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# Infant Health and Academic Achievement in Childhood

Kajal Lahiri

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# Infant Health and Academic Achievement in Childhood

Pinka Chatterji, Dohyung Kim, and Kajal Lahiri*

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**Abstract**

Research has shown that birth weight has a lasting impact on adult outcomes such as education and earnings. This paper examines the role of nutritional intake in utero on academic achievement in childhood, which may provide a link between birth weight and adult outcomes, and further investigates its implication on the black-white test score gap. Using the same PSID-CDS data source as was used in Johnson and Schoeni (2011), we build on the literature by employing the fetal growth rate as a proxy for fetal nutrition and proposing a nested error component two-stage least squares (NEC2SLS) estimator that uses internal instruments in a way analogous to Hausman and Taylor (1981) estimator. In particular, this alternative estimator allows us to exploit information on the single observation within family, which comprises a third of our sample, as well as obtain coefficient estimates for the time-invariant variables such as race and maternal education. These would not be feasible with the usual fixed effects estimation. We estimate positive and significant effects of fetal growth rate on math and reading scores of children, those effects being concentrated over the low birth weight range. However, they appear to contribute little to the black-white gap in test scores.

**Keywords:** birth weight, academic achievement, black-white test score gap

**JEL classification:** I12, I20

*Chatterji: University at Albany and NBER; Kim: University at Albany; Lahiri: University at Albany.

# 1 Introduction

The extensive literature linking infant health to long-term outcomes shows that those born heavier achieve higher educational attainment and earnings, and have lower health risk at their adulthood. Studies using twin samples and natural experiments provide compelling evidence on the causal role of fetal nutrition in determining adult outcomes (Almond and Mazumder 2011, Behrman and Rosenzweig 2004, Black et al. 2007, Lindeboom et al. 2010, Neelsen and Stratmann 2011, Royer 2009; van Ewijk 2011). However, much less is known about the mechanism through which low birthweight translates into poor outcomes at adulthood.

The leading explanation for the association between birth weight and adult outcomes has drawn on the Barker hypothesis[1] which associates low birth weight with adult chronic diseases. In this explanation, low birth weight has indirect consequences on adult productivity where adult health plays a mediating role. There exists an alternative hypothesis that may help to explain the association between birth weight and adult outcomes. Researchers in medical science have long thought that the uterine malnutrition can impair the cognitive development of children, which may persist into their adulthood (Morgane et al. 1993). This explanation is consistent with the evidence that the effect of infant health appears to emerge *before* any adult chronic condition can develop from fetal insult (Currie and Hyson 1999, Conley and Bennett 2000, Hack *et al.* 2001, Oreopoulos *et al.* 2008).

Several studies examine the test score gap among the low-birthweight children and use fixed effects estimation to address the omitted variable bias. However, the estimated effects are often insignificant after controlling for the family fixed effects. These null findings may be explained by inadequate statistical power as the size of siblings or twins sample is typically small and the fixed effects estimation only exacerbates the problem by exploiting only the variation within families. Moreover, when they use a sample of singletons, researchers often

[1] Barker (1995, 1998) claims that the uterine environment is crucial for adult health that fetal insults can cause adult chronic diseases such as the heart disease or the diabetes.

use birth weight only, failing to account for the gestational age that may have separate effects on child academic achievement. In this case, it is difficult to interpret the estimated coefficient for birth weight in the context of fetal nutrition argument because low birth weight can reflect either a slow fetal growth rate (uterine malnutrition) or a preterm birth.

In this paper, we investigate the role of fetal nutritional intake in determining child academic achievement and its implication on the black-white test score gap. We use the same PSID-CDS data source as is used in Johnson and Schoeni (2011), but add recent observations and employ the extended model that contains unobserved child endowment in addition to unobserved mother endowment. Based on this extended model, we propose the nested error component two-stage least square (NEC2SLS) estimator which uses internal instruments for endogenous covariates in a way analogous to Hausman and Taylor (1981) estimator. Unlike the usual mother fixed effects (MFE) estimation, the alternative estimation method enables us to exploit information on the single observation within family which comprises about 35% of our sample as well as obtain consistent estimates under the identification assumptions less strict than those required for GLS. Furthermore, we are able to estimate consistently the coefficients for mother-specific and time-invariant covariates such as race and maternal education, which would not be feasible with the usual fixed effects estimator.

Using the NEC2SLS estimator, we estimate positive and significant effects of fetal growth rate, a proxy for nutritional intake in utero, on math and reading test scores of children. We find that those effects are concentrated over the low birth weight range and modest in magnitude. Overall, our results suggest that the cognitive deficiency of low-birthweight children may be one mechanism through which fetal malnutrition generates poor adult outcomes. However, the estimated racial gap in test scores changes little after controlling for fetal growth rate. This suggests that the birth-weight effect contributes little to the black-white test score gap.

The rest of the paper is organized as follows: In the next section, we provide a brief overview on the related literature. In section 3 and 4, we describe the data set and develop the nested error component model. In section 5, we provide evidence that the NECGLS estimates are inconsistent and explain an alternative NEC2SLS estimator. In section 6, we present the results and discuss. In the last section, we conclude.

# 2 Literature

The interest in the relation between birthweight and cognitive ability dates back at least a century ago (Asher 1946). Observational studies generally find a positive association between birth weight and IQ (Sorensen 1997, Breslau 2001, Hack 2002), but a spurious association has been suspected since unobserved family backgrounds or a genetic composition may be responsible for both infant health and child cognitive outcomes. For example, in a pioneering study on the 1950-1954 British cohorts, Record, McKeown, and Edwards (1969) finds a strong association between birthweight and verbal test scores, but little evidence of the association within families.

Within-twin studies can provide compelling evidence on the causal role of fetal nutrition in determining cognitive development of children, but the results are generally mixed. Boomsma *et al.* (2001) report that the birthweight effect on child IQ can be found among dizygotic twin pairs, but not among monozygotic twin pairs, suggesting that the genetic composition may be a mediating factor while Petersen et al. (2009) find a significant effect of birth weight among the Danish male twins regardless of zygosity, but not among the female twins. In a study using a sample of Danish twins, Christensen *et al.* (2006) find significant effects of birth weight on test scores although the magnitude is small. More recently, Figlio et al. (2013) use a large registry data on twins in Florida and find the birth-weight effect on test scores, which is remarkably stable across school grades as well as socio-economic backgrounds.

Several studies from economics use sibling samples of recent cohorts to address concern for omitted variables. In a study that uses a Canadian registry data, Oreopoulos et al (2008) find infant health has positive and significant effects on short-term health outcomes and adult outcomes, but not for the language arts scores after controlling for the twin or sibling fixed effects. Other within-sibling studies on U.S. cohorts also find the estimates become insignificant when the MFE estimation is used. In a paper that examines comprehensive life-cycle outcomes, Johnson and Schoeni (2011) use mother fixed effects and report a substantial gap in test scores among the male siblings who are born at 1.5kg birth weight. However, their estimates are statistically insignificant at the conventional level and the model contains birth weight spline that allows a jump at the low birth weight cutoff, which may be implausible. Fletcher (2011) also find some evidence of positive association between birth weight and test scores, but the estimates for birth weight are found to be insignificant within families. Moreover, since these studies do not control for gestational age in the birth weight regression, it is difficult to interpret what the estimated effects of birth weight actually captures.

