Do 'Skills Beget Skills'? Evidence on Dynamic Complementarities in Cognitive and Non-cognitive Skills in Childhood

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Abstract

We use exogenous variation in the skills that children have at the beginning of kindergarten to measure the extent to which “skills beget skills”. Children who are relatively older when they begin kindergarten score higher on measures of cognitive and non-cognitive achievement at the beginning of kindergarten. Their scores on cognitive assessments grow faster during kindergarten and first grade, consistent with complementarities between existing stocks of skills and the acquisition of additional skills. However, after first grade the scores of younger entrants catch up. We find no evidence that the growth in non-cognitive measures differ between older and younger entrants. Finally, we provide evidence suggesting that schools are not the cause of the younger students’ faster growth after first grade.

JEL Codes: I21, J24

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1. Introduction

There is a growing literature that posits that the human capital production function is characterized by complementarities within and between skills (Cunha, Heckman, Lochner, and Masterov 2006; Cunha and Heckman 2007; Aizer and Cunha 2012). Complementarity within skill implies that the return to investments in skill, for example cognitive functioning, is higher for those with a higher initial level of skill. Complementarity between skills, for example between cognitive and non-cognitive functioning, implies that the return to investments in skill is higher for those with a higher initial level of a different, but complementary skill. The importance for public policy of whether human capital accumulation is characterized by such complementarities has been made convincingly by Heckman and colleagues.\(^1\) If there are such complementarities in the production of human capital, then early investment in children’s skill development will have large returns because they raise the return to future investments. This may be especially true for early investments in children from disadvantaged families.

We use exogenous variation in skills at the beginning of kindergarten that are driven by differences in children’s kindergarten entrance age to directly assess whether there are complementarities in the production of skill. Despite its importance, the empirical literature on complementarities in skill production is limited because of the difficulty in identifying exogenous sources of variation in skills. We argue that children’s kindergarten entrance age provides such variation and thus affords an opportunity to study complementarities in skill production.\(^2\) Those who are older when they begin formal schooling do so with a larger accumulated stock of human capital and at a more advanced developmental stage, and as a result, score higher on tests of cognitive ability at the time of entry. If children’s learning process is characterized by complementarities between existing skills and the ability to acquire new skills, then one might expect that older entrants will learn more during kindergarten and each

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\(^1\) See, for example, studies listed at http://www.heckmanequation.org

\(^2\) Most of the variation in children’s age on the first day of kindergarten is driven by the combination of when their birthday happens to fall within the year and the school or state’s kindergarten entrance cut off. The remaining variation in entrance age is driven by the small fraction of children whose parents hold them back a year or have them start earlier than proscribed by their school or state’s entrance law. This type of non-random variation in entrance age is easily accounted for by the instrumental variables strategy we describe below.
subsequent grade, in which case age-related differences in skills grow as children progress through school.

Consider estimates in Figure 1, which shows the percentile score on reading (Panel A) and math (Panel B) tests from kindergarten through eighth grades for a sample selected from the Early Childhood Longitudinal Survey-kindergarten (ECLS-K) cohort. Separate lines are shown for the top and bottom quartile of kindergarten entrance age and the top and bottom quartile of family income. The large differences in test scores between children from richer and poorer families have justly received volumes of attention. Notably, differences in kindergarten test scores between older and younger entrants are on the order of one-third (for reading) to one-half (for math) the size of the differences in scores between the richest and poorest children. In reading, the difference in scores between children from the richest and poorest quartiles of family income is 28 percentile points. The gap between the youngest and oldest quartile of children is nine percentile points. In math, the gap in scores between the richest and poorest quartiles is 31 percentile points, while the gap between the oldest and youngest quartiles of children is 14 percentile points.

Just as the difference in test scores between children from rich and poor families reflects differences in skills, differences in test scores between older and younger entrants also reflect differences in skill. Older entrants had an extra year to experience investments (both directly from their parents and from preschool and other activities). However, unlike differences in skills due to income, differences in skills with respect to entrance age are plausibly exogenous and unrelated to differences in family income or other determinants of achievement. The exogeneity of school entry age provides a credible and innovative way to assess whether a higher initial skill level leads to a more or less rapid accumulation of skills from subsequent investment (schooling)—i.e., whether the production of human capital during childhood is characterized by dynamic complementarities.

Figure 1 also shows how achievement changes over time. After kindergarten, the age-related gaps clearly get smaller while the income-related gaps persist (and perhaps diverge

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3 More precisely, these are the top and bottom quartile of predicted entrance age, the age a child would enter kindergarten if she entered when first allowed to do so according to the state kindergarten entrance cutoff. The sample construction and variable creation is discussed in detail below.
slightly). The convergence in achievement between older and younger school entrants as children progress through school reflected in Figure 1 is consistent with existing evidence that indicates that there is little or no long-term economic payoff to being older at kindergarten entry.\(^4\) This fade out is seemingly inconsistent with the hypothesis of complementarities in the production of human capital, although we argue below that complementarities may be masked or undone by compensating investment decisions by parents, teachers, or schools.

In this paper we investigate the effect of entrance age on cognitive and non-cognitive skills through the lens of an economic model of complementarities in human capital acquisition (Cunha and Heckman 2007). The inclusion of non-cognitive outcomes is a notable contribution of our research. This is an important gap in knowledge because of the growing evidence that socio-emotional attributes (e.g., impulse control, self-regulation) of a child are associated with adult outcomes (Kaestner and Callison 2011; Heckman et al. 2006; Heckman et al. 2013). Indeed, the potential importance of socio-emotional attributes during childhood is underscored by the inability of traditional human capital theory to explain the failure of many families and children to invest in schooling and other forms of human capital that have documented, large benefits. It is unlikely that financial barriers prevent such investment, which opens up the possibility that non-monetary costs of investment, which may depend on behavioral traits such as impulse control, are an explanation for this lack of investment. In addition, the “dynamic complementarity” hypothesis applies to both within-skill and between-skill complementarities, and by examining both types of skill, we provide a more comprehensive assessment of the hypothesis.

To accomplish the goals of our study, we use data from the Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (ECLS-K) and the National Longitudinal Survey of Youth (children of 1979 cohort), and a research design that exploits the discontinuity in age at school entry that is created by state minimum age of entry laws. This research design has been used extensively in several previous studies and it is generally accepted that entry age provides an exogenous source of variation in human capital at the time of school entry.

