test column where we report p-values.

First, note we cannot reject the null, and we conclude that CAPI and ACASI methods generate similar estimates of beliefs. We arrive at this conclusion by testing that the coefficient on “dummy for alternative scenario #1” is equal to zero. This is the case if we test the coefficients on each equation separately or if we perform a joint F-test in which the null hypothesis is that the four coefficients on the “dummy for alternative scenario #1” are all equal to zero. The F statistic is 1.08 with a corresponding p-value equal to 0.364.

We find mixed results about whether the definition of scenarios matter for beliefs or not. On one hand, the coefficients on the dummies for alternative scenario #2 imply uniformly higher beliefs for all parameters ψ . The results for “dummy for alternative scenario #2” are particularly striking because both the separate and the joint tests reject the null hypothesis of no difference.

On the other hand, the results based on the analysis of the coefficients on the “dummy for alternative scenario #3” are not as conclusive. True, the F statistic is large enough to reject the null hypothesis that the coefficients are all equal to zero, but it is possible that this result is likely driven by the large differences regarding $\mu_{\psi,0}$. The regressions involving the

beliefs about $\mu_{\psi,1}$, $\mu_{\psi,2}$, and $\mu_{\psi,3}$ do not show differences between the baseline and alternative scenario #3.

The main lesson from this analysis is that it is necessary to more deeply investigate how the framing of scenarios affects the elicitation of beliefs.

4.3 Preferences

Appendix Figure A4 plots the demand function of investment for each level of income (left panel) and the Engel curve for each level of price (right panel). Clearly, the demand for investments is a decreasing function of prices, and as income rises, so does the amount of investments chosen by the respondents.

We can estimate shares for each respondent i from: $\hat{s}_i = \frac{1}{9} \sum_{m=1}^3 \sum_{n=1}^3 s_{i,m,n}$. In our sample, the mean and median shares of expenditure on investments are around 8%. In comparison, Lino (2012) reported shares of investment at around 7% for low-income parents. Given the estimated shares, we estimate Equation (13) to recover factor scores $\alpha_{i,1}$ and $\alpha_{i,2}$ for each mother i . Table 5 displays summary statistics for the parameters that describe preferences. When we account for heterogeneity in beliefs, we find that the typical woman has $\alpha_{i,1}$ equal to 3% and $\alpha_{i,2}$ close to 8%. There is heterogeneity in preferences. The coefficient of variation for $\alpha_{i,1}$ is about 50%, and the one for $\alpha_{i,2}$ is a little over 20%. These figures are much lower than the coefficients of variation found for beliefs about the technology of skill formation.¹³

4.4 Objective Estimation of the Technology of Skill Formation

¹³ The preference parameters are correlated. An increase in $\alpha_{i,1}$ by one standard deviation is associated with an increase over half a standard deviation in $\alpha_{i,2}$. The preference parameters $\alpha_{i,1}$ and $\alpha_{i,2}$ are negatively and weakly correlated with $\mu_{i,\psi,0}$. One standard deviation increase in $\mu_{i,\psi,0}$ is associated with a 10% standard deviation reduction in $\alpha_{i,1}$ or $\alpha_{i,2}$. For $j = 2,3$, one standard deviation increase in $\mu_{i,\psi,j}$ is associated with approximately a 15% and 25% increase in $\alpha_{i,1}$, respectively. For $\alpha_{i,2}$, these figures are 8% and 15%, respectively. A small difference is that $\alpha_{i,1}$ is weakly correlated with $\mu_{i,\psi,1}$ (one standard deviation increase in $\mu_{i,\psi,j}$ is associated with an increase in $\alpha_{i,1}$ that is 10% of its standard deviation), while $\alpha_{i,2}$ is not.

We rely on the CNLSY/79 data to objectively estimate the technology of skill formation - Equation (1). Appendix B provides a description of the data set and summary statistics for the variables and the sample used in these analyses.