We build on the literature by addressing these limitations. First, we use the same PSID-CDS data source as used in Johnson and Schoeni (2011) and present some evidence on a potential misspecification in birth weight spline. Second, we employ the fetal growth rate as a direct measure of the nutritional intake in utero. Third, we extend the model following the literature and propose an alternative estimation method that exploits information more efficiently than the usual MFE estimation. Finally, we investigate the implication of birth-weight effects on racial disparity in test scores, which would not be feasible when the MFE estimation were used.

# 3 Data

We use the 1997, 2002/3, and 2009 waves of Child Development Supplement of the Panel Study of Income Dynamics (PSID-CDS). The CDS provide reliable information on the assessments of academic achievement of children who are born between 1984 and 1997 in the PSID households. In 1997, the first wave of CDS interviewed $2,394$ families on $3,563$ children with ages twelve or less and these children were reinterviewed in 2002/3 and 2009 if they were aged eighteen or less at the time of interview. Hence, the data set includes multiple observations, at most three, for each child.

We restrict our sample to children whose primary caregiver is the biological mother so that the MFE estimates can provide estimates that are robust to the unobserved genetic composition as well as the unobserved family background. To access information on maternal and family characteristics, we further restrict our sample to the children whose mother is the head or wife of a PSID household, whose information can be obtained from the PSID main files. Table 1 gives the summary statistics on the variables used and the comparison between the full CDS sample and the sibling sample. Notice that, by exploiting information in the full sample, one can potentially increase the sample size by more than 50%. Otherwise, the two samples are quite comparable.

## 3.1 Infant health

The PSID-CDS contains detailed information on infant health. In particular, the primary caregiver, who is the biological mother in our sample, reports the birth weight of children along with the gestational age in weeks. In the literature, alternative measures of fetal nutrition have been used: Birth weight (or log of birth weight) and fetal growth rate.[2] Conceptually, birth weight is determined simultaneously by fetal growth rate and gestational age. Therefore, if birth weight is used as a sole measure for infant health given a sample of singletons, it is difficult to distinguish the effects of uterine nutrition from those of gestational age.[3] For this reason, the literature in medical science almost always controls for gestational age when birth weight is the variable of interest. Nevertheless, this has not been recognized well in within-sibling studies from economics, leading them to use birth weight as a sole measure of infant health.

[2] Fetal growth rate was considered in the related literature. For example, see Behrman and Rosenzweig (2004).

[3] As opposed to the literature studying birth weight, there is another strand of literature in medical science that focuses on the consequences of preterm birth. Regarding to the cognitive outcomes, see Bhutta (2002), for example.

Our preferred measure of fetal nutritional intake will be fetal growth rate, which is defined as birth weight divided by gestational age in weeks. However, we also use birth weight in order to examine the nonlinear effects which have been documented in many studies.[4] In either case, we control for the indicator for preterm birth, which is defined as being unity if the gestational age is less than 37 and zero otherwise, as a robustness check. Then, the coefficient for birth weight can be interpreted as a proxy for fetal nutrition. In the next section, we will discuss in detail about birth weight spline which will capture the nonlinear effects of birth weight.

## 3.2 Academic Achievement

To measure the academic achievement of children, we use scores on the subtests of Woodcock-Johnson Psycho-Educational Battery-Revised (WJ-R), each capturing a different cognitive ability. Applied Problems measures the skills in solving practical problems in mathematics. The subtest is administered to all children aged three and above. Passage Comprehension measures the skills in reading comprehension and the amount of vocabulary. This subtest is administered to older children (aged six and above) since it requires reading ability. Because children took these tests at different ages, we use the standardized scores which are designed to provide a normative score having the mean of 100 and the standard errors of 15. These standardized scores are age-adjusted in reference to the national average of the monthly age of the child.

## 3.3 Other covariates

One advantage of using CDS is that the rich and reliable information on family and maternal characteristics can be obtained by matching the CDS to the PSID main files. In the regression,

[4] See Almond, Chay, and Lee (2005), Behrman and Rosenzweig (2004), Currie and Moretti (2007), Royer (2009) for nonlinear effects of birth weight on various outcomes. Among the studies that examine cognitive abilities, Boardman et al. (2002) use a sample of U.S. children from the NLSY and find larger cognitive deficits at the left-hand tail of birth-weight distribution. Similarly, Figlio et al. (2013) find nonliear effects of birth weight on test scores among the sample of U.S. twins born in Florida.

we include the demographic characteristics such as sex, race, and child age measured in months (white and female as reference groups). The child age at the assessment is exogenous by construction because we use the standard test scores that are aged-adjusted.

To control for the family characteristics that may affect birth weight as well as the academic achievement at childhood, we include log of permanent family income, which is measured by six-year average of family incomes in terms of 2007-constant dollars. We also control for the indicator for mother being single at child's birth, and the indicators for maternal age at child birth being less than 20 and over 35. We include in all regressions a set of indicators for birth order, which has been shown to affect cognitive abilities of children (Black et al. 2005, Sulloway 2007). Years of education of the mother and a measure for the home environment that gives cognitive stimulation and emotional support, which have been shown to be most important predictors of test scores in the literature, are included in the regressions.

# 4 Model

We begin with the model considered in Johnson and Schoeni (2011) where only a mother endowment is included and a piecewise linear specification is used for birth weight. We focus on the spline specification in the following subsection and extent the model to include a child endowment in the next subsection.

## 4.1 Nonlinear Effects of Birth Weight

Prior studies often find nonlinearity in birth-weight effects, although the exact shape of nonlinearity may depend on the outcomes examined. The specification they use can be written as

$$y_{ijt} = \alpha + \delta D_{ij} + \gamma^L D_{ij}(BW_{ij} - 1.5) + \gamma^N (1 - D_{ij})(BW_{ij} - 1.5) + x_{ijt}\beta + m_i + e_{ijt} \quad (1)$$

where $y_{ijt}$ denotes a test score assess at the survey wave $t$ of child $j$ of mother $i$, $D_{ij}$ a binary indicator of low birth weight (less than 2.5kg), $BW_{ij}$ the birth weight, $x_{ijt}$ the child and family characteristics, $m_i$ the unobserved endowment of mother $j$, and $u_{ij}$ the error terms.

The equation (1) serves two purposes. First, by allowing two different slopes for birth weight ($\gamma^L$ and $\gamma^N$), it can accommodate the potential nonlinearity in birthweight effects. Second, $\hat{\delta}$ will give the estimated test scores gap, which is incurred by potentially higher penalty rate over the low birthweight range, evaluated at a particular point (1.5kg) in birth weight distribution. One unintended consequence of this rather unusual specification is that it allows a jump at the 2.5kg knot as is depicted in the Panel A in Figure 1.

This implicit modeling assumption can be tested by adding a binary indicator of low birthweight in the usual continuous piecewise regression. The columns (1) and (5) in Table 2 provide some evidence that a jump may be implausible: The estimated jump is statistically insignificant and the magnitude is implausibly large. Moreover, the estimated slopes of birth weight spline for Passage Comprehension indicate that birth weight imposes penalty on Passage Comprehension scores, which is counter-intuitive.