\(^4\) See Black et al (2011) and Dobkin and Ferreira (2010). Bedard and Dhuey (2012), by contrast, argue that entrance age has a modest effect on adult wages.
Results from our analysis provide mixed evidence for the existence of complementarities in human capital production. On average, between the start of kindergarten and the spring of first grade, the achievement of children who entered school at an older age and at a higher level of achievement experienced larger gains in reading and math test scores. After first grade, though, younger entrants experience faster growth in scores, leading to a convergence with their older peers. In addition, we find no evidence that non-cognitive skills grow faster or slower for older children. Finally, we find no evidence that the convergence in test scores after first grade is due to the influence of schools.

2. Conceptual Model and Empirical Approach

Conceptual Model

The potential effects of age at school entry on cognitive achievement can be examined through the lens of a basic model of human capital accumulation in which parents, schools, and others make investments in children and test scores reflect the accumulated stock of human capital at the time of the assessment. Algebraically, the model can be represented as:

\[
(1) \quad h_{i,t} = h_{i,0} + \sum_{t=1}^{E_t} \{\theta_{i,t} y_{i,t} - \delta h_{i,t-1}\}
\]

where \(h_{i,0}\) is an initial endowment of human capital for child \(i\), \(y_{i,t}\) represents investments by parents in child \(i\) at time \(t\), \(\theta_{i,t}\) is the return to investments, and \(\delta\) is depreciation. We assume that the level of investment depends on the existing level of human capital and the return to investment \([i.e. y_{i,t} = y_{i,t}(h_{i,t-1}, \theta_{i,t})]\), and the return to investment depends on the child’s level of human capital and age \([i.e. \theta_{i,t} = \theta_{i,t}(h_{i,t-1}, Age_{i,t})]\). The dependence of the return to investment on age captures the fact that children’s development is a complex interaction of biological influences and experiences and so the efficacy of a particular investment depends on a child’s brain architecture and biological maturity.\(^5\) The effect of teaching letter and number recognition, for example, depends both on the child’s brain developmental stage and on his or her existing level of human capital.

The human capital model of equation (1) incorporates potential dynamic and complementary aspects of the process of skill formation that have been highlighted and modeled by Cunha and Heckman (2007). Cunha and Heckman (2007) refer to self-productivity, which is the notion that higher levels of skills in one period lead to higher levels of skills in future periods, or \( dh_{i,t}/dh_{i,t-1} > 0 \). This complementarity could come about because the returns to investments are higher among higher ability children \( (d \theta_{i,t}/dh_{i,t-1} > 0) \). A growing, interdisciplinary literature argues that higher-level brain functions depend on lower-level brain functions developed earlier in a child’s life (Knudsen et al 2006; NSCDC 2007). Thus, more able children, or children with better developed capabilities, are more able to process new information and thus have higher returns to future investments.

Dynamic complementarities could also arise if parents (or teachers) invest more in higher ability children \( (dy_{i,t}/dh_{i,t-1} > 0) \), although this type of complementarity is due to behavioral responses and not a consequence of the production function. Alternatively, if parents or teachers divert resources towards under-performing children, this inequality could be negative. Thus, whether “skills beget skills” depends both on how returns to investments respond to the existing level of human capital (i.e. the technology of the production function) and also on how parents and teachers’ investment decisions depend on past human capital (i.e. a behavioral response).

To illustrate the effect of entrance age on achievement at the beginning of kindergarten, compare the achievement of children who began kindergarten at age five and age six, roughly corresponding to the youngest and oldest in a class. Denote the child who begins kindergarten at age six as child \( i \). Her human capital at the beginning of kindergarten is \( h_{i,t} = h_{i,0} + \sum_{t=1}^{6} \{ \theta_{i,t} y_{i,t} - \delta h_{i,t-1} \} \). Similarly, denote the child who begins at age five as child \( j \). Her human capital at the beginning of kindergarten is \( h_{j,t} = h_{j,0} + \sum_{t=1}^{5} \{ \theta_{j,t} y_{j,t} - \delta h_{j,t-1} \} \). Assuming that the level of investments, the returns to investment, and depreciation are the same during the first five years of each child’s life, then the difference in human capital between the two children at the very beginning of kindergarten is \( h_{i,t} - h_{j,t} = \theta_{i,6} Y_{i,6} - \delta h_{i,5} \), which is the net investment that the older child received during the year prior to kindergarten entry. According to equation (1), this difference in achievement at the time of school entry will be positive unless depreciation offsets the investment (negative net investment). Empirically, we find this difference to be
positive; older entrants have a higher level of cognitive achievement than younger entrants when they both start school.

Our principle focus is on differences in the growth of human capital between older and younger school entrants, as this is a direct assessment of the dynamic complementarity hypothesis. Again denote the child who begins kindergarten at age six as $i$ and the child who begins at age five as $j$. From our model of human capital accumulation, child $i$’s growth in scores from one year to the next is given by:

$$(2) \quad h_{i,t} - h_{i,t-1} = \Delta h_{i,t} = \theta_{i,t}Y_{i,t} - \delta h_{i,t-1}$$

which is a measure of the level of net investment in the current period. Similarly, child $j$’s growth is given by $\theta_{j,t}Y_{j,t} - \delta h_{j,t-1}$. The differential growth in human capital between these two children is

$$(3) \quad \Delta h_{i,t} - \Delta h_{j,t} = \{\theta_{i,t}Y_{i,t} - \theta_{j,t}Y_{j,t}\} - \delta\{h_{i,t-1} - h_{j,t-1}\}$$

The difference in the change in human capital between older and younger school entrants reflects the difference in investments, the returns to these investments, and depreciation.

Since, empirically, older entrants begin kindergarten with a higher level of skills than their younger classmates, the dynamic complementarity hypothesis predicts that the return to investment is higher among older children ($\theta_{i,t} > \theta_{j,t}$) and perhaps that older children will also have more investments made in them ($Y_{i,t} > Y_{j,t}$). If both of these inequalities hold, then $\Delta h_{i,t} - \Delta h_{j,t} > 0$ and the gap in skills between older and younger children will diverge. More specifically, in our model, if we observe that older entrants have a faster growth in test scores, it must be the case that either returns are higher for them, investments in them are larger, or both. If we observe the convergence of skills (i.e. that older entrants have a slower growth in scores from one year to the next), then either $\theta_{j,t}Y_{j,t} > \theta_{i,t}Y_{i,t}$, which means that the younger entrant had a higher return and/or had compensating investments made in her; or $\theta_{i,t}Y_{i,t} - \theta_{j,t}Y_{j,t} < \delta\{h_{i,t-1} - h_{j,t-1}\}$, which would be the case if investment differences were small relative to the effect of depreciation. Overall, a valid assessment of the importance of dynamic
complementarities is whether the achievement profiles of older and younger school entrants diverge.

