The Production of Child Human Capital: Endowments, Investments and Fertility

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March 1, 2012

Abstract

We study how endowments, investments and fertility interact to produce human capital in childhood. First we explore the human capital production function. Exploiting an exogenous source of investment, the launch of Head Start in 1966, to identify the impact of investments (preschool) on child human capital (IQ), we find strong evidence of complementarity between investments and early human capital as evidenced by greater gains from preschool on the IQ of those with the highest initial human capital. Second, because this complementarity generates incentives for parents to invest in children with higher initial levels of human capital, we explore how investments respond to child endowments and find that they are reinforcing. Third, the degree of reinforcement increases with family size. Thus, in addition to the tradeoff in quantity and average quality, an increase in quantity also leads to greater variation in quality, due to both greater variation in endowments (from higher fertility) and greater reinforcing investments. Finally, we show that our findings are replicated by a quantity-quality trade-off model in which children are heterogeneous with respect to their endowment and parental preferences feature weak complementarity between quality and quantity as well as moderate aversion to inequality in the human capital of children.

1 Introduction

Growing evidence points to the important role that conditions in early childhood play in determining adult human capital and earnings. Measures of human capital at ages 6-8, for example, can explain 12 (20) percent of the variation in adult educational attainment (wages) (McLeod and Kaiser, 2004;

*We thank Joe Altonji, Angela Fertig, conference and seminar participants at UCSB, the AEA annual meeting, the NBER Children's meeting UCSD, Brown, OSU, University of Minnesota, Washington University in St. Louis, and Yale University, for helpful comments. Funding was generously provided by NSF grant # NSF- SES 0752755 and the National Institutes of Health - National Institute of Aging (P30 AG12836), the Boettner Center for Pensions and Retirement Security, and the NICHD R24 HD-0044964.

Currie and Thomas, 1999). Theoretical models of the production of human capital also support an important role played by early human capital which is largely determined by parents through initial endowments and investments in children (Becker, 1981; Cunha and Heckman, 2007). To better understand the production of human capital in early childhood, we study the nature of parental investments, including their productivity and interaction with existing stocks of human capital and endowments, their allocation across children, and their interaction with the fertility decision.

To this end we ask and answer three fundamental questions related to the production of human capital in early childhood. First, are existing stocks of human capital and investment substitutes or complements in the production of future stocks of human capital? Second, what is the relationship between parental investments and endowments? In other words, do more highly endowed children receive more or fewer investments? And third, does family size affect the relationship between investments and endowments?

To answer the first question, we exploit exogenous variation in investment in the form of preschool enrollment to identify whether early human capital and parental investments are complements in the production of child human capital. Specifically, our data consists of a low income sample of siblings that includes multiple measures of human capital over several periods of childhood and spans the launch of Head Start in 1965/6. We use this exogenous increase in preschool availability to identify the impact of preschool enrollment on child IQ and cognitive achievement as well as any complementarities with early stocks of human capital in a family fixed effect/sibling comparison framework. We find that preschool enrollment has a positive and significant impact on four year IQ for all, but that the impact is largest for those with higher stocks of "early human capital" as measured by cognitive development at eight months of age. By seven years, the effect of preschool on IQ and achievement has faded for all but highly developed infants for whom the impact persists.

To empirically examine how investments respond to endowments, we introduce two innovations to the analysis. First, we generate a measure of endowment that addresses issues of endogeneity and measurement error. To address the former, we can control for prenatal investments which are usually unobserved and correlated with both initial endowments and postnatal investments, generating a significant source of omitted variable bias in an analysis that cannot control for prenatal investments. For the latter, we factor analyze the orthogonal components to prenatal investments of multiple measures of health at birth. Second, we introduce a new measure of parental investment that is a measure of the quality of the interaction of the mother and child as rated by a psychologist.[1] We present evidence that parents invest more in children with higher endowments, consistent with strong complementarities in the production of human capital.

We follow with our third and final question: how fertility interacts with endowments and investments to produce human capital in childhood. The existing literature on fertility and child human

[1] For example, these include ratings of how focused the mother is on the child and how responsive she is to the child's needs.

capital generally considers the effects of fertility on average investment and human capital. We too start with this type of analysis. We use two instruments for fertility: multiple births and fetal deaths. We find that children in larger families are of lower quality on average as measured by 4 year IQ, 7 year IQ and achievement.

We build upon these findings with an analysis of the impact of fertility on the distribution of endowments, investments and child human capital within a household. We find that investments are more reinforcing in large families and that endowments also vary more widely in large families. Together, these two factors yield the prediction that variability of child quality within family (since it is a function of endowments and investments) increases with fertility, which is what we find. In fact, our data show that the highest quality child in a large family is comparable to the highest quality child in a small family. In contrast, the lowest quality child in a large family has much lower human capital than the lowest quality child in a small family. These relationships cannot be explained by birth order.

Finally, we show that our findings can be replicated by a model that has the following features: (i) a production function that features strong complementarity; (ii) children are heterogeneous with respect to endowments; (iii) parents have moderate aversion to inequality in human capital across children; (iv) the budget constraint features a quality-quantity trade-off as in Becker and Lewis (1973); (v) the utility function exhibits moderate complementarity between fertility and inequality-adjusted average human capital across their children.

Our results have important implications for our understanding of the human capital production function and the interaction between initial levels of human capital and investments, as well as how they interact with fertility. In addition, by providing new estimates of the impact of Head Start on multiple measures of cognitive ability and achievement that exploits exogenous variation in Head Start availability within family, our results also contribute to the growing literature on the impact of Head Start and other high quality preschool interventions (Currie and Thomas, 1995; Garces, Currie and Thomas, 2002; Ludwig and Miller, 2007.) The rest of the paper is organized in five parts. In Section II, we establish that preschool investments and early human capital are complements in the production of late human capital. In Section III, we examine how parental investment responds to initial levels of human capital. In Section IV, we consider how fertility affects the human capital of children in a family and how endowments and fertility interact in the allocation of investments in human capital across children. In Section V, we describe the basic features of a model that is consistent with our findings, explain how we match it to the data, and show that it reproduces the qualitative and quantitative features of the data. In the last section, we conclude.

2 Are Investments and Early Human Capital Complements in the Production of Later Human Capital?

2.1 Background

The theory underlying the first part of our empirical analysis derives from a model originally developed by Becker and Tomes (1986) that incorporates the insights of Cunha and Heckman (2007). In Becker and Tomes, parents maximize each child's total wealth through investments in human capital and/or financial bequests. At the optimal, returns to investments in human capital and financial bequests are equalized. Importantly, their model assumes that childhood can be reduced to a one-period model, so their framework does not differentiate investments in early childhood from investments in adolescent periods.

Cunha and Heckman (2007) extend the model, incorporating many insights from recent research in child development. They introduce two important concepts that influence our work. The first is the idea of "critical periods" which is the idea that certain dimensions of human development can only be affected in certain periods of the lifecycle of an individual. For example, the evidence from numerous studies suggests that IQ can be manipulated at early ages, but that it is largely stable by age 10, implying that investments before age 10 can affect IQ, but not investments made after age 10 (O'Connor et al, 2000; Hopkins and Brecht, 1975). This insight underscores the selection of our measures of child human capital (IQ at ages four and seven, cognitive achievement at age seven).

The second concept is the notion of "dynamic complementarity": human capital in one period raises the productivity of investment in a future period. There is very little empirical work on this topic. Cunha, Heckman, and Schennach (2010), who use the CNLSY/79 data, find estimates for the elasticity of substitution between early stocks of human capital and investments that range between 1.457 and 2.410, consistent with complementarity between early human capital and investments. Furthermore, they find that complementarity becomes stronger as children age. Heckman et al (2010) using quantile regression techniques, find that the Perry Preschool Program had the largest effects on cognitive achievement among those at the top of the distribution. While they do not have measures of initial human capital, they argue that the stronger effects at the top of the distribution are consistent with complementarity of initial human capital and investments.[2]

The present study differs from previous work in that we have measures of early and late human capital and we exploit a plausibly exogenous measure of investment – preschool enrollment as affected by the creation of Head Start, a fully subsidized preschool program established in 1965-66 for low-income children. Simply by virtue of being born after 1962, some of the children in our sample had access to a fully subsidized preschool program, while their siblings, by virtue of being born prior to 1962, did not. Moreover, we have multiple measures of human capital taken for each child at birth, eight months, four years and seven years.

[2] This assumes child rank within the distribution of test scores is preserved with the intervention.

2.2 Data

The National Collaborative Perinatal Project (NCPP) contains comprehensive information on maternal and paternal characteristics, prenatal conditions, birth outcomes and follow-up information through age seven for a cohort of roughly 59,000 births between 1959 and 1965 (of which 17,000 are siblings) in 12 sites (located in 11 central cities) throughout the US. Mothers were recruited for participation in the NCPP primarily through public clinics associated with academic medical centers. As such, they are characterized by greater poverty and less education than the general population at the time. Sample characteristics are presented in Appendix Table 1. Follow-up information on the children was collected at ages eight months, one year, four years and seven years and includes the results of extensive physical, pathological, psychological, and neurological examinations.

At birth, the measures of human capital available in the data include birth weight, head circumference, body length, weeks of gestation, and whether the doctor confirms or suspects a neurological abnormality in the neonate.

At age 8 months, two measures of human capital are taken: the Mental and Motor Bayle Scores of development. The 8 month measure of mental development is our preferred measure of early human capital. To generate this score, the examiner presents a series of test materials to the child and observes the child's responses and behaviors and evaluates individuals along three scales (mental, motor and behavior). The mental scale evaluates several types of abilities: sensory/perceptual acuities, discriminations, and response; acquisition of object constancy; memory learning and problem solving; vocalization and beginning of verbal communication; basis of abstract thinking; habituation; mental mapping; complex language; and mathematical concept formation (see Appendix A for the individual items).[3] In our sample, the mental Bayley score varies from 0 to 99, with an average of 79 and a standard deviation of 6. Within families, the average difference is two thirds of the cross sectional standard deviation (first panel, Figures 1 and 2).

Later measures of a child cognitive human capital are collected at ages four (IQ) and seven (IQ, reading and math achievement). There is considerable variation in these measures both across and within families. For example, the average four year IQ is 99 and seven year IQ is 96 with standard deviations of 17 and 15, respectively. Within family, the average differences are 11 and 12 points, respectively (second panel, Figures 1 and 2).

To support our use of the eight month Bayley as a measure of early human capital, we compare its ability to predict future cognitive ability/achievement with that of birth weight which has been used extensively in the literature as a measure of initial human capital (eg, Datar et al, 2010; Hsin, 2009). We find that the 8 month Bayley score is more predictive of nearly every measure of human capital at later ages than is birth weight, with 2 exceptions. In both OLS and family fixed effect settings, the 8 month Bayley is either similar to or more predictive of any cognitive delay at age one, speech delay at age three, IQ at age four and seven and math (but not reading) achievement

[3] The 8 month Bayley Motor Development scale assesses muscle control (control of the body) and large and fine motor coordination.

at age seven (Appendix Table 2). We attribute this to the fact that the Bayley score is a more precise measure of cognitive human capital than birth weight which is a more general measure of human capital.

2.3 Empirical Strategy

To test the hypothesis that early human capital and investments are complements in the production of late human capital, we estimate the following production function:

$$h_{2,i,j} = \gamma_1 h_{1,i,j} I_{2,i,j} + \gamma_2 I_{2,i,j} + \gamma_3 h_{1,i,j} + \gamma_4 X_{i,j} + u_j + \nu_{i,j}$$

where late human capital of child i in family j ($h_{2,i,j}$) is measured as IQ at age four, or IQ, reading and math achievement at age seven; investment ($I_{2,i,j}$) is preschool enrollment at age four, and child early human capital ($h_{1,i,j}$) is measured by the eight month mental Bayley test score. The main effects of investment and early human capital are included, as is the interaction term $h_{1,i,j} I_{2,i,j}$ which captures the presence, if any, of dynamic complementarities in early human capital and investments in the production of late human capital. Also included are u_j, a family-specific fixed effect, and $X_{i,j}$, a vector of characteristics that varies across siblings within family and includes child gender, birth order, maternal age at birth, income at birth and marital status at time of birth. The inclusion of the family fixed effect allows us to control for any unobserved differences across families that might be correlated with both children's early human capital and investment (e.g., in our data, more educated mothers are more likely to enroll their children in preschool).

In general, it is not straightforward to obtain consistent estimates of γ_1. Investment is likely endogenous and may, for example, be correlated with parental characteristics as well as child-specific characteristics that the parents observe about their children, but the psychologist and the researcher do not. We argue that variation in our measure of investment (preschool enrollment at age four) is likely exogenous as it appears to be driven by the launch of Head Start as an 8 week summer program in 1965 which was then expanded in 1966 to a part day nine month program.[4] In our sample, preschool enrollment increases significantly and discontinuously among four year olds in 1966 and continues to increase slightly each year through 1970, the end of our study period (Figure 3). The sudden increase in preschool enrollment observed (from seven to 12.5 percentage points, an increase of 73 percent, between 1965 and 1966) combined with the fact that our sample is a low income urban sample, suggests that the arguably exogenous launch of Head Start in 1965/1966 is largely responsible for this growth in preschool enrollment.[5]

[4] In 1960, there were 3.97 million 4 year olds (the primary age of those served by Head Start). By 1968 Head Start served 733,000 children in its summer program and 212,000 children in its full year program.

[5] Moreover, evidence presented by Ludwig and Miller (2009) shows that Head Start was launched in 1966 but continued to expand in the years after (owing largely to continual recruitment of providers in the early years) which would explain why the trend in preschool enrollment observed in our data jumps discontinuously in 1966 but then continues to increase in the years immediately after. For example, in 1966, only $8 million was spent on its 9 month program (serving 20,000 children) but by 1968, $239 million had been allocated to serve 212,000 children.

Since our sample includes siblings born to the same family before and after 1962 (four years before the Head Start expansion in 1966), within a given family, some children had no access to Head Start at age four, while others, by virtue of being born after 1962, did. This, we argue, provides the exogenous variation in investment within family that we need for identification. To control for the fact that access to Head Start increases with birth order, we control for birth order and its interaction with preschool enrollment in the regression as well.

2.4 Results

2.4.1 Evidence of the Exogeneity of Preschool Enrollment

Before presenting the results of estimating equation (1), we present two pieces of evidence to support our contention that preschool enrollment is exogenous in this sample. First, we link preschool enrollment in our sample with local (county) levels of Head Start funding by regressing an indicator for preschool enrollment at age four in each year (1963-1970) on county level funding of Head Start in 1968 (Table 1).[6] We find that Head Start spending per poor person in the county of residence in 1968 does not predict preschool enrollment in our sample in 1963, 64 or 65, but that it does predict preschool enrollment in 1966 – 1970 (Table 1, Panel A), though many of the estimates are imprecise.[7] However, the results are larger and more precise for less educated mothers (those most likely to be eligible for Head Start): when we restrict our sample to mothers with no more than a high school degree (90% of our sample) the estimated relationship between local Head Start spending and preschool enrollment increases and become significant (Table 1, Panel B). Finally, we include maternal fixed effects in a regression of preschool enrollment on a variable that is the interaction between local Head Start spending (in 1968) and an indicator equal to one in all years after Head Start was established.[8] We continue to find a strong relationship between local Head Start spending and the probability of preschool enrollment within family (Table 1, Panel C).

A second piece of evidence of the exogeneity of preschool enrollment is that preschool attendance is uncorrelated with early human capital. In the cross section (Table 2, Panel A) and within family (Table 2, Panel B), there is no significant relationship between preschool attendance and any of

[6]These data on Head Start spending at the county level in 1968 were generously provided by Jens Ludwig and Doug Miller. For the earliest years of the program they found that only county funding levels for 1968 and 1972 were credible, which is why we use only the 1968 data (1972 is beyond our time frame). While Ludwig and Miller calculate per capita Head Start funding for their analysis, because our sample is a low income sample, we calculate spending per poor person in the county.

[7]Head Start funding in 1968 for these 11 cities ranges from \$4 to \$29 per poor person (in 1968 dollars) and preschool enrollment in 1968 ranges from 6 to 15 percentage points among mothers with no more than a high school degree in our sample. The results from our analysis suggest that a doubling of Head Start funding (across cities) increases the probability of enrollment in preschool by 50%. Ludwig and Miller (2007) find that doubling Head Start funding in low income counties increases Head Start enrollment by 100%. However, our results are not directly comparable. Ludwig and Miller focus on differences across low income counties, while our sample is drawn from moderate income urban counties where we might expect the impact to differ.

[8]In other words, this is equal to zero in all years prior to 1966 and equal to local head start spending in all years after 1966. The main term of local Head Start spending in 1968 is subsumed by the maternal fixed effect. We do not include year dummies (which reduces precision), but rather a quadratic time trend.

our measures of early human capital (birth weight, gestation, eight month Bayley Score, child social/emotional development), consistent with exogenous preschool enrollment resulting from the creation of Head Start.[9]

2.4.2 Preschool Attendance and Human Capital at Four Years

Estimates of equation 1 including maternal fixed effect shows that 1) preschool enrollment is highly productive of four year IQ ($\gamma_2 > 0$) and that 2) preschool enrollment and early human capital are indeed complements in the production of four year IQ ($\gamma_1 > 0$). Specifically, a child who attends preschool has an IQ at age four that is 16 percent of a standard deviation higher than a sibling within the same family who did not go to preschool (Table 3). If that child also had a high level of early human capital, then the effect of preschool attendance on four year IQ would be even larger. For example, evaluated at the average within family difference in 8 month Bayley scores, a sibling with a higher Bayley score who attended preschool would have a four year IQ that was 33 percent of a standard deviation higher than his siblings with lower early human capital (about five IQ points). Since birth order is also correlated with preschool enrollment in these data, we also include an interaction between birth order and early human capital in these regressions which has no effect on four year IQ and which allows us to rule out the possibility that the interaction term preschool*early human capital simply reflects a preschool*birth order effect.