Other columns in Table 2 show our replication of Table 3 in Johnson and Schoeni (2011). From column (2) to (4), we gradually add more observations to increase statistical power on the continuous piecewise spline specification. We find positive and significant effects of birth weight on Applied Problems, but not on Passage Comprehension. Before we employ an alternative estimation strategy that will increase efficiency, we extend Johnson and Schoeni (2011)'s model to a two-way nested error component model.

## 4.2 Nested Error Component Model

We consider a two-fold nested error component model, which has been often used in the education production literature (Todd and Wolpin 2003, Kim and Frees 2006) and in other context (Baltagi et al. 2001). In particular, Boardman et al. (2002) estimate this model using the Maximum Likelihood Estimator to find the test score gap among low-birthweight and very-low-birthweight children. The model can be written as

$$y_{ijt} = x_{ijt}\beta + w_{ij}\gamma + z_i\delta + u_{ijt} \tag{2}$$

where test score $y$ in survey year $t$ of child $j$ of mother $i$ is a function of birth weight and a set of child and family characteristics $(x_{ijt}, w_{ij}, z_i)$. $x_{ijt}$ denote the vector of time-varying child and family characteristics, $w_{ij}$ the vector of time-constant child-specific characteristics including birthweight, and $z_i$ are the vector of time-constant mother-specific characteristics. We write the disturbance as

$$u_{ijt} = m_i + c_{ij} + e_{ijt} \tag{3}$$

where $m_i$ denotes the maternal endowment of mother $i$, $c_{ij}$ denotes the child endowment of child $j$ nested in mother $i$, and $e_{ijt}$ denotes the error term. Equation (3) corresponds naturally to the nested grouping in our data set.

Note that equation (2) is more general than equation (1) in that the child endowment is included in addition to the mother endowment. In this model, the mother fixed effects estimation can be inconsistent if the child endowment is correlated with the explanatory variables. In equation (2), we use a similar but different set of explanatory variables from that of the previous model. [5]

[5] The details on the set of covariates are discussed in the data section. The difference can be summarized as the different measures of infant health rather than sole birth weight, permanent income instead of income at child's birth, two indicators for mother's age being less than 20 and more than 35 at child's birth rather than continuous measure of maternal age at child's birth.

# 5 Estimation

## 5.1 Nested Error Component GLS (NECGLS)

We discuss the NECGLS estimation which will serve as a building block for the NEC2SLS estimator. Under the assumptions that

$$m_i \sim i.i.d(0, \sigma_m^2) \tag{4}$$

$$c_{ij} \sim i.i.d(0, \sigma_c^2) \tag{5}$$

$$e_{ijt} \sim i.i.d(0, \sigma_e^2), \tag{6}$$

the NECGLS is consistent and efficient. For the NECGLS estimation, we first transform the equation (2) by Fuller and Battese (1973) transformation. The transformed equation can be written as

$$\tilde{y}_{ijt} = \tilde{x}_{ijt}\beta + \tilde{w}_{ij}\gamma + \tilde{z}_i\delta + \tilde{u}_{ijt} \tag{7}$$

where tilda indicates that the variable is Fuller-Battese transformed (see Fuller and Battese 1973, Baltagi et al. 2001).[6] Then we can obtain the NECGLS estimates by OLS regression of the transformed equation (7).

Note that the NECGLS estimates will be inconsistent if the one of the assumptions (4) and (5) is violated. The child fixed effects (CFE) estimation is robust to either the correlated mother endowment $m_i$ or the child endowment $c_{ij}$, but it is not an option for our purpose because only the estimates $\hat{\beta}$ can be obtained while the coefficient of interest lies in $\gamma$. The MFE estimation has been widely used in the literature under the implicit assumption that only the mother endowment $m_i$ might be correlated with the covariates. However, in our model, even the MFE estimation can be inconsistent at the presence of correlated child component $c_{ij}$.

[6] There are multiple ways of estimating the variance components. We estimate the variance components using a method suggested in Fuller and Battese (1973).

In our context of two-way nested error component model, there can be three different Hausman tests because there are potentially two different robust estimates: the CFE and MFE (Hausman 1978, Kim and Frees 2006). Our focus should be on the general test concerning with the CFE whose estimates are robust to either the correlated child or mother endowment. However, we will also present the result from the Hausman test concerning the MFE since it is the benchmark model in the literature, although the test can stand alone provided that the child endowment is uncorrelated. In the next section, we will show that the Hausman tests of the NECGLS estimates against the CFE estimates as well as the mother fixed effects (MFE) estimates strongly indicate that some of the covariates are correlated with either the child or mother component (or both).

## 5.2 Nested Error Component 2SLS (NEC2SLS)

Based on the Hausman tests that will be presented in the next section, we will assume that some of the covariates are correlated, but the others are exogenous as has been done in the Hausman and Taylor estimation (1981). Before proceeding to the consistent estimation under those assumptions, we first note that a time-varying variable $x_{ijt}$ can be decomposed into three components. For convenience, we rewrite equation (7) in a simple form as

$$\tilde{y}_{ijt} = \tilde{x}_{ijt}\beta + \tilde{u}_{ijt}$$

where all the variables are Fuller-Battese transformed. For any given $\tilde{x}_{ijt}$, it is easy to show that

$$\tilde{x}_{ijt} = (\tilde{x}_{ijt} - \bar{x}_{ij.}) + (\bar{x}_{ij.} - \bar{x}_{i..}) + \bar{x}_{i..} \tag{8}$$

where $\bar{x}_{ij.} \equiv \sum_{t=1}^{T} \tilde{x}_{ijt}$ denotes the mean of $\tilde{x}_{ijt}$ over time (or the child mean) and $\bar{x}_{i..} \equiv \sum_{t=1}^{T} \sum_{j=1}^{J} \tilde{x}_{ijt}$ the mean of $\tilde{x}_{ijt}$ over time and child (or the mother mean).[7] In matrix form,

[7] Analogously, if the variable does not vary over time, but varies across children, the decomposition will contain two components where the decomposition will be $\tilde{z}_{ij} = (\tilde{z}_{ij} - \bar{z}_{i.}) + \bar{z}_{i.}$.

we can write the decomposition (8) as

$$X = Q_1 X + Q_2 X + PX$$

where $Q_1 X$ denotes the deviation from the child mean, $Q_2 X$ denotes the child deviation from the mother mean, and $PX$ denotes the mother mean. Then, the GLS estimates can be obtained from performing the 2SLS estimation where the list of instruments is $A = (Q_1 X, Q_2 X, PX)$. Now we partition $X = (X_1, X_2)$ where $X_1$ is uncorrelated with $m$ and $c$, but $X_2$ is correlated with $m$ and $c$. Under the assumption, the NEC2SLS estimator is the 2SLS estimator where the list of instruments is $B = (X_1, Q_1 X_2)$. In the next section, we will discuss how we partition $X$ based on the Hausman tests.