Theoretically, the return to investments of older entrants could be higher because of the effect of the level of skill on the return to skill—dynamic complementarities—or because age has an independent effect on skill accumulation through mechanisms (e.g., brain development) other than cognitive or non-cognitive skill accumulation. We are interested in identifying the former effect—dynamic complementarities—and in the empirical analysis we adjust explicitly for differences in age to control for any potential age effects. Specifically, we include quarter of birth dummy variables so the age variation that is unaccounted for is at most one quarter, which limits the scope for age to be the cause of differences in the growth in cognitive and non-cognitive skills. Moreover, including or excluding these quarter of birth controls has little impact on results. In sum, while we cannot perfectly control for age in the empirical analysis, it is highly unlikely that the differences in growth of skills between older and younger school entrants that we observe empirically is due to age.

**Socio-emotional and Behavioral Outcomes**

The model of human capital investment above can also be used to model children’s socio-emotional and behavioral development, which we also refer to as non-cognitive development. These behavioral skills and traits include self-regulation, attentiveness, persistence, and ability to deal with adversity, among other things, and have been extensively documented and studied (See, for example, Heckman 2007; Center for the Developing Child at Harvard 2011). Many of these skills are developed by parents and through children’s other early-life experiences (such as preschool) and investments. Thus, at the start of kindergarten, we would expect to see that older entrants score higher on measures of non-cognitive abilities, just as they score higher on measures of reading and math ability. Age at school entry will affect a child’s socio-emotional and behavioral development over time if there are complementarities between the acquisition of new non-cognitive skills and the existing level of non-cognitive skills. Thus, the potential differences in development due to different school starting ages that were derived in equations (2) and (5) also apply to non-cognitive outcomes.

The possibility of dynamic effects between cognitive and non-cognitive skills underscores the importance of studying the effect of age at school entry on both cognitive and
non-cognitive developmental outcomes. If age at entry affects cognitive skills, then under a
dynamic model of skill formation, age at entry will also affect non-cognitive skills, which will in
turn affect cognitive skills, and so on. Thus, any initial effect of age at school entry on skill
formation will grow over time if skill formation is complementary between periods and across
types of skills.

**Empirical Specification**

We use this model of human capital accumulation as a guide to interpreting empirical
models of the effect of entrance age on both the level and change over time (between grades) in
skills. We model the level of skills as:

\[
y_{i,t} = \alpha + \beta_t EA_i + \pi_t X_{i,t} + \epsilon_{i,t}
\]

where \(y_{i,t}\) is a reading or math test score, or a measure of non-cognitive skills. \(EA_i\) is the child’s
kindergarten entrance age and \(X_{i,t}\) are time-varying covariates that we describe in more detail
below. \(\epsilon_{i,t}\) is an error term. The effect of entrance age on outcomes is given by \(\beta_t\), which we
allow to vary by grade (in the NLSY-Children) or survey round (in the ECLS-K). As described
above, in the context of our model, the coefficient on entry age, \(\beta_t\), is \(\theta_{i,6} \gamma_{i,6} - \delta h_{i,5}\).

We estimate models of the change in the test scores between two successive rounds of
our surveys to investigate whether these differences in skill lead to differences in subsequent
returns to investments. These models are given by

\[
\Delta y_{it} = \alpha' + \beta'_t EA_i + \pi'_t X_{it} + e_{it}
\]

In the context our model, the coefficient on entrance age, \(\beta'_t\), is described in equation (3) and is
given by \(\{\theta_{i,t} y_{i,t} - \theta_{j,t} y_{j,t}\} - \delta \{h_{i,t-1} - h_{j,t-1}\}\).

**The Role of Schools**

The model above does not distinguish between investments made by parents and by
schools; and both may change over time. Schools and teachers’ objective functions are
potentially varied, are unknown, and may not necessarily align with those of parents. So it is not clear how schools respond to children of different ages and different initial skill levels. In particular, schools may place weight on raising the achievement of the lower-ability students, even at the expense of higher ability students. This is especially true when schools and teachers are evaluated through high-stakes test, such as the fraction of children that meet some minimum score or competency level. More generally, to the extent that schools mix together children of different ability levels in the same classroom, or track students with different abilities into different classrooms, schools can compensate or exacerbate initial skill differences. Thus, even if dynamic complementarities characterize the “private” production function of skill that a child would experience if a parent could optimally invest in their child each period, dynamic complementarities may not characterize the “social” production function of skill. We address this issue empirically, by examining models that include school fixed effects and models of data aggregated to the school level. If schools offset the advantages that older children enjoy, then we should see that the effect of entrance age on the growth of test scores is smaller within schools than between them. These models are discussed in more detail in Section 6.

3. Data

We use data from two surveys: the Early Childhood Longitudinal Study-Kindergarten Class of 1998-1999 (which we refer to below as the ECLS) and the National Longitudinal Survey of Youth-1979-Children and Young Adult Surveys (which we refer to as the NLSY). The ECLS is a longitudinal survey that began with a random sample of over 1000 kindergarten classrooms in the fall of 1998. Children, their parents, teachers, and school administrators were sampled in the fall of 1998, the spring of 1998, the fall of 1999, and in the spring of 2000, 2002, 2004, and 2007, corresponding to on-track children being in first, third, fifth, and eighth grade. We assign to each child in the ECLS the statewide public-school kindergarten cutoff in place in the fall of 1998, even if the child attends a private school. We drop from the sample children who

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6 Neal and Schanzenbach (2010) show that accountability programs lead teachers to shift effort towards children who are on the margin of passing.
live in any of the seven states that did not have a uniform statewide cutoff. A child’s kindergarten entrance age is calculated as his or her age on September 1, 1998 (or 1997, if the child is repeating kindergarten). Our final sample includes approximately 15,000 students in the fall of kindergarten; the exact number varies slightly across dependent variables. There is substantial attrition in the data, however. Our sample sizes in fifth and eighth grades are about 8300 and 6900, respectively. We have re-estimated models using a balanced sample observed over multiple time periods and find similar results to those reported below.