2.4.3 Preschool Enrollment and Human Capital at Seven Years (IQ and Achievement)

The estimated impact of preschool on human capital fades by age seven for all but those with the highest levels of initial human capital. For seven year IQ and math achievement, the main effects of preschool enrollment and early human capital decline considerably, but not their interaction, which remains large (Table 3A). Thus, for those with higher early human capital, the impact of preschool lasts significantly longer than for others.

To explore other potential sources of heterogeneity in the effect of preschool on seven year IQ, we interact preschool with birth weight, birth order, and gender and find no significant effects (Table 3B). In results not presented here, we also find that the effect of preschool does not vary with maternal characteristics (education, age or income). We do, however, find a significant interaction effect for another measure of early human capital: advanced emotional and social development at 8 months of age which is both positively related to seven year IQ and interacts positively and significantly with preschool enrollment in the production of seven year IQ (Table 3B). When we include both terms and their interaction with preschool (8 month Bayley*preschool and Advanced emotional development*preschool) the former is unchanged while the latter effect declines slightly and is no longer significant. However, it should be noted that only 203 children are classified as

[9] Maternal characteristics (education in particular) are, however, correlated with preschool enrollment in the cross section, necessitating the need to include a maternal fixed effect. Without a maternal fixed effect, there is a large and significant impact of preschool enrollment on child IQ at age 4 for all children.

advanced in these data. Moreover, the 8 month Bayley and emotional development are highly correlated, which is consistent with existing psychological research establishing that cognitive and emotional development in infancy and early childhood are related. Some psychologists argue that emotional development is a function of cognitive development and others that relationship is more mutual (Lazarus, 1984).

We conclude that the estimated complementarity between investments and human capital is empirically meaningful and has important implications because it provides incentives for parents to invest in a reinforcing manner (i.e., to invest in children with higher initial levels of human capital) since the returns are higher. Such an investment strategy would exacerbate initial differences in human capital among siblings. However, if parents have a preference for equality among offspring, (as posited by some existing theoretical models), then this would suggest that parents face a tradeoff in their investment decisions: compensating investments to achieve equality vs. reinforcing to increase their overall returns. In the next section, we explore how parental investment decisions interact with a child's initial human capital.

3 Human Capital at Birth and the Allocation of Parental Investments

3.1 Background

There is some evidence with respect to the question of whether parents invest in a compensatory or reinforcing manner. However, it is limited by both lack of data on initial endowments and few measures of parental investments that vary within household and do not reflect decisions made by the child. Existing work based on data that do not include measures of initial endowments include Hanushek (1992) who finds that having a sibling with higher measured achievement is positively correlated with own achievement (which he argues is inconsistent with reinforcing investment). Two papers (Ashenfelter and Rouse, 1998 and Behrman, Rosenzweig and Taubman, 1994) base their identification on differences in education and earnings of identical twins relative to fraternal twins, arguing that (unobserved) endowments of identical twins are more similar. They find that differences in earnings and schooling are greater for fraternal twins who have more dissimilar endowments and interpret this as evidence of reinforcing investments. Rozensweig and Wolpin (1988) find that children with better health endowments are more likely to be breastfed. Pitt et al (1990) relies upon a residual in a human capital production function as a proxy for initial endowment and finds that the more highly endowed receive more nutrition in a developing country setting. More recent work (Datar et al, 2010) uses birth weight as a measure of initial endowment and shows that parental investment (as measured by breast feeding, nursery school enrollment and maternal time) increases with the endowment but doesn't link endowments and investments with future human capital production.

There is some evidence of heterogeneity in investment patterns. Hsin (2009), using data from the PSID, finds that less educated mothers invest in a reinforcing manner while more educated mothers invest in a compensatory manner. This is consistent with recent work by Rosenzweig and Zhang (2009) who find evidence of reinforcing investment in China, a relatively poor country, and Black, Devereaux and Slavanes (forthcoming) who find evidence of compensatory investment in Norway, a rich county.

There are three main innovations of our analysis of whether parental investments compensate or reinforce initial endowments. First, we develop an alternative measure of parental investment that captures the quality of the mother-child interaction as evaluated by a psychologist. This builds on existing work in economics that has focused less on parental time and more on the quality of time as measured by parenting skills (Paxson and Schady, 2007). Second, we address the possibility that traditional measures of human capital at birth (ie, birth weight) are both measured with error and potentially endogenous because they already reflect prenatal investments. Third, we explore how the investment decision interacts with the fertility decision. We discuss each in turn.

3.2 A New Measure of Investment: Parenting

In this subsection we describe our measure of parental investment. Because it differs from more traditional measures of investment (eg, time), we follow with arguments to justify this measure.

3.2.1 Construction of the Measure of Parental Investment from the NCPP Data

Our specific measure of investment is derived from a psychologist's rating of the interaction between mother and child at eight months of age along the following six dimensions: maternal expression of affection (negative to extravagant), handling of the child (rough to very gentle), management of the child (no facilitation to over directing), responsiveness to the needs of the child (unresponsive to absorbed), her focus during the child's examination (self to child), and her own evaluation of the child (critical to effusive). A final, 7th dimension is the child's appearance (unkempt to overdressed). To develop a measure of parenting, we use factor analysis (principal factors, unrotated) for the six measures (Table 4). We compute the relative importance of each of the measures in the construction of the factor which depends on the share of true variance to total variance. We find that responsiveness and affection towards the child are the most important, while appearance and handling are the least important. The higher this share, the higher its weight in the construction of the factor.[10]

For the single measure of investment generated in this fashion and which varies from -7.3 to 7.3 in

[10]Note that our measures of investments are discrete, not continuous. In Appendix B, we develop an algorithm to extract the investment factor by explicitly recognizing the discreteness of the variables. We find that the correlation between the Regression method and the methodology developed in Appendix B is between 86%-90%. For this reason, our empirical analysis uses the scores produced by the Regression method which assumes that the measures are continuous.

the sibling subsample (with a higher value indicating greater investment), 65% of the sample receive the same score (.059) corresponding to average or normal values for all six measures, but there is still variance. Figure 4 displays the distribution of this measure of investment in the cross section in the first graph and within family differences in this measure of investment in the second graph. Within family, for exactly half the sample, there is no difference in parenting across siblings. But for those families that exhibit different parenting across siblings, the differences can be quite large. This is consistent with existing work which has shown that in one to two thirds of families, parents "differentiate in terms of closeness, support and comfort" beginning in early childhood (Suitor et al, 2008, page 334). Throughout the text and tables, we refer to this measure of investment as "quality of parenting," though it can also be thought of as a measure of favoritism.[11]

3.2.2 Justification

We argue that the above measure of investment is preferable to more traditional measures such as parental time, nutrition or education. With respect to parental time, not only is time spent with a specif child in a household difficult difficult to measure, but most variation in parental time between siblings is driven by birth order and/or maternal work, both of which likely exert independent effects on child outcomes (Price, 2009). In contrast, evidence suggests that between one third and two thirds of parents exhibit preferential treatment towards one sibling and that this does not vary systematically with birth order (Suitor et al, 2008). With respect to nutrition, variation within households exists and has been measured in developing countries, but in the US, there is less evidence of nutritional variation within household due in part to insufficient data. Finally, variation in educational attainment suffers from the fact that children are also involved in the decision (and the financing at higher levels), so that it does not just reflect parental investments.

A second argument for using "parenting" as a measure of investment comes from extensive research in developmental psychology and neurobiology showing that the quality of maternal-child attachments in the first years of life is an important determinant of a child's development, especially cognitive development. The theoretical foundation of this research derives from "attachment theory" which stipulates that a strong bond between child and primary care giver serves to provide a secure base from which an infant can explore the world. More specifically, having a secure base enables the infant to "engage in a variety of adult-supervised learning experiences [including] exploratory interactions with objects and social partners that lead to eventual mastery of these domains" (Seifer and Schiller, 1995). Key to the establishment of this "secure base," is a high degree of maternal sensitively and responsiveness to infant signals. In a review of the empirical research on the relationship between early maternal-infant attachment and later child outcomes, Ranson and Urichuk (2008) conclude that the evidence strongly supports a strong relationship between

[11] Paxson and Schady (2007) represent the first attempt in the economics literature to positively link the quality of parenting with cognitive development in a sample of low income families in Ecuador.

maternal-infant attachment in infancy with later cognitive outcomes (eg, IQ, reading and GPA). [12]

More recently, neurobiologists have posited that strong attachment in infancy fosters brain growth and development, providing a biological basis for widely accepted psychological theory of "attachment" (Schore, 2001). The experimental research in neurobiology generally supports a strong role for early attachment in the neurobiology of brain development. [13]

A third and final justification of our use of parenting as a measure of parental investment is our finding that it is correlated with two other more traditional measures of investment – parental time and the Home Observation for Measurement of the Environment (HOME) score, collected by the PSID Child Development Supplement (CDS).[14] The CDS Parental Warmth scale is based on interviewer observations as to whether the parent shows verbal, physical, and emotional affection towards the child and whether the parent interacts by joking, playing, participating in activities with child or showing interest in the child's activities. We argue that this measure of warmth is sufficiently similar to our measure of parenting and that by showing its positive correlation with the two other more traditional measures of parental investment, HOME score and time, both across and within families in the PSID (Appendix Table 3), we provide further justification of our use of parenting as a measure of parental investment.[15]

3.3 Measures of Endowments that Address Measurement Error and Endogeneity

In our empirical analysis, we construct an alternative measure of endowment to address both measurement error and potential endogeneity associated with more commonly used measures of endowment such as birth weight. To address issues of measurement error, we exploit the fact that we have multiple measures of health at birth (birth weight, gestation, head circumference and body length) to conduct a factor analysis to find a single common underlying factor.

With respect to endogeneity, this arises from the fact that typical measures of initial human capital such as birth weight might not only reflect endowment, but might also reflect prenatal investments. If so, the concern would be that any correlation between initial human capital and post-natal investments might simply reflect serial correlation in investments. For example, in our data, measures of prenatal investment such as prenatal nutrition (maternal weight gain) and smoking are positively correlated with investment during the postnatal period.

To address this concern, we construct a measure of human capital at birth that we argue is

[12] The research also supports a strong relationship between attachment and social-emotional and mental health outcomes.

[13] See the Institute of Medicine's From Neurons to Neighborhoods: The Science of Early Childhood Development (2000) for a review.

[14] Among the many items that constitute the HOME score are the number of books available to the child, how often the child goes to museums, how often the child goes to the theater, and how often the mother read to or with the child.

[15] The Appendix contains a description of how we construct the PSID sample and our three measures of parental investments (warmth, time and HOME score).

plausibly net of maternal investments during the prenatal period. To do so, we follow Rosenzweig and Wolpin (1988) and consider a production function for human capital at birth that includes the following inputs: the initial endowment of the child, maternal prenatal investments (nutrition and smoking), whether the mother was trying to conceive (a measure of the "wantedness" of the child), a family-specific term (to capture, for example, genetics) and an idiosyncratic child specific error term. Because we have measures of maternal prenatal investments that differ for children within the same family, we can estimate the above production function and calculate the residual which we argue consists of the child's endowment and an idiosyncratic child specific error term.

More formally, let $y_{i,j,k}$ denote the birth outcome k (birth weight, head circumference, body length and gestation) of child i born in family j. Let $c_{i,j}$ denote a quadratic in the number of cigarettes that mother j smoked while pregnant with child i. Let $w_{i,j}$ denote the weight of mother j when she became pregnant with child i and $g_{i,j}$ denote the weight gain while pregnant with child i, let $WANT_{i,j}$ reflect whether the mother reports she was trying to conceive child i. Let η_j denote the maternal fixed-effect. The term $\varepsilon_{i,j}$ denotes the endowment of child i. Let $\nu_{i,j,k}$ denote the idiosyncratic component of birth outcome k. Assume that:

$$y_{i,j,k} = \beta_{0,k} + \beta_{1,k}c_{i,j} + \beta_{2,k}w_{i,j} + \beta_{3,k}g_{i,j} + \beta_{4,j}WANT_{i,j} + \delta_k\eta_j + \alpha_k\varepsilon_{i,j} + \nu_{i,j,k}$$

Our goal is to obtain an estimate of $\varepsilon_{i,j}$, the child endowment. A simple fixed-effect procedure allows us to obtain $\beta_{0,k}$, $\beta_{1,k}$, $\beta_{2,k}$, $\beta_{3,k}$, and $\beta_{4,k}$. The estimated coefficients for each of the five measures of conditions at birth in the data are presented in Table 5. Once we know these components, we can predict the residual term $u_{i,j,k}$ for each birth outcome k:

$$u_{i,j,k} = \alpha_k\varepsilon_{i,j} + \nu_{i,j,k}$$

As argued by Rosenzweig and Wolpin (1988), each predicted residual term approximates the endowment of the child net of the presumably most important maternal prenatal investments (smoking and nutrition). However, we extend this further to address potential measurement error in a measure of endowment that is based on a single measure of health at birth. To do so we take advantage of the fact that we have multiple measures of health at birth to estimate $\varepsilon_{i,j}$ for all children i. We recover the endowment by factor analyzing the residuals $u_{i,j,k}$. Table 5 presents the estimates of the newborn health production function and Table 6 shows the estimated factor loadings, α_k , and the variance of the uniquenesses $\nu_{i,j,k}$. The factor explains 80% of the cross-sectional variance of birth weight, almost 70% of the variance in head circumference and body length, and 22% of the variance in weeks of gestation. The inverse ordering is true for the variance of measurement error: weeks of gestation has the largest amount of measurement error, followed by body length and head circumference. Birth weight has the least amount of measurement error. These findings are reflected in the scoring coefficients that are used to predict the unbiased factor of human capital at birth.

3.4 Results: Endowments and the Allocation of Investments within Families

We run regressions of our measure of postnatal investment on child endowment (as measured above) including maternal fixed effects and other characteristics of the offspring as before. In each column of Table 7 we present estimates from regressions of parental investment, as measured by the quality of parenting at 8 months of age, on different measures of endowment. The first measure of endowment is birth weight. Within family, the child with higher birth weight receives more investment in the form of higher quality parenting. The results suggest that a one standard deviation difference in birth weight between siblings can explain ten percent of the average difference in investment between siblings within families.

When we consider that birth weight may be endogenous because it already reflects maternal prenatal investments and use instead the residual from a birth weight production function which includes maternal smoking, pre-pregnancy weight and weight gain as regressors (Table 5) we find that the relationship still holds, though it is slightly attenuated (Table 7, column 2). In columns 3-8 we present estimates based on different measures of health at birth (gestation, body length, head circumference) and their corresponding residual measures and the same pattern emerges. In the last two columns we present estimates for a measure of endowment based on factor scores of multiple measures of health at birth (birth weight, head circumference, body length, gestation), and factor scores based on the four residuals from the newborn health production function. The results based on factor scores of the four measures of health at birth (column 9) are similar though slightly smaller than the birth weight result in column 1 and the results based on factor scores of the four residuals is still positive and significant, but only 40 percent of the original estimate.

The results suggest that postnatal investments are greater for more highly endowed children – consistent with reinforcing investments. However, some of this relationship captures serial correlation in prenatal and postnatal investments.

4 Endowments, Investments, and Fertility

Having established, empirically, that children with higher endowments receive more investments, we turn to our third question of how fertility affects investments and child human capital in the household. This analysis proceeds in two steps. First we follow the existing literature and estimate the effect of fertility on the average human capital of the children in a family. Second, we examine how fertility affects the distribution of investments and human capital in a family.

4.1 Causal Evidence on how Fertility Affects Average Child Quality

In our estimation of the effect of fertility on the average human capital of children in a family, we adress the endogeneity of fertility using two instruments for family size. The first instrument we exploit is whether a multiple birth occurred after the birth of the study child. We refer to this as IV2 and the first stage is as follows:

$$\begin{aligned} Fertility_{i,j} &= \pi_0 + \pi_1 Multiple\ Birth_j + \pi_2 pregnancies_{i,j} + \pi_3 DOB_{i,j} + \pi_4 X_{i,j} + \pi_5 AMC_j + \\ & \quad \pi_6 Year\ of\ Birth_{i,j} + \pi_7 Truncate_{i,j} + \varepsilon_{i,j} \end{aligned}$$

$Multiple\ Birth_j$ takes on a value of 1 if mother j had a multiple birth after the birth of the study child (773 instances in these data). However, because the probability of a multiple birth increases in the number of pregnancies, we also control for the number of pregnancies since the study birth (the latter is included in the second stage as well). This instrument has been used previously in the literature (e.g., Black, Salvanes, and Deveraux 2005; Angrist, Lavy, and Schlosser, 2010). It has been subject to the criticism, however, that because multiple births typically have lower endowments, families that invest in a compensatory manner will shift investments away from the multiple births and towards the other children in the household, reducing the negative impact of fertility on child quality (Rosenzweig and Zhang, 2009).

Our second instrument is whether the mother had a subsequent fetal/neonatal death (IV3):

$$\begin{aligned} Fertility_{i,j} &= \pi_0 + \pi_1 Fetal/Neonaltal\ Death_j + \pi_2 pregnancies_{i,j} + \pi_3 DOB_{i,j} + \pi_4 X_{i,j} + \pi_5 AMC_j + \\ & \quad \pi_6 Year\ of\ Birth_{i,j} + \pi_7 Truncate_{i,j} + \varepsilon_{i,j} \end{aligned}$$

Both instruments differ in ways that we believe should be reflected in the second stage results. IV1 based on multiple births should lead to a smaller negative second stage estimate than the IV strategy based on fetal death (IV2). This is because we would expect investments to be higher in existing children with a future multiple birth than those with a (future) fetal death if twins have lower endowments and thus existing singleton children, who have higher relative endowments, receive more investments.

The results of the two first stages are presented in Table 9. Multiple births increases fertility by 1 and fetal death reduces fertility by less than 1 (-.712) suggesting some replacement fertility in the event of a fetal death. The F statistics range from 24 to 63 depending on specification.

OLS and IV estimates of the relationship between quantity and quality are presented in Table 10. An additional child reduces child quality as measured by IQ at age 4 by 6 percent of a standard deviation in OLS regressions. The IV1 estimate based on multiple births is small and insignificant (-.026), while the IV2 estimate based on fetal death is -.114 suggesting that a reduction in fertility by 1 child via fetal death increases child IQ by 11 percent of a standard deviation or 1.7 points. For the 7 year quality measures (IQ, Math and Reading achievement), the results are similar though generally insignificant for the IV1 estimates (multiple births).