The NEC2SLS estimator is consistent under the identification assumptions less strict than those required for the GLS estimation since $X_1$ is allowed to be correlated with either the mother endowment $m_i$ or the child component $c_{ij}$. On the other hand, the NEC2SLS estimator may require stricter identification assumptions than the MFE estimation. However, by relaxing some of those assumptions, we can exploit information on the single observations within families which comprise almost a half of the entire sample.[8] Moreover, we can recover estimates for the coefficients of the time-constant mother-specific covariates such as maternal education and race, which is not feasible in the MFE estimation. This allows us to investigate the implication of birthweight effects on racial disparity.

# 6 Result

We begin with presenting the NECGLS estimates along with evidence of inconsistency. Table 3 shows the NECGLS estimates on equation (2). The estimates suggest that fetal growth rate

[8]Even the MFE estimation may be inconsistent at the presence of correlated child component (Kim and Frees 2006). The NEC2SLS estimator can potentially address this problem. However, the particular NEC2SLS that is used in this paper requires the identification assumption under which the MFE estimator is always consistent.

has positive and significant effects on test scores. However, the chi-square statistics strongly indicate inconsistency of the NECGLS estimation. With a single exception, we can reject the null hypothesis of uncorrelated child and mother endowment at the conventional level of significance as can be seen at the bottom of Table 3. In particular, the $t$-statistics from the Hausman tests suggest that the family income and home environment are the major source of endogeneity regardless of the alternative hypothesis (either against CFE or MFE). The detailed results of Hausman tests can be found in the Appendix Table 1 and 3.

Based on the diagnostic results above, we allow for the two explanatory variables, family income and home environment to be correlated with the child or mother endowment, but assume that the other covariates are exogenous. Under these assumptions, we estimate equation (2) using 2SLS where the child component of family income and home environment is excluded from the list of instruments. In effect, all the components of the exogenous variables will serve as the internal instruments for the child means of family income and home environment, which are the only endogenous components.

Table 4 presents the results from the NEC2SLS estimation described above. After addressing the endogeneity from the child means of family income and home scale, we find the positive and significant effects of fetal growth rate on test scores. The magnitude is somewhat larger for Applied Problems, but the estimated effects are highly significant for both tests. Notice that the chi-square statistics for the Hausman tests become substantially smaller as are shown at the bottom of Table 4. Hence, we cannot reject the null hypotheses either against the CFE or the MFE at the conventional level of significance. The detailed results of Hausman tests can be found in the Appendix Table 2 and 4.

Table 5 summarizes the results when the different measures of infant health are used.[9] As can be seen in the $p$-values from the Hausman tests reported at the bottom of each panel, in no regression we can reject the null hypothesis that the NEC2SLS estimates are statistically

[9] We do not report the CFE and MFE estimates since the results are similar to those in Table 3 regardless of specification. We cannot reject the null hypothesis that the NEC2SLS estimates are consistent at the presence of the unobserved child or mother component. These results can be provided upon request.

different from the robust estimates. Panel A in Table 5 shows that the significant and positive effect of fetal growth rate on test scores remains robust after controlling for preterm birth. In particular, columns (3) and (6) of panel A suggest that the consequences of initial health endowment may be more pronounced as the mothers are less educated. The estimated coefficient of interactive term between fetal growth rate and maternal education shows the cognitive penalty of fetal malnutrition gets larger as the primary caregiver has less years of education. In Panel B of Table 5, we present results when birth-weight spline is used. In columns (1) and (4) of Panel B, we find positive and significant effects of fetal nutritional intake on test scores consistently over the low birth weight range. In contrast, the size of the effects is much smaller and the estimates are often statistically insignificant over the normal birth-weight range. Since the preterm birth is controlled for in columns (2) and (5), we can interpret the coefficient for birth weight as a proxy for nutrition intake in utero. Overall, the gain in test scores appears to be modest as increasing 1kg of birth weight within the low birth weight range translates into one third standard deviation in test scores.

We further investigate the implication of fetal nutrition on racial disparity in test scores, by comparing the estimated test score gap by race, before and after controlling for infant health measure in the test score equation. From column (1) to (3) in Table 6, we add maternal education in years and fetal growth rate to see how much of the racial gap can be explained by those factors. The estimated black-white gap in test scores is remarkably robust after the inclusion of maternal education and fetal growth rate while the estimated Latino-white gap closes substantially after controlling for maternal education. Overall, the results in Table 6 suggest that fetal nutritional intake may not contribute much to the racial disparity in test scores.

## 7 Conclusion

The literature that finds strong association between infant health and adult outcomes often gives the interpretation that infant health has long lasting health consequences such as adult chronic conditions, which may in turn affect adult productivity. However, medical literature also long suggested that fetal malnutrition can impair the cognitive development of children, which may persist into adulthood. While the former explanation emphasizes the role of infant health in determining adult health, the latter explanation suggests a direct consequence of infant health on child outcomes, which may persist and accumulate over time. Therefore, finding the evidence that infant health affects child outcomes can constitute an alternative mechanism through which infant health determines adult outcomes. Indeed, the cognitive gap among those born with low birthweight has long been observed, but a spurious has been suspected since, for example, unobserved family background may explain both infant health and cognitive ability.

To control for omitted variables, several studies exploit variation within families, but they often find insignificant effects of birth weight on test scores. However, these null findings may be driven by a lack of statistical power arising from the limited size of twin/sibling sample or the estimation method (family fixed effects estimation). Moreover, some of recent within-sibling studies fail to account for the gestational age confounding the interpretation on the estimated coefficient for birth weight.

To address concerns for endogeneity as well as efficiency, we use the NEC2SLS estimator which allows us to increase the sample size by 50 percent as well as use more information from the variation between families than the MFE estimation, and still provide consistent estimates under the identification assumptions less strict than those in the GLS estimation. Furthermore, we can estimate the coefficient for maternal education and the racial disparity in test scores using this estimator. We use the fetal growth rate as a direct measure of nutritional intake in utero and find a positive and significant effect of fetal growth rate on academic achievement of children. This suggests that cognitive gains in childhood from better nutritional intake in utero may constitute an alternative pathway through which birth weight determines adult outcomes such as education and earnings. Also, we investigate its implication on black-white test score gap by adding measures of infant health to test score equation and examining the change in the estimated racial disparity. We find that controlling for infant health changes little of the estimated black-white test score gap. Therefore, infant health appears to contribute little to the black-white test score gap.