Our measures of cognitive skills are children’s scores on reading and math assessments. These assessments consist of, first, a ten to twenty item routing test. Performance on these questions dictates the difficulty level of a secondary section of the test. The combination of correct answers (and skips) on each section of the test is then used to create an item response theory (IRT) scaled score that is comparable across children at a point in time (even though they were given different sets of questions in the second section of the test) and from one year to the next. The comparability of scores from one survey round to the next is important because it allows us to estimate the difference regression models described above. We also computed each child’s (within-sample) percentile score on each test among children assessed in the same survey round.

Our analysis of the ECLS uses five measures of non-cognitive skills measured by teachers’ reports about children during the kindergarten through fifth grade interviews. The measures are called Approach to Learning, Self-Control, Interpersonal Skills, Externalizing Problem Behaviors, and Internalizing Problem Behaviors. Appendix 1 reproduces information from the ECLS documentation regarding these specific measures. Each measure is designed to capture a difference aspect of a child’s social skills, personality, and ability to learn and form relationships. For example, the “Approach to Learning” scale asks teachers to rate the child’s frequency of exhibiting characteristics such as “shows eagerness to learn new things” and

7 These states are Colorado, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, and Vermont.

8 All children receive the same routing test in kindergarten and first grade. The routing test in subsequent interviews is updated to reflect age-appropriate material. Additional details are available in the ECLS-K user manual (Tourangeau et al 2009).
“works independently.” Teachers use a scale of one (meaning “Never”), two, three, or four (“Very often”) to describe answers to six such questions. The “Approach to Learning” score is given by the simple average of the six scores. The other measures are similarly constructed as averages of underlying responses. For Approach to Learning, Interpersonal Skills, and Self-Control, a higher score means that the child is “better,” so to speak. A lower score is more desirable on the Internalizing Problem Behaviors and Externalizing Problem Behaviors scales.

The National Longitudinal Survey of Youth—Children and Young Adult Surveys provide information on children born to female members of the original NLSY-1979 cohort (who themselves were born between 1957 to 1964 and who were living in the United States in 1978). We focus on children in kindergarten through sixth grade. Children and mothers were interviewed every two years between 1986 (when mothers were aged 22 to 29) and 2010 (when mothers were aged 46 to 53).

Children’s cognitive achievement is measured by the Peabody Individual Achievement Test (PIAT) for math, reading recognition and reading comprehension. The validity and reliability of these assessments are well documented (Baker and Mott 1989). Notably, all children age five and over take the same PIAT test, but begin the test at different points appropriate for their age. A basal and ceiling are established for each child and scores are calculated as the ceiling minus the number of incorrect answers between the basal and ceiling. This provides a consistent metric to assess changes in test scores over time.

Children’s non-cognitive development is measured by the Behavioral Problems Index (BPI), which consists of a total scale and subscales that are created from mothers’ responses to 28 questions about their children’s behavior over the preceding three months (Peterson and Zill 1986). The BPI questions are used to create two separate scales that measure internalizing and externalizing behaviors. The same questions are also grouped into six sub-scales that measure children’s antisocial behavior, anxiousness/depression, headstrongness, hyperactivity, immature dependency, and peer conflict/social withdrawal. We largely find no relationship between entrance age and any of the BPI scales, so for the sake of brevity we only report results using the externalizing and internalizing subscales. Additional details about the questions in the BPI and
the creation of the various subscales are in the documentation for the NLSY-Children and Young Adult Surveys.9

Table 1 provides a descriptive overview of the children in the ECLS and the NLSY, separately by predicted entrance age, the instrument that we use in our analysis below. Predicted entrance age is the age the child’s entrance age if she began kindergarten when first allowed to by state law. This measure of entrance age is determined by the combination of a child’s birthday and the state kindergarten entrance cutoff. Unlike the child’s actual entrance age, predicted entrance age is not affected by parents’ decision to have their children begin kindergarten a year early or late. The median predicted entrance age is 5.3 years old in the ECLS and is 5.4 years old in the NLSY. The difference in predicted entrance age between children above and below the median is, of course, a half of a year in both datasets. The difference in actual entrance age is slightly smaller, 0.4 years in the ECLS and 0.3 years in the NLSY, which reflects that some children who would be younger entrants if they began kindergarten when first allowed to instead “redshirt” and begin kindergarten the following year. Similarly, some children who would be among the oldest children in their class if they started when proscribed by law actually enter a year earlier (either by petitioning their local school or by going to a private school). Both of these choices will reduce the disparity in actual entrance age.

The remainder of the table shows differences in other outcomes measured in kindergarten between children whose predicted entrance age falls above or below the median (and thus these differences can be interpreted as reduced-form effects of a half-year difference in predicted entrance age on outcomes). In the ECLS, older children score 2.7 points higher on the math test and 1.8 points higher on the reading test. The standard deviation of math and reading scores are about 9 and 10, so the differences represent about 30 and 22 percent of the standard deviation. The differences in the PIAT scores in the NLSY range from 0.6 to 0.9 points, or 10 to 15 percent of the standard deviations of these scores.

The next rows of Table 1 indicate that differences in non-cognitive skills between older and younger entrants are small, but noticeable. Recall that the scales in the ECLS range from one to four. The standard deviation of these scales ranges from about 0.5 to 0.7. Older children score

9 See https://www.nlsinfo.org/content/cohorts/nlsy79-children/other-documentation/researchtechnical-reports
0.2 higher (i.e. better) on the Approach to Learning scale and 0.1 points higher (better) on the Interpersonal Skills and Self-Control scales. Lower scores are more desirable on the Internalizing and Externalizing scales and older entrants score about 0.1 points lower than younger entrants in kindergarten. Although these differences are small in magnitude, they represent about 30 percent of the standard deviation in scores. We find no differences in average scores on the Internalizing and Externalizing Behaviors scales in the NLSY.

Finally, the last rows of Table 1 indicate that there are small differences in socioeconomic characteristics between the families of children with above and below average predicted entrance age. In particular, in both datasets, children whose predicted entrance age is below the median tend to have slightly more educated mothers and come from wealthier families. These differences, though small and not always statistically significant, indicate that the unconditional differences in mean outcomes in the table perhaps understate the differences once we control for the separate influences of these socioeconomic outcomes.