4.2 How Fertility Affects the Distribution of Investments within a Family

We follow with an exploration of whether and how this reinforcing investment behavior varies with fertility. To do so, we estimate the ability of initial endowment to predict both parental investments at 8 months and future human capital (seven year IQ) within family, stratified by fertility. We find that within family, the relationship between initial endowments and postnatal investments is stronger for larger families (Table 11, Panel A). This is true for each of the four measures of initial endowment that we use though we only present the results for the residual birth weight used in Table 8. We interpret this finding as evidence that investments tend to be even more reinforcing in larger than smaller families. An implication of this interpretation is that the relationship between a child's initial endowment and later human capital should be stronger in large families.[16]

We test the latter empirically by examining how the relationship between endowment and later human capital (measured by seven year IQ) varies with fertility. We find that the positive correlation between a child's endowment and his/her later human capital increases with family size (Table 11, Panel B).[17] A second implication is that the spread in child human capital should likewise increase with family size. We show this in Figure 6 where we present the maximum and minimum IQ at age seven by family size.[18] On can clearly see that the difference between minimum IQ and maximum IQ within a family increases with family size. For a two child family, this difference is 40% of a standard deviation, for a four child family the difference increases to 100% of a standard deviation. Interestingly, this increase in the difference is driven entirely by declines in the minimum. The maximum human capital of children in large families is the same as the maximum in small families, but the minimum is much lower. It has been well documented that average human capital is lower in large families and the same is true in these data. However, the results here show that this difference is driven by differences at the bottom of the distribution of child human capital, not the top. This pattern can be explained by two forces: 1) the fact that the variance in endowment increases with family size (Figure 6, second panel), and 2) greater reinforcing investments in large families (Figure 6, third panel, and Table 11).

We corroborate these findings with another data source - the NLSY- CM. The NLSY includes data on birth weight and child human capital (PPVT and Math scores). We see the same pattern in the NLSY (Figure 7A and 7B): both the spread in endowments and child human capital increase with family size, with the increase driven by declines at the bottom of the distribution. We also use the NLSY data to explore whether birth order can explain the patterns observed (Figure 7C).

[16] Previous work examining whether investments are compensatory or reinforcing has relied on this strategy. Previous work did not have measures of endowment, but rather assumed endowments were more similar between identical twins than fraternal twins and examined whether sibling differences in outcomes were greater among fraternal twins relative to identical twins.

[17] While this evidence is consistent with greater reinforcing investment in large families it could also be consistent with different production functions based on family size which we cannot rule out.

[18] observed in the data.

While we observe significant birth order effects, they only explain a third of the difference between the maximum and minimum child human capital within family.

5 Model

From our empirical analysis, we learn that (1) the production function of human capital exhibits complementarity between stocks of human capital and investments; (2) parents allocate more investments to children that have higher endowments; (3) the average child quality decreases while the dispersion of child quality increases with fertility. As we now show, these findings can be explained by the Becker and Lewis (1973) model extended to allow for heterogeneity across children with respect to their endowments and parental preferences that feature weak complementarity between quality and quantity and moderate aversion to inequality in the human capital of children in the household.

5.1 Preferences and Constraints

Formally, let $c_j \in \mathbb{R}_{++}$ denote the consumption of household j. Assume that $n_j \in \{1, ..., N\}$ children live in this household j and let $\bar{h}_j$ denote the (inequality-adjusted) average human capital (or quality) across the children in household j:

$$\bar{h}_j = \left[\sum_{i=1}^{n_j} \frac{1}{n_j} \left(h_{i,j} \right)^{\alpha} \right]^{\frac{1}{\alpha}} \tag{1}$$

where $h_{i,j} \in \mathbb{R}_{++}$ is the human capital of the i^{th} child and $\alpha \in (-\infty, 1]$ denotes the parent's aversion to inequality with respect to the human capital of the children. When $\alpha = 1$, the parent only cares about the average human capital across children. As $\alpha \rightarrow -\infty$, the parent has extreme aversion to inequality and cares about the minimum stock of human capital across the children in the household.

Let $h_{i,j,0}$ denote the endowment of child i and $x_{i,j}$ is the parental investment on child i's human capital. The production function is:

$$h_{i,j} = \beta_0 + \beta_1 h_{i,j,0} + \beta_2 x_{i,j} + \beta_3 x_{i,j} h_{i,j,0} \tag{2}$$

This production function features the interaction $x_{i,j} h_{i,j,0}$ that captures the complementarity between parental investments and the initial human capital of children. The strenght of this complementarity is higher the higher the coefficient β_3.

The utility function of the parent is quadratic in consumption, fertility, and (inequality-adjusted) average quality:

$$u\left(c_j, n_j, \bar{h}_j, \omega_j\right) = c_j + \delta_1 n_j + \delta_2 \bar{h}_j - \frac{\delta_3}{2} c_j^2 - \frac{\delta_4}{2} n_j^2 - \frac{\delta_5}{2}\left(\bar{h}_j\right)^2 + \delta_6 c_j n_j + \delta_7 n_j \bar{h}_j + \sum_{n=1}^{N} \omega_{j,n} \mathbf{1}\left(n_j = n\right). \quad (3)$$

The parameters δ_1 and δ_2 represent the level of the marginal utility with respect to fertility and average quality, relative to that of consumption. The parameter δ_3, δ_4, and δ_5 determine how fast the marginal utility of consumption, fertility, and average quality decay as each of these terms increase. The parameter δ_6 captures the complementarity or substitution between consumption and fertility while δ_7 quantifies that of fertility and average quality. The $\omega_{j,n}$ are idiosyncratic preference shocks that affect fertility, but not investment choices. The shocks ω_j are useful to generate the variability of fertility by levels of income. We assume that the shocks are normally distributed with mean zero and variance $\sigma_\omega^2\left(y_j\right)$. Because the shocks do not affect investments, in the second stage we work with the "partial" utility function:

$$\tilde{u}\left(c_j, n_j, \bar{h}_j\right) = c_j + \delta_1 n_j + \delta_2 \bar{h}_j - \frac{\delta_3}{2} c_j^2 - \frac{\delta_4}{2} n_j^2 - \frac{\delta_5}{2}\left(\bar{h}_j\right)^2 + \delta_6 c_j n_j + \delta_7 n_j \bar{h}_j$$

Finally, let y_j denote the family income, $\bar{c}$ the minimum consumption per child, and π the price of the investment good. The budget constraint is:

$$c_j + \bar{c} n_j + \frac{\pi}{n_j^\kappa} \sum_{i=1}^{n_j} x_{i,j} = y_j, \quad (4)$$

where $\kappa \in (0,1)$ are the "returns to scale" as in Rosenzweig and Zhang (2009). In the classic Becker and Lewis (1973) model, children are homogeneous in their endowment so at the optimal the parent chooses to invest exactly the same amount in each child. To be able to reproduce the findings that the inequality in investments and in human capital increases with fertility, we extended the model to allow for heterogeneity in endowments, which generates heterogeneity in investments. Note that the expenditure on investment is $E_{n,j} = \pi n_j^{1-\kappa} \bar{x}_j$, where $\bar{x}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} x_{i,j}$.

5.2 The Problem of the Parent

Because the number of children take on discrete values, we can't use first-order conditions to determine the policy function for fertility. For tractability, we break up the problem of the parent into two stages. In the first stage, the parent takes as given her income and the distribution of endowments and chooses how many children she will have. In the second stage, the children are born and their endowments are realized. The parent chooses how to allocate income between investments and consumption. We characterize the optimal allocation of investments by the necessary first-order conditions and explore their information to estimate the parameters of the model.

5.2.1 The Second Stage

Suppose that in the first stage the parent chooses to have n_j children. In the beginning of the second stage, the parent observes the endowment vector $h_{j,0}^{n_j} = \left(h_{1,j,0}, ..., h_{n_j,j,0}\right)$, where the superscript n_j in $h_{j,0}^{n_j}$ denotes the lenght of the endowment vector. Given income y_j, the problem of the parent is:

$$V\left(n_j, y_j, h_{j,0}^{n_j}\right) = \max_{c_j, x_{1,j}, ..., x_{n_j,j}} \tilde{u}\left(c_j, n_j, \bar{h}_j\right)$$

subject to (1), (2), (3), and (4).

For families that choose to have only one child, the first-order condition is simply:

$$\left(\beta_2 + \beta_3 h_{1,j,0}\right)\left(\delta_7 + \delta_2 - \delta_5 h_{1,j,1}^{\alpha}\right) = \left[1 + \delta_6 - \delta_3\left(y_j - \pi x_{1,j} - \bar{c}\right)\right] \tag{5}$$

Equation (5) clarifies the role played by the parameter δ_5 in determining the relationship between parental investments and the child's endowment. The left-hand side of (5) states the marginal utility of quality, while the right-hand side of that same equation shows the marginal utility of consumption. At the optimal, parents must be indifferent between allocating an extra dollar to investment or to consumption.

Consider two families, L and H, that are identical in every aspect, except with regards to the child endowment. Without loss of generality, let $h_{1,L,0} < h_{i,H,0}$. Let $x_{1,L}$ denote the value at which (5) holds for family L:

$$\left(\beta_2 + \beta_3 h_{1,L,0}\right)\left(\delta_7 + \delta_2 - \delta_5 h_{1,L,1}^{\alpha}\right) = 1 + \delta_6 - \delta_3\left(y_j - \pi x_{1,L} - \bar{c}\right). \tag{6}$$

In general, $x_{1,L}$ does not satisfy the first-order condition for family H. On one hand, the higher value of the endowment $h_{1,H,0}$ affects both terms on the left-hand side of (6). Whether the term $\left(\beta_2 + \beta_3 h_{1,L,0}\right)\left(\delta_7 + \delta_2 - \delta_5 h_{1,L,1}^{\alpha}\right)$ is smaller or greater than the term $\left[1 + \delta_6 - \delta_3\left(y_j - \pi x_{1,L} - \bar{c}\right)\right]$ depends on the value of the parameter δ_5. If δ_5 is sufficiently low, then the left-hand side is smaller than the right-hand side of of (6), when evaluated at $x_{1,L}$ and $h_{1,H,0}$. The equality can be restored if $x_{1,H}$ is greater than $x_{1,L}$. *Ceteris paribus*, the difference between $x_{1,H}$ and $x_{1,L}$ is smaller the greater the value of the the parameter δ_3 which dictates how fast the marginal utility of consumption increases as we reduce consumption.

For families with more than one child, the optimal allocation of investments across children depends on the parental aversion to inequality in human capital. For $\alpha = 1$ and the production function (2), the parent chooses to invest only on the child with the highest endowment.

For $\alpha \in (-\infty, 1)$, the problem can be characterized by the necessary first-order conditions. Without loss of generality, consider the first-order condition for investments in the first child:

$$\frac{1}{n_j^{\kappa}}\left[1 + \delta_6 n_j - \delta_3\left(y_j - \frac{\pi}{n_j^{\kappa}}\sum_{i=1}^{n_j} x_{i,j} - \bar{c} n_j\right)\right] =$$

$$\left[\frac{1}{n_j}\sum_{i=1}^{n_j} h_{1,j,1}^{\alpha}\right]^{\frac{1-\alpha}{\alpha}} h_{1,j,1}^{\alpha-1}\left(\beta_2+\beta_3 h_{1,j,0}\right)\left\{\delta_7+\frac{\delta_2}{n_j}-\frac{\delta_5}{n_j}\left[\frac{1}{n_j}\sum_{i=1}^{n_j} h_{1,j,1}^{\alpha}\right]\right\}. \tag{7}$$

To more easily see how α affects the allocation of investments and the inequality in the human capital of children, take the ratio of the first-order condition for investments in the first child to that of the second child:

$$\ln\left[\frac{h_{1,j,1}}{h_{2,j,1}}\right]=\frac{1}{1-\alpha}\ln\left[\frac{(\beta_2+\beta_3 h_{1,j,0})}{(\beta_2+\beta_3 h_{2,j,0})}\right]. \tag{8}$$

The lower the value of α, the higher the parental concerns about inequality. In fact, note that $\lim_{\alpha\to-\infty}\frac{h_{1,j,1}}{h_{2,j,1}}=1$, and the parent chooses investments so that the human capital of the children are equal. On the other hand, if $h_{1,j,0}>h_{2,j,0}$, then $\lim_{\alpha\to 1}\frac{h_{1,j,1}}{h_{2,j,1}}=\infty$.

5.2.2 The First Stage

The solution of the second stage generates indirect utility functions $V(n,y,h_0^n)$ for every number of children n. Let $F_{h_0^n}$ denote the joint distribution of the vector $h_0^n=(h_{1,0},...,h_{n,0})\in\mathbb{R}_{++}^n$. Remember that at the time that the parent is making the fertility choices, the endowments of the children are not known. Let

$$EV(n,y)=E\left[V(n,y,h_0^n)\right],$$

that is, $EV(n,y)$ is the expected indirect utility associated with having n children and income y. The expected indirect utility function contains all the information about the second stage that is known by the parent at the first stage. The parent chooses the number of children that maximize the expected indirect utility function. Formally,

$$n_j^*=\arg\max_{n\in\{1,...,N\}}\left\{EV(1,y_j)+\omega_{1,j},EV(2,y_j)+\omega_{2,j},...,EV(N,y_j)+\omega_{N,j}\right\}.$$

5.3 Model Estimation and Simulation

5.3.1 Estimation Moments

To investigate how well the model can generate the empirical patterns that we observe in the data, it is necessary to specify the values of variables in the model. We set $N=6$ because less than 2% of the families in our data have more than 6 children. It is important to remark that we do not observe consumption in our data. Consequently, we assume that there is only one good that can be used for parental consumption, the child consumption, and investments so that the prices $\bar{c}=\pi=1$. This restriction, together with the budget constraint, generates a value for family consumption.

Note that the ratio of the first-order conditions (8) provide a moment restriction that we can use to estimate the parameter α. Analogously, (7) can be used to estimate the parameters $\delta_2,\delta_3,\delta_5,\delta_6$, and δ_7. The list of instruments that we use in our GMM procedure are (1) a constant; (2) the endowments of children; (3) the instruments for fertility; (4) the parental income; (5) the interactions between endowments and instruments for fertility; (6) the interactions between parental income and the instruments for fertility.

We specify the following parametric form for the variance of the idiosyncratic preference shocks:

$$\ln \sigma_{\omega}^{2}\left(y_{j}\right)=\lambda_{1}+\lambda_{2} y_{j}$$

To estimate the parameters δ_1, δ_4, λ_1, and λ_2 we match the choice probabilities in the data $\Pr\left(n_j = n|\, y_j\right)$ with the quantities that are simulated by the model, $\widehat{\Pr}\left(n_j = n|\, y_j\right)$.

Finally, we need moment restrictions and data that can be used to estimate the parameter κ. As indicated before, $E_{n,j}$ is the total parental expenditure on investments of a family that has exactly n children. Let M_n denote the number of families that have n children and let E_n denote the average investment across all families that have exactly n children, so that

$$E_{n}=\frac{1}{M_{n}} \sum_{j=1}^{M_{n}} E_{n, j}=\frac{1}{M_{n}} \frac{\pi}{n_{j}^{\kappa}} \sum_{j=1}^{M_{n}} \sum_{i=1}^{n_{j}} x_{i, j}^{*}=\pi n_{j}^{1-\kappa} \frac{1}{M_{n}} \frac{1}{n_{j}} \sum_{j=1}^{M_{n}} \sum_{i=1}^{n_{j}} x_{i, j}^{*}=\pi n_{j}^{1-\kappa} \bar{x}_{j, n}.$$

Note that the log of the ratio of E_n to E_1 satisfies:

$$\ln \left(\frac{E_{n}}{E_{1}}\right) \equiv z_{n}=(1-\kappa) \ln n+\ln \left(\frac{\bar{x}_{j, n}}{\bar{x}_{j, 1}}\right),$$

so the higher the value of κ, the lower the rate that expenditures increase with fertility n. It is interesting to note that $\frac{E_n}{\bar{x}_{j,n}}$ is the average expenditure per unit of investment in a family of size n. Under this interpretation, the amount $(1-\kappa)$ is the elasticity of expenditure per unit of investment with respect to fertility.

To implement this moment, we need information on the average total expenditure by families E_n. We use the information from the report by Lino (2010) that estimates the cost of raising children for different family sizes, household income levels, and parental marital status for different years from the Consumer Expenditure Survey.

5.3.2 Parameter Values and Model Fit

Table 12 shows the point estimates and standard errors of the model parameters. We focus our discussion on the parameters α, κ, and δ_7. Starting from the parameter α, we find that the function (1) is close to the Cobb-Douglas formulation, indicating that parents have moderate to strong aversion to inequality in human capital of children. However, as we will show below, this aversion is not strong enough to make parental investments compensate for low investments.

The parameter $\kappa = 0.3381$ indicates that the elasticity of parental average expenditure per child with respect to fertility is such that an extra child increases expenditures per unit of investment by about 67%.

Finally, note that $\delta_7 = 0.0512$, indicating weak complementarity between quantity and quality in the parental preferences. This arises in our context even though at least one of the instruments (twinning) suggest weak impact of fertility on child quality. The reason the complementarity parameter is less important in our model is because parents, to some extent, "pick winners". As we showed in Section 3, the higher the endowment of the child, the greater the parental investments on that child. Furthermore, investments become more reinforcing the larger the family size. Together, these results imply that the average quality across all children decreases slowly, while the inequality within a family increases sharply as fertility increases.

5.3.3 Simulation Results

We now show that the model reproduces the main empirical relationships that we document above. To test how the model fits the data, Figure 8 plots the mean and the variance of fertility by income. Note that mean fertility decreases with income both in the data as well as in the model simulation. The variance of the fertility also decreases with income, again both in the data and in the model.