Table 5					
Maternal Beliefs about the Technology of Skill Formation					
	25th percentile	Median	75th percentile	Mean	Variance
$\alpha_{i,1}$	0.026 (0.000)	0.031 (0.000)	0.040 (0.001)	0.031 (0.000)	0.00024 (0.00001)
$\alpha_{i,2}$	0.067 (0.000)	0.078 (0.001)	0.094 (0.001)	0.079 (0.000)	0.00031 (0.00001)

Note: Standard errors in parentheses.

In order to objectively estimate the technology of skill formation, we assume that the dependent variable in Equation (2), $q_{1,i}$, is the child's cognitive development around age 24 months, which in the CNLSY/79 is measured by the MSD scale. In order to maintain comparability with the analysis in Section 4.2, we transform maternal answers into a scale measured in time (i.e., age in months) using the IRT model estimated with the NHANES dataset.

Correspondingly, x_i is investment during the first 24 months of the child's life. In the CNLSY/79, investment is measured by the HOME-SF. As in Cunha, Heckman, and Schennach (2010), we factor analyze the items of the HOME-SF scale. In their analysis, the scale of the factor was set by the number of children's books in the household. Although this is a valid metric, this was not convenient for the current study. To maintain consistency with the analysis in Section 4 above, it is necessary to set the location and scale of the instrument in a metric of time (months per year). Details of the procedure are also described in Appendix B.

Finally, $q_{0,i}$ is measured by the child's health at the time of birth. Among other information, the CNLSY/79 data set asks parents to report the child's weight and length at birth, the length of the gestation, and the number of days that the child spent in the hospital

after birth. In order to produce a scalar variable, we factor analyze the four measures above and extract one factor. The location and scale of the factor are set by the gestation length. This is convenient because gestation length is measured in number of months, which is the same unit used for cognitive skills around 24 months.¹⁴

Table 6				
Objective Estimation of the Technology of Skill Formation				
Dependent variable: Natural log of skills around age 24 months ¹				
Maternal Fixed Effect Procedure				
	13 to 35 Months	16 to 32 Months	19 to 29 Months	22 to 26 Months
	(1)	(2)	(3)	(4)
Natural logarithm of health at birth ²	0.563*** (0.138)	0.509*** (0.165)	0.600** (0.304)	0.19 (0.488)
Natural logarithm of investments ³	0.180*** (0.020)	0.199*** (0.027)	0.257*** (0.038)	0.283*** (0.081)
Constant	1.822*** (0.308)	1.999*** (0.368)	1.702** (0.676)	0.92 (1.703)
Observations	4,721	3,515	2,243	1,014
R-squared	0.734	0.624	0.516	0.61
Number of Mothers	3,042	2,542	1,814	915

Robust standard errors in parentheses. All regressions have dummy variables for: (i) the child's gender, (ii) the child's birth order, (iii) child's year of birth, (iv) the child's age at the time of the measurement of the MSD score, and (v) maternal age at the time of the child's birth. *** p<0.01, ** p<0.05, * p<0.1

¹Skills are measured by the Motor-Social Development Scale and are scaled in "mental" age of development.

²Health at birth is captured by factor analyzing weight at birth, length at birth, gestational age, and number of days in hospital. The scale and location of the factor are determined by gestational age.

³Investments are measured by the components of the HOME-SF instrument. We factor analyze the items and set the location and the scale of the factor in months/year of direct engagement between mother and child.

We use within-family variation to estimate the parameters of the technology of skill formation. Thus, in the empirical application that follows, we consider the following parameterization of the technology of skill formation:

¹⁴ Tables B1-B3 in Appendix B describe in detail summary statistics for the CNLSY/79 variables that we use for the estimation of the technology of skill formation (2). For example, the stocks of skills for the typical Hispanic, black, and white children around 24 months are, respectively, 24, 26.4 and 25.6 months. The black-white difference is not statistically significant. The advantage of black children in the MSD scale arises partly due to the fact that they exhibit superior performance in motor items. In terms of investments, the typical white child tends to receive around 2.2 months of investments per year, while the median black child receives only 1.5 months per year. This difference is statistically significant even after we account for the differences in family backgrounds of children.

$$\ln q_{1,i,l} = \psi_{0,i} + \psi_1 \ln q_{i,0} + \psi_2 \ln x_i + \psi_3 \ln q_{i,0} \times \ln x_i + R_{i,l}\beta + v_{i,l} \quad (14)$$

where the index l denotes the birth order of the child and $R_{i,l}$ the observed characteristics of child l (e.g., the child's gender, birth order, year of birth, and the age at the time of the MSD test).