4. The impact of entrance age on cognitive and non-cognitive skills in Kindergarten

We begin the analysis with estimates of the association between entrance age and measures of cognitive and non-cognitive skills measured in kindergarten. In the ECLS, the exams are taken in the fall of kindergarten, so differences in scores between older and younger entrants reflect differences in skills acquired before any (or much) kindergarten instruction has taken place. In the NLSY, exams were administered throughout the year so in these models we also condition on the number of months between school entry and when the test was taken. We interpret differences in outcomes between older and younger entrants as reflecting the return to the extra year of investment by parents (and preschools and other influences) during the extra year prior to beginning kindergarten.

We estimate the model:

\[ Y_{ik} = \alpha_k EA_i + \beta_k X_{ik} + \epsilon_{ik} \]

where \( Y_{ik} \) is a measure of cognitive or non-cognitive skills for child \( i \) measured in kindergarten and \( EA_i \) is the child’s kindergarten entrance age. \( X_{ik} \) is a set of control variables measured in
kindergarten and includes the child’s race and Hispanic ethnicity, indicators for parents’ family
type and marital status, census region, urbanicity, parents’ log income and education, the log of
family size, and children’s quarter of birth. If a child has a missing value for any of these
variables, we code the variable as zero. We also include a full set of indicators that a child has
either a missing or imputed value for each covariate. The NLSY models also control for the
mother’s AFQT score.

It is well-known that entrance age may be endogenous because some children start earlier
or later than dictated by the state cutoff. There are a few ways address this endogeneity, though
in practice the results are not very sensitive to the choice. We adopt the approach used in Elder
and Lubotsky (2009), who instrument the actual entrance age, \( EA_i \), with the entrance age the
child would be if she began kindergarten when proscribed by the state entrance law. We refer to
this as the predicted entrance age, \( PEA_i \). To be clear, variation in predicted entrance age arises
from two sources: variation across states in the kindergarten cutoff date and variation in
birthdates relative to the cutoff date.\(^{10}\) Note, however, that our model includes quarter of birth
fixed effects, so our estimates are not affected by unobserved or unmeasured differences between
children born in different seasons.\(^{11}\)

Table 2 shows the relationship between entrance age and cognitive and non-cognitive
outcomes in kindergarten. Each row of the table reports the sample size for the particular model,
the mean and standard deviation of the dependent variable, and then OLS and IV estimates of the
effect of school entry age. The IV estimates from the ECLS data indicate that being a year older
at the start of kindergarten is associated with scoring 7.55 points higher on the math test and 5.44
points higher on the reading test. These differences are large and reflect 83 and 53 percent of the

\(^{10}\) Another method is to use a regression discontinuity design and generate estimates based on a contrast
based on children born on either side of the cutoff. Elder and Lubotsky’s (2009) evidence indicates that
the relationship between entrance age and children’s test scores is close to linear, in which case the RD
and IV methods produce estimates that are similar to one another, though in the Elder and Lubotsky
analysis the RD estimates have larger standard errors. Barua and Lang (2011) discuss the relationship
between these various estimators and alternative policy effects of interest.

\(^{11}\) The association between season of birth and outcomes, and the implications for a variety of research
designs, is studied by Bound and Jaeger (2000), Cascio and Lewis (2006), and Buckles and Hungerman
(2013). In our case, inclusion of the quarter of birth fixed effects has no effect on our estimates and thus
we are confident that within-year patterns of fertility do not materially affect our results.
standard deviation of scores. The results from the NLSY are quite similar: being a year older at entry is associated with a score 3.35 points higher on the PIAT Math test, 2.40 points higher on the reading recognition test, and 2.51 points higher on the reading comprehension test. These effects represent 54, 40, and 48 percent of the standard deviation of scores, respectively.

We also find large effects of entrance age on the non-cognitive outcomes in the ECLS: being a year older at entry is associated with scoring 0.42 points higher on the Approach to Learning scale, which is 62 percent of the standard deviation of the scores. Being a year older is associated with doing better on the remaining four measures in the ECLS, with effect sizes relative to the standard deviation ranging from 30 percent (for Interpersonal skills) to 18 percent (for Externalizing behavior). In the NLSY, however, we find no meaningful relationship between the internalizing and externalizing scores and entrance age.

Overall, estimates in Table 2 confirm the descriptive evidence presented in Figure 1 and are consistent with the previous literature that found substantial differences in cognitive achievement between older and younger school entrants. Our finding of an impact of entrance age on non-cognitive measures in kindergarten, at least for the ECLS sample, is consistent with similar evidence from England presented in Cornelissen et al (2013). It is worth noting that estimates in Table 2 are not sensitive to the inclusion of maternal/family characteristics, which is consistent with the small differences in these factors by entrance age shown in Table 1 and the plausible exogeneity of the instrument. We now turn to an assessment of whether these initial and large differences in skills in kindergarten affect the returns to additional years of schooling.

5. The impact of entrance age on the change in test scores and non-cognitive outcomes

Models of the change in test scores provide a direct assessment of whether an early advantage is associated with faster accumulation of skills. To examine this issue, we estimate models of the form

\[
Y_{it} - Y_{it-1} \equiv \Delta Y_{it} = a_t E A_i + b_t X_{it} + v_{it}
\]
where, as above, $EA_i$ and $X_{it}$ are entrance age and the same covariates described above. The coefficient on entrance age, $a_t$, captures the combined effects of differences in the returns to investments, the quantity of investment, and depreciation between older and younger children. As in the previous section, we instrument entrance age with a child’s predicted entrance age.

Table 3 presents results from instrumental variable estimates of the effect of entrance age on the change in reading and math test scores in the ECLS data. The average change in math test scores between the fall and spring of kindergarten was 10.5 points; the standard deviation of the change was 6.8 points. Being a year older at entry is associated with having a 2.5 point faster growth in math test scores, or 37 percent of the standard deviation of the change in scores. Being a year older at entry is also associated with having 1.3 points faster growth in math test scores between the spring of kindergarten and the spring of first grade; this represents 11 percent of the standard deviation in the growth of scores. The models of reading test scores produce similar results: being a year older at entry is associated with 3.1 points faster growth in scores, or 39 percent of the standard deviation, between the fall and spring of kindergarten. Being a year older is also associated with 4.2 points faster growth in reading test scores between the spring of kindergarten and first grade. This represents 26 percent of the standard deviation in reading scores.

