The Human Capital Dynamic Linkage in Early Childhood Development: How Pre-Kindergarten Experience Affects Schooling Outcomes

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Abstract

This paper uses a multi-stage education model to identify the human capital dynamic linkage in early childhood development, namely how children's pre-kindergarten human capital levels affect their schooling efficiency and outcomes. The human capital dynamic linkage is significantly positive, and estimation without controlling for endogeneity is downward biased. The human capital dynamic linkage differs across subject areas, and exhibits complementariy with other family educational inputs. Conventional program evaluation ignoring this dynamic linkage may have wrong policy implications.

1. Introduction

Generally speaking, what is the human capital dynamic linkage? This term captures an idea that all of us are too familiar with: We have to learn basic knowledge and skills first, and then use the basic knowledge and skills we have learned to learn more advanced knowledge and skills. In short, education occurs in hierarchical stages, and learning at lower stages act as the stepping stone for learning at higher stages.

There is a direct implication from this human capital dynamic linkage. When individuals learn basic knowledge and skills, the direct benefit is that their current human capital levels increase; moreover, the indirect benefit is that they are better prepared for learning more advanced knowledge and skills, so their human capital accumulation rate is higher in the future. The more basic is the knowledge and skills, the bigger indirect benefit it generates. Intuitively it is worthwhile to invest heavily to build a solid foundation upon which all subsequent education relies. The hierarchical nature of the education process dictates asymmetry between lower stages and higher stages of education.

The human capital dynamic linkage is a well accepted theoretical specification of the education production technology. Ben-Porath (1967) and Lucas (1988) take the continuous time specification where the rate of human capital accumulation is increasing in existing human capital stock. In more recent work, Driskill and Horowitz (2002) and Su (forthcoming) adopt similar multi-stage education models where human capital output from a lower stage acts as an intermediate input and improves the learning efficiency at a higher stage of education. However, although too familiar to reject, there is very little empirical analysis of the human capital dynamic linkage. Is our impression really supported by the data? If yes, how strong is the indirect effect channeled through the human capital dynamic linkage? So far the existing literature sheds little light on these questions.

In this paper I attempt to identify the human capital dynamic linkage at the very beginning of the education process for everyone, namely in early childhood development. The focal question is: how do children's pre-kindergarten experience and hence human capital levels affect their learning efficiency and schooling outcomes? This is made feasible by a multi-stage education model where pre-kindergarten human capital level acts as an intermediate input in the education production technology at the formal schooling stage.

It is not hard to realize that the major obstacle to identification is endogeneity. At any point in time, existing human capital stock is endogenously determined through past education decisions, which in turn depend on unobserved factors that also affect current education outcomes, so direct estimation without controlling for endogeneity may lead to bias. Identification is facilitated with the help of a specially designed longitudinal dataset covering the early childhood, where children's birth weight is used as an instrument to their pre-kindergarten human capital levels. Under the identifying assumption, the difference in children's birth weight acts as a source of exogenous variation and help identify the human capital dynamic linkage.

Another advantage of this multi-stage education model is that it disentangles the impact from the human capital dynamic linkage and other education inputs, and even allows interaction between them. So when studying the long-term effect of education programs, it becomes feasible to distinguish the indirect effect channeled through the human capital dynamic linkage from the effects of other education inputs. Only then can we answer some of the previously overlooked issues. Some of the questions are: To what extent does the human capital dynamic linkage interact with other education inputs? Consequently, what are the education policy implications, say, early intervention versus remedial measurement, and policies targeting certain subgroups versus policies generally applicable to the entire population? When the data suggest faster decay rate of the initial benefit from early intervention programs (like Head Start) for black than white students, what fraction can be attributed to weak human capital dynamic linkage, and what fraction to their inferior family background and poorer schooling quality? The answers to these questions are of significant policy importance.

Using the Early Childhood Longitudinal Study - Kindergarten class from the Department of Education, I estimate a two-stage education model with the following results. First, persistent unobserved factors affect both the pre-kindergarten stage and the formal schooling stage, so the pre-kindergarten human capital level is endogenous, and direct estimation without controlling for endogeneity generates downward bias. Secondly, using children's birth weight as the instrument to control for endogeneity, the human capital dynamic linkage in early childhood development is significantly positive. Higher pre-kindergarten human capital level leads to higher learning efficiency and hence higher incremental human capital output from the two years of formal schooling, kindergarten and the first grade. This confirms our intuition and suggests significant indirect impact of education programs rippled through subsequent stages. Thirdly, the human capital dynamic linkage differs across subjects like reading, mathematics and general knowledge. A 1% initial difference in the pre-kindergarten human capital levels leads to a

0.15% additional difference in mathematics, 0.28% in reading, and 0.56% in general knowledge after two years of schooling. Hence when different education programs target different subjects, the conventional program evaluation approach that ignores this channel is most biased against education programs where the long-term indirect effects are the biggest. This paper strongly suggests that the human capital dynamic linkage be properly taken into account for program evaluation. Last but not the least, dividing the entire sample into sub-groups along different dimensions of family background, I find that the human capital dynamic linkage is substantially higher for children from advantaged family background. This implies complementarity in the education technology. After controlling for family background, the human capital dynamic linkage is substantially higher for black than white students, suggesting that the observed faster decay rate of initial benefits from early intervention programs for black students is solely due to their inferior family background and poorer schooling quality.

The remaining of the paper is structured as follows. Section 2 compares and connects the current paper to the existing literature. Section 3 proposes the multi-stage education model. Section 4 introduces the dataset used for estimation and discusses the identification strategy. The estimation results are reported in section 5. Section 6 discusses the importance of recognizing the human capital dynamic linkage in program evaluation and its policy implications. Section 7 draws the conclusion.

2. Literature review

This paper draws connections from several strands of the existing literature. First of all, there exists a vast literature on early childhood development. Economists, together with developmental psychologists and scholars from other disciplines, attempt to identify the factors that affect early childhood development. Among others, Ruhm (2000), Waldfogel, Han and Brooks-Gunn (2002), Waldfogel (2002) and Baum (2003) study the impact of child care and early maternal employment on children's cognitive outcomes. The evidence is mixed, depending on the timing and duration of maternal employment, its impact on the cognitive stimulation and emotional support provided to children, and its impact on family income. Glewwe and Jacoby (1995), Glewwe, Jacoby and King (2001) and Glewwe and King (2001) study the impact of early childhood malnutrition on cognitive development and academic achievement. They find that better-nourished children perform significantly better in school for two reasons. On one hand they enter school earlier and thus have more time to learn; on the other hand and more importantly, they are better prepared and thus have greater learning productivity per year of schooling. Later I follow the guidelines in the existing literature when choosing the instruments for children's pre-kindergarten human capital levels, resulting from early childhood development.

In the program evaluation literature, Currie (2001) and Currie and Thomas (1995, 2000, 2002) attempt to study the impact, both short-term and long-term, of early childhood educational programs, especially that of Head Start. While the existing literature has developed methods to control for selection bias in program participation and determine the direct benefit of an education program, there is difficulty associated with identifying the long-term indirect effect. Without a multi-stage education model that directly captures the human capital dynamic linkage, the best result that can be obtained is human capital correlation across various stages of education, and it is ambiguous to which factor this (lack of) correlation can be attributed. In Currie and Thomas (2000), the authors can only claim that "the effects of Head Start may fade out more rapidly among black students, at least in part because black Head Start children are more likely to subsequently attend inferior schools." With the multi-stage education model that directly captures the human capital dynamic linkage, this paper disentangles the impact from the human capital dynamic linkage and other education inputs. This analysis contributes to the current program evaluation literature by offering a general setup with which the long-term indirect effect associated with any education program can be identified, and pointing out the substantial downward bias if it were to be ignored.