Table 6 shows the estimated parameters of the technology of Equation (14). In all of the regressions we show in Table 6, we control for the child's age at the time of the interview, the child's year of birth (to account for cohort effects), dummy variables for maternal age at the time of the child's birth, a dummy variable for the child's gender, and dummy variables for the child's birth order.¹⁵

We start by showing the results when we use the least restricted sample: we include all children whose age at the time of the MSD measurement is between 13 and 35 months.¹⁶ For this sample, the elasticity of skills with respect to investment (i.e., the parameter ψ_2) is 18%. This means that a 10% increase in investments translates into a 1.8% increase in skills at age 24 months. Column (2) restricts the age range of children at the time of the interview to 16 and 32 months. Interestingly, we find that the elasticity parameter is about 10% higher (around 20%). Column (3) displays the results when we work with an even more restricted sample: we only include the children who are between 19 and 29 months old. We find ψ_2 to be significantly higher in this sample: the elasticity in the overall sample is 26%, which is about 43% higher than when we work with the least restricted sample.¹⁷ The higher values of ψ_2 may be due to the fact that the components of the MSD instrument applied to older children focus on developmental dimensions that are more affected by parental investments. Another possibility is that the families for which we observe child

¹⁵ To focus on the parameter of interest, Appendix Table B4 reports our estimates for the other parameters in (18) for the full sample regression.

¹⁶ We choose ages 13, 16, 19, and 22 as the cutoff ages owing to the structure of the MSD instrument. As explained in Section 3.1, Part E of the MSD instrument is given to children who are at least 13 and at most 15 months old. The parents of children who are at least 16 and at most 18 months old respond to Part F. Part G is assigned to the parents of children who are between 19 and 21 months old. Finally, Part H is answered by parents whose children are at least 22 and at most 47 months. The end date is determined so that age 24 months is the center of the interval.

¹⁷ If we only include the respondents whose development is measured between 22 and 26 months, our estimate for γ is 28%. However, the sample size becomes too small to be decomposed in the smaller subsamples presented in Table 5.

development more closely at around 24 months are the same families that have high values of ψ_2 .

4.5 Quantifying the Importance of Expectations

Before we present the results of changing parental beliefs, we briefly compare the importance of preference parameters and beliefs in explaining heterogeneity in investments. Table 7 shows the result of our analysis, and to generate it, we first simulated investments for the situation in which preference parameters, beliefs, income, and prices were set at their median levels. In the first row, we investigate how investments change if we set the parameter α_1 at the 75th percentile (which corresponds to a 28% change in α_1), while maintaining everything else at the 50th percentile. As shown in the first row, investments would increase by 1.6%, which implies an elasticity of 5.8%.

If we move the parameter α_2 from median to the 75th percentile, the move corresponds to a change of 21.4%. Investments, in this case, increase by 18.3%. Thus, the elasticity is high, at 85.2%.

Table 7					
Comparative Statics of Investments					
	Median	75th percentile	% Change in investments	% Change in parameter	Elasticity
α_1	1.70	1.73	0.02	28.0%	5.8%
α_2	1.70	2.01	0.18	21.4%	85.2%
$\mu_{\psi,2}$	1.70	1.77	0.04	72.0%	5.8%
$\mu_{\psi,3}$	1.70	1.70	0.00	257.1%	0.1%
$\mu_{\psi,3}$	1.70	1.86	0.09	257.1%	3.6%

This table shows the comparative statics of optimal investments in relation to preference and belief parameters. Each row shows what happens to investments as we move one parameter and fix the other parameters at the median value. In the last row, we replace the human capital at birth from the mean value to the value at the first percentile.