Beyond first grade, however, there is convergence in test scores. From first to third, third to fifth, and from fifth to eighth, being older at entry is associated with slower growth in reading and math test scores. For example, being a year older at kindergarten entry is associated with having 2.9 points slower growth in math scores and 1.6 points slower growth in reading scores between third and fifth grade; these represent 23 and 11 percent of the standard deviations in the growth of scores. Being a year older is associated with 3.0 and 3.7 points slower growth in math and reading scores between fifth and eighth grade – 23 and 21 percent of the standard deviations in the growth of scores.

---

12 In a human capital accumulation framework (Todd and Wolpin 2007), the change in skills is a function of last period investment and returns to that investment (equation 4). Therefore, the model contains variables that proxy for those quantities such as entry age, which is a determinant of the return to investment.

13 To be precise, we estimate changes between successive rounds of the survey, not between actual grade levels. In the ECLS, on track children (i.e. those who are not held back or do not skip a grade) will be in 1st, 3rd, 5th, and 8th grade in each round and we label the tables as changes between these grades.
Table 4 shows analogous results for the NLSY sample.\textsuperscript{14} Estimates indicate that being a year older is associated with faster growth (17\% of a standard deviation) in math achievement between kindergarten and second grade, although not statistically significant, and then slower growth in math scores between first and sixth grades with statistically significant slower growth between second and fifth grades. Estimates for reading recognition and reading comprehension are uniformly small and not statistically different from zero, which indicate that older and younger school entrants had similar growth in reading scores.

Tables 5a, 5b, and 6 present instrumental variables estimates of the effect of entrance age on the change in non-cognitive scores in the ECLS and NLSY. Table 5a shows estimates of the effect of entry age on Approach to Learning, Interpersonal Skills, and Self-control in the ECLS. Table 5b shows similar estimates for Internalizing and Externalizing Behaviors in the ECLS. Table 6 shows results for Internalizing and Externalizing Behaviors in the NLSY. Recall from Table 2 that entrance age is most strongly associated with scoring higher on the Approach to Learning scale.

Estimates in Table 5a indicate that the advantage of older children in kindergarten fades away as children progress through school. Being a year older at entry is associated with a relative decline in the Approach to Learning score between first and third grade of 0.18 points, or 28 percent of the standard deviation of the change in this score, with a further decline of 0.05 points from third to fifth grade. Table 2 also indicated smaller effects of entrance age on Interpersonal Skills and Self-Control scores. The point estimates in Table 5a indicate that these initial differences also fade away, though many of the estimates are not statistically different from zero. The results in Tables 5b and 6 largely show that entrance age is unrelated to changes in the Internalizing and Externalizing Behavior scores (recall, though, that in the NLSY we did not find any differences in these scores at the beginning of kindergarten).

The results in Tables 3 and 4 provide some support for the idea of complementarities in human capital accumulation in kindergarten and first grade in the ECLS, and perhaps in the NLSY for math. The faster growth in test scores among older entrants is consistent with these children having either a higher return to schooling and/or receiving more investments. After first

\textsuperscript{14} In the NLSY, we first observe children in either Kindergarten or 1\textsuperscript{st} grade, so on track children will be in 2\textsuperscript{nd}, 4\textsuperscript{th}, and 6\textsuperscript{th} grade.
grade, test scores between older and younger entrants converge, which is inconsistent with complementarities within and between skills. However, it may be the case that children with higher levels of human capital experience a higher return to investments, but these higher returns are masked by larger investments being made in the human capital of younger children within the grade. We do not find any support for complementarities in non-cognitive scores. Our results in Tables 5a, 5b, and 6 indicate that the initial differences in non-cognitive scores that appear at the beginning of kindergarten fade away as children progress through school. Importantly, our evidence is not consistent with a complementarity between the existing level of cognitive and non-cognitive skills and improvements in non-cognitive skills over time.

6. Do schools offset the initial advantage that older children enjoy?

Teachers and schools may actively or passively work to compress entrance age-related differentials and thereby obscure or undo complementarities in the production of skill. For example, instructional time may be focused on children who are doing poorly. This may be particularly important in the context of high-stakes tests such as those that have arisen with the No Child Left Behind legislation and similar state policies that preceded it. In addition, class materials and lesson plans may be designed for the skill level of the average student, perhaps slowing down the progress of better students, and schools may assign children into classrooms to purposefully mix students with different levels of preparation or skills. We assess the overall contribution of these mechanisms by separately examining how entrance age differences evolve within the same school, compared to how they evolve across schools. If there is a large role for teachers and schools in compressing the distribution of achievement, we would expect entrance age-related differences within the same school to converge over time, especially relative to entrance age effects between schools. For this analysis, we use data only form the ECLS because there is no school identifying information in the NLSY data and too few children per school.

We estimate the effect of entrance age on the level of test scores in the fall of kindergarten and on the subsequent changes in test scores in regression models estimated with school fixed effects (which we refer to as within-school models) and models on data that has been aggregated to the school level (between school models). The between-school model for mean kindergarten test scores at school $s$ is given by
and the between-school model for the growth in test scores is given by

\[
\Delta \overline{Y}_{st} = a_t \overline{EA_s} + b_t \overline{X_{st}} + \overline{\varepsilon_{st}}
\]

where $\Delta \overline{Y}_{st}$ is the change in the average test score for school $s$ from time $t - 1$ to $t$.

Observations in the between-school model are weighted by the number of observations in the school. Our sample for the change in test scores between time $t - 1$ and $t$ are children who remained in the same school in both years. We also omit models of the change in test scores between 5th and 8th grade since under 10 percent of children in the data remain in the same school between those two years.

We instrument the average entrance age in the school, $\overline{EA_s}$, with the average predicted entrance age, $\overline{PEA_s}$. Across-school differences in entrance age (and predicted entrance age) are driven by differences in the distribution of births across the year and, more importantly, by the state kindergarten cutoff. For example, in 1998 the kindergarten entrance cutoff in California was December 2nd and the average entrance age was 5.2 years old. The cutoff in Illinois was September 1st and consequently the average entrance age was 5.4, about two and a half months older. As this example illustrates, the variation in entry age is small and primarily from state variation in entry age laws. It is unlikely that these small entrance age differences will lead to differences in school curriculum, instructional focus, or other mechanisms described earlier that may lead to a masking of complementarities in skill accumulation.