Methodologically this paper is closely related to Su (2004). In that paper a similar multi-stage education model is proposed, and the data reveal that the human capital dynamic linkage from high school to post-secondary schooling is significantly positive. This current paper extends the analysis in that paper in several directions. First, within the entire hierarchical education process, new data reveal the human capital dynamic linkage in early childhood development, i.e., it is significantly positive from pre-kindergarten to the formal schooling stage. Second, direct assessment is taken to measure a child's cognitive achievement at both stages, as against the crude proxy of education degrees. So in the education production technology, the human capital input and output are measured on the same scale, and the incremental value associated with a certain stage can be directly computed by differencing the starting and ending values. This allows easy interpretation of the human capital dynamic linkage as what percentage point of additional difference is caused by a 1% initial difference in the human capital levels. Furthermore, having the multiple dimensional measurements on reading, mathematics and general knowledge enables us to estimate the differential human capital dynamic linkage within individual subject, which plays an important role in evaluating education programs targeting at different subjects. Last but not the least, this paper emphasizes the interaction between the human capital dynamic linkage and other family educational inputs, and offers some explanation to the standing question in the literature on the faster decay rate of the initial benefit from early intervention programs for black than white students.

3. The multi-stage education model

Children's cognitive development starts before formal schooling, and the knowledge and skill they accumulate early at home determine their readiness and efficiency for human capital accumulation in later schooling process. This human capital dynamic linkage is captured in the following two-stage education production functions. The pre-kindergarten stage is labeled as stage 1 with the following education technology:

$$y_{i1} = \mathbf{x}_{i1}'\beta_1 + u_{i1} \tag{1}$$

Here for a child i, y_{i1} is his pre-kindergarten human capital level, $\mathbf{x}_{i1}$ is the vector of exogenous explanatory variables relevant at this stage, β_1 is the vector of corresponding parameters, and u_{i1} is the random term.

The formal schooling stage, more specifically, kindergarten and the first grade, is labeled as stage 2. In this stage, a child uses the knowledge and skills he has accumulated in stage 1, y_{i1}, together with other education inputs $\mathbf{x}_{i2}$, to produce human capital output y_{i2} according to the following technology:

$$y_{i2} = \alpha y_{i1} + \mathbf{x}_{i2}'\beta_2 + u_{i2} \tag{2}$$

Here α is the parameter capturing the human capital dynamic linkage across these two stages. Besides, $\mathbf{x}_{i2}$ is the vector of exogenous explanatory variables relevant at stage 2, β_2 is the vector of corresponding parameters, and u_{i2} is the random term.

For an individual i, it is assumed that $E(u_{i1}|\mathbf{x}_{i1}, \mathbf{x}_{i2}) = E(u_{i2}|\mathbf{x}_{i1}, \mathbf{x}_{i2}) = 0$, $E(u_{i1}^2|\mathbf{x}_{i1}, \mathbf{x}_{i2}) = \boldsymbol{\sigma}_1^2$, $E(u_{i2}^2|\mathbf{x}_{i1}, \mathbf{x}_{i2}) = \boldsymbol{\sigma}_2^2$, and $E(u_{i1}u_{i2}|\mathbf{x}_{i1}, \mathbf{x}_{i2}) = \rho\sigma_1\sigma_2$.

It is further assumed that there is no correlation in the random terms across individuals, i.e., $E(u_{is}u_{js'}|\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{x}_{j1}, \mathbf{x}_{j2}) = 0$ for $i \neq j$ and $s,\ s' \in \{1,\ 2\}$.

Notice that the self selection problem (endogeneity of y_{i1} hinges crucially on the parameter ρ. If $\rho = 0$, then we know that $E(u_{i2}|y_{i1}, \mathbf{x}_{i2}) = 0$, there is no self selection based on unobserved factors, and direct estimation of equation (2) itself is consistent. If $\rho \neq 0$, the regressor y_{i1} is correlated with the random term u_{i1}, direct estimation of equation (2) without controlling for the endogeneity of y_{i1} may lead to bias. How to find valid instruments for the regressor y_{i1} is the main task and will be discussed in detailed in the next section.

Together equations (1) and (2) form a simultaneous equations model of multi-stage education technologies. This simultaneous equations model resembles a dynamic panel data model, where lagged value of the dependent variable has explanatory power. To help understand the crucial identifying assumptions, it is worthwhile to compare the current model with a usual dynamic panel data model for their similarities and differences.

First, in a dynamic panel data model, it is implicitly assumed that the observations over time are generated from a stationary data generating process, i.e., the regression model is time-invariant. On the other hand, the current simultaneous equations model explicitly captures the hierarchical nature of educational system, where learning technologies at lower education stages and higher education stages need not and should not be the same. More specifically, in the context of early childhood development, we know that pre-kindergarten education is mainly home-based, yet kindergarten and the first grade education is mainly school-based. A priori it is reasonable to expect different learning technologies at these two stages, where parent-child interaction dominates the pre-kindergarten stage, yet teacher-student interaction plays a bigger role in formal schooling. Consequently the learning technologies at the two stages may involve different types of education inputs, as schooling quality is irrelevant at the pre-kindergarten stage yet essential in formal schooling. In terms of notation, it is possible that $\mathbf{x}_{i1} \neq \mathbf{x}_{i2}$. Hence, in a dynamic panel data model, the exogenous variables do not contribute to identify the parameter α associated with the lagged dependent variable. There identification is only feasible when $T \geq 3$, so there are sufficiently lagged values of the dependent variable as instruments. In the current model, the excluded exogenous variables, those in $\mathbf{x}_{i1}$ but not in $\mathbf{x}_{i2}$, identify the parameter α even when $T = 2$ (See Bhargava and Sargan (1983), Arellano (1990), Bover (1991), Becker, Grossman and Murphy (1994)).

Second, the interpretations are different for the initial values of the dependent variable. In a dynamic panel data model, the initial value is not intrinsically different from any other observations at any other time period. The data generating process has been running for long and the first observation may be interpreted as at its long run equilibrium level. Some econometricians make use of the initial conditions to construct extra moment conditions to improve estimation efficiency (See Blundell and Bond (1998)). In the current model, the initial value is intrinsically the first realization in the entire education process. No human capital accumulation could take place before a child is formed, hence the first stage education technology has no built in dynamic component. This unique directionality is closely associated with the hierarchical nature in the education process.

When allowing interaction between the human capital dynamic linkage and other education inputs, equation (2) is modified to take the following version:

$$y_{i2} = \alpha y_{i1} + \alpha' y_{i1} 1(\mathbf{x}_{2i} \geq \underline{\mathbf{x}_2}) \ + \mathbf{x}_{2i}' \beta_2 + u_{2i} \tag{3}$$

where 1(.) is the indicator function that takes the value 1 if the statement in the parenthesis holds true and 0 otherwise. Along different dimensions of family background such as the highest education level of parents or total family income, the interaction term is generated. So the parameter α captures the base effect of the human capital dynamic linkage when other education input is low ($\mathbf{x}_{2i} < \underline{\mathbf{x}_2}$), and the parameter α' measures the additional effect of the human capital dynamic linkage when other education input is high ($\mathbf{x}_{2i} \geq \underline{\mathbf{x}_2}$). If α' is significantly positive, the marginal effect of the human capital dynamic linkage is higher when the level of other education input is high, then the education technology exhibits complementarity between the two inputs.

4. Data description

The dataset used for estimation is the Early Childhood Longitudinal Study - Kindergarten Class of 1998-1999 (hereinafter referred to as ECLS-K). This study is conducted by the National Center for Education Statistics and is one of the first nationally representative studies of early childhood development and educational experiences. In this study, a nationally representative sample of children are followed from kindergarten through the fifth grade starting in the fall of 1998. In the fall of 1998 and spring of 1999, base year data were collected when children were in kindergarten. In the fall of 1999, data were collected on a subsample of the children when they entered the first grade; and in the spring of 2000, data were again collected for the full sample of children when they were in the first grade. Two more waves of data collection are planned for the spring of 2002 and

2004, when the children are in the third and fifth grade respectively. So far the released dataset include information on kindergarten and the first grade only.