Figure 9A, 9B, and 9C reproduce Figures 7A, 7B, and 7C that we report in Section 4. Note that the support of the distributions of the endowment, investments, and child quality becomes larger as fertility increases. Under the assumption that the endowments are draws from an identical (but not independent) distribution, the larger the sample size, the greater the difference between the maximum and minimum endowment. Because parents reinforce differences through investments, the distance between maximum and minimum investments also increase. The combination of both lead the maximum and minimum quality within the household to increase with fertility.

With the assumption that $\bar{c} = \pi = 1$, we can construct the share of income that is allocated to investments. Figure 10 compares the data that we construct with the implied shares from the model. Both in the data and in the model, the share of income decays with income, but the fit of the model is better in smaller than in larger families.

6 Conclusions

Using a unique source of data that contains extensive information on prenatal investments, postnatal investments and the human capital measured at multiple periods during childhood, we established empirically that 1) early human capital and investments are complements in the production of late human capital, 2) parental investments reinforce differences, and 3) the degree of reinforcement increases with family size.

We show that these findings can be replicated from a model that features quality-quantity interaction in the budget equation as in Becker and Lewis (1973), a production function of human capital in which endowments and investments are complements, endowments are heterogeneous across children, parental preferences exhibit weak complementarity between quality and quantity and moderate aversion to inequality in human capital across children.

Our empirical findings and our simulation results suggest that the quality-quantity trade-off model, when extended to allow for heterogeneity across children in a household, generates implications for the distribution of human capital within households.

A Individual Items of Bayley Scale of Mental Development at Age 8 Months

1. Social smiles.
2. Visually recognizes mother.
3. Eyes follow pencil.
4. Reacts to paper on face.
5. Searches with eyes for sound.
6. Vocalizes to social stimulus.
7. Manipulates ring.
8. Vocalizes two syllables.
9. Regards cube.
10. Glances from one object to another.
11. Anticipatory adjustment to lifting.
12. Reacts to dissapearance of face.
13. Reaches for ring.
14. Plays with rattle.
15. Fingers hand in play.
16. Follows vanishing ring.
17. Aware of strange situation.
18. Follows vanishing spoon.
19. Eyes follow ball across table.
20. Carries ring to mouth.
21. Manipulates table edge slightly.
22. Inspects own hands.
23. Closes on dangling ring.
24. Turns head to sound of bell.
25. Turns head to sound of rattle.
26. Reaches for cube.
27. Active table manipulations.
28. Regards pellet.
29. Approaches mirror image.
30. Picks up cube.

31. Exploitive paper play.
32. Retains two cubes.
33. Discriminates strangers.
34. Vocalizes attitudes.
35. Recovers rattle in crib or playpen.
36. Reaches persistently.
37. Turns head after dropped objective.
38. Lifts cup.
39. Reaches for second cube.
40. Enjoys frolic play.
41. Transfers objects hand to hand.
42. Sustains inspection of ring.
43. Plays with string.
44. Picks up cube directly and easily.
45. Pulls string, secures ring.
46. Enjoys sound production.
47. Lifts cup by handle.
48. Retains two cubes.
49. Attends to scribbling.
50. Looks for dropped object.
51. Manipulates bell, interest in details.
52. Responds playfully to mirror.
53. Vocalizes four different syllables.
54. Pulls string purposefully to secure ring.
55. Responds to social play.
56. Attempts to secure three cubes.
57. Rings bell imitatively.
58. Responds to name.
59. Says Da-Da or equivalent.
60. Uncovers toy.
61. Adjusts to words.
62. Fingers holes in peg board.
63. Puts cube in cup.
64. Looks for content of box.

B Factor Analysis of Investment Variables

B.1 Ordered and Discrete Measurements

Let λ_i denote parental investment, which we assume is a latent variable. Let $d_{i,k}$ denote error-ridden measurements of λ_i, $k = 1, ..., K$. The variables $d_{i,k}$ take on discrete values in the set $\{1, ..., L\}$. We impose an ordered choice representation. Let $d^*_{i,k}$ denote the latent value of $d_{i,k}$ and assume that

$$d^*_{i,k} = x_i \beta_k + f_k(\lambda_i) + \varepsilon_{i,k}$$

The x_i are observed variables that affect the $d^*_{i,k}$. The components $\varepsilon_{i,k}$ are independent measurement errors. Let $\{c_{k,0}, c_{k,1}, ..., c_{k,L}\}$ denote constants. We observe the discrete random variable $d_{i,k}$:

$$d_{i,k} = l \Longleftrightarrow c_{k,l-1} \leq d^*_{i,k} \leq c_{k,l}.$$

Our goal is to estimate and predict the scores of the factor λ_i. In order to do that, we need to identify the distribution of λ_i and the function $f_k(\lambda_i)$. To carry out this task, we proceed in two stages. In the first stage, we estimate a model in which $f_k(\lambda_i) = \alpha_k \lambda_i$. This assumption is invoked in the linear factor model when the measurement is continuous, so it is a natural benchmark to check if the scores we obtain by explicitly recognizing the discreteness of the measurements are correlated with the ones generated by the factor score via the regression method that we use in our empirical analysis.

In the second stage, we investigate departures of the linearity assumption and postulate $f_k(\lambda_i) = \alpha_k \lambda_i + \gamma_k \lambda_i^2$. This nonlinearity may capture the fact that a change in $d_{i,k}$ from "1" to "2" may imply a larger (or smaller) increase in investments, than a change in $d_{i,k}$ from "$L-1$" to "L".

B.1.1 Index is a Linear Function of Factor

We start by considering a model in which

$$d^*_{i,k} = x_i \beta_k + \alpha_k \lambda_i + \varepsilon_{i,k}.$$

It is important to keep in mind that factor models require a location and scale normalization. In our empirical analysis, we impose the restriction that $E(\lambda_i) = 0$ and one factor loading is set to one, (e.g., $\alpha_1 = 1$). Because the observed variable is discrete, we set $Var(\varepsilon_{i,k}) = 1$ for all k. Finally, the vector x_i cannot contain a constant variable, because an intercept cannot be separately identified from the parameters $c_{k,l}$.

Assuming Normality Our goal is to estimate the density of the factor λ_i conditional on the random vector $\{d_{i,1}, ..., d_{i,K}\}$, which we denote by $p(\lambda_i | d_{i,1}, ..., d_{i,K})$. A simple recursive algorithm can be developed if we assume that the factor $\lambda_i \sim N(\mu_\lambda, \sigma_\lambda^2)$ and measurement errors $\varepsilon_{i,k} \sim N(0,1)$.

Under the assumption of normality, the conditional density $p(\lambda_i | d_{i,1}, ..., d_{i,k})$, $k \leq K$, is the density of a normal random variable with mean $\mu_{\lambda,k}$ and variance $\sigma_{\lambda,k}^2$, where:

$$\begin{aligned}
\mu_{\lambda,k} &= E(\lambda_i | d_{i,1}, ..., d_{i,k}) \\
\sigma_{\lambda,k}^2 &= Var(\lambda_i | d_{i,1}, ..., d_{i,k})
\end{aligned}$$

To derive these expressions, suppose that we observe $d_{i,1} = l$ and let $\omega_i \sim N(0,1)$. Clearly, $\lambda_i = \mu_\lambda + \sigma_\lambda \omega_i$. We can update the mean and variance of the factor:

$$\begin{aligned}
\mu_{\lambda,1} &= E(\lambda_i | d_{i,1} = l) = \mu_\lambda + \sigma_\lambda E(\omega_i | d_{i,1} = l) \\
&= \mu_\lambda + \sigma_\lambda E(\omega_i | c_{1,l-1} \leq x_i \beta_1 + \alpha_1 \mu_\lambda + \alpha_1 \sigma_\lambda \omega_i + \varepsilon_{i,k} \leq c_{1.l}) \\
&= \mu_\lambda + \frac{\alpha_1 \sigma_\lambda^2}{(1 + \alpha_1^2 \sigma_\lambda^2)^{\frac{1}{2}}} \frac{\phi(z_{i,1,l-1}) - \phi(z_{i,1,l})}{\Phi(z_{i,1,l}) - \Phi(z_{i,1,l-1})}
\end{aligned}$$

where $z_{i,1,l} = \frac{c_{1,l} - x_i \beta_1 - \alpha_1 \mu_\lambda}{(1+\alpha_1^2 \sigma_\lambda^2)^{\frac{1}{2}}}$, ϕ is the PDF of a standardized normal random variable and Φ is its CDF.

We proceed in similar fashion with the variance:

$$\begin{aligned}
\sigma_{\lambda,1}^2 &= Var(\lambda_i | d_{i,1} = l) = \sigma_\lambda^2 Var(\omega_i | d_{i,1} = l) \\
&= \sigma_\lambda^2 Var(\omega_i | c_{1,l-1} \leq x_i \beta_1 + \alpha_1 \mu_\lambda + \alpha_1 \sigma_\lambda \omega_i + \varepsilon_{i,k} \leq c_{1.l}) \\
&= \frac{\alpha_1^2 \sigma_\lambda^4}{(1 + \alpha_1^2 \sigma_\lambda^2)} \left[1 + \frac{z_{i,1,l-1} \phi(z_{i,1,l-1}) - z_{i,1,l} \phi(z_{i,1,l})}{\Phi(z_{i,1,l}) - \Phi(z_{i,1,l-1})} - \left(\frac{\phi(z_{i,1,l-1}) - \phi(z_{i,1,l})}{\Phi(z_{i,1,l}) - \Phi(z_{i,1,l-1})} \right)^2 \right] + \sigma_\lambda^2
\end{aligned}$$

The algorithm provides a set of recursive update formulas for means and variances:

$$\mu_{\lambda,k+1} = \mu_{\lambda,k} + \frac{\alpha_{k+1} \sigma_{\lambda,k}^2}{\left(1 + \alpha_{k+1}^2 \sigma_{\lambda,k}^2\right)^{\frac{1}{2}}} \frac{\phi(z_{i,k+1,l-1}) - \phi(z_{i,k+1,l})}{\Phi(z_{i,k+1,l}) - \Phi(z_{i,k+1,l-1})}$$

$$\sigma_{\lambda,k+1}^2 = \sigma_{\lambda,k}^2 + \frac{\alpha_{k+1}^2 \sigma_{\lambda,k}^4}{\left(1 + \alpha_{k+1}^2 \sigma_{\lambda,k}^2\right)} \left[1 + \frac{z_{i,k+1,l-1} \phi(z_{i,k+1,l-1}) - z_{i,k+1,l} \phi(z_{i,k+1,l})}{\Phi(z_{i,k+1,l}) - \Phi(z_{i,k+1,l-1})} - \left(\frac{\phi(z_{i,k+1,l-1}) - \phi(z_{i,k+1,l})}{\Phi(z_{i,k+1,l}) - \Phi(z_{i,k+1,l-1})} \right)^2 \right]$$

One can then estimate the factor score as $\mu_{\lambda,K} = E(\lambda_i | d_{i,1}, ..., d_{i,K})$.

Relaxing Normality Although convenient, the normality assumption may be too strict for our dataset. Instead, we assume that the factor λ_i is distributed according to a mixture of J normal distributions. That is, we assume that $\lambda_i \sim MN\left(\left\{\mu_{\lambda,j}, \sigma^2_{\lambda,j}, \pi_{\lambda,j}\right\}_{j=1}^{J}\right)$ where the term $\pi_{\lambda,j}$ is the weight of the elemtent j. We impose the condition that $\sum_{j=1}^{J} \pi_{\lambda,j} = 1$. It is easy to extend the recursive rules above for the mean and variances for each element of the mixture. To complete the algorithm, it is necessary to derive a recursive rule for update of the mixture weights $\pi_{\lambda,j}$. To derive the rule, note that the probability that $d_{i,1} = l$ conditional on the element j is

$$\Pr\left(d_{i,1} = l \mid x_i, j\right) = \Phi_j\left(z_{i,1,l}\right) - \Phi_j\left(z_{i,1,l-1}\right).$$

Therefore, we update the weights according to the following rule:

$$\pi_{\lambda,j,k+1} = \frac{\pi_{\lambda,j,k} \Pr\left(d_{i,k} = l \mid x_i, j\right)}{\sum_{m=1}^{J} \pi_{\lambda,m,k} \Pr\left(d_{i,k} = l \mid x_i, m\right)}$$

Findings We compare the investment factor produced by expliciting accounting for the fact that investments are ordered discrete variables with the factors scored by the Regression method assuming that the measures are continuous random variables. When we assume that the distribution of the factor is a mixture of two elements, we find that the correlation between the two distinct measures of investment to be around 86%. When we model the distribution of the factor as a mixture of three elements, we find that the correlation is even higher, around 89%. The major differences are not with respect to mean and variance (because these moments can be matched by the location and scale normalizations), but both the skewness and kurtosis. The factor scores produced by our method generates a distribution with positive skewness, while that obtained from the Regression method is negative. On the other hand, the distribution in the Regression method has more than twice the kurtosis from our method.

Appendix Figure 1 displays the scatterplot of both measures. This figure is produced by assuming that the distribution of the factor follows a mixture of two normal random variables. As can be seen, there is strongly correlation between the two random variables, but the relationship is also slightly nonlinear.

B.1.2 Index is a Quadratic Function of Factor

We now turn to the following model

$$d^*_{i,k} = x_i\beta_k + \alpha_k\lambda_i + \gamma_k\lambda_i^2 + \varepsilon_{i,k}.$$

We need to identify the distribution of λ_i and the factor loadings α_k and γ_k. However, only the location and scale normalizations are not enough, because each equation adds two factor loadings that need to be identified. We assume that $\alpha_k = 1$ for at least three measurements (e.g., $\alpha_1 = \alpha_2 =$

$\alpha_3 = 1$) and that $\gamma_k = 0$, for at least two measures for which $\alpha_k = 1$, and $\gamma_k = \gamma$ for the remaining measures (e.g., $\gamma_1 = \gamma_2 = 0$).

To see how we can identify the remaining factor loadings, note that we can work with the index $d^*_{i,k}$ because it is identified up to scale (Matzkin, 1992). The indexes are:

$$\begin{aligned}
d^*_{i,1} &= x_i\beta_1 + \lambda_i + \varepsilon_{i,1}, \\
d^*_{i,2} &= x_i\beta_2 + \lambda_i + \varepsilon_{i,2}, \\
d^*_{i,3} &= x_i\beta_3 + \lambda_i + \gamma\lambda_i^2 + \varepsilon_{i,3}, \\
d^*_{i,k} &= x_i\beta_k + \alpha_k\lambda_i + \gamma\lambda_i^2 + \varepsilon_{i,k}, \text{ for } k = 4, ..., K.
\end{aligned}$$

We can apply Kotlarski's Theorem and identify the distribution of λ_i. Then, taking the covariance between $d^*_{i,1}$ and $d^*_{i,3}$, conditional on x_i, yields:

$$cov\left(d^*_{i,1}, d^*_{i,3}\middle| x_i\right) = \sigma^2_\lambda + \beta E\left(\lambda_i^3\right).$$

Because we know the distribution of λ, we know the moments σ^2_λ and $E\left(\lambda_i^3\right)$. As a result, we recover β from the covariance. The remaining covariances are then used to identify the factor loadings α_k for $k = 4, ..., K$.

Findings We approximate the distribution of λ_i with a mixture of normals with two elements. We find evidence of nonlinearity. More specifically, $\gamma = -0.019$ (with standard error 0.0014). Because all $\alpha_k > 0$, our findings suggest a concave relationship between the investment factor and the index that generates the discrete measurements. This implies that our factor scores produced by the Regression method slightly underestimates investments when they are high.