Table 7 presents IV estimates of the effect of entrance age on the growth in scores, estimated from both within- and between-school models. The estimates indicate that, especially after kindergarten, the effect of entrance age on the change in test scores is fairly similar between schools as it is within schools. The within-school estimates indicate that being a year older at entry is associated with an increase in reading and math scores between the fall and spring of kindergarten of about 2.5 and 1.8 points. The between-school estimates indicate that being a year older at entry is associated with a 5.6 point increase in reading scores and a 5.4 point increase in
math scores. From the spring of kindergarten to the spring of first grade, being a year older at entry is associated with an increase in reading and math scores of 4.4 and 1.2 points in the within-school model and with an increase of 3.6 and 1.3 points in the between school model. After first grade, estimates from both between and within school models indicate that there is general convergence in the scores of older and younger children.

The estimates in Table 7 imply that unmeasured school investments are not the cause of the convergence in test scores after first grade and that schools influence is not masking dynamic complementarities of the production function. Small differences in entry age that are driven mostly by different state entry age cutoffs are unlikely to be associated with differences in curriculum and teacher effort that may affect more or less skilled children. If schools were offsetting the initial advantages of older children, we should observe a pattern of greater divergence of test scores between older and younger entrants in the between-school analysis than in the within-school analysis. This is not the case suggesting that schools are not the source of convergence.

7. Conclusions

Understanding if and when there are complementarities in the production of human capital is important for targeting and designing policies to improve the long-run human capital of children from disadvantaged backgrounds. If there are strong complementarities, then early investments in skills may have especially large returns because they increase the level and returns to future investments. While compelling, the empirical literature on complementarities in skills is still very much being developed.

In this paper, we have exploited a large and plausibly exogenous difference in skills at the time of entry to school to directly assess the complementarity hypothesis. Theoretically, if the production function of skill is characterized by complementarities within and between skills, then the documented initial advantage in both cognitive and non-cognitive skills of children who enter at an older age will lead to an increasing advantage in skills because of higher returns to additional investment and possibly greater investment. We test this hypothesis by examining the change in cognitive and non-cognitive skills as children in two large, nationally representative surveys progress through school.
We find some evidence to support the complementarity hypothesis: reading and math test scores grow faster among older entrants during kindergarten and first grade. We find no evidence that non-cognitive skills grow faster for older entrants. After first grade, however, the test scores of younger entrants grow faster than those of their older classmates. These findings are consistent with other work that finds that the effects on test scores from participating in Head Start (Currie and Thomas 1995) or attending a small class in kindergarten (Krueger and Whitmore 2001) fade as children age. Importantly, we provide evidence that the failure to find much support for the dynamic complementarity hypothesis is not because schools are offsetting the initial advantage of older and more skilled entrants.

8. References


Table 1
Sample Means and Proportions of Selected Variables by Predicted Entry Age
Kindergarten Sample

<table>
<thead>
<tr>
<th></th>
<th>ECLS-K</th>
<th>NLSY</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Below Median Predicted Entry Age</td>
<td>Above Median Predicted Entry Age</td>
</tr>
<tr>
<td>Predicted entry age</td>
<td>5.1</td>
<td>5.7</td>
</tr>
<tr>
<td>Actual entry age</td>
<td>5.2</td>
<td>5.6</td>
</tr>
<tr>
<td>Math IRT score</td>
<td>25.0</td>
<td>27.7</td>
</tr>
<tr>
<td>Reading IRT score</td>
<td>34.3</td>
<td>36.1</td>
</tr>
<tr>
<td>App. to Learning</td>
<td>2.9</td>
<td>3.1</td>
</tr>
<tr>
<td>Interpersonal Skills</td>
<td>2.9</td>
<td>3.0</td>
</tr>
<tr>
<td>Self-control</td>
<td>3.0</td>
<td>3.1</td>
</tr>
<tr>
<td>Internalizing Beh.</td>
<td>1.6</td>
<td>1.5</td>
</tr>
<tr>
<td>Externalizing Beh.</td>
<td>1.7</td>
<td>1.6</td>
</tr>
<tr>
<td>Mother HS+</td>
<td>89.0%</td>
<td>87.9%</td>
</tr>
<tr>
<td>Mother college+</td>
<td>24.6%</td>
<td>23.0%</td>
</tr>
<tr>
<td>Parents married</td>
<td>65.3%</td>
<td>63.5%</td>
</tr>
<tr>
<td>Family Income</td>
<td>$55,036</td>
<td>$50,785</td>
</tr>
<tr>
<td></td>
<td>Number of Obs.</td>
<td></td>
</tr>
</tbody>
</table>

|                           | Below Median Predicted Entry Age | Above Median Predicted Entry Age | Difference |
| Predicted entry age       | 5.2                         | 5.7                       | 0.5        |
| Actual entry age          | 5.3                         | 5.6                       | 0.3        |
| PIAT Math                 | 15.1                        | 16.1                      | 0.9        |
| PIAT Read. Rec.           | 17.1                        | 17.7                      | 0.6        |
| PIAT Read. Comp.          | 16.4                        | 17.1                      | 0.7        |
| Internalizing Beh.        | 3.0                         | 2.9                       | -0.0       |
| Externalizing Beh.        | 7.3                         | 7.3                       | -0.0       |
| Mother HS+                | 74.3%                       | 74.3%                     | -0.0       |
| Mother college+           | 14.8%                       | 13.3%                     | -1.5       |
| Parents married           | 63.9%                       | 65.9%                     | 1.9        |
| Family Income             | $42,130                     | $41,396                   | -$734      |
| Mother’s AFQT             | 35.6                        | 34.9                      | -0.7       |
| Number of Obs.            | 1445                        | 1485                      | 40         |

Notes: In the ECLS-K, the sample sizes in the bottom row refer to the number of observations with valid data for the reading test score and all covariates used in the subsequent regressions. The sample sizes for the math test scores and non-cognitive measures are slightly different. Family income in the ECLS-K refers to annual income when the child is in kindergarten and is measured in 1998 dollars. In the NLSY, sample sizes in bottom row refer to the number of observations with valid data for the reading recognition test score and all covariates used in the subsequent regressions. The sample sizes for the math test scores, reading comprehensions test scores, and the non-cognitive measures are slightly different. The median predicted entrance age is 5.3 years old in the ECLS-K and is 5.4 years old in the NLSY.
Table 2
OLS and IV Estimates of the Effect of Entry Age on Cognitive and Non-cognitive Outcomes
Kindergarten Sample