Although short, this current longitudinal dataset covers the transitional process from pre-kindergarten to formal schooling, and focuses on children's adjustment in this transitional process. It provides a rich array of information by surveying not only the children, but also their parents, their teachers and the school administrators. It allows good control of observed heterogeneity.

In the first four surveys, any two consecutive surveys are spaced only half a year apart. The short time period cannot generate sufficient variation for identification purpose, and the colinearity problem arises from high persistence in children's before and after human capital levels. So we lump the information in the four surveys and divide the process into two bigger stages. More specifically, we extract information mainly from the first survey to know about children's pre-kindergarten conditions, and information from the second, the third and the fourth surveys to know about children's conditions during kindergarten and the first grade. This leaves roughly a two-year gap in between the two stages, and there is sufficient variation for identifying the human capital dynamic linkage. Given the advantage of repeated surveys, for time invariant variables, some missing data in early rounds can be inferred from available data in later rounds, so I compile the information from all four rounds to minimize the missing data problem. Since the recall error tends to be higher as time passes, when there is inconsistency in the data across surveys, I keep the earliest data unless the correction is confirmed more than once in later rounds.

4.1. How to measure children's human capital

A prerequisite to identifying the human capital dynamic linkage is the precise measurement of a child's human capital (in this case his cognitive ability), and this dataset is especially suited to that purpose. In the survey, a child's cognitive ability was directly assessed on a one-on-one basis by a trained professional. The cognitive assessment focuses on three general areas of competence: (1) language use and literacy (reading), (2) mathematics, and (3) knowledge of the social and physical world (refereed to as general knowledge). The assessment is carried out in two steps. In the first step, a uniform question set on each of the three subjects is administered to a child, the result of which provides a crude estimate of this child's achievement level. Based on the initial result, in the second step, one test form with the appropriate difficulty level is chosen out of several alternative forms varied by their levels of difficulty. This suitably difficult test is again administered to the child. The child not bored by too easy questions nor frustrated by too hard questions, the result is maximized measurement accuracy and assessment efficiency.

In the reading assessment there are five proficiency levels. These five levels reflect a progression of knowledge and skills. If a child has mastered one of the higher levels, he or she is very likely to have passed the items that comprise the lower levels with little difficulty. These five levels are: (1) identifying the upper- and lower-case letters of the alphabet by name; (2) associating letters with sounds at the beginning of words; (3) associating letters with sounds at the ends of words; (4) recognizing common words by sight; and (5) reading word in context. The hierarchical nature here is quite obvious and consistent with our daily intuitions.

Similarly, the items in the mathematics assessment are grouped into five-level proficiency levels, although the math clusters are less homogeneous in content than the reading clusters. The five levels include: (1) identifying some one–digit numerals, recognizing geometric shapes, and one-to-one counting up to ten objects; (2) reading all one-digit numerals, counting beyond ten, recognizing a sequence of patterns, and using non standard units of length to compare objects; (3) reading two-digit numerals, recognizing the next number in a sequence, identifying the ordinal position of an object, and solving a simple word problem; (4) solving simple addition and subtraction problems; and (5) solving simple multiplication and division problems and recognizing more complex number patterns.

The general knowledge assessment consists of science and social studies material. The science items measure two broad classes of science competencies: a) conceptual understanding of scientific facts; and b) skills and abilities to form questions about the natural world, to try to answer them on the basis of the tools and evidence collected, and to communicate answer and how the answers are obtained. Social studies material includes questions relating to history/government, culture, geography and economics. The assessment items draw on children's experience with their environment, and many questions relate to more than one of the categories. However, the subject matter of the general knowledge assessment is too diverse and insufficiently ranked to permit formation of a set of proficiency levels.

The score we use to measure a child's cognitive level is the IRT (Item Response Theory) scale score. This scale score relies crucially on the uniform test in step one, and the core set of items shared among the different forms in the step two tests. A common scale is thus established even when children take different forms in the step two tests. The IRT procedure analyzes the pattern of right, wrong and omitted responses and determine a child's true ability to discriminate right from wrong and his guessing ability. It is then possible to estimate the score - the number of correct responses - a child would have achieved if all of the items in all of the step two test forms had been administered. The probabilistic nature places each child on a continuous ability scale. So within each subject of reading, mathematics and general knowledge, a child's pre-kindergarten human capital y_{i1} is measured by the IRT scale scores (READ, MATH and GEKN), and the human capital output from two years of schooling y_{i2} is the additional number of questions that a child can answer correctly and equals the difference between the starting and ending values (READG, MATHG and GEKNG). Notice that the scores are not comparable across subjects due to different numbers of total questions available.

4.2. Identifying strategy

The explanatory variables in the multi-stage education model can be categorized into three groups. The first group contains those that have impact on both the pre-kindergarten stage and the formal schooling stage, i.e., they belong to $\mathbf{x}_{i1} \cap \mathbf{x}_{i2}$. More specifically, the explanatory variables include the child's gender (MALE), his race/ethnic background (WHITE, BLACK, HISPANIC, ASIAN and RACEOTH), the residential location (URBAN, SUBURBAN, and RURAL), and his family background such as parental education level (PARED), total family income (INC), and family preference towards education attainment (EDEXP). These variables are included in both stages of education and they are time-invariant, so their presence increases the explanatory power of the model but does not help identify the human capital dynamic linkage that we are interested in.

The second group contains the variables that arguably have direct impact only on the pre-kindergarten stage but not the formal schooling stage, namely they belong to $\mathbf{x}_{i1} \backslash \mathbf{x}_{i2}$. If these variables can be justified as exogenous, then their exclusion from the formal schooling stage makes them valid instruments and help identify the human capital dynamic linkage between the two stages. Following the existing literate on early childhood development, I choose two variables as candidates: the birth weight of a child (BIRTHW) and the maternal employment status between a child's birth and kindergarten (EMPLOY). The validity of the two instruments depends crucially on the following assumptions.

When considering equation (1), the orthogonality condition between the random term u_{i1} and the two instruments are valid by assumption. Within the pre-kindergarten stage, the two instruments captures all impact from unobserved factors that are correlated with them, so the remaining part is orthogonal. However, being orthogonal to u_{i1} does not necessarily imply being orthogonal to u_{i2}. The exogeneity of these instruments in equation (2) needs further assumption.

A child's birthweight (BIRTHW) reflects his physical condition, which can be thought as a raw input in initial cognitive development. The validity of it being an instrument relies on it being uncorrelated to u_{i2}. Obviously the birth weight of a child may be affected by many factors such as disease or maternal nutrition and substance usage during pregnancy, and these factors may be correlated with other unobserved factors that affect schooling outcomes at the formal schooling stage. It is assumed that the family background variables fully capture the impacts from those unobserved factors so that u_{i2} is uncorrelated with the child's birth weight.

The maternal employment (EMPLOY) may be more problematic. There may be autocorrelation in maternal employment status over time. As there is no information on the maternal employment status when the child is in school, using the pre-kindergarten maternal employment status in the schooling stage may simply capture the effect of the omitted variable, instead of the human capital dynamic linkage we expect to identify. Again since maternal employment status is highly correlated with family background variables such as parental education level and total family income, it is hoped that the family background variables capture the impact from maternal employment when the child is in school, thus leave u_{i2} uncorrelated with the pre-kindergarten maternal employment status. Since EMPLOY is almost uncorrelated with BIRTHW (with correlation coefficient 0.002), including both should increase the explanatory power at the pre-kindergarten stage if both are valid instruments. Over-identification tests are later conducted.