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Table 1: Correlation between Local Head Start Spending Per Poor Person 1968 and Preschool Enrollment

Panel A: Full Sample

	1963-1964	1965	1966	1967	1968	1969	1970
Local HS spending per poor person in 1968	0.000309	0.0006	0.00452	0.00308	0.00361	0.00157	0.00132
	[0.000982]	[0.00113]	[0.00180]	[0.00177]	[0.00224]	[0.00185]	[0.00175]
Observations	6122	5099	5442	5571	6178	5616	1627
R-squared	0.012	0.021	0.021	0.019	0.017	0.034	0.048

Robust standard errors in brackets

Panel B: Limiting to Mothers with no More than a High School Degree

	1963-1964	1965	1966	1967	1968	1969	1970
Local HS spending per poor person in 1968	0.000158	0.000692	0.00525	0.00392	0.0044	0.00342	0.00463
	[0.000754]	[0.00102]	[0.00176]	[0.00162]	[0.00187]	[0.00162]	[0.00169]
Observations	5637	4642	4875	4990	5538	4872	1308
R-squared	0.008	0.013	0.023	0.022	0.016	0.022	0.047

Panel C: Include Mother FE

	ALL	<=HS
Local HS Spending (=0 in years prior to 1966)	0.00183	0.00251
	[0.000978]	[0.00101]
Observations	0.894	0.882
R-squared	12938	11670

Robust standard errors in brackets
OLS results in planels A and B of a regression of an indicator for preschool enrollment on a measure of local Head Start Spending
includes controls for offspring gender, birth order dummies, maternal race, maternal education, maternal age, marital status and family income at birth
FE Regressions in panel C include controls for gender, birth order, maternal age, marital status, family income at birth and a quadratic in year of birth
Local (county) Head Start spending per poor person in 1968 ranges from $3 to $29

Table 2 Determinants of Investment Across Families: Dependent Variable= Preschool

Panel A: OLS Regressions	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Birth Weight - Standardized	-0.00247						-0.00297
	[0.00402]						[0.00419]
Low Birth Weight		0.00111					
		[0.0107]					
Weeks of Gestation at Birth			-0.00094				
			[0.00112]				
Premature birth				0.0151			
				[0.0113]			
8 Month Mental Bayley - Standardized					0.000834	0.00384	0.00158
					[0.00354]	[0.00448]	[0.00369]
8 Month Motor Bayley - Standardized						-0.00517	
						[0.00423]	
Maternal Education at Birth	0.00392	0.00391	0.00386	0.00387	0.00391	0.00391	0.00392
	[0.000820]	[0.000820]	[0.000819]	[0.000819]	[0.000819]	[0.000819]	[0.000820]
Maternal Age at Birth	0.000277	0.00027	0.000236	0.00026	0.00024	0.000245	0.00027
	[0.000762]	[0.000762]	[0.000762]	[0.000762]	[0.000761]	[0.000762]	[0.000762]
Family income (real) at pregnancy in $1000	0.000216	0.000212	0.000203	0.000202	0.000211	0.000204	0.000216
	[0.000286]	[0.000286]	[0.000286]	[0.000286]	[0.000286]	[0.000286]	[0.000286]
Married	-0.00713	-0.00722	-0.00859	-0.00848	-0.00754	-0.0073	-0.0071
	[0.00987]	[0.00987]	[0.00987]	[0.00987]	[0.00985]	[0.00986]	[0.00987]
Black	0.0208	0.0208	0.0197	0.0196	0.0202	0.0211	0.0207
	[0.0479]	[0.0479]	[0.0478]	[0.0478]	[0.0478]	[0.0478]	[0.0479]
White	-0.102	-0.102	-0.103	-0.103	-0.103	-0.103	-0.102
	[0.0472]	[0.0472]	[0.0472]	[0.0472]	[0.0472]	[0.0472]	[0.0472]
Hispanic	-0.0611	-0.0614	-0.0617	-0.0618	-0.0616	-0.0613	-0.0611
	[0.0543]	[0.0543]	[0.0542]	[0.0542]	[0.0542]	[0.0542]	[0.0543]
Male	-0.013	-0.0134	-0.0135	-0.0134	-0.0134	-0.0136	-0.0129
	[0.00662]	[0.00659]	[0.00658]	[0.00658]	[0.00657]	[0.00658]	[0.00663]
First born	0.0373	0.0377	0.0369	0.037	0.0373	0.0391	0.0368
	[0.0132]	[0.0132]	[0.0132]	[0.0132]	[0.0132]	[0.0132]	[0.0132]
Second Birth	0.0349	0.0352	0.0348	0.035	0.0349	0.0355	0.0347
	[0.0112]	[0.0112]	[0.0112]	[0.0112]	[0.0112]	[0.0112]	[0.0112]
Third or Fourth Birth	0.0112	0.0114	0.0105	0.0107	0.0112	0.0114	0.0111
	[0.00958]	[0.00957]	[0.00957]	[0.00958]	[0.00957]	[0.00957]	[0.00958]
Observations	10156	10156	10132	10132	10167	10160	10156
R-squared	0.047	0.047	0.048	0.048	0.047	0.047	0.047

Panel B: Maternal FE Regressions	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Birth Weight - Standardized	0.00039						0.00151
	[0.00857]						[0.00880]
Low Birth Weight		-0.00928					
		[0.0191]					
Weeks of Gestation at Birth			-0.00209				
			[0.00190]				
Premature birth				0.00789			
				[0.0187]			
8 Month Motor Bayley - Standardized						-0.00298	
						[0.00680]	
8 Month Mental Bayley - Standardized					-0.00309	-0.00147	-0.00327
					[0.00569]	[0.00679]	[0.00584]
Observations	10157	10157	10133	10133	10168	10161	10157
R-squared	0.739	0.739	0.739	0.739	0.738	0.738	0.739

Standard errors in brackets

AMC FE and year of birth indicators included in top panel

Maternal FE and year of birth indicators included in bottom panel

Table 3A Are Investments and Endowments Complements in the Production of Child Human Capital?

	IQ 4	IQ 7	Read	Math
Investment(preschool)*8 Month Bayley	0.165	0.104	0.0298	0.16
	[0.0420]	[0.0415]	[0.0473]	[0.0507]
8 Month Mental Bayley - Standardized	0.152	0.164	0.0199	0.0381
	[0.0298]	[0.0293]	[0.0315]	[0.0337]
Investment(Preschool)	0.163	0.0196	-0.0287	0.00878
	[0.0382]	[0.0395]	[0.0411]	[0.0440]
BO*8 Month Bayley	-0.00707	-0.0103	0.00393	0.00798
	[0.00709]	[0.00711]	[0.00763]	[0.00817]
Maternal Age at Birth	-0.0074	-0.0224	-0.00563	0.0177
	[0.0224]	[0.0226]	[0.0235]	[0.0252]
Family income (real) at pregnancy in $1000	0.000584	0.00101	-0.00134	8.57E-05
	[0.00117]	[0.00120]	[0.00125]	[0.00134]
Married	-0.0391	-0.0175	-0.0477	-0.101
	[0.0494]	[0.0503]	[0.0522]	[0.0558]
Male	-0.111	0.0282	-0.17	-0.0746
	[0.0214]	[0.0219]	[0.0227]	[0.0243]
First born	-0.202	-0.0144	-0.0598	-0.133
	[0.101]	[0.0852]	[0.0886]	[0.0948]
Second Birth	-0.0788	-0.00775	-0.0385	-0.00745
	[0.0789]	[0.0691]	[0.0717]	[0.0767]
Third or Fourth Birth	-0.0199	0.00099	0.013	0.0223
	[0.0539]	[0.0501]	[0.0519]	[0.0556]
Observations	9956	9229	9204	9205
R-squared	0.844	0.845	0.815	0.787

Standard errors in brackets

Maternal FE and all controls from previous table included in all regressions

Table 3B Heterogeneity in Impact of Preschool on 7 Year IQ

	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Preschool	0.193	0.01	0.197	0.0102	0.221	-0.0476	0.182	-0.00642	0.19	0.0223	0.00722	-0.112	0.0596	-0.0265
	[0.0257]	[0.0393]	[0.0256]	[0.0391]	[0.0492]	[0.0770]	[0.0353]	[0.0498]	[0.0251]	[0.0388]	[0.0925]	[0.121]	[0.109]	[0.152]
Preschool*bw			-0.0331	-0.00195									-0.0406	-0.0361
			[0.0303]	[0.0455]									[0.0315]	[0.0476]
Preschool*BO					-0.0107	0.0158							-0.0161	0.0174
					[0.0132]	[0.0192]							[0.0128]	[0.0189]
Preschool*male							0.0217	0.0366					0.0209	0.0465
							[0.0502]	[0.0681]					[0.0496]	[0.0683]
Preschool*8 Month Bayley									0.0679	**0.108**			0.0447	**0.114**
									[0.0301]	[0.0408]			[0.0347]	[0.0484]
Preschool*advanced social/emotional development											0.65	**0.614**	0.648	**0.403**
											[0.261]	[0.329]	[0.265]	[0.337]
Preschool*normal social/emotional development											0.195	0.127	0.18	-0.0392
											[0.0960]	[0.125]	[0.104]	[0.142]
Birth Weight - Standardized			0.127	0.146									0.0758	0.113
			[0.0109]	[0.0211]									[0.0113]	[0.0218]
8 Month Mental Bayley - Standardized									0.186	0.127			0.168	0.121
									[0.00959]	[0.0148]			[0.0111]	[0.0167]
Advanced Social/Emotional Development											0.491	0.233	0.0926	0.017
											[0.0758]	[0.0997]	[0.0781]	[0.102]
Normal Social/Emotional Development											0.265	0.0989	0.00523	-0.045
											[0.0324]	[0.0446]	[0.0353]	[0.0476]
Observations	9339	9340	9330	9331	9228	9229	9339	9340	9339	9340	9325	9326	9205	9206
R-squared	0.289	0.839	0.3	0.842	0.289	0.84	0.289	0.839	0.322	0.844	0.298	0.84	0.327	0.848

Standard errors in brackets

Regressions include controls listed previously

ALL OLS regressions include controls for maternal characteristics (education, age, race, family income), offspring characteristics (birth order, gender, year of birth and AMC indicators.)

ALL FE regressions include controls for maternal age, family income, birth order, gender and year of birth indicators

Note: only 208 observations with advanced social/emotional development at 8 months of age.

Table 4: A Measure of Parental Investment: Factor Analysis

Factor analysis/correlation	Number of obs = 31538
Method: principal factors	Retained factors = 3
Rotation: (unrotated)	Number of params = 18

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.43651	1.298	1.2976	1.2976
Factor2	0.13851	0.10684	0.1251	1.4227
Factor3	0.03167	0.04018	0.0286	1.4513
Factor4	-0.00851	0.08304	-0.0077	1.4437
Factor5	-0.09155	0.08883	-0.0827	1.361
Factor6	-0.18038	0.03883	-0.1629	1.198
Factor7	-0.21921		-0.198	1

LR test: independent vs. saturated: chi2(28) = 2.9e+04 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
Appearance of Child	0.1751	0.1166	0.1212	0.9411
Responsivenes of Mother	0.5889	0.1525	-0.0017	0.63
Affection	0.6213	-0.1497	0.0097	0.5915
Focus on child	0.4744	-0.2363	0.0007	0.7191
Management of Child	0.3324	0.0991	-0.0451	0.8776
Attention to Child	0.3056	0.096	-0.1127	0.8847
Handling of Child	0.4941	0.066	0.0463	0.7493

Scoring coefficients (method = regression)

Variable	Factor1	Factor2	Factor3
Appearance of Child	0.06217	0.10178	0.12009
Responsivenes of Mother	0.28604	0.18732	-0.00392
Affection	0.31456	-0.18048	0.01248
Focus on child	0.19967	-0.24249	-0.00068
Management of Child	0.12527	0.09371	-0.04763
Attention to Child	0.11425	0.08734	-0.11782
Handling of Child	0.20764	0.07053	0.05466

Table 5: Correlations in Prenatal and Postnatal Investments

	Post Natal Investment
Weight Gain During Pregnancy	0.00401
	[0.00202]
Pre-Pregnancy Weight	0.00231
	[0.00191]
Cigarettes per day	-0.00435
	[0.00550]
Cigarettes per day squared	8.26E-05
	[0.000143]
Trying to Conceive	0.0281
	[0.0356]
Observations	11540
R-squared	0.677

Standard errors in brackets

Post Natal Investment is the measure of quality of parental interaction measured at 8 monhts of age.

Table 6: Estimating Endowments from a Newborn Health Production Function

	Birth Weight		Head Circ		Body Length		Gestation	
	OLS	**FE**	**OLS**	**FE**	**OLS**	**FE**	**OLS**	**FE**
Pre pregnancy weight	0.0165	0.0457	0.0178	0.0358	0.0185	0.0366	0.000169	0.0288
	[0.00170]	[0.00438]	[0.00179]	[0.00482]	[0.00173]	[0.00499]	[0.00121]	[0.00353]
Pre-pregnancy weight squared	-2.50E-05	-4.68E-05	-3.35E-05	-4.63E-05	-3.67E-05	-5.27E-05	8.14E-06	-2.48E-05
	[5.62e-06]	[1.34e-05]	[5.93e-06]	[1.48e-05]	[5.73e-06]	[1.53e-05]	[4.03e-06]	[1.09e-05]
Weight gain during pregnancy	0.0532	0.0689	0.0335	0.0413	0.0318	0.0382	0.0422	0.0595
	[0.00185]	[0.00249]	[0.00197]	[0.00286]	[0.00191]	[0.00296]	[0.00128]	[0.00192]
Weight gain squared	-0.00045	-0.00045	-0.00024	-0.0002	-0.00025	-0.0002	-0.00051	-0.00051
	[3.23e-05]	[4.06e-05]	[3.40e-05]	[4.51e-05]	[3.29e-05]	[4.66e-05]	[2.25e-05]	[3.22e-05]
Cigarettes per day	-0.0264	-0.00075	-0.0197	0.00294	-0.0235	0.000388	-0.00203	0.00704
	[0.00176]	[0.00371]	[0.00185]	[0.00406]	[0.00179]	[0.00420]	[0.00125]	[0.00300]
Cigarettes per day squared	0.000407	7.43E-05	0.000266	-8.84E-05	0.000388	7.14E-05	3.62E-05	-6.80E-05
	[5.59e-05]	[9.42e-05]	[5.86e-05]	[0.000103]	[5.67e-05]	[0.000107]	[3.97e-05]	[7.64e-05]
Trying to get pregnant	-0.0576	0.0644	-0.0335	0.0532	-0.0382	0.0427	-0.0242	0.0577
	[0.0200]	[0.0243]	[0.0210]	[0.0269]	[0.0203]	[0.0279]	[0.0141]	[0.0194]
Maternal Age at Birth	-0.0024	-0.0668	0.00238	-0.0451	0.000861	-0.0554	-0.00286	-0.08
	[0.00163]	[0.0148]	[0.00172]	[0.0163]	[0.00166]	[0.0168]	[0.00116]	[0.0120]
Family income (real) at pregnancy in $1000	0.00117	-0.00032	0.00231	0.00062	0.000627	-0.00057	-0.00014	0.000565
	[0.000594]	[0.000792]	[0.000624]	[0.000873]	[0.000603]	[0.000906]	[0.000420]	[0.000638]
Married	-0.00464	-0.0926	-0.0327	-0.0467	-0.0207	-0.0895	-0.00087	-0.0329
	[0.0204]	[0.0321]	[0.0214]	[0.0354]	[0.0207]	[0.0367]	[0.0145]	[0.0260]
Observations	15803	15804	15185	15186	15118	15119	15913	15914
R-squared	0.221	0.777	0.183	0.757	0.171	0.718	0.115	0.669

Standard errors in brackets

All Regressions include child gender, birth order indicators and year of birth indicators
OLS regressions also include city of birth FE and controls for maternal education

Table 7: Factor Loadings and Variances of Uniqueness

Variable	Factor Loadings	Variance of Uniqueness	Fraction of Total Variance Explained by the Factor
Standardized Birth Weight	0.899	0.192	0.813
Standardized Head Circumference at Birth	0.823	0.323	0.704
Standardized Body Length at Birth	0.805	0.352	0.681
Standardized Weeks of Gestation	0.466	0.782	0.357

Determining the Number of Factors

Factor	Eigenvalue
Factor1	2.350
Factor2	-0.026
Factor3	-0.050
Factor4	-0.129

Factor Scoring by the Regression Method

Variable	Scoring Coefficients
Standardized Birth Weight	0.486
Standardized Head Circumference at Birth	0.260
Standardized Body Length at Birth	0.233
Standardized Weeks of Gestation	0.071
Number of Observations	13147

Table 8: How Endowments Affect Postnatal Investments (High Quality Parenting) Within Family

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Birth Weight - Standardized	0.0618									
	[0.0191]									
BW Residual Endowment		0.0592								
		[0.0219]								
Gestation - Standardized			0.043							
			[0.0128]							
Gestation Residual Endowment				0.0355						
				[0.0140]						
Body Length - Standardized					0.0234					
					[0.0138]					
Body Length Residual Endowment						0.0268				
						[0.0152]				
Head Circumference - Standardized							0.0277			
							[0.0155]			
Head Circumference Residual Endowment								0.0272		
								[0.0172]		
Factor Scores of BW, gestation, body length, and head circumference									0.05	
									[0.0174]	
Factor Scores from residuals of BW, gestation, body length, and head circumferen										0.0203
										[0.00791]
Observations	12611	11598	12582	11568	12469	11473	12515	11515	12420	11425
R-squared	0.664	0.676	0.664	0.676	0.668	0.681	0.665	0.678	0.67	0.683

Standard errors in brackets

Also included are maternal fixed effect, indicators for child birth order, indicators for year of birth, controls for offspring gender, income and marital status at time of birth.

Impact of within family standard deviation increase in endowment on investment	(1)	(2)
	0.043775	0.038233

Table 9 First Stage Regressions Dependent Variable = Total Fertility

	IV1	IV2
Multiple pregnancies since study child, 7 years-later	1.024	
	[0.106]	
Fetal/Neonatal death since study child		-0.712
		[0.0265]
Maternal education at birth	-0.0378	-0.0384
	[0.0049]	[0.0049]
Maternal age at birth	0.152	0.157
	[0.0024]	[0.0024]
Black	0.33	0.324
	[0.0382]	[0.0373]
Hispanic	0.0539	0.0156
	[0.0714]	[0.0695]
Real Family Income at pregnancy $1000	-0.0031	-0.0029
	[0.0007]	[0.0007]
Male	-0.0073	-0.002
	[0.0190]	[0.0186]
Married	0.425	0.434
	[0.0304]	[0.0299]
Truncate	0.0006	0.0004
	[0.00003]	[0.00003]
First born	-1.734	-1.764
	[0.0218]	[0.0212]
8 Month Mental Bayley - Standardized	-0.0563	-0.0615
	[0.0126]	[0.0124]
Real income when study child is age 7 in $1000	0.0002	0.0017
	[0.0012]	[0.0012]
Irregular source of income when study child is age 7	-0.0481	-0.0557
	[0.0225]	[0.0221]
Mother is married when study child is age 7	0.017	-0.0164
	[0.0280]	[0.0273]
Number of pregnancies since study child, 7 years later	0.611	0.798
	[0.0123]	[0.0135]
Observations	24802	24802
R-Squared	0.508	0.525

Robust standard errors in brackets.

Table 10 Impact of Total Fertility on 4 Year IQ, 7 Year IQ and Achievement

	4 Year IQ			**7 Year IQ**		
	OLS	**IV1**	**IV2**	**OLS**	**IV1**	**IV2**
Total Fertility	-0.0597	-0.026	-0.114	-0.0547	-0.0497	-0.0929
	[0.0034]	[0.0386]	[0.0171]	[0.0032]	[0.0374]	[0.0159]
Observations	26832	26471	26471	27664	27603	29485
R-Squared	0.299	0.301	0.292	0.338	0.34	0.313
	7 Year Math Score			**7 Year IQ**		
	OLS	**IV1**	**IV2**	**OLS**	**IV1**	**IV2**
Total Fertility	-0.0433	-0.046	-0.0589	-0.0528	-0.0478	-0.0483
	[0.0034]	[0.0377]	[0.0170]	[0.0032]	[0.0380]	[0.0178]
Observations	27676	27512	29388	27664	27500	29375
R-Squared	0.171	0.171	0.158	0.225	0.226	0.208

Robust standard errors in brackets.

We add the following variables as control: dummy variables indicating whether the child is first-born or not, race, ethnicity, and gender; a dummy variable indicating marital status at pregnancy and another one indicating marital status at age 7 of the study child; maternal age at birth, maternal education, family income at pregnancy, family income at age 7 of study child, irregular source of income at age 7 of study child, and number of pregnancies by age 7 of study child.