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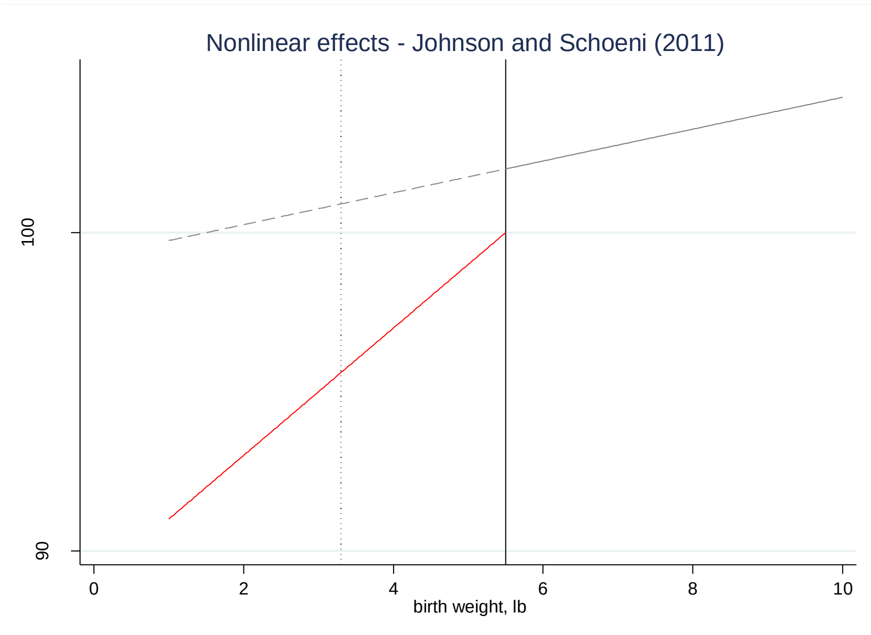
Figure 1 – Schematic representation of piecewise regressions

Panel A. Discontinuous piecewise regression with a jump at 2.5kg (5.5lb)




Panel B. Continuous piecewise regression with a knot at 2.5kg

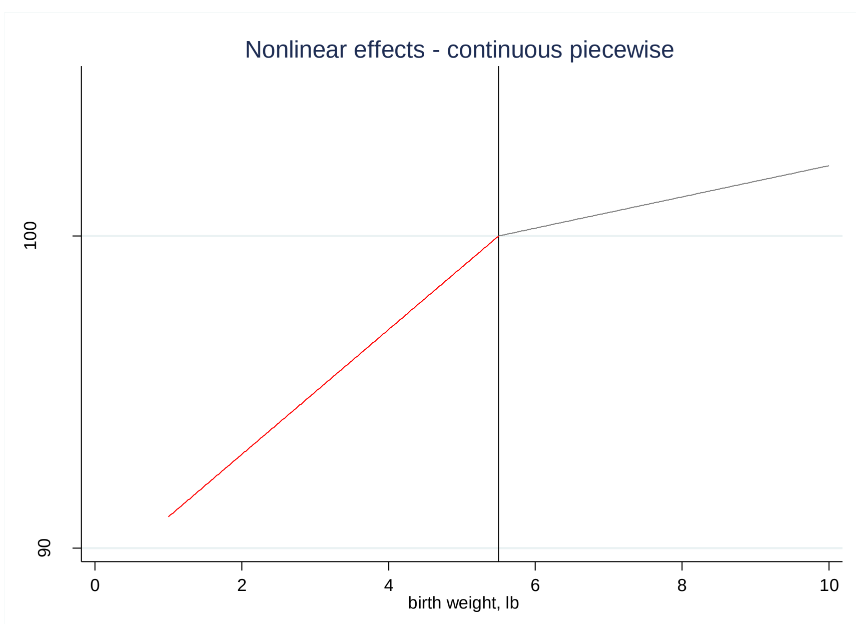


Table 1 – Summary Statistics

| Variables | Full sample | | | Sibling sample | | |
|---|---|---|---|---|---|---|
| | N | Mean | SD | N | Mean | SD |
| *Test scores* | | | | | | |
| Applied Problems | 4,610 | 104.03 | 16.94 | 3,005 | 104.75 | 16.93 |
| Passage Comprehension | 4,107 | 102.67 | 16.63 | 2,665 | 102.75 | 16.77 |
| *Time-varying characteristics* | | | | | | |
| Family income | 5,734 | 54044.7 | 58274.7 | 3,711 | 56261.8 | 63061.8 |
| Mother working | 5,734 | 0.681 | 0.47 | 3,711 | 0.658 | 0.47 |
| Child age in months | 5,734 | 121.2 | 56.39 | 3,711 | 121.2 | 55.6 |
| *Time-invariant child characteristics* | | | | | | |
| Birthweight (kg) | 2,676 | 3.326 | 0.63 | 1,737 | 3.341 | 0.64 |
| Low birthweight (< 2.5kg) | 2,676 | 0.086 | 0.28 | 1,737 | 0.087 | 0.28 |
| Gestational age in weeks | 2,676 | 39.479 | 2.19 | 1,737 | 39.511 | 2.12 |
| Female | 2,676 | 0.487 | 0.50 | 1,737 | 0.491 | 0.50 |
| Maternal age at child birth | 2,676 | 27.195 | 5.56 | 1,737 | 26.922 | 5.42 |
| Mother age at child birth < 20 | 2,676 | 0.089 | 0.28 | 1,737 | 0.090 | 0.29 |
| Mother age at child birth > 35 | 2,676 | 0.065 | 0.25 | 1,737 | 0.054 | 0.23 |
| Mother single at child birth | 2,676 | 0.291 | 0.45 | 1,737 | 0.276 | 0.45 |
| 1st born | 2,676 | 0.394 | 0.49 | 1,737 | 0.319 | 0.47 |
| 2nd born | 2,676 | 0.352 | 0.48 | 1,737 | 0.405 | 0.49 |
| 3rd born | 2,676 | 0.169 | 0.37 | 1,737 | 0.180 | 0.38 |
| 4th born | 2,676 | 0.057 | 0.23 | 1,737 | 0.060 | 0.24 |
| 5th or more | 2,676 | 0.028 | 0.17 | 1,737 | 0.035 | 0.18 |
| Home environment | 2,676 | 19.188 | 3.56 | 1,737 | 19.372 | 3.62 |
| *Time-invariant maternal characteristics* | | | | | | |
| Nonlatino white | 2,676 | 0.515 | 0.50 | 1,737 | 0.537 | 0.50 |
| Nonlatino African American | 2,676 | 0.377 | 0.48 | 1,737 | 0.351 | 0.48 |
| Latino | 2,676 | 0.062 | 0.24 | 1,737 | 0.069 | 0.25 |
| Other race | 2,676 | 0.046 | 0.21 | 1,737 | 0.044 | 0.20 |
| Mother's education (years) | 2,676 | 12.859 | 2.54 | 1,737 | 12.792 | 2.59 |

Table 2 – Test of Jump at the Knot (2.5kg)

| | Applied Problems | | | | Passage Comprehension | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| A jump at 2.5kg | -5.428 | | | | -11.420 | | | |
| | (5.975) | | | | (8.688) | | | |
| Birth weight (<2.5kg) | 5.115 | 6.766* | 8.476** | 7.109** | -10.185 | 5.632 | 5.960 | 5.226 |
| | (6.081) | (3.674) | (3.363) | (2.824) | (19.446) | (9.853) | (7.513) | (4.315) |
| Birth weight (>= 2.5kg) | 1.706 | 1.843 | 2.678 | -0.109 | -0.844 | 0.777 | 1.447 | 0.316 |
| | (2.753) | (2.673) | (2.252) | (1.249) | (2.780) | (2.779) | (2.052) | (1.171) |
| Number of mothers | 193 | 193 | 199 | 775 | 180 | 180 | 191 | 747 |
| Number of children | 361 | 361 | 375 | 1449 | 326 | 326 | 351 | 1371 |
| Number of observations | 536 | 536 | 661 | 2627 | 440 | 440 | 565 | 2273 |
| F-statistic | 0.27 | 0.96 | 1.82 | 4.92 | 0.24 | 0.19 | 0.29 | 1.10 |
| *p*-value | 0.60 | 0.33 | 0.18 | 0.03 | 0.63 | 0.66 | 0.59 | 0.29 |
| Continuous spline? | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Wave 3 included? | No | No | Yes | Yes | No | No | Yes | Yes |
| Male pairs only? | Yes | Yes | Yes | No | Yes | Yes | Yes | No |

*Note:* All regressions include mother fixed effects and the set of controls identical in Johnson and Schoeni (2011). The set of covariates includes race, family income at child birth, maternal age at birth, a set of indicators for mother being single at birth, birth order, and child's year of birth. Standard errors in parentheses are clustered at the mother level. * p<0.10, ** p<0.05, *** p<0.01.