Next, we investigate how parental beliefs affect investments. If we increase $\mu_{\psi,2}$ by 72% (from median to 75th percentile), investments increase by 4.1%, which implies an

elasticity of 5.8%. If we change $\mu_{\psi,3}$ from median to the third quartile—which is equivalent to an increase of 257.1%—investments change by only 0.2%, which indicates negligible elasticities. However, this is driven by the point at which the log of natural log of child development is evaluated (which is at the median value). If we evaluate the elasticity at the first percentile of q_0 , the elasticity is 3.6%.

Finally, we use our data to answer the following question. Suppose we were to carry out an intervention that set maternal beliefs exactly equal to the parameters of the technology of skill formation as estimated from the CNLSY/79. What would be the impact of such intervention on investment?

As shown in Table 8, our estimates suggest that such policy would increase investments by at least 4% and at most 12%. In other words, although many mothers underestimate the importance that investments play in the development of their children’s skills, the model suggests that the channel through which beliefs affect investments—namely, maternal preferences for child development—is not strong enough to be a major determinant of investment.

Table 8				
Maternal Beliefs and Technology				
Cases	Factual investment	Counterfactual investment	% Change	Effect size
$\mu_{\psi,2} = 0.267$ $\mu_{\psi,3} = 0.000$	1.84	1.92	4.4%	10.3%
$\mu_{\psi,2} = 0.454$ $\mu_{\psi,3} = 0.000$	1.84	2.05	11.7%	26.9%

The model can be used to generate estimates of the effect sizes of policies that change maternal beliefs. The effect sizes are between 10% and 27%. If the effect size is 10% and we assume that the intervention treats parents separately and that there is no attrition, it

would necessitate a sample size of 3,140 parents, half in the treatment group and the other half in the control group. If the sample size is 27%, then it is necessary to have 532 study participants, half in each group.

What would such an intervention look like? Suskind et al (2013) showed that it is possible to improve the home language environment children experience through an intervention that provides quantitative linguistic feedback in order to influence adult linguistic behavior and, as a result, a child's early language environment. In order to provide quantitative linguistic feedback, the authors utilized the Language Environment Analysis (LENA) technology as a tool to analyze verbal interactions and reinforce behavior change. The LENA technology provides counts of adult words (AWC) as well as conversation turns (CTC). Baseline LENA outcome measures were obtained from a sample of non-parental caregivers and their typically developing children aged 10 to 40 months. Caregivers participated in a one-time educational intervention focusing on enriching a child's home language environment, interpreting feedback from the baseline LENA recordings, and setting language goals for the following session. LENA recordings were obtained weekly to measure linguistic behavior. Caregivers showed a significant and prolonged increase from mean baseline to mean post-intervention AWC and CTC as measured by LENA. The AWC increased by approximately 36% and the CTC by about 25%. Preliminary results indicate that a one-time educational intervention combined with quantitative linguistic feedback may have a positive effect on caregiver language output, thus enhancing the child's language environment.

Conclusion

In this paper, we presented a simple model in which mothers have subjective expectations about the technology of skill formation. We show that the model can be used to evaluate the impact of policies that affect maternal knowledge about the importance of investments for developing the human capital of children. In order to be empirically useful, it is necessary to separately identify heterogeneity in expectations from heterogeneity in beliefs.

We proposed to solve this problem by collecting data on subjective expectations about the technology of skill formation. We surveyed a sample of socioeconomically disadvantaged, pregnant African-American women. By comparing the subjective expectations with the objective estimates of the technology of skill formation, we found evidence that our respondents may underestimate the elasticity of child development with respect to investments.

We also elicited data that allows us to estimate the parameters that describe parental preferences. We did so to evaluate the impact of a policy that would move expectations from the median value in our sample to the objective estimate based on the CNLSY/79. We found that investments would increase by about 10% and that the children's stocks of cognitive skills at age 20 months would increase by about 5%. The values are higher for mothers whose beliefs are below the median.

In future work, we will follow the respondents longitudinally and see if measures of expectations are correlated with parental investments once we account for other state variables that may be correlated with beliefs and investments, such as maternal skills, family income, and others. This will be an important step in validating the measures of beliefs and preferences proposed in this paper.

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