Table 11: How Do Reinforcing Investments Vary with Fertility?

Panel A: Outcome=Post Natal Investments	**2 kids**	**>2 kids**	**>3 kids**
BW Residual Endowment	0.05	0.0823	0.138
	[0.0255]	[0.0459]	[0.158]
Observations	9589	1937	262
R-squared	0.73	0.448	0.475

Panel B: Outcome = 7 Year IQ	**2 kids**	**>2 kids**	**>3 kids**
BW Residual Endowment	0.118	0.215	0.444
	[0.0246]	[0.0424]	[0.123]
Observations	8250	1776	251
R-squared	0.866	0.696	0.633

Standard errors in brackets

All regressions include full controls and maternal FE

Table 12

Model Parameters

	Point Estimate	Std. Error
δ_1	4.5072	0.1232
δ_2	1.0004	0.0406
δ_3	0.0150	0.0031
δ_4	0.9969	0.1579
δ_5	0.0527	0.0183
δ_6	-0.0261	0.0094
δ_7	0.0512	0.0179
α	0.1606	0.0681
κ	0.3381	0.0944
λ_1	4.2584	0.1285
λ_2	-0.0288	0.0097

Figure 1: Bayley at 8 Mo. and IQ at 4 and 7 Years

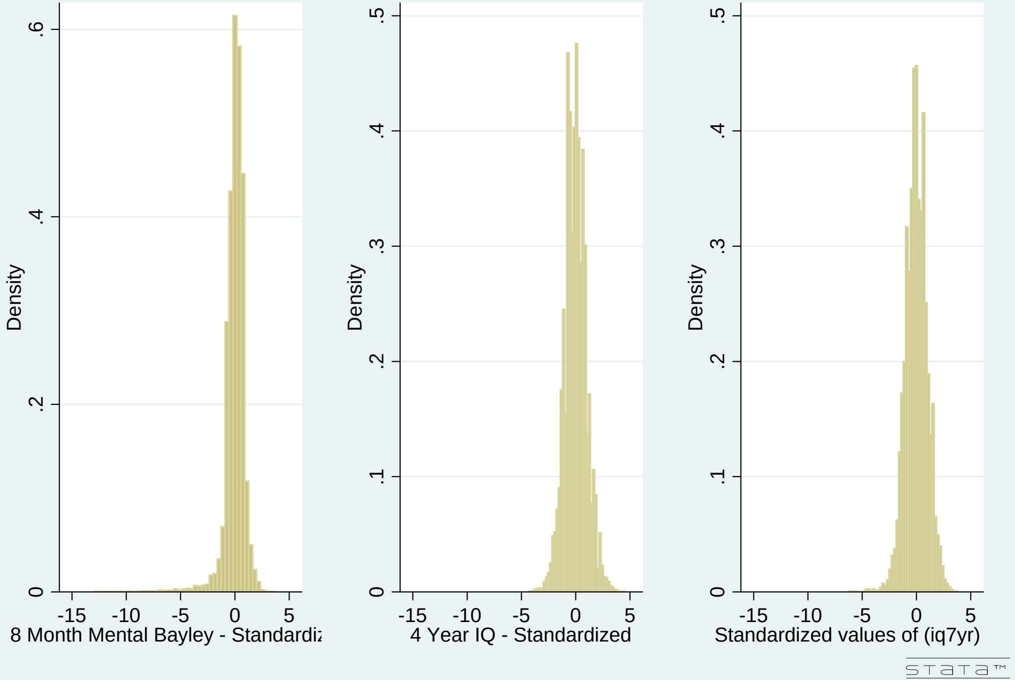
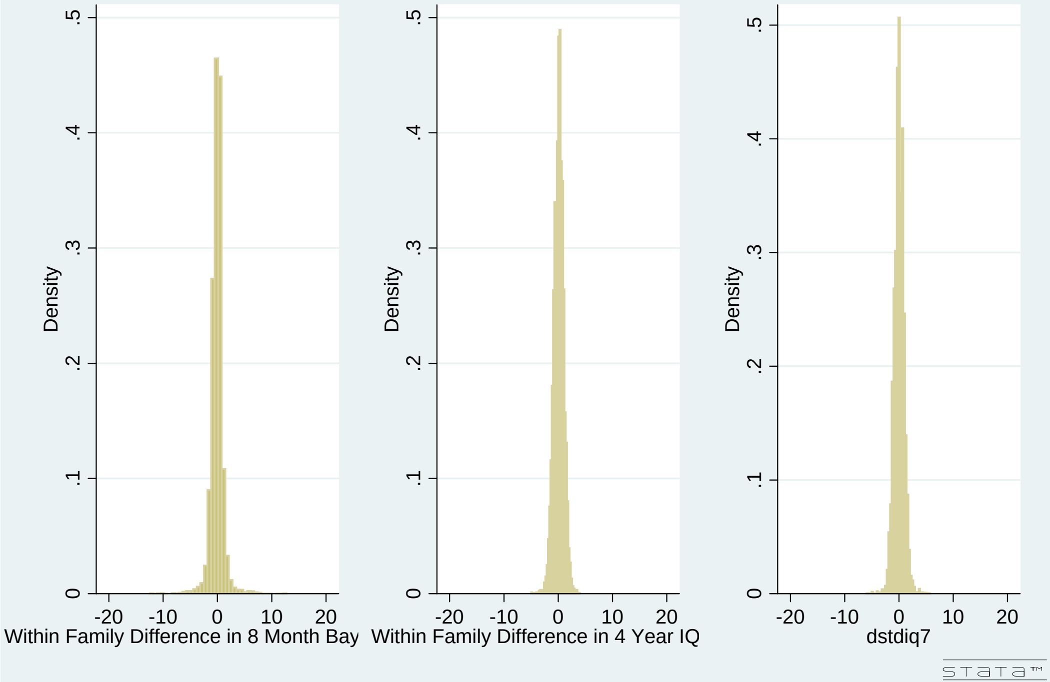


Figure 2: Within Family Variation in Bayley and IQ



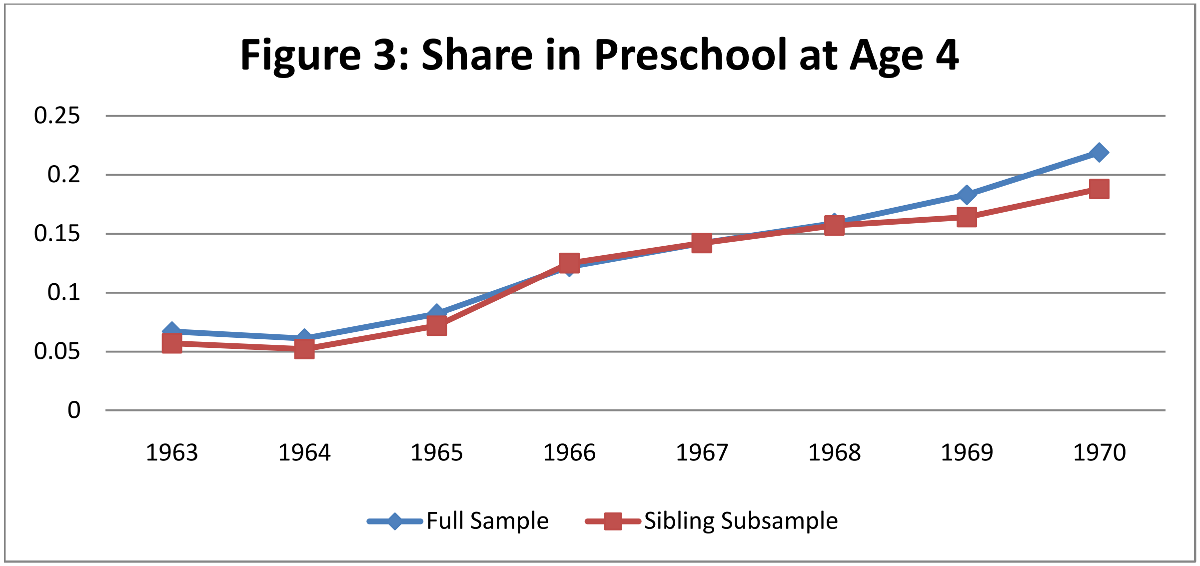
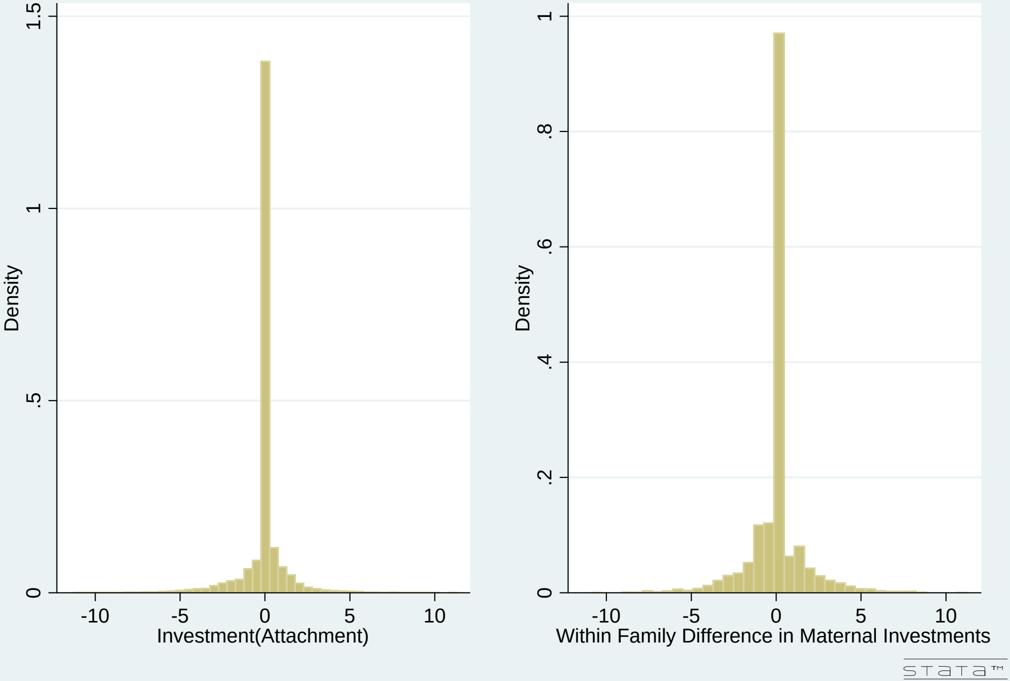


Figure 3: Share in Preschool at Age 4
0.25
0.2
0.15
0.1
0.05
0
1963
1964
1965
1966
1967
1968
1969
1970
Full Sample
Sibling Subsample

Figure 4: Variation in Investment, Between & Within Families



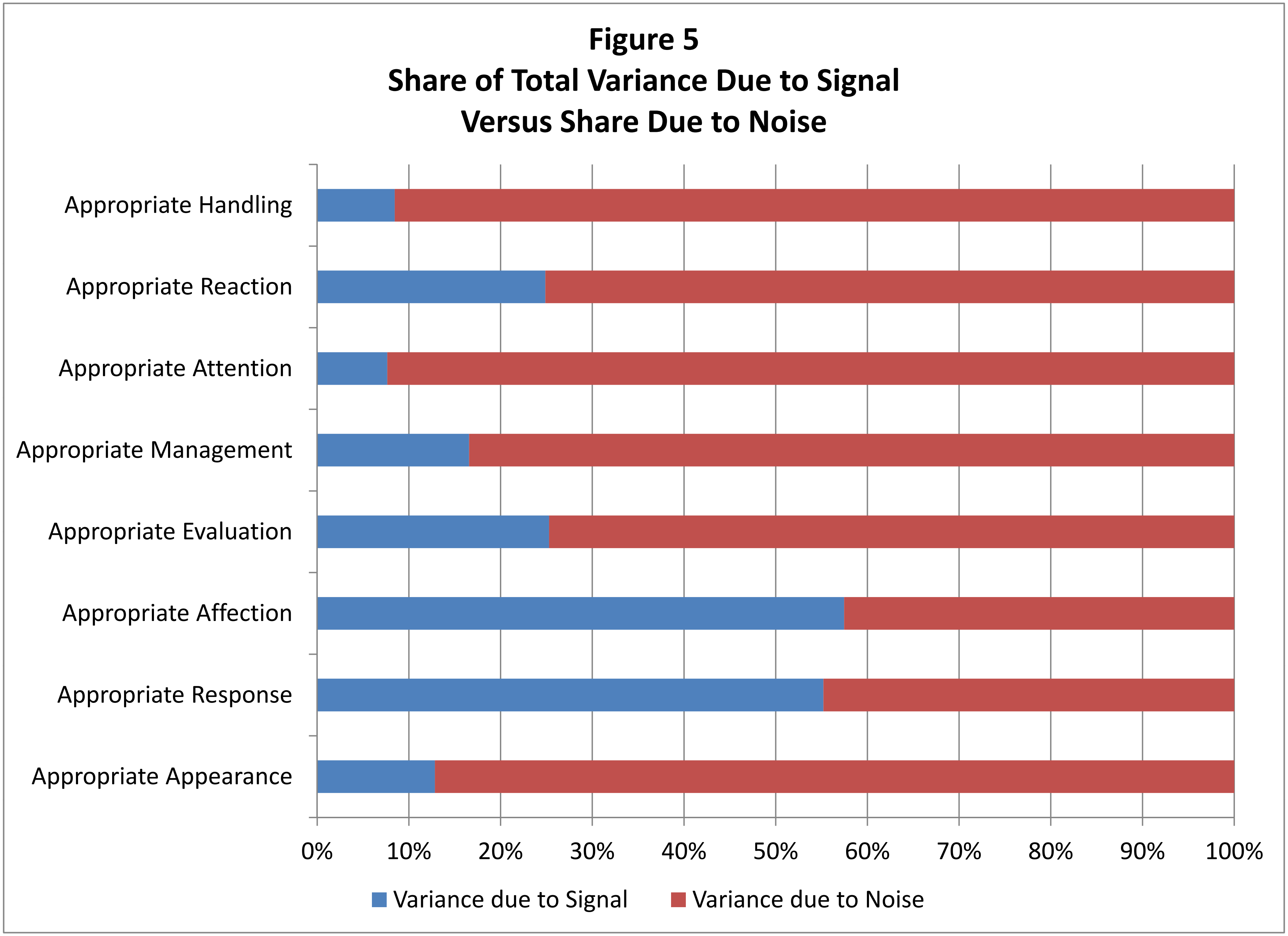


Figure 5
Share of Total Variance Due to Signal
Versus Share Due to Noise
Appropriate Handling
Appropriate Reaction
Appropriate Attention
Appropriate Management
Appropriate Evaluation
Appropriate Affection
Appropriate Response
Appropriate Appearance
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Variance due to Signal
Variance due to Noise

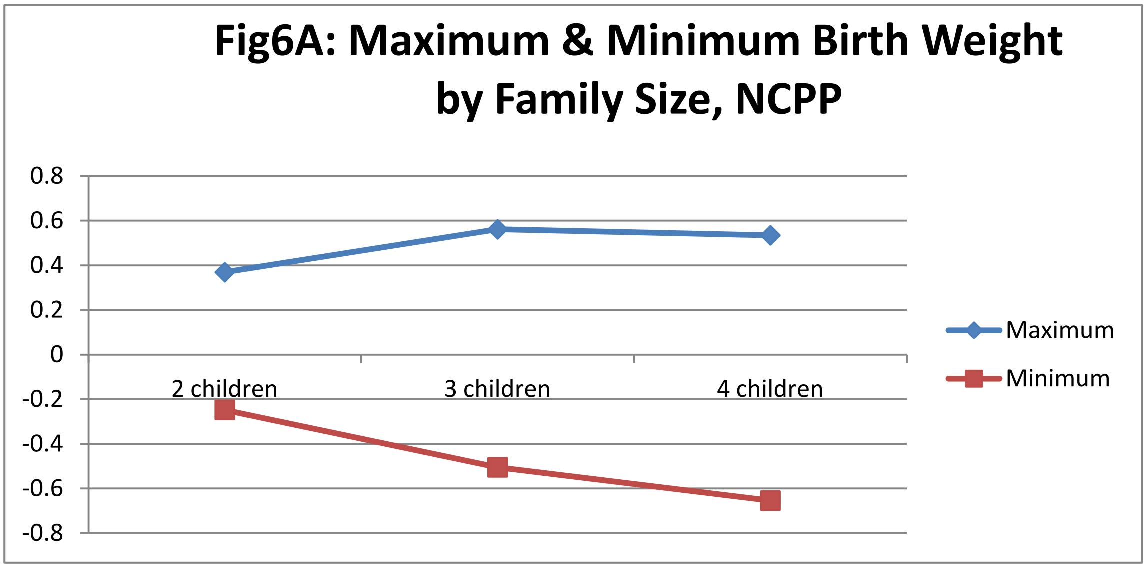


Fig6A: Maximum & Minimum Birth Weight by Family Size, NCPP
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
2 children
3 children
4 children
Maximum
Minimum