The third group of explanatory variables are those that may have impact only on the formal schooling stage but not the pre-kindergarten stage, i.e., they belong to $\mathbf{x}_{i2} \backslash \mathbf{x}_{i1}$. The most prominent candidate is the schooling quality, such as whether it is private or public (PRISCH). There are also other variables such as the highest and lowest base teacher salary, but missing data is a major problem there, and I decide not to use them. Also the third category may include the child's physical condition when in school, measured as his height and weight when entering kindergarten (HEIGHT and WEIGHT). However, all these variables in the third category may reflect parental decisions that also depend on some unobserved factors in u_{i2}, so their exogeneity may be hard to justify. The benefit from increasing the explanatory power has to be balanced against the potential risk of biasing the estimates. Thus the estimation is conducted both with and without these variable. Comparing the results is a crude form of robustness check of the model.

4.3. The summary statistics

Table 1 defines the variables used in estimation. In total there are 17,212 observations, and missing data come from the following aspects. First, as discussed in Allison (2001), if missing data is on the dependent variable, extra information on the explanatory variables has no contribution on the estimation efficiency. In the current two-stage education model with three subjects, there are six dependent variables as READ, MATH, GEKN, READG, MATHG and GEKNG. Overall 3,458 observations have missing data on at least one of these variables, either because the children were not in the wave of survey, or English is not the native language and tests were not applicable. These 3,458 observations are dropped from the sample.

Within the remaining sample, there are 722 observations that have missing data on family background variables as PARED, INC and EDEXP. These variables are essential in controlling for observed heterogeneity. Furthermore, the validity of the instruments relies crucially on the assumption that these variables capture the impact of unobserved factors that are correlated with the instruments at the formal schooling stage, so their inclusion is necessary in both stages. Again I drop the 722 observations.

Next, there are 660 observations that have missing data on the two instruments (BIRTHW and EMPLOY). The information from the instruments is the source of exogenous variation at the formal schooling stage, without which identification of the human capital dynamic linkage is impossible. Hence I drop the additional 660 observations.

Last, there are 31 observations missing data on HEIGHT and WEIGHT. These two variables play no essential role in identification, yet including them may increase the explanatory power of the model. Since missing data problem is not severe here, I can afford including these variables in the formal schooling stage and drop the 31 observations with missing data. On the other hand, there are 1,958 observations missing information on the highest/lowest base teacher salary, and preliminary estimation suggests that they add little explanatory power to the model. I decide not to include these variables for the estimation, in that the cost of sharply reduced sample size outweighs the negligible benefit of improved

R-squared. In the end, the sample consists of 12,341 observations, or 71.7% of the original sample size. The summary statistics are reported in Table 2.

As can be seen, on average, the highest education level of the parents is between having some college education and having a bachelor's degree; the annual family income is $54,519; and parents expect their children to finish college with a bachelor's degree. 76% of mothers worked between the child's birth and kindergarten, and the average birth weight of a child is 7.4 pounds. When entering kindergarten, an average child is 44.7 inches tall and 46.4 pounds heavy, and 23% of them go to private kindergarten and/or private elementary school. Before kindergarten, an average child can correctly answer 23.5 questions in reading, 20.5 in mathematics and 22.9 in general knowledge. After kindergarten, the child can correctly answer 33.4 questions more in reading, 23.8 more in mathematics, and 12.6 more in general knowledge. It is obvious that there is progress in children's cognitive development due to the two years of schooling.

5. Estimation results

The two-stage least squares approach is adopted for identification. All reported t-statistics are computed using robust standard errors. Also the second-stage standard errors are properly adjusted for using the fitted value instead of the true value of y_{i1} as a regressor. Every estimation is carried out using test scores in three subjects separately, differentiating the human capital dynamic linkage across subjects.

5.1. Positive human capital dynamic linkage

Reported in Table 3 is the pre-kindergarten stage of education. The results are fairly standard and agree well with the existing literature. As can be seen, children's early developments in the three subjects are far from uniform. For example, girls outperform boys in reading, yet boys outperform girls in general knowledge, and both perform equally well in mathematics. Compared to white children, children from all other race/ethnic background perform significantly worse in all three subjects; with the only exception that Asian children outperform white children in reading, and the two subgroups are indistinguishable in mathematics. Family background plays the essential role in early childhood development, as children from families with better educated parents, higher income and/or higher expectation of educational achievement perform significantly better in all three subjects.

The power of the instruments varies across subjects. As children's birth weight has significantly positive impact on their cognitive development in all three subjects, maternal employment status in early childhood has insignificantly negative impact on children's development in reading and mathematics, yet significantly positive impact on general knowledge. These variables together explain 20-30% of the total variation in the observed outcomes.

Table 4 reports the estimation results for the formal schooling stage. Both the ordinary least squares (OLS) approach and the instrumental variable (IV) approach are adopted. There is prominent distinction between the two. The OLS estimate of the human capital dynamic linkage is consistently negative, being insignificant in reading and significant in mathematics and general knowledge; yet the IV estimate is consistently significantly positive. On other explanatory variables, OLS consistently produces highly significantly positive parameters on family background variables like PARED, INC and EDEXP, yet these parameters turn consistently negative in IV estimation and lose their significance. The discrepancy between the OLS and IV results suggests that endogeneity may be a serious problem.

Hausman test is conducted with regard to the endogeneity issue. Under the null hypothesis of no endogeneity, i.e., $\rho = 0$, OLS is both consistent and efficient. However, OLS becomes inconsistent if the null is invalid, yet IV is always consistent. In all cases, the Hausman test rejects the null at 1% significance level. Furthermore, since OLS produces substantial downward bias as against IV on the parameter α capturing the human capital dynamic linkage, the correlation in the random terms across the two stages is expected to be negative. The data confirm this negative correlation. Using residuals from the pre-kindergarten stage, and the "true" residuals from the formal schooling stage by properly taking into account the extra variation introduced by the 2SLS approach, I find ρ to be between -0.47 and -0.68, smallest (in absolute value) in mathematics and largest in general knowledge. Big deviation of ρ from 0 is again a sign of serious endogeneity problem.

One explanation of this negative correlation may arise from parental choices. Observing somewhat disappointing outcome at early childhood, parents may seek professional advice, intensive training and other means to give the child extra help. Another more biology-based explanation concerns the way a child's brain develops. The human brain has about 50 trillion synapses at birth, reaches a peak of one quadrillion by age three, and half of which are lost by age fifteen. While the large number of synaptogenesis at birth is largely under genetic control (Shore

1997), synapses are lost through the "pruning" of unused neural connections and the selective strengthening of those that are used frequently (Huttenlocher 1984). Naturally there is negative correlation if the pruning of certain synapses is once and for all.

On the other hand, the familiar notion of positive correlation overtime through innate ability is explicitly captured by the positive human capital dynamic linkage. Strictly speaking, what we tend to think as the innate ability is just the knowledge and skills a child acquires at the very early stage of development, which affects his future learning efficiency. This is exactly the positive human capital dynamic linkage identified, after properly controlling for endogeneity. A 1% advantage at the beginning of kindergarten leads to an additional 0.87-0.92% advantage in reading, 0.44-0.47% advantage in mathematics, and 0.55-0.88% advantage in general knowledge. Local the education technology is convex. A small deficiency in a child's cognitive development may magnify itself over time and become more and more costly to redress. This is of significant policy implication.

Another issue here is how useful are those variables that show up only at the formal schooling stage, namely HEIGHT, WEIGHT and PRISCH. As can be seen, they are all insignificantly in reading and add negligible explanatory power (R-squared increases by only 1%); PRISCH is significant in mathematics and R-squared increases by 19%; and all three are significant in general knowledge, and R-squared doubles.