Table 3 – Effects of Fetal Growth Rate on Test Scores, NECGLS Estimates

| WJ Achievement test | Applied Problems | | | | Passage Comprehension | | | |
|---|---|---|---|---|---|---|---|---|
| | NECGLS | | Hausman test | | NECGLS | | Hausman test | |
| | | | vs. CFE | vs. MFE | | | vs. CFE | vs. MFE |
| | bhat | *t*-stat | *t*-stat | | bhat | *t*-stat | *t*-stat | |
| Family income | 1.802 | 4.49 | -4.19 | -3.43 | 2.171 | 5.04 | -2.48 | -2.35 |
| Mother working | -0.295 | -0.58 | -0.42 | 0.21 | -0.131 | -0.24 | 0.18 | 0.34 |
| Child age | -0.030 | -7.31 | 2.63 | 2.21 | -0.084 | -16.41 | 1.74 | 1.48 |
| Fetal growth rate | 0.064 | 3.17 | | -0.67 | 0.044 | 2.14 | | 0.05 |
| Female | -0.526 | -1.08 | | 0.39 | 2.556 | 5.06 | | -0.86 |
| Maternal age at child birth < 20 | -3.309 | -3.41 | | -1.14 | -2.417 | -2.40 | | -0.54 |
| Maternal age at child birth > 35 | 2.205 | 2.12 | | 0.36 | 2.327 | 2.21 | | -1.77 |
| Mother single at child birth | -1.372 | -1.77 | | -0.08 | -1.788 | -2.25 | | 0.14 |
| 2nd born | -1.201 | -2.28 | | -1.78 | -1.278 | -2.32 | | -1.95 |
| 3rd born | -2.119 | -2.86 | | -0.38 | -3.756 | -4.95 | | -1.09 |
| 4th born | -0.185 | -0.16 | | 0.75 | -3.756 | -3.27 | | 0.28 |
| 5th or more born | -5.512 | -3.11 | | -1.15 | -4.192 | -2.32 | | 0.74 |
| Home scale | 0.342 | 4.16 | | -2.35 | 0.365 | 4.33 | | -2.86 |
| African American | -8.089 | -10.38 | | | -4.083 | -5.15 | | |
| Latino | -4.642 | -3.19 | | | -5.320 | -3.69 | | |
| Other | -1.279 | -0.74 | | | -1.912 | -1.10 | | |
| Mother's education | 1.099 | 7.25 | | | 0.794 | 5.10 | | |
| N | 4609 | | | | 4106 | | | |
| Chi-squared statistic | | | 17.99 | 31.40 | | | 6.22 | 20.00 |
| (*p*-value) | | | (0.000) | (0.003) | | | (0.101) | (0.095) |

Table 4 – Effects of Birthweight on Test Scores, NEC2SLS Estimates

| | Applied Problems | | | | Passage Comprehension | | | |
|---|---|---|---|---|---|---|---|---|
| | NEC2SLS | | Hausman test | | NEC2SLS | | Hausman test | |
| | | | vs. CFE | vs. MFE | | | vs. CFE | vs. MFE |
| | bhat | *t*-stat | *t*-stat | | bhat | *t*-stat | *t*-stat | |
| Family income | -0.083 | -0.13 | -2.23 | -0.02 | 0.723 | 0.96 | -0.85 | -0.50 |
| Working | 0.023 | 0.04 | -1.26 | -0.47 | 0.132 | 0.23 | -0.32 | -0.11 |
| Child age | -0.023 | -5.36 | -0.22 | 0.05 | -0.078 | -14.04 | -0.31 | -0.33 |
| Fetal growth rate | 0.067 | 3.34 | | -0.80 | 0.047 | 2.28 | | -0.05 |
| Female | -0.557 | -1.14 | | 0.47 | 2.515 | 4.97 | | -0.78 |
| Maternal age at child birth < 20 | -3.411 | -3.50 | | -1.05 | -2.519 | -2.49 | | -0.46 |
| Maternal age at child birth > 35 | 2.329 | 2.23 | | 0.28 | 2.394 | 2.26 | | -1.81 |
| Mother single at child birth | -2.474 | -3.02 | | 0.77 | -2.690 | -3.14 | | 0.76 |
| 2nd born | -1.393 | -2.60 | | -1.38 | -1.440 | -2.57 | | -1.66 |
| 3rd born | -2.338 | -3.11 | | -0.12 | -3.931 | -5.13 | | -0.91 |
| 4th born | -0.373 | -0.33 | | 0.89 | -3.894 | -3.38 | | 0.37 |
| 5th or more born | -5.669 | -3.18 | | -1.09 | -4.300 | -2.38 | | 0.78 |
| Home scale | 0.123 | 0.97 | | -0.99 | 0.150 | 1.13 | | -1.94 |
| African American | -9.325 | -11.20 | | | -5.107 | -5.88 | | |
| Latino | -5.328 | -3.62 | | | -5.897 | -4.04 | | |
| Other | -1.652 | -0.96 | | | -2.256 | -1.29 | | |
| Mother's education | 1.377 | 8.33 | | | 1.026 | 5.85 | | |
| N | 4452 | | | | 4106 | | | |
| Chi-squared statistic | | | 2.06 | 18.47 | | | 2.48 | 11.16 |
| (*p*-value) | | | (0.560) | (0.141) | | | (0.479) | (0.597) |

Table 5 –Effects of Fetal Nutrition on Test Scores, NEC2SLS and MFE estimates

| | Applied Problems | | | Passage Comprehension | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Fetal nutrition* | | | | | | |
| Fetal growth rate | 0.067*** | 0.059*** | 0.289*** | 0.047** | 0.036* | 0.222** |
| | (0.020) | (0.021) | (0.104) | (0.021) | (0.022) | (0.108) |
| Fetal growth rate * Maternal education | | | -0.018** | | | -0.015** |
| | | | (0.008) | | | (0.008) |
| Preterm birth | | -1.286 | -1.200 | | -1.660* | -1.588* |
| | | (1.040) | (1.040) | | (1.075) | (1.076) |
| N | 4609 | 4609 | 4609 | 4106 | 4106 | 4106 |
| *p*-value (vs. CFE) | 0.560 | 0.564 | 0.571 | 0.478 | 0.494 | 0.525 |
| *p*-value (vs. MFE) | 0.141 | 0.154 | 0.151 | 0.597 | 0.633 | 0.344 |
| *Panel B: Birth weight spline* | | | | | | |
| Birth weight (<2.5kg) | 5.357** | 5.629*** | N.A. | 4.415** | 4.186** | N.A. |
| | (1.517) | (1.727) | | (1.542) | (1.766) | |
| Birth weight (>=2.5kg) | 0.714 | 0.810* | | 0.337 | 0.290 | |
| | (0.554) | (0.571) | | (0.565) | (0.582) | |
| Preterm birth | | 0.324 | | | -0.502 | |
| | | (1.189) | | | (1.235) | |
| N | 4609 | 4609 | | 4106 | 4106 | |
| *p*-value (vs. CFE) | 0.487 | 0.553 | | 0.690 | 0.616 | |
| *p*-value (vs. MFE) | 0.190 | 0.248 | | 0.801 | 0.740 | |

*Note:* Standard errors are in parentheses. All regressions include the same set of covariates as in Table 3. * p<0.10, ** p<0.05, *** p<0.01.