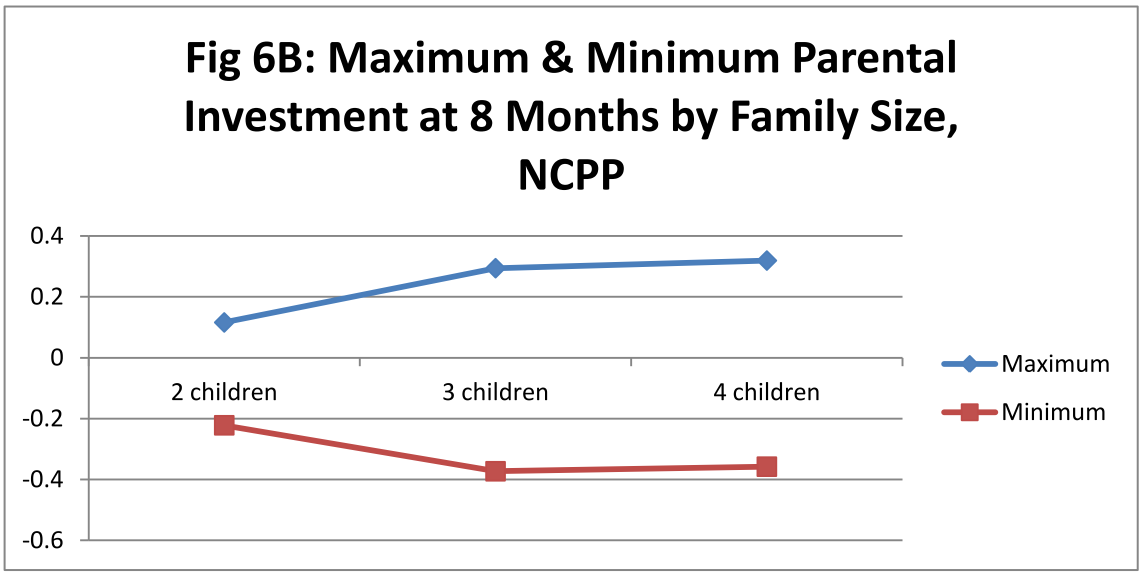


Fig 6B: Maximum & Minimum Parental Investment at 8 Months by Family Size, NCPP
0.4
0.2
0
-0.2
-0.4
-0.6
2 children
3 children
4 children
Maximum
Minimum

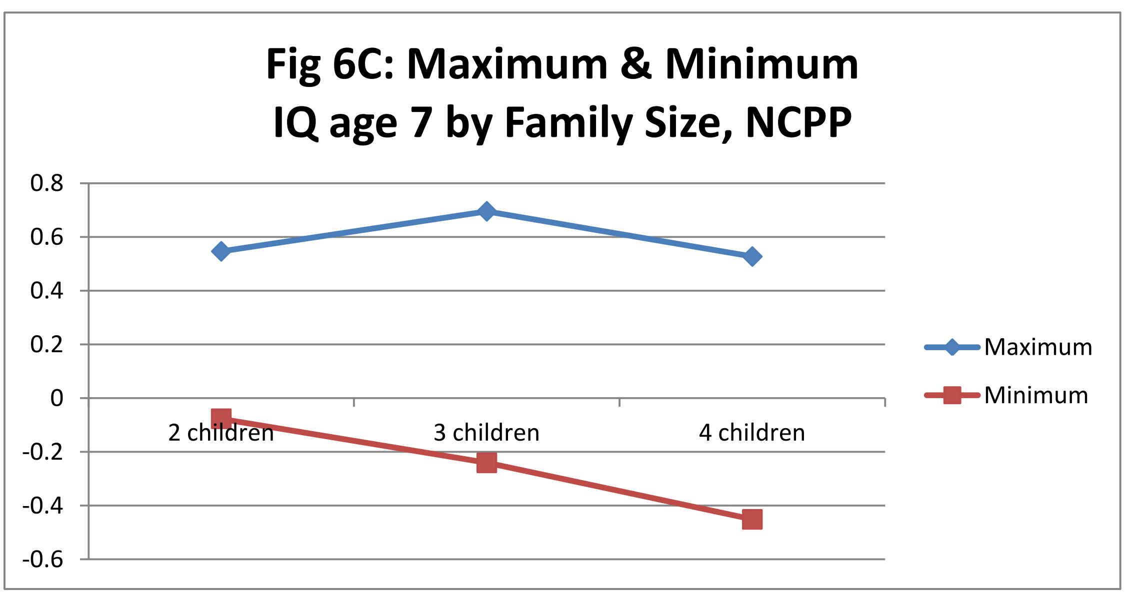


Fig 6C: Maximum & Minimum IQ age 7 by Family Size, NCPP
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
2 children
3 children
4 children
Maximum
Minimum

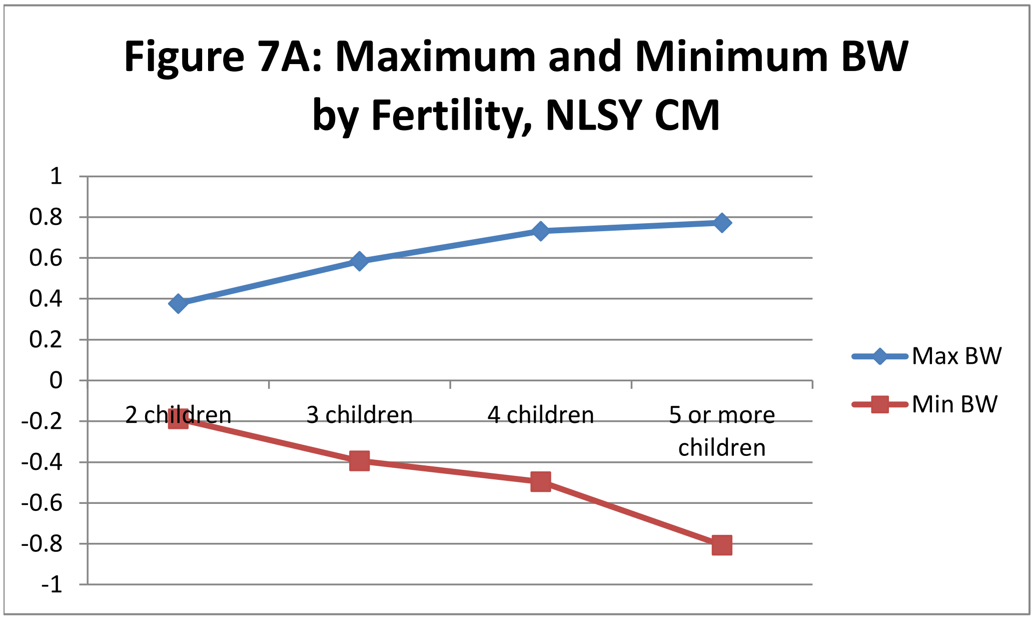


Figure 7A: Maximum and Minimum BW by Fertility, NLSY CM
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2 children
3 children
4 children
5 or more children
Max BW
Min BW

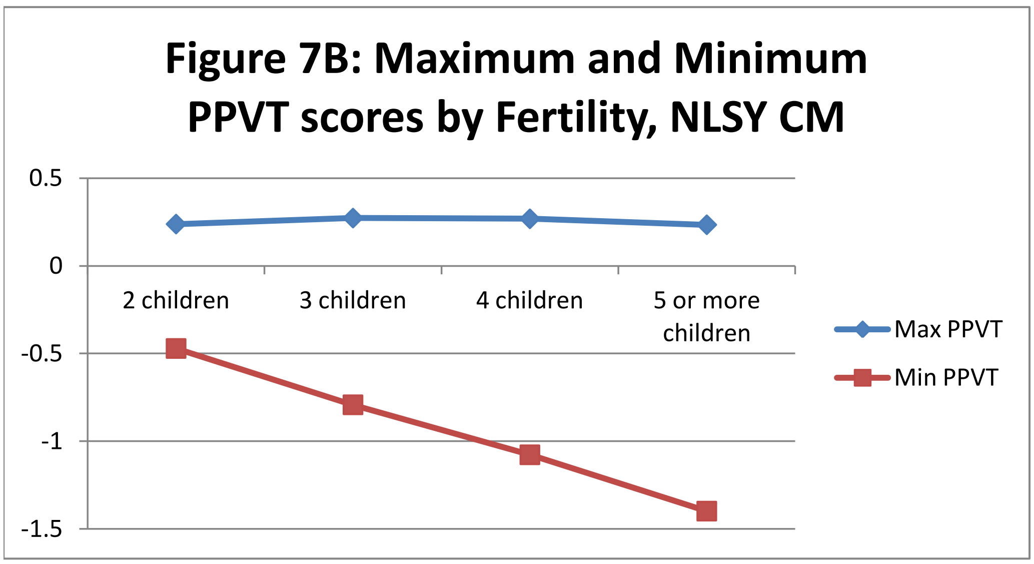


Figure 7B: Maximum and Minimum PPVT scores by Fertility, NLSY CM
0.5
0
-0.5
-1
-1.5
2 children
3 children
4 children
5 or more children
Max PPVT
Min PPVT

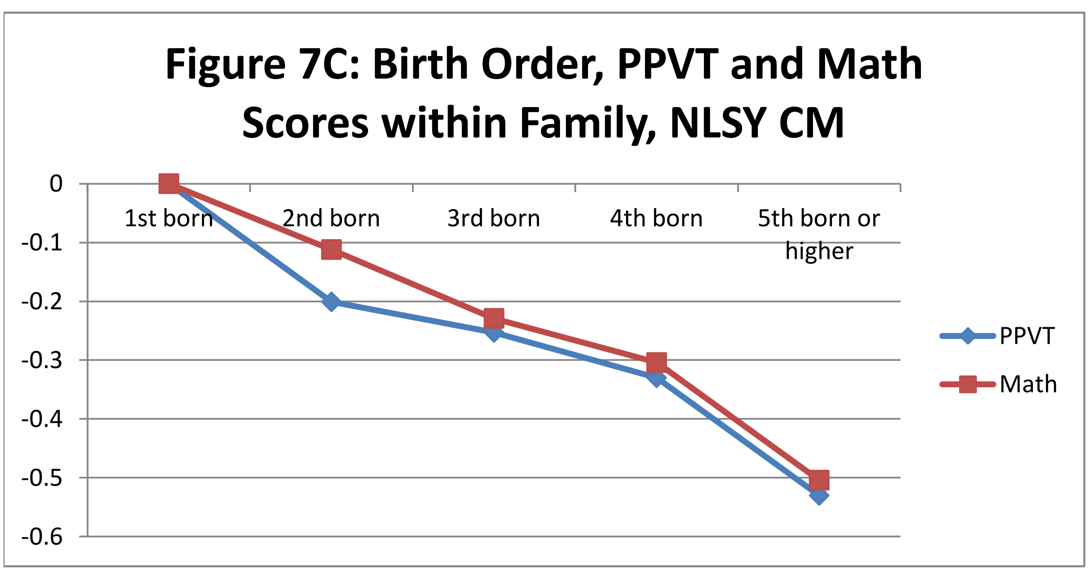


Figure 7C: Birth Order, PPVT and Math Scores within Family, NLSY CM
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
1st born
2nd born
3rd born
4th born
5th born or higher
PPVT
Math