An overall problem with the formal schooling stage estimation is that all the explanatory variables together explain only a small fraction of total variation in the outcomes (R-squared ranges from 0.0061 to 0.0485). This problem is not new, as it constantly shows up in the dynamic panel data model, where lagged value of the dependent variable has weak explanatory power on the first-order difference. There when T is large, lagged value of the first-order difference can be used as an instrument to increase the explanatory power. That solution cannot be applied here since education technologies are different across stages, and lagged value of the first-order difference may still correlate with the current stage random term.

5.2. Over-identification test

Since we have two instruments (BIRTHW and EMPLOY),.it is feasible to conduct over-identification test. As discussed in section 4, EMPLOY is the more problematic one. Following Woodbridge (2002), this is done by regressing the residuals from the formal schooling stage on all the exogenous variables, and the resulting

R^2 is such that NR^2 has asymptotic χ^2-distribution with degree of freedom 1. The p-value in reading is 0.013, in mathematics 0.0004, and in general knowledge less than 0.0001. Overall the tests reject the null that both instruments are valid.

A closer look into the residual regression confirms our initial suspect that EMPLOY may be problematic. Under the null of both valid instruments, no variable should have significant explanatory power in the residuals. However, in reading and mathematics, while all other exogenous variables remain insignificant with p-value greater than 0.75, EMPLOY alone is significant with p-value 0.016 in reading and less than 0.001 in mathematics. In general knowledge, BIRTHW turns marginally significant with p-value 0.087, and EMPLOY has a p-value less than 0.001.

Next I check how big an impact the statistically significant invalid instrument has on the estimation results. It is done by including EMPLOY in the formal schooling stage and use BIRTHW alone for identification. The results are reported in Table 5. Compared to results in Table 4 where both BIRTHW and EMPLOY are used as instruments, it is obvious that the potential bias on reading and mathematics is not nearly as severe as that on general knowledge. More specifically, if we focus on the parameter α capturing the human capital dynamic linkage, it changes from 0.9159 to 0.9491 in reading, a 3.6% increase; from 0.4366 to 0.4508 in mathematics, a 3.3% increase; but from 0.5502 to 0.0160, a 97% decrease in general knowledge, and total loss of significance! Similarly, when HEIGHT, WEIGHT and PRISCH are added, including EMPLOY in the formal schooling stage changes the parameter α from 0.8681 to 0.9064 in reading, a 4.4% increase; from 0.4744 to 0.4923 in mathematics, a 3.8% increase; but from 0.8846 to 0.3934, a 55.5% decrease. Overall this examination restores us some confidence in the estimation results in reading and mathematics, knowing that even invalid instrument of EMPLOY has only small impact on the parameter we are interested in; yet it strongly cautions us on taking the results in general knowledge at face value, knowing that the invalid instrument may bias the results to a substantial degree. Only for the completeness of structure, are subsequent results reported in all three subjects, reading, mathematics and general knowledge.

5.3. Complementarity among education inputs

Another focus of this paper is the interaction between the human capital dynamic linkage and other family educational inputs. This is done by including interaction terms. I create two dummy variables PAREDH (=1 if PARED>3 and 0 otherwise) and INCH (=1 if INC>25000 and 0 otherwise), and interact them with the fitted values of READ, MATH and GEKN. Following (3), the associated parameter α'captures complementarity among education inputs if it is positive.

Table 6 reports the interaction between the human capital dynamic linkage and parental education level. As can be seen, although small compared to the magnitude of α (2% in reading, 1.3% in mathematics and 5.6% in general knowledge), the parameter α' is significantly positive. Table 7 report the interaction between the human capital dynamic linkage and family income. Again being between 2.8-3.4% of the magnitude of α, the parameter α' is significantly positive. Since parental education level is highly correlated with family income (with correlation coefficient 0.5568), both results suggest that the human capital dynamic linkage is stronger for students from superior family background, and hence there is complementariy between the human capital dynamic linkage and other family educational inputs.

A standing question in the literature is why the initial benefit from early intervention program (Head Start) decays much faster for black than white children (Currie and Thomas (1995, 2000 and 2002)). The current model enables us to disentangle the impacts from the human capital dynamic linkage and other subsequent education inputs, and determine whether this faster decay rate is due to weaker human capital dynamic linkage or inferior family background. The analysis is restricted to black and white students, with total 9505 observations. The results are reported in Table 8. The significantly negative parameter on BLACK suggests a lower intercept, yet the significantly positive parameter on the interaction term suggests a larger slope. Controlling for other observable factors, a 3% increase in children's pre-kindergarten cognitive development brings black children to the similar rate of future cognitive development in formal schooling, and the bigger is the initial increase, the larger is black children's advantage over white children. This suggests two main reasons explaining the faster decay rate in Head Start. First the program may not be of sufficiently high quality, so that the initial increase in children's cognitive development is small, and the intercept effect dominates the slope effect. Second, the inferior family background of black children has negative effect on their human capital dynamic linkage in preserving (and even magnifying) the initial benefit.

6. Discussion

This paper identifies the human capital dynamic linkage in early childhood development, which is of enormous policy importance. Education policies target at improving the human capital output through changing some educational input. In our simple two-stage education model (1) and (2), suppose the program targets the pre-kindergarten stage by changing some x_1, then the total effects of the program may be decomposed into two or three components as follows.

The first component, the short-term direct effect, has been extensively studied in the existing literature. It is given by $\frac{\partial y_1}{\partial x}$, the instantaneous effect of the program when it is effective. The program evaluation literature has developed various approaches to control for the selection bias in the participation decision, and the short-term direct effect has been the central research interest. This paper takes it as the starting point and builds upon it.

The second component, the long-term indirect effect, is the main contribution of the current paper. The indirect effect is given by $\frac{\partial y_2}{\partial y_1}\frac{\partial y_1}{\partial x}$, channeled through the human capital dynamic linkage. As we have discussed, the parameter $\alpha = \frac{\partial y_2}{\partial y_1}$ captures the human capital dynamic linkage, that higher pre-kindergarten human capital level improves the learning efficiency in formal schooling and hence the incremental value of the human capital output. Given the significantly positive human capital dynamic linkage, program evaluation that focuses on the short-term direct effect only is missing a significant component of the total effect, and based upon which the policy implications may be quite misleading. If the above evaluation is used to choose among programs covering different stages of education, it is biased against educational programs effective in early stages. If it is used to choose among programs covering the same stage but aiming at different subjects, it is biased against the one that has the biggest human capital dynamic linkage. The conventional program evaluation practice favors least the educational programs that are supposed to have the most important impact in shaping children's lifetime achievements. This paper strongly suggests that the long-term indirect effect through the human capital dynamic linkage be properly taken into account.

The third and last component, the possibly long-term direct effect, is given by $\frac{\partial y_2}{\partial x}$. It is automatically 0 when $x \in \mathbf{X}_1 \backslash \mathbf{X}_2$, but may exist when $x \in \mathbf{X}_1 \cap \mathbf{X}_2$. For example, if a program aims at improving parental education levels, so that better educated parents are more likely to better raise their kids, then the third component exists. As can be seen, the long-term impact of family background is mostly subsumed in the human capital dynamic linkage. When the human capital dynamic linkage is present, the family background variables such as parental education level, family income and expectation on children's education attainment, turn either insignificant or even significantly negative. This implies that family impact on a child's cognitive development comes mainly at very early stages, most likely before formal schooling even starts. So if an education program aims at improving family background, the timing of it would be essential in determining the policy effect, as indicated in the results.

Another focus of the paper is the complementarity between the human capital dynamic linkage and other family educational inputs ($\alpha' > 0$). The complementarity adds complication in the debate on whether education policies should target students from disadvantaged families or be generally applicable. If the policy maker is concerned only with equity and education policies mainly act as a method of redistribution, the answer is unambiguous that a targeted policy is preferred. If the policy maker ever puts some weight on efficiency, the complementarity may reverse the policy recommendation. The analysis involves the second derivative of the education production technology. Given a fixed size of public resources, it is believed that students from disadvantaged families benefit more marginally than those from advantaged families because of diminishing marginal returns (concavity). Or in our terminology, students from disadvantaged families have bigger short-term direct benefit from the program. However, the complementarity between the human capital dynamic linkage and other family educational inputs implies that students from advantaged families would have bigger long-term indirect benefit from the program, should they be allowed to participate. Detailed cost-benefit analysis is needed before any conclusion can be drawn. But the importance of including the long-term indirect effect in program evaluation is obvious.