Table 6 – Role of Fetal Nutrition in Determining Racial Disparity in Test Scores, NEC2SLS estimates

| | Applied Problems | | | Passage Comprehension | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| African American | -10.134*** | -9.700*** | -9.353*** | -5.525*** | -5.537*** | -5.141*** |
| | (0.850) | (0.831) | (0.833) | (0.877) | (0.866) | (0.869) |
| Latino | -9.152*** | -5.373*** | -5.345*** | -8.665*** | -5.924*** | -5.923*** |
| | (1.469) | (1.474) | (1.470) | (1.443) | (1.461) | (1.459) |
| Other | -1.628 | -1.853 | -1.682 | -2.217* | -2.409* | -2.300* |
| | (1.676) | (1.733) | (1.729) | (1.664) | (1.746) | (1.745) |
| Maternal education | | 1.383*** | 1.375*** | | 1.030*** | 1.023*** |
| | | (0.166) | (0.165) | | (0.176) | (0.175) |
| Fetal growth rate | | | 0.059*** | | | 0.036* |
| | | | (0.021) | | | (0.022) |
| Preterm birth | | | -1.286 | | | -1.660* |
| | | | (1.040) | | | (0.341) |
| N | 4609 | 4452 | 4452 | 4106 | 4106 | 4106 |

*Note:* Standard errors are in parentheses. All regressions include the same set of covariates as in Table 3. * p<0.10, ** p<0.05, *** p<0.01.

Appendix Table 1 – Hausman test for MFE vs. NECGLS, Applied Problems

| Applied Problems | Mother FE | | | NECGLS | | | Hausman test, MFE vs. GLS | | |
|---|---|---|---|---|---|---|---|---|---|
| | bhat | se | *t*-stat | bhat | se | *t*-stat | Diff_b | Diff_se | *t*-stat |
| Family income | -0.089 | 0.682 | -0.13 | 1.802 | 0.402 | 4.49 | -1.891 | 0.551 | -3.43 |
| Working | -0.197 | 0.699 | -0.28 | -0.295 | 0.510 | -0.58 | 0.098 | 0.479 | 0.21 |
| Child age | -0.023 | 0.005 | -4.60 | -0.030 | 0.004 | -7.31 | 0.007 | 0.003 | 2.21 |
| Fetal growth rate | 0.045 | 0.034 | 1.33 | 0.064 | 0.020 | 3.17 | -0.018 | 0.028 | -0.67 |
| Female | -0.364 | 0.639 | -0.57 | -0.526 | 0.488 | -1.08 | 0.162 | 0.413 | 0.39 |
| Maternal age at child birth < 20 | -4.508 | 1.432 | -3.15 | -3.309 | 0.970 | -3.41 | -1.199 | 1.053 | -1.14 |
| Maternal age at child birth > 35 | 2.741 | 1.811 | 1.51 | 2.205 | 1.039 | 2.12 | 0.536 | 1.484 | 0.36 |
| Mother single at child birth | -1.481 | 1.524 | -0.97 | -1.372 | 0.775 | -1.77 | -0.108 | 1.312 | -0.08 |
| 2nd born | -1.986 | 0.687 | -2.89 | -1.201 | 0.527 | -2.28 | -0.785 | 0.441 | -1.78 |
| 3rd born | -2.441 | 1.130 | -2.16 | -2.119 | 0.742 | -2.86 | -0.321 | 0.852 | -0.38 |
| 4th born | 0.864 | 1.801 | 0.48 | -0.185 | 1.133 | -0.16 | 1.049 | 1.400 | 0.75 |
| 5th or more born | -8.379 | 3.052 | -2.75 | -5.512 | 1.774 | -3.11 | -2.867 | 2.483 | -1.15 |
| Home environment | 0.038 | 0.153 | 0.25 | 0.342 | 0.082 | 4.16 | -0.304 | 0.129 | -2.35 |
| African American | | | | -8.089 | 0.779 | -10.38 | | | |
| Latino | | | | -4.642 | 1.453 | -3.19 | | | |
| Other | | | | -1.279 | 1.721 | -0.74 | | | |
| Mother's education | | | | 1.099 | 0.152 | 7.25 | | | |
| N | 2852 | | | 4609 | | | | | |
| Chi-squared (*p*-value) | | | | | | | | | 31.40 (0.003) |

*Note*: We suppress the CFE estimates since they are not of interest in themselves, but only serve as the consistent estimates under the alternative hypothesis in the Hausman tests.

Appendix Table 2 – Hausman test for MFE vs. NEC2SLS, Applied Problems

| Applied Problems | Mother FE | | | NEC2SLS | | | Hausman test, MFE vs. 2SLS | | |
|---|---|---|---|---|---|---|---|---|---|
| | bhat | se | *t*-stat | bhat | se | *t*-stat | Diff_b | Diff_se | *t*-stat |
| Family income | -0.089 | 0.682 | -0.13 | -0.083 | 0.628 | -0.13 | -0.007 | 0.265 | -0.02 |
| Working | -0.197 | 0.699 | -0.28 | 0.023 | 0.518 | 0.04 | -0.220 | 0.469 | -0.47 |
| Child age | -0.023 | 0.005 | -4.60 | -0.023 | 0.004 | -5.36 | 0.000 | 0.003 | 0.05 |
| Fetal growth rate | 0.045 | 0.034 | 1.33 | 0.067 | 0.020 | 3.34 | -0.022 | 0.028 | -0.80 |
| Female | -0.364 | 0.639 | -0.57 | -0.557 | 0.490 | -1.14 | 0.194 | 0.411 | 0.47 |
| Maternal age at child birth < 20 | -4.508 | 1.432 | -3.15 | -3.411 | 0.974 | -3.50 | -1.097 | 1.049 | -1.05 |
| Maternal age at child birth > 35 | 2.741 | 1.811 | 1.51 | 2.329 | 1.045 | 2.23 | 0.412 | 1.479 | 0.28 |
| Mother single at child birth | -1.481 | 1.524 | -0.97 | -2.474 | 0.819 | -3.02 | 0.994 | 1.286 | 0.77 |
| 2nd born | -1.986 | 0.687 | -2.89 | -1.393 | 0.536 | -2.60 | -0.593 | 0.430 | -1.38 |
| 3rd born | -2.441 | 1.130 | -2.16 | -2.338 | 0.752 | -3.11 | -0.103 | 0.844 | -0.12 |
| 4th born | 0.864 | 1.801 | 0.48 | -0.373 | 1.139 | -0.33 | 1.237 | 1.395 | 0.89 |
| 5th or more born | -8.379 | 3.052 | -2.75 | -5.669 | 1.782 | -3.18 | -2.710 | 2.477 | -1.09 |
| Home environment | 0.038 | 0.153 | 0.25 | 0.123 | 0.127 | 0.97 | -0.085 | 0.086 | -0.99 |
| African American | | | | -9.325 | 0.833 | -11.20 | | | |
| Latino | | | | -5.328 | 1.470 | -3.62 | | | |
| Other | | | | -1.652 | 1.730 | -0.96 | | | |
| Mother's education | | | | 1.377 | 0.165 | 8.33 | | | |
| N | 2852 | | | 4609 | | | | | |
| Chi-squared (*p*-value) | | | | | | | | | 18.47 (0.141) |