Figure 8: Mean and Variance of Fertility

As a Function of Income

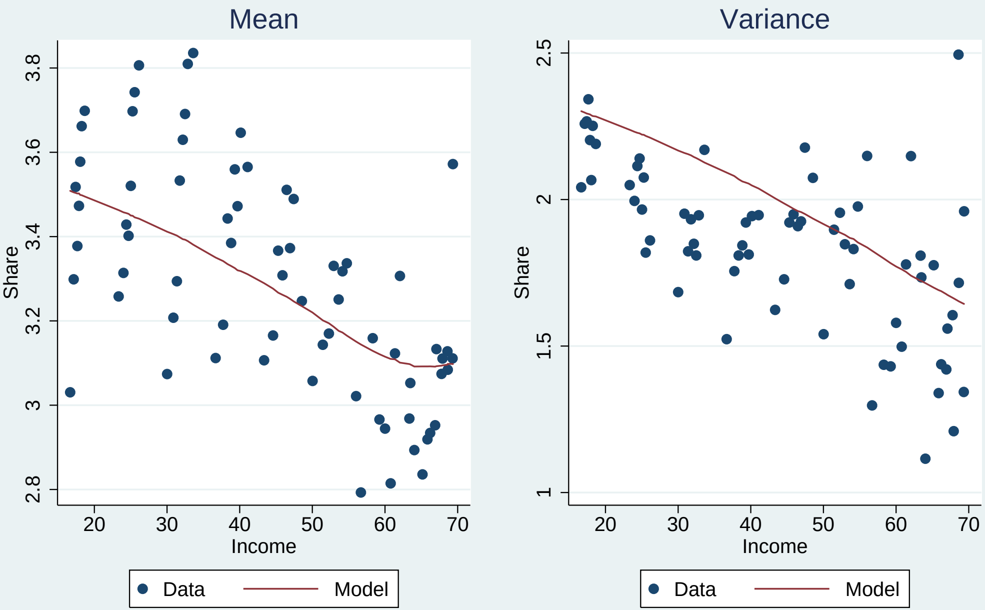


Figure 9A
Max and Min Endowments by Family Size, Model

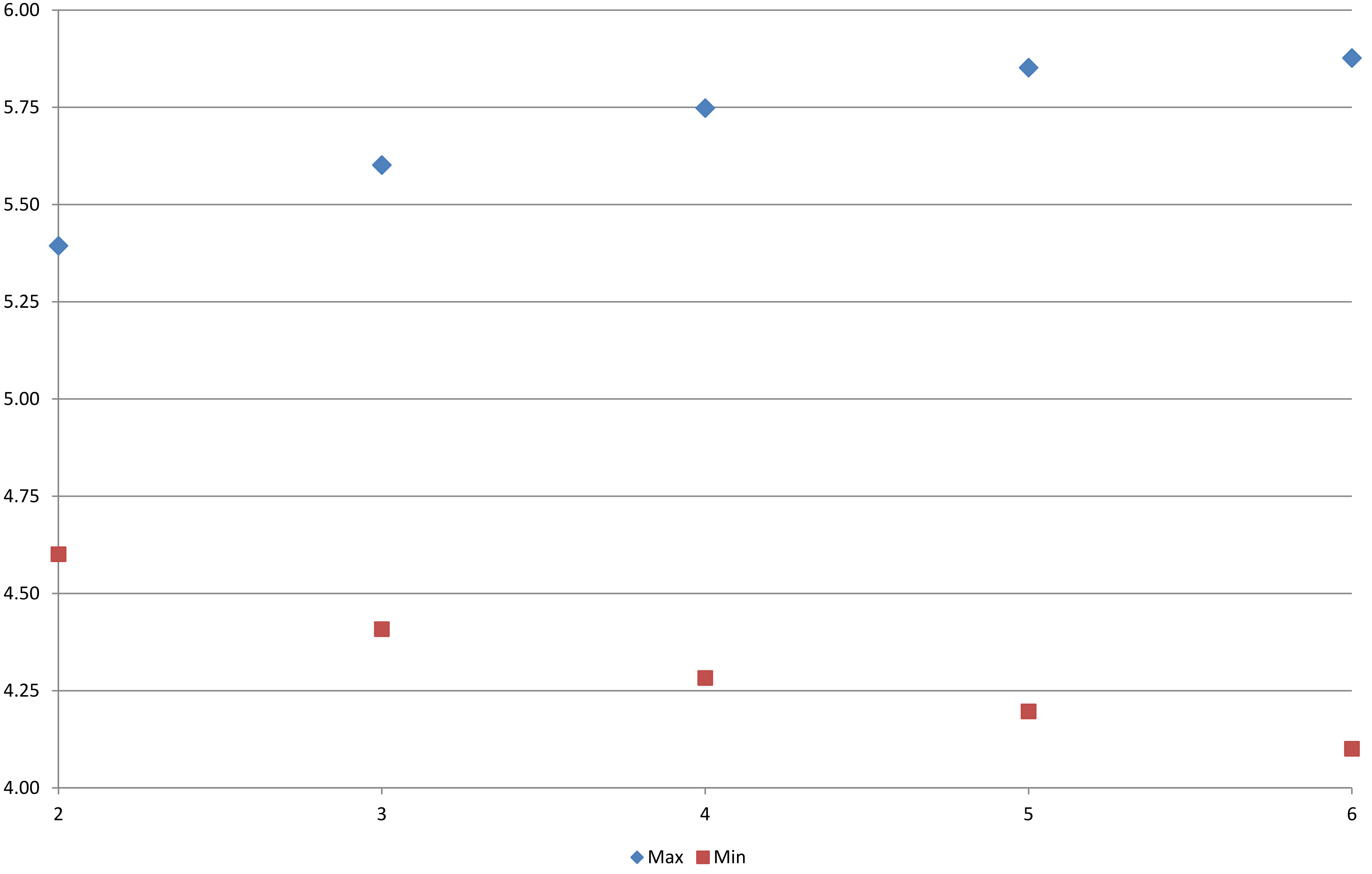


Figure 9B
Max and Min Investments by Family Size, Model

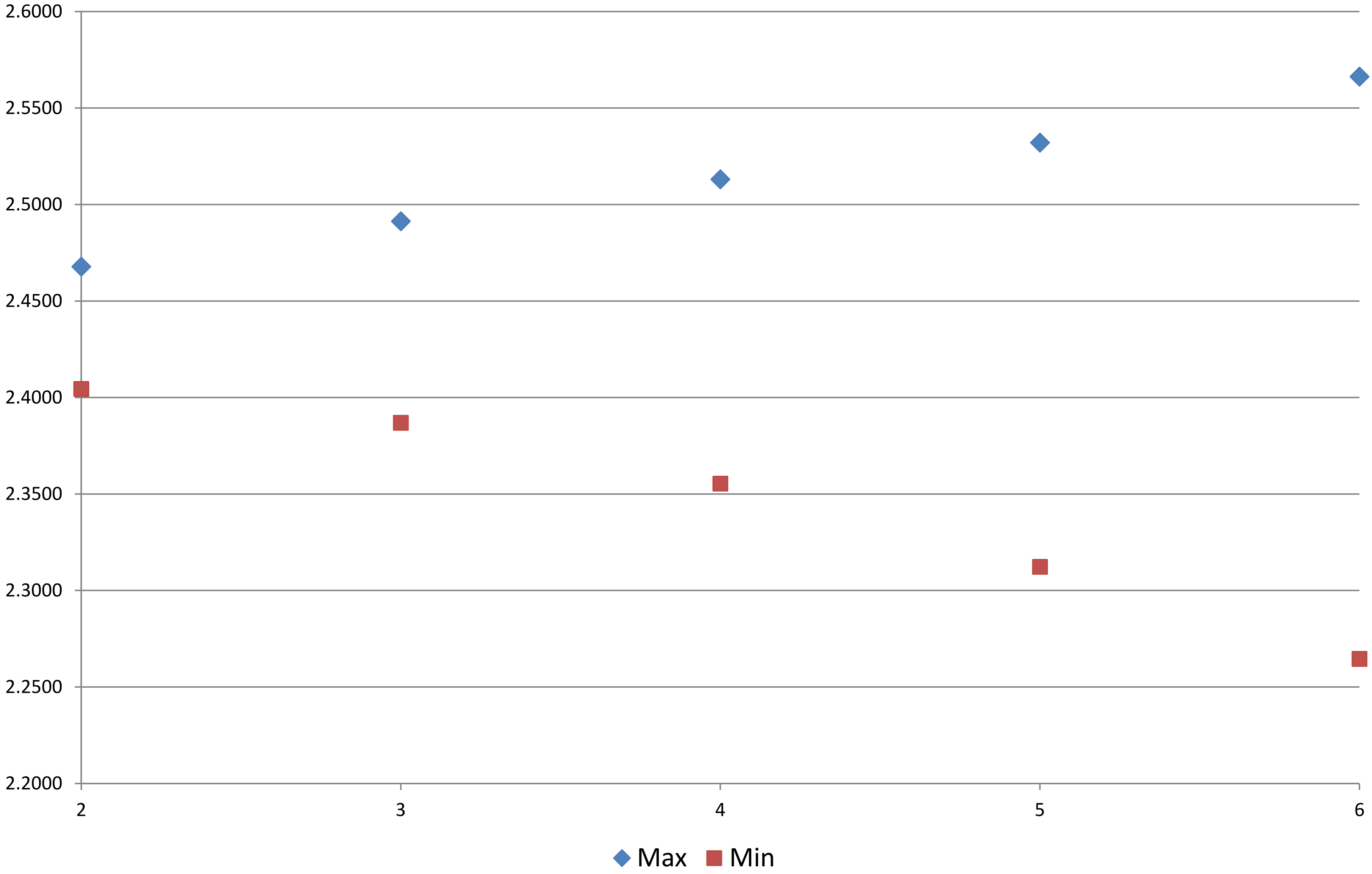


Figure 9C
Max and Min Human Capital by Family Size, Model

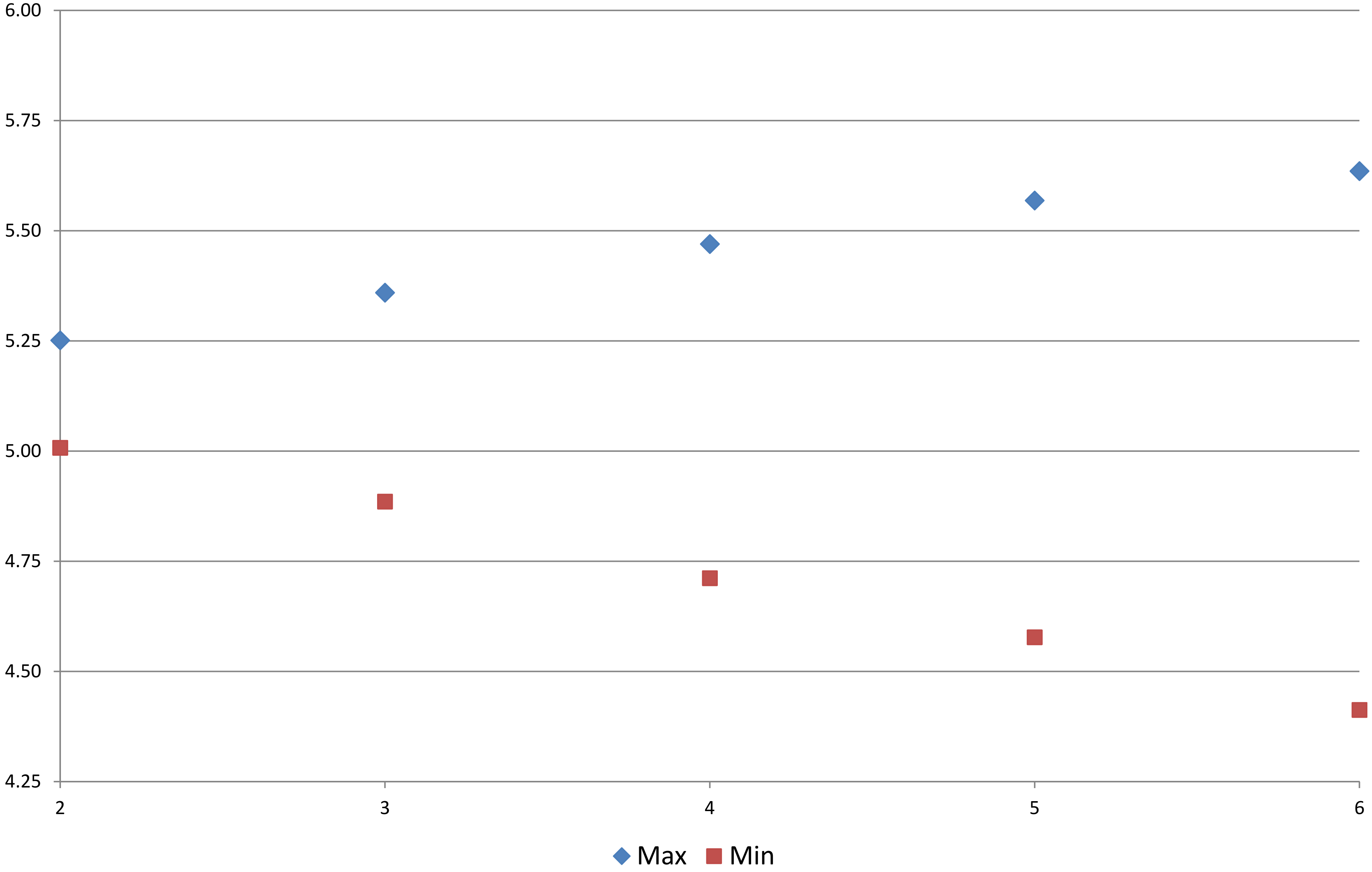
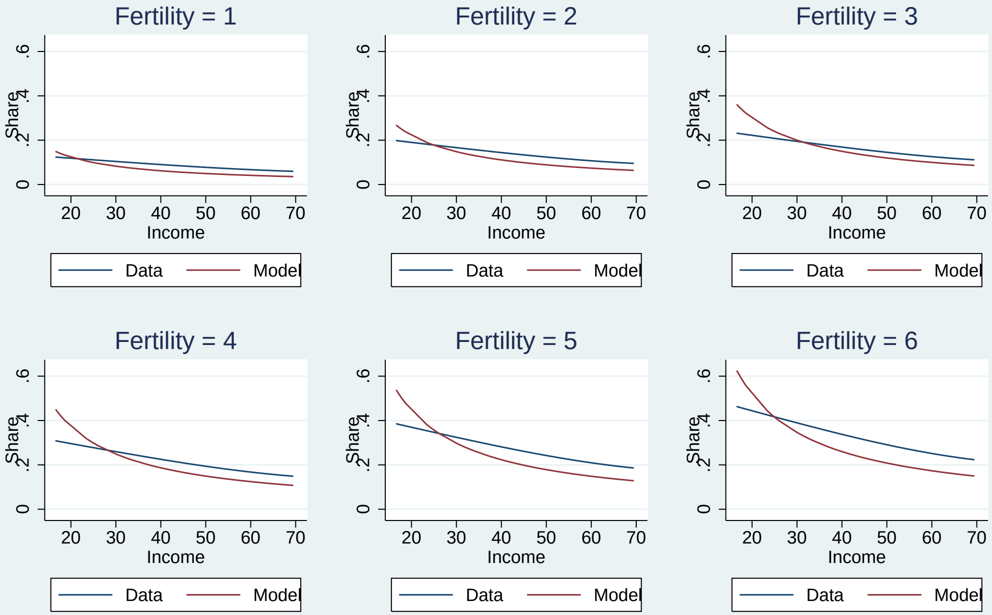


Figure 10: Share of Income Allocated to Investment

As a Function of Income and Fertility



Appendix I – Individual Items Bayley Scale of Mental Development (8 Month)

1. Social smiles
2. Visually recognizes mother
3. Eyes follow pencil
4. Reacts to paper on face
5. Searches with eyes for sound
6. Vocalizes to social stimulus
7. Manipulates ring
8. Vocalizes 2 syllables
9. Regards cube
10. Glances from one object to another
11. Anticipatory adjustment to lifting
12. Reacts to disappearance of face
13. Reaches for ring
14. Plays with rattle
15. Fingers hand in play
16. Follows vanishing ring
17. Aware of strange situation
18. Follows vanishing spoon
19. Eyes follow ball across table
20. Carries ring to mouth
21. Manipulates table edge slightly
22. Inspects own hands
23. Closes on dangling ring
24. Turns head to sound of bell
25. Turns head to sound of rattle
26. Reaches for cube
27. Active table manipulations
28. Regards pellet
29. Approaches mirror image
30. Picks up Cube
31. Exploitive paper play
32. Retains 2 cubes
33. Discriminates strangers
34. Vocalizes attitudes
35. Recovers rattle in crib or playpen
36. Reaches persistently

37. Turns head after dropped object
38. Lifts cup
39. Reaches for second cube
40. Enjoys frolic play
41. Transfers object hand to hand
42. Sustains inspection of ring
43. Plays with string
44. Picks up cube directly and easily
45. Pulls string, secures ring
46. Enjoys sound production
47. Lifts cup by handle
48. Retains 2 cubes
49. Attends to scribbling
50. Looks for dropped object
51. Manipulates Bell: Interest in details
52. Responds playfully to mirror
53. Vocalizes 4 different syllables
54. Pulls string purposively to secure ring
55. Responds to social play
56. Attempts to secure 3 cubes
57. Rings bell imitatively
58. Responds to name
59. Says Da-Da or equivalent
60. Uncovers toy
61. Adjusts to words
62. Fingers holes in peg board
63. Puts cube in cup
64. Looks for contents of box

Appendix Table 1 Sample Means

	Overall		Std Dev. Within Family	Mean Difference Within Family			
				Raw		Standardized	
Maternal Characteristics	mean	Std Dev		mean	Std Dev	mean	Std Dev
Maternal Age	25.68	5.09					
Maternal Education	11.11	4.59					
Socio economic Index (Duncan)	50.44	21.25					
Married	0.86						
Black	0.42						
White	0.54						
Hispanic	0.03						
First Birth	0.13						
Second Birth	0.23						
Third or Fourth Birth	0.35						
Male	0.50						
Investments							
Maternal Investment	-0.07	0.83	0.48	0.54	0.9		
Preschool Attendance	0.13			0.15			
Cognitive Measures							
8 Month Bayley Score	79.32	6.04	3.30	4.6	5.8	0.75	0.93
4 year IQ	98.77	16.70	7.00	11.9	9.7	0.72	0.58
7 Year IQ	96.31	14.80	6.10	10.7	8.8	0.7	0.58
Newborn Health							
Birth Weight (kg)	3.18	0.57	0.23	0.44	0.49	0.66	0.73
Gestation at Birth (weeks)	39.23	3.00	1.70	3.2	5.2		
Lbw	0.11			0.14			
Premature	0.10			0.17			
Head Circumference	33.68	1.59	0.75				
Body Length	50.02	2.75	1.40				
Endowment based on Factor Score (of standardized measures of newborn hea	0.00	0.93	0.41				
Residualized Endowment based on Factor Scores	0.00	0.87	0.87				

standardized: distrbution tranformed to normal with mean 0 and standard deviation of 1

Appendix Table 2: Predictive Abilities of 8 Month Bayley and Birth Weight- OLS and FE Results

OLS	Any Cognitive delay - 1 year			Abnormal Language Reception - 3 year			Abnormal Language Expression - 3 Year			IQ - 4 year			IQ - 7 year			Reading - 7 year			Math - 7 year		
8 Month Mental Bayley - Standardized	-0.157		-0.154	-0.0461		-0.0407	-0.0508		-0.0474	0.205		0.184	0.191		0.174	0.0851		0.0711	0.141		0.13
	[0.00231]		[0.00237]	[0.00695]		[0.00714]	[0.00691]		[0.00709]	[0.00940]		[0.00977]	[0.00857]		[0.00888]	[0.00939]		[0.00976]	[0.00960]		[0.00998]
Birth Weight - Standardized		-0.0603	-0.0189		-0.034	-0.0239		-0.0263	-0.0148		0.135	0.0782		0.12	0.0667		0.0767	0.0555		0.081	0.0421
		[0.00309]	[0.00273]		[0.00751]	[0.00770]		[0.00753]	[0.00769]		[0.0105]	[0.0107]		[0.00979]	[0.0100]		[0.0102]	[0.0106]		[0.0105]	[0.0109]
Observations	11863	11851	11851	5375	5366	5366	5336	5327	5327	10303	10292	10292	10936	10925	10925	10897	10886	10886	10896	10885	10885
R-squared	0.29	0.042	0.293	0.079	0.074	0.08	0.047	0.04	0.048	0.264	0.242	0.267	0.293	0.271	0.296	0.163	0.161	0.165	0.111	0.099	0.113
test of equality of coefficients			F (1, 22841) = 1124			F (1,5351) = 2.1			F (1,5312) = 2.1			F (1,10280) = 42.31			F (1,10915) = 51.57			F (1, 10876) = 0.99			F (1, 10875) = 28.07
			(p=0.000)			(p=0.1476)			(p=0.0047)			(p=0.0000)			(p=0.0000)			(p=0.3206)			(p=0.0000)

Maternal race, education, income, marital status, age, child gender, birth order, AMC and and year of birth also included

Maternal FE	Any Cognitive delay - 1 year			Abnormal Language Reception - 3 year			Abnormal Language Expression - 3 Year			IQ - 4 year			IQ - 7 year			Reading - 7 year			Math - 7 year		
8 Month Mental Bayley - Standardized	-0.148		-0.143	-0.0284		-0.0286	-0.0233		-0.0183	0.128		0.116	0.14		0.124	0.0422		0.0295	0.0923		0.0779
	[0.00389]		[0.00398]	[0.0121]		[0.0124]	[0.0121]		[0.0124]	[0.0138]		[0.0142]	[0.0124]		[0.0127]	[0.0138]		[0.0142]	[0.0152]		[0.0156]
Birth Weight - Standardized		-0.0801	-0.03		-0.00947	-0.000858		-0.0413	-0.0356		0.11	0.0709		0.143	0.1		0.0888	0.0789		0.116	0.0899
		[0.00689]	[0.00624]		[0.0176]	[0.0180]		[0.0181]	[0.0185]		[0.0197]	[0.0201]		[0.0183]	[0.0186]		[0.0195]	[0.0201]		[0.0215]	[0.0221]
Observations	11864	11852	11852	5376	5367	5367	5337	5328	5328	10304	10293	10293	10937	10926	10926	10898	10887	10887	10897	10886	10886
R-squared	0.735	0.662	0.736	0.761	0.76	0.761	0.75	0.75	0.75	0.839	0.837	0.84	0.837	0.835	0.838	0.801	0.802	0.802	0.757	0.757	0.759
test of equality of coefficients			F(1,4659) = 196			F (1,1719) = 1.36			F (1,1694) = 0.51			F (1,3875) = 2.80			F (1,4223) = 0.98			F (1,4200) = 3.29			F (1,4197) = 0.12
			(p=0.000)			(p=0.2437)			(p=0.4752)			(p=0.0944)			(p=0.3219)			(p=0.0700)			(p=0.7266)

Maternal age, marital status, income, child gender, birth order and year of birth also included

Standard errors in brackets

Appendix Table 3 Parental Time, Parental Warmth and the Home Score - Evidence from the PSID

Panel A: Correlation between Parental Time and Parental Warmth Scale

Dependent Variable= Standardized Parental Warmth Scale															
	OLS												Fixed Effect		
Age Range	One to Eight Months			One to Twelve Months			One to Sixteen Months			One to Twenty Months			All Ages		
Standardized Parental Quality Time	0.161			0.13			0.119			0.0894			0.092		
	(0.087)			(0.060)			(0.045)			(0.041)			(0.036)		
Standardized Parental Quality Time		0.117			0.111			0.103			0.0654			0.069	
(Weekday)		(0.080)			(0.056)			(0.041)			(0.039)			(0.035)	
Standardized Parental Quality Time			0.0748			0.107			0.0776			0.0766			0.062
(Weekend)			(0.088)			(0.066)			(0.053)			(0.043)			(0.031)
Observations	66	69	67	130	134	131	187	190	188	256	259	258	2663	2690	2703
R-squared	0.292	0.248	0.262	0.127	0.120	0.110	0.143	0.136	0.123	0.117	0.110	0.110	0.136	0.128	0.130

Panel B: Correlation between Home Score and Parental Warmth Scale

Dependent Variable= Standardized Parental Warmth Scale															
	OLS												Fixed Effect		
Age Range	One to Eight Months			One to Twelve Months			One to Sixteen Months			One to Twenty Months			All Ages		
Full HOME Score	0.394			0.478			0.402			0.350			0.006		
	(0.257)			(0.186)			(0.152)			(0.121)			(0.0391)		
HOME Cognitive Stimulation		0.521			0.469			0.465			0.453			0.0128	
Subscore		(0.221)			(0.169)			(0.145)			(0.116)			(0.026)	
HOME Emotional Support			-0.0155			0.218			0.114			0.032			-0.0043
Subscore			(0.204)			(0.155)			(0.117)			(0.089)			(0.035)
Observations	72	72	72	140	140	140	200	200	200	274	274	274	3334	3334	3334
R-squared	0.248	0.294	0.201	0.148	0.149	0.099	0.146	0.168	0.102	0.122	0.162	0.079	0.100	0.104	0.097

Robust standard errors in parentheses

All regressions include controls for maternal characteristics (age, education, income, cognitive skills as measured by a reading test, and noncognitive skills as measured by the Rosenberg Self-Esteem Score and the Pearlin Self-Efficacy Scale) and offspring characteristics (race, gender, birth order, and age in months). In the fixed-effect specification, we add a polynomial of fourth-order in age as well as the interaction of age with marital status at birth, race of the child, and gender of the child.

Appendix Figure 1

Scatterplot of Factor Scores