7. Conclusion

This paper reconfirms the main theme in Su (2003) that in the hierarchically organized educational system, existing human capital improves future learning efficiency, and the human capital dynamic linkage across education stages is significantly positive. More specifically, this relationship holds true in early childhood development, where the human capital dynamic linkage shapes the so-called innate ability in later schooling. Total effects of program intervention are decomposed into the short-term direct effect and long-term indirect effect. The significantly positive long-term indirect effect challenges conventional program evaluation that focuses only on the short-term direct effect.

With the specially designed dataset, starting and ending human capital are measured on the same scale, so the difference is the incremental value attributed explicitly to the stage of schooling under concern. The estimated elasticity suggests that the higher is the existing human capital level, the faster is the human capital accumulation rate, so the education production technology exhibits local convexity in early childhood development. This strongly favors early intervention programs against later remedial policies, as a small initial deficiency in a child's cognitive development may magnify itself over time and become more and more costly to redress.

With direct assessment of children's cognitive development in three subjects as reading, mathematics and general knowledge, human capital is measured along multiple dimensions. Within each subject, the human capital dynamic linkage is estimated, and they differ across subjects. This moves us one step closer towards understanding the different nature of learning in different subjects, based upon which education policies may have different priorities.

The current longitudinal dataset available for public use includes only four rounds of surveys and covers two years. Obviously the estimation efficiency would be enhanced when information from more recent surveys is released and covers a longer time span. Also there are remaining stages in the prevalent education system consisting of primary, secondary and tertiary stages, and the human capital dynamic linkage across other stages may be different. For example, the local convexity of the education production technology may turn into concavity; otherwise the divergent trend may lead to far more dispersed distribution than observed in the data. With the help of the multi-stage education model, these questions may be answered when new data become available.

References

Allison, Paul D. "Missing Data. Series: Quantitative Applications in the Social Sciences". Sage Publications, 2001.

Arellano, Manuel. "Testing for Autocorrelation in Dynamic Random Effects Models". Review of Economic Studies, January 1990, 57(1), pp. 127-134.

Baum, Charles L., II. "Does Early Maternal Employment Harm Child Development? An Analysis of the Potential Benefits of Leave Taking". Journal of Labor Economics, April 2003, 21(2), pp. 409-448.

Becker, Gary S., Grossman, Michael and Murphy, Kevin M. "An Empirical Analysis of Cigarette Addiction". American Economic Review, June 1994, 84(3), pp. 396-418.

Ben-Porath, Yoram. "The Production of Human Capital and the Life Cycle of Earnings". Journal of Political Economy, Aug., 1967, 75(4), pp. 352-365.

Bhargava, Alok and Sargan, J. D. "Estimating Dynamic Random Effects Models from Panel Data Covering Short Time Periods". Econometrics, November 1983, 51(6), pp. 1635-1659.

Blundell, Richard and Bond, Stephen. "Initial Conditions and Moment Restrictions in dynamic Panel Data Models". Journal of Econometrics, November 1998, 87(1), pp. 115-143.

Bover, Olympia. "Relaxing Intertemporal Separability: A Rational Habits Model of Labor Supply Estimated from Panel Data". Journal of Labor Economics, January 1991, 9(1), pp. 85-100.

Currie, Janet. "Early Childhood Education Programs". Journal of Economic Perspectives, Spring 2001, 15(2), pp. 213-238.

——— and Thomas, Duncan. "Does Head Start Make a Difference?" American Economic Review, June 1995, 85(3), pp. 341-364.

——— and ———. "School Quality and the Longer-term Effects of Head Start". Journal of Human Resources, Autumn 2000, 35(4), pp. 755-774.

——— and ———. "Longer-term Effects of Head Start". American Economic Review, Sept. 2002, 92(4), pp. 999-1012.

Driskill, Robert A. and Horowitz, Andrew. “Investment in Hierarchical Human Capital”, Review of Development Economics, Feb. 2002, 6(1), pp. 48-58.

Glewwe, Paul and Jacoby, Hanan G. "An Economic Analysis of Delayed Primary School Enrollment in a Low Income Country: The Role of Early Childhood Nutrition". Review of Economics and Statistics, Feb. 1995, 77(1), pp. 156-169.

———, ——— and King, Elizabeth M. "Early childhood Nutrition and Academic Achievement: a Longitudinal analysis". Journal of Public Economics, 2001, 81, pp. 345-368.

——— and King, Elizabeth M. "The Impact of Early childhood Nutritional Status on cognitive Development: Does the Timing of Malnutrition Matter?" World Bank Economic Review, 2001, 15(1), pp. 81-113.

Huttenlocher, Peter R. "Synapse Elimination and Plasticity in Developing Human Cerebral Cortex". American Journal of Mental Deficiency 88, pp. 488-496.

Lucas, Robert E. Jr. " On the Mechanics of Economic Development", Journal of Monetary Economics, July 1988, 22(1), pp. 3-42.

Ruhm, Christopher J. "Parental Employment and Child Cognitive Development", NBER working paper #7776, April 2000.

Shore, Rima. "Rethinking the Brain: New Insights into Early Development". New York, Families and Work Institute, 1997.

Su, Xuejuan. "The Allocation of Public Education Funds in a Hierarchical Educational System". Journal of Economic Dynamics and Control, forthcoming.

———. "An Empirical Analysis of the Human Capital Dynamic Linkage from High School to Post-Secondary Education". Mimeo, Indiana University 2003.

Waldfogel, Jane, Han, Wen-Jui and Brooks-Gunn, Jeanne. "The Effects of Early Maternal Employment on Child Cognitive Development". Demography, May 2002, 39(2), pp. 369-392.

Waldfogel, Jane. "Child Care, Women's employment, and Child Outcomes". Journal of Population Economics, August 2002, 15(3), pp. 527-548.

Woodbridge, Jeffrey M. "Econometric Analysis of Cross Section and Panel Data". MIT press, 2002.

Table 1 Definition of the Variables

MALE	Gender of child, 1 male, 0 female
WHITE*	Whether child is white, 1 yes, 0 no
BLACK	Whether child is African American, 1 yes, 0 no
HISPANIC	Whether child is Hispanic, 1 yes, 0 no
ASIAN	Whether child is Asian, 1 yes, 0 no
RACEOTH	Whether child is native Hawaiian, Pacific islander, American Indian, Alaska native or more than one race (non-Hispanic), 1 yes, 0 no
URBAN*	Whether family location in central city, 1 yes, 0 no
SUBURBAN	Whether family location in urban fringe and large town, 1 yes, 0 no
RURAL	Whether family location in small town and rural, 1 yes, 0 no
PARED	Parent highest education, 1 junior high school, 2 senior high school, 3 high school diploma, 4 some college – no degree, 5 Bachelor's degree, 6 master's degree, 7 Doctorate or professional degree
INC	Household annual income in dollars, average between 1998 and 1999
EDEXP	Parent education expectation of child, 1 less than high school diploma, 2 high school diploma, 3 some college, 4 Bachelor's degree, 5 master's degree, 6 PH. D., MD, or other higher degree
EMPLOY	Whether mother worked between child's birth and kindergarten, 1 yes, 0 no
BIRTHW	Child birth weight in pounds, information compiled from 4 surveys
READ	Child's pre-kindergarten human capital as reading IRT score
MATH	Child's pre-kindergarten human capital as math IRT score
GEKN	Child's pre-kindergarten human capital as general knowledge IRT score
HEIGHT	Child height when entering kindergarten
WEIGHT	Child weight when entering kindergarten
PRISCH	Whether kindergarten and/or elementary school is private, 1 yes, 0 no
READG	Gain in reading IRT score after kindergarten and 1st grade
MATHG	Gain in math IRT score after kindergarten and 1st grade
GEKNG	Gain in general knowledge IRT score after kindergarten and 1st grade