*Note*: We suppress the CFE estimates since they are not of interest in themselves, but only serve as the consistent estimates under the alternative hypothesis in the Hausman tests.

Appendix Table 3 – Hausman test for MFE vs. NECGLS, Passage Comprehension

| Passage Comprehension | Mother FE | | | NECGLS | | | Hausman test, MFE vs. GLS | | |
|---|---|---|---|---|---|---|---|---|---|
| | bhat | se | *t*-stat | bhat | se | *t*-stat | Diff_b | Diff_se | *t*-stat |
| Family income | 0.589 | 0.798 | 0.74 | 2.171 | 0.430 | 5.04 | -1.582 | 0.672 | -2.35 |
| Working | 0.066 | 0.805 | 0.08 | -0.131 | 0.556 | -0.24 | 0.197 | 0.583 | 0.34 |
| Child age | -0.078 | 0.006 | -12.58 | -0.084 | 0.005 | -16.41 | 0.005 | 0.004 | 1.48 |
| Fetal growth rate | 0.045 | 0.037 | 1.22 | 0.044 | 0.020 | 2.14 | 0.001 | 0.031 | 0.05 |
| Female | 2.140 | 0.699 | 3.06 | 2.556 | 0.505 | 5.06 | -0.416 | 0.483 | -0.86 |
| Maternal age at child birth < 20 | -3.081 | 1.586 | -1.94 | -2.417 | 1.007 | -2.40 | -0.664 | 1.225 | -0.54 |
| Maternal age at child birth > 35 | -0.620 | 1.973 | -0.31 | 2.327 | 1.054 | 2.21 | -2.947 | 1.668 | -1.77 |
| Mother single at child birth | -1.584 | 1.689 | -0.94 | -1.788 | 0.796 | -2.25 | 0.204 | 1.489 | 0.14 |
| 2nd born | -2.266 | 0.748 | -3.03 | -1.278 | 0.551 | -2.32 | -0.987 | 0.506 | -1.95 |
| 3rd born | -4.783 | 1.212 | -3.95 | -3.756 | 0.759 | -4.95 | -1.028 | 0.945 | -1.09 |
| 4th born | -3.332 | 1.909 | -1.75 | -3.756 | 1.149 | -3.27 | 0.423 | 1.525 | 0.28 |
| 5th or more born | -2.200 | 3.251 | -0.68 | -4.192 | 1.803 | -2.32 | 1.992 | 2.705 | 0.74 |
| Home environment | -0.054 | 0.169 | -0.32 | 0.365 | 0.084 | 4.33 | -0.418 | 0.146 | -2.86 |
| African American | | | | -4.083 | 0.792 | -5.15 | | | |
| Latino | | | | -5.320 | 1.442 | -3.69 | | | |
| Other | | | | -1.912 | 1.737 | -1.10 | | | |
| Mother's education | | | | 0.794 | 0.156 | 5.10 | | | |
| N | 2405 | | | 4106 | | | | | |
| Chi-squared (*p*-value) | | | | | | | | | 20.00 (0.095) |

*Note*: We suppress the CFE estimates since they are not of interest in themselves, but only serve as the consistent estimates under the alternative hypothesis in the Hausman tests.

Appendix Table 4 – Hausman test for MFE vs. NEC2SLS, Passage Comprehension

| Passage Comprehension | Mother FE | | | NEC2SLS | | | Hausman test, MFE vs. 2SLS | | |
|---|---|---|---|---|---|---|---|---|---|
| | bhat | se | *t*-stat | bhat | se | *t*-stat | Diff_b | Diff_se | *t*-stat |
| Family income | 0.589 | 0.798 | 0.74 | 0.723 | 0.752 | 0.96 | -0.134 | 0.267 | -0.50 |
| Working | 0.066 | 0.805 | 0.08 | 0.132 | 0.570 | 0.23 | -0.065 | 0.569 | -0.11 |
| Child age | -0.078 | 0.006 | -12.58 | -0.078 | 0.006 | -14.04 | -0.001 | 0.003 | -0.33 |
| Fetal growth rate | 0.045 | 0.037 | 1.22 | 0.047 | 0.021 | 2.28 | -0.002 | 0.031 | -0.05 |
| Female | 2.140 | 0.699 | 3.06 | 2.515 | 0.506 | 4.97 | -0.375 | 0.482 | -0.78 |
| Maternal age at child birth < 20 | -3.081 | 1.586 | -1.94 | -2.519 | 1.011 | -2.49 | -0.562 | 1.222 | -0.46 |
| Maternal age at child birth > 35 | -0.620 | 1.973 | -0.31 | 2.394 | 1.060 | 2.26 | -3.014 | 1.664 | -1.81 |
| Mother single at child birth | -1.584 | 1.689 | -0.94 | -2.690 | 0.857 | -3.14 | 1.105 | 1.455 | 0.76 |
| 2nd born | -2.266 | 0.748 | -3.03 | -1.440 | 0.559 | -2.57 | -0.825 | 0.497 | -1.66 |
| 3rd born | -4.783 | 1.212 | -3.95 | -3.931 | 0.767 | -5.13 | -0.852 | 0.939 | -0.91 |
| 4th born | -3.332 | 1.909 | -1.75 | -3.894 | 1.153 | -3.38 | 0.562 | 1.522 | 0.37 |
| 5th or more born | -2.200 | 3.251 | -0.68 | -4.300 | 1.809 | -2.38 | 2.100 | 2.701 | 0.78 |
| Home environment | -0.054 | 0.169 | -0.32 | 0.150 | 0.133 | 1.13 | -0.203 | 0.104 | -1.94 |
| African American | | | | -5.107 | 0.869 | -5.88 | | | |
| Latino | | | | -5.897 | 1.459 | -4.04 | | | |
| Other | | | | -2.256 | 1.746 | -1.29 | | | |
| Mother's education | | | | 1.026 | 0.176 | 5.85 | | | |
| N | 2405 | | | 4106 | | | | | |
| Chi-squared (*p*-value) | | | | | | | | | 11.16 (0.597) |

*Note*: We suppress the CFE estimates since they are not of interest in themselves, but only serve as the consistent estimates under the alternative hypothesis in the Hausman tests.