Table 2 Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
MALE	0.51	0.50	0	1
WHITE	0.63	0.48	0	1
BLACK	0.14	0.34	0	1
HISPANIC	0.12	0.33	0	1
ASIAN	0.05	0.21	0	1
RACEOTH	0.06	0.24	0	1
URBAN	0.38	0.48	0	1
SUBURBAN	0.39	0.49	0	1
RURAL	0.23	0.42	0	1
PARED	4.20	1.22	1	7
INC*	54519	39497	1	200000
EDEXP	4.08	1.08	1	6
EMPLOY	0.76	0.43	0	1
BIRTHW	7.39	1.32	1	14
READ*	23.53	8.85	10.50	81.26
MATH*	20.53	7.24	7.00	56.91
GEKN*	22.92	7.47	6.99	46.12
HEIGHT	44.71	2.17	35	58
WEIGHT	46.44	8.68	23	100
PRISCH	0.23	0.42	0	1
READG*	33.37	10.14	0.74	64.67
MATHG*	23.77	6.44	0.35	46.90
GEKNG*	12.61	4.71	0.01	38.44

Note: * This is taken the natural logarithm when used in the regression.

Table 3 the Pre-Kindergarten Stage

dependent variable	READ		MATH		GEKN	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
MALE	-0.0599	-11.03	-0.0048	-0.88	0.0138	2.56
BLACK	-0.0492	-5.63	-0.1200	-13.18	-0.2565	-26.46
HISPANIC	-0.1016	-11.20	-0.1236	-13.45	-0.1898	-20.00
ASIAN	0.0505	3.41	0.0125	0.89	-0.2475	-16.83
RACEOTH	-0.0776	-6.47	-0.1037	-8.58	-0.1574	-12.79
SUBURBAN	-0.0039	-0.61	-0.0078	-1.21	-0.0064	-1.03
RURAL	-0.0535	-7.34	-0.0413	-5.50	-0.0249	-3.35
PARED	0.0622	21.02	0.0613	19.57	0.0567	18.13
INC	0.0697	14.97	0.0732	14.06	0.0787	13.49
EDEXP	0.0281	10.40	0.0270	9.58	0.0189	6.73
EMPLOY	**-0.0018**	**-0.27**	**-0.0013**	**-0.20**	**0.0142**	**2.19**
BIRTHW	**0.0108**	**5.18**	**0.0169**	**7.85**	**0.0108**	**5.02**
INTERCEPT	1.9699	42.85	1.7456	34.09	1.9129	33.57
R-Squared	0.2126		0.2245		0.2926	

Table 4 the Formal Schooling Stage

dependent var. READG	OLS Coeff.	OLS t-stat	IV Coeff.	IV t-stat	OLS Coeff.	OLS t-stat	IV Coeff.	IV t-stat
MALE	-0.0601	-9.00	-0.0076	-0.39	-0.0619	-9.20	-0.0116	-0.58
BLACK	-0.1045	-8.73	-0.0541	-2.44	-0.1074	-8.90	-0.0589	-2.61
HISPANIC	-0.0104	-0.95	0.0848	2.46	-0.0096	-0.87	0.0806	2.32
ASIAN	0.0204	1.25	-0.0217	-0.88	0.0222	1.36	-0.0186	-0.75
RACEOTH	-0.0513	-3.38	0.0211	0.68	-0.0516	-3.40	0.0171	0.55
SUBURBAN	-0.0092	-1.24	-0.0066	-0.70	-0.0108	-1.42	-0.0084	-0.89
RURAL	-0.0138	-1.46	0.0345	1.72	-0.0168	-1.76	0.0292	1.45
PARED	0.0225	6.51	-0.0349	-1.79	0.0231	6.66	-0.0314	-1.59
INC	0.0348	6.45	-0.0302	-1.33	0.0359	6.63	-0.0256	-1.12
EDEXP	0.0157	4.44	-0.0101	-1.04	0.0157	4.44	-0.0087	-0.89
HEIGHT					0.0038	1.76	0.0032	1.20
WEIGHT					-0.0001	-0.12	-0.0003	-0.43
PRISCH					-0.0149	-1.86	-0.0158	-1.62
READ	**-0.0039**	**-0.27**	**0.9159**	**2.99**	**-0.0056**	**-0.38**	**0.8681**	**2.80**
INTERCEPT	2.9878	46.76	1.1138	1.77	2.8174	28.65	1.0731	1.70
R-Squared	0.0469		0.048		0.0475		0.0485	
ρ	0		-0.6001		0		-0.5800	
Hausman test:	p-value = 0.0002				p-value = 0.0005			

dependent var. MATHG	OLS Coeff.	OLS t-stat	IV Coeff.	IV t-stat	OLS Coeff.	OLS t-stat	IV Coeff.	IV t-stat
MALE	0.0094	1.61	0.0096	1.45	0.0073	1.26	0.0091	1.55
BLACK	-0.1128	-10.60	-0.0403	-1.73	-0.1171	-10.89	-0.0384	-1.81
HISPANIC	-0.0140	-1.47	0.0574	2.47	-0.0137	-1.43	0.0605	2.90
ASIAN	-0.0249	-1.93	-0.0276	-1.83	-0.0246	-1.91	-0.0313	-2.33
RACEOTH	-0.0508	-4.08	0.0087	0.40	-0.0516	-4.14	0.0115	0.58
SUBURBAN	0.0038	0.58	0.0073	0.96	-0.0004	-0.06	0.0020	0.30
RURAL	-0.0086	-1.03	0.0137	1.18	-0.0149	-1.76	0.0084	0.80
PARED	0.0128	4.35	-0.0220	-2.09	0.0143	4.85	-0.0222	-2.32
INC	0.0180	3.90	-0.0241	-1.83	0.0209	4.47	-0.0231	-1.94
EDEXP	0.0080	2.59	-0.0071	-1.29	0.0083	2.67	-0.0076	-1.53
HEIGHT					0.0046	2.39	0.0005	0.28
WEIGHT					-0.0004	-0.85	-0.0004	-0.76
PRISCH					-0.0373	-5.46	-0.0455	-6.49
MATH	**-0.1274**	**-9.86**	**0.4366**	**2.67**	**-0.1278**	**-9.85**	**0.4744**	**3.21**
INTERCEPT	3.2398	59.28	2.1954	7.12	3.0293	34.14	2.0809	7.36
R-Squared	0.0288		0.0156		0.0314		0.0186	
ρ	0		-0.4721		0		-0.4933	
Hausman test:	p-value = 0.0001				p-value < 0.0001			

dependent var.	OLS		IV		OLS		IV	
GEKNG	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
MALE	0.0334	4.08	0.0151	1.28	0.0329	4.00	0.0155	1.19
BLACK	-0.1476	-10.13	0.1397	1.56	-0.1487	-10.11	0.2308	2.28
HISPANIC	-0.0629	-4.53	0.1488	2.22	-0.0653	-4.70	0.2022	2.68
ASIAN	-0.0356	-1.78	0.2442	2.75	-0.0370	-1.86	0.3132	3.14
RACEOTH	-0.0422	-2.50	0.1326	2.32	-0.0423	-2.51	0.1836	2.87
SUBURBAN	0.0105	1.10	0.0166	1.38	0.0083	0.85	0.0120	0.89
RURAL	0.0080	0.73	0.0336	2.13	0.0053	0.48	0.0375	2.13
PARED	0.0195	4.42	-0.0433	-2.15	0.0206	4.66	-0.0589	-2.61
INC	0.0341	5.40	-0.0543	-1.93	0.0355	5.55	-0.0766	-2.44
EDEXP	0.0186	4.42	-0.0022	-0.27	0.0185	4.42	-0.0073	-0.82
HEIGHT					-0.0043	-1.56	-0.0205	-5.44
WEIGHT					0.0016	2.32	0.0017	1.92
PRISCH					-0.0151	-1.44	-0.0390	-2.67
GEKN	**-0.5512**	**-32.67**	**0.5502**	**1.62**	**-0.5492**	**-32.28**	**0.8846**	**2.32**
INTERCEPT	3.6272	49.35	1.4413	2.13	3.7288	30.39	1.5563	2.02
R-Squared	0.1201		0.0061		0.1207		0.0125	
ρ	0		-0.5851		0		-0.6778	
Hausman test:	p-value = 0.0001				p-value < 0.0001			

Table 5 Over-Identification Test on EMPLOY

dependent var.	READG		MATHG		GEKNG	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
MALE	-0.0057	-0.29	0.0096	1.46	0.0241	2.00
BLACK	-0.0539	-2.43	-0.0405	-1.74	-0.0037	-0.04
HISPANIC	0.0888	2.57	0.0599	2.57	0.0475	0.65
ASIAN	-0.0212	-0.86	-0.0251	-1.66	0.1137	1.18
RACEOTH	0.0239	0.77	0.0104	0.47	0.0483	0.78
SUBURBAN	-0.0062	-0.66	0.0077	1.01	0.0142	1.19
RURAL	0.0355	1.78	0.0135	1.16	0.0195	1.20
PARED	-0.0371	-1.89	-0.0230	-2.18	-0.0130	-0.59
INC	-0.0334	-1.47	-0.0263	-1.99	-0.0138	-0.46
EDEXP	-0.0110	-1.13	-0.0074	-1.34	0.0080	0.96
READ (fitted)	**0.9491**	**3.09**				
MATH (fitted)			**0.4508**	**2.75**		
GEKN (fitted)					**0.0160**	**0.04**
EMPLOY	**0.0189**	**1.85**	**0.0244**	**2.90**	**0.0488**	**3.60**
INTERCEPT	1.0416	1.65	2.1631	7.00	2.4894	3.37
R-Squared	0.0484		0.0165		0.0076	

Table 6 Complementarity with Parent Education Level

dependent variable	READG		MATHG		GEKNG	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
MALE	-0.0084	-0.43	0.0102	1.56	0.0160	1.39
BLACK	-0.0545	-2.47	-0.0416	-1.81	0.1237	1.40
HISPANIC	0.0829	2.42	0.0560	2.44	0.1363	2.06
ASIAN	-0.0188	-0.76	-0.0263	-1.76	0.2325	2.67
RACEOTH	0.0200	0.65	0.0080	0.36	0.1230	2.19
SUBURBAN	-0.0064	-0.69	0.0074	0.98	0.0166	1.41
RURAL	0.0339	1.70	0.0139	1.21	0.0324	2.10
PARED	-0.0489	-2.47	-0.0349	-3.20	-0.0610	-3.04
INC	-0.0298	-1.33	-0.0241	-1.85	-0.0501	-1.82
EDEXP	-0.0098	-1.01	-0.0070	-1.28	-0.0011	-0.15
READ (fitted)	**0.8893**	**2.92**				
READ (fitted)*PAREDH	**0.0181**	**3.88**				
MATH (fitted)			**0.4086**	**2.52**		
MATH (fitted)*PAREDH			**0.0055**	**4.22**		
GEKN (fitted)					**0.4698**	**1.41**
GEKN (fitted)*PAREDH					**0.0262**	**4.70**
INTERCEPT	1.2094	1.94	2.2942	7.51	1.6600	2.49
R-Squared	0.0499		0.0174		0.0084	
ρ	-0.5948		-0.4569		-0.5640	

Table 7 Complementarity with Family Income

dependent variable	READG		MATHG		GEKNG	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
MALE	-0.0085	-0.44	0.0097	1.48	0.0156	1.34
BLACK	-0.0480	-2.18	-0.0375	-1.62	0.1372	1.54
HISPANIC	0.0857	2.50	0.0581	2.51	0.1461	2.19
ASIAN	-0.0193	-0.79	-0.0267	-1.77	0.2393	2.71
RACEOTH	0.0227	0.74	0.0097	0.44	0.1309	2.31
SUBURBAN	-0.0067	-0.72	0.0072	0.95	0.0165	1.38
RURAL	0.0326	1.64	0.0130	1.12	0.0326	2.09
PARED	-0.0335	-1.73	-0.0215	-2.04	-0.0419	-2.10
INC	-0.0562	-2.45	-0.0387	-2.83	-0.0681	-2.36
EDEXP	-0.0093	-0.97	-0.0068	-1.23	-0.0016	-0.21
READ (fitted)	**0.8768**	**2.88**				
READ (fitted)*INCH	**0.0249**	**4.98**				
MATH (fitted)			**0.4180**	**2.56**		
MATH (fitted)*INCH			**0.0144**	**3.54**		
GEKN (fitted)					**0.5157**	**1.53**
GEKN (fitted)*INCH					**0.0145**	**2.40**
INTERCEPT	1.4440	2.31	2.3687	7.60	1.6530	2.45
R-Squared	0.0512		0.0169		0.0067	
ρ	-0.5927		-0.4674		-0.5776	

Table 8 Black and White Comparison

dependent variable	READ		MATH		GEKN	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
MALE	-0.0585	-9.59	-0.0022	-0.36	0.0194	3.27
BLACK	-0.0630	-6.93	-0.1314	-13.87	-0.2734	-27.34
SUBURBAN	-0.0154	-2.12	-0.0194	-2.64	-0.0266	-3.85
RURAL	-0.0576	-7.07	-0.0446	-5.30	-0.0313	-3.88
PARED	0.0593	17.41	0.0627	17.50	0.0521	15.11
INC	0.0592	11.30	0.0608	10.40	0.0670	10.70
EDEXP	0.0351	10.95	0.0332	10.00	0.0283	8.79
EMPLOY	**-0.0006**	**-0.08**	**-0.0019**	**-0.25**	**0.0064**	**0.87**
BIRTHW	**0.0125**	**5.36**	**0.0192**	**7.94**	**0.0136**	**5.79**
INTERCEPT	2.0608	39.88	1.8368	31.87	2.0150	32.68
# of obs.	9505		9505		9505	
R-Squared	0.1872		0.2104		0.2893	

dependent variable	READG		MATHG		GEKNG	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
MALE	-0.0149	-0.80	0.0044	0.61	0.0184	1.52
BLACK	-1.0525	-3.22	-0.7451	-3.06	-2.4416	-8.01
SUBURBAN	0.0006	0.06	0.0081	0.90	0.0090	0.65
RURAL	0.0317	1.53	0.0169	1.36	0.0190	1.23
PARED	-0.0252	-1.41	-0.0151	-1.41	-0.0072	-0.45
INC	-0.0248	-1.31	-0.0169	-1.46	-0.0103	-0.49
EDEXP	-0.0163	-1.43	-0.0086	-1.30	0.0057	0.62
READ (fitted)	**0.7988**	**2.75**				
READ (fitted)*BLACK	**0.3323**	**3.11**				
MATH (fitted)			**0.3183**	**2.00**		
MATH (fitted)*BLACK			**0.2470**	**2.90**		
GEKN (fitted)					**-0.2252**	**-0.78**
GEKN (fitted)*BLACK					**0.8388**	**8.25**
INTERCEPT	1.4075	2.24	2.4524	7.71	3.2457	5.29
R-Squared	0.0523		0.0193		0.0089	
ρ	-0.5651		-0.4176		-0.3413	