<table>
<thead>
<tr>
<th>ECLS-K (Fall kindergarten)</th>
<th>NLSY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obs.</td>
<td>Mean/ S. D.</td>
</tr>
<tr>
<td>Math IRT</td>
<td>14,887</td>
</tr>
<tr>
<td>Reading IRT</td>
<td>14,039</td>
</tr>
<tr>
<td>Approach to Learning</td>
<td>15,262</td>
</tr>
<tr>
<td>Interpersonal Skills</td>
<td>14,540</td>
</tr>
<tr>
<td>Self-control</td>
<td>14,703</td>
</tr>
<tr>
<td>Internalizing Behavior</td>
<td>14,892</td>
</tr>
<tr>
<td>Externalizing Behavior</td>
<td>15,075</td>
</tr>
</tbody>
</table>

Note: OLS and IV models also control for child’s race and Hispanic ethnicity, the presence of each biological parent in the household, parents’ marital status, Census region, urbanicity, parents’ education, family income, and quarter of birth. If a child has a missing value for any of these variables, we code the variable as zero. We also include a full set of indicators that a child has either a missing or imputed value for each covariate. The NLSY models also control for the mother’s AFQT score. In IV models, actual entry age is instrumented with predicted entry age. Standard errors in the ECLS are clustered at the school level.
<table>
<thead>
<tr>
<th>Change in scores from:</th>
<th>Obs.</th>
<th>Mean/ S. D.</th>
<th>IV</th>
<th>Obs.</th>
<th>Mean/ S. D.</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spring Kindergarten – Fall Kindergarten</td>
<td>14,175</td>
<td>10.45/ 6.81</td>
<td>2.53*/(0.31)</td>
<td>13,363</td>
<td>11.48/ 8.00</td>
<td>3.09*/(0.42)</td>
</tr>
<tr>
<td>1st Grade – Spring Kindergarten</td>
<td>12,037</td>
<td>24.94/ 11.61</td>
<td>1.28*/(0.53)</td>
<td>11,562</td>
<td>31.24/ 15.76</td>
<td>4.17*/(0.73)</td>
</tr>
<tr>
<td>3rd Grade – 1st Grade</td>
<td>10,199</td>
<td>37.04/ 15.41</td>
<td>-1.50*/(0.71)</td>
<td>9,936</td>
<td>49.06/ 19.18</td>
<td>-1.84*/(1.01)</td>
</tr>
<tr>
<td>5th Grade – 3rd Grade</td>
<td>8,147</td>
<td>24.03/ 12.68</td>
<td>-2.86*/(0.74)</td>
<td>8,095</td>
<td>22.84/ 14.72</td>
<td>-1.62*/(0.82)</td>
</tr>
<tr>
<td>8th Grade – 5th Grade</td>
<td>6,565</td>
<td>16.87/ 13.09</td>
<td>-3.01*/(0.74)</td>
<td>6,513</td>
<td>18.49/ 17.77</td>
<td>-3.68*/(1.06)</td>
</tr>
</tbody>
</table>

Notes: All models condition on the covariates described in the text and in the note to Table 2. Actual entry age is instrumented with predicted entry age.
<table>
<thead>
<tr>
<th>Change in scores from:</th>
<th>Obs.</th>
<th>Mean/ S. D.</th>
<th>IV</th>
<th>Obs.</th>
<th>Mean/ S. D.</th>
<th>IV</th>
<th>Obs.</th>
<th>Mean/ S. D.</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>2nd Grade – Kindergarten</td>
<td>1479</td>
<td>16.24/8.37</td>
<td>1.45/(1.27)</td>
<td>1460</td>
<td>17.25/8.46</td>
<td>1.21/(1.27)</td>
<td>1349</td>
<td>15.25/8.65</td>
<td>0.22/(1.35)</td>
</tr>
<tr>
<td>3rd Grade – 1st Grade</td>
<td>1562</td>
<td>16.04/8.29</td>
<td>-1.95/-(1.04)</td>
<td>1560</td>
<td>14.73/7.98</td>
<td>0.38/-(1.01)</td>
<td>1451</td>
<td>13.19/8.27</td>
<td>-0.18/-(1.09)</td>
</tr>
<tr>
<td>4th Grade – 2nd Grade</td>
<td>1502</td>
<td>12.44/8.41</td>
<td>-3.21* / -(1.34)</td>
<td>1498</td>
<td>11.85/7.70</td>
<td>0.11/-(1.21)</td>
<td>1450</td>
<td>9.75/8.76</td>
<td>0.66/-(1.45)</td>
</tr>
<tr>
<td>5th Grade – 3rd Grade</td>
<td>1515</td>
<td>9.12/8.12</td>
<td>-2.46* / -(1.03)</td>
<td>1517</td>
<td>10.02/7.64</td>
<td>0.21/-(0.98)</td>
<td>1482</td>
<td>8.29/8.49</td>
<td>-0.66/-(1.09)</td>
</tr>
<tr>
<td>6th Grade – 4th Grade</td>
<td>1440</td>
<td>6.96/7.55</td>
<td>-0.98/-(1.07)</td>
<td>1443</td>
<td>9.21/8.45</td>
<td>-0.56/-(1.21)</td>
<td>1422</td>
<td>6.68/9.02</td>
<td>0.04/-(1.32)</td>
</tr>
</tbody>
</table>

Notes: All models condition on the covariates described in the text and in the note to Table 2. Actual entry age is instrumented with predicted entry age.
Table 5a
IV Estimates of the Effect of Entry Age on the Change in Non-cognitive Outcomes
Early Childhood Longitudinal Study

<table>
<thead>
<tr>
<th>Change in scores from:</th>
<th>Obs.</th>
<th>Mean/ S. D.</th>
<th>IV</th>
<th>Obs.</th>
<th>Mean/ S. D.</th>
<th>IV</th>
<th>Obs.</th>
<th>Mean/ S. D.</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spring Kindergarten – Fall Kindergarten</td>
<td>14079</td>
<td>0.13/0.53</td>
<td>0.00/(0.02)</td>
<td>13349</td>
<td>0.15/0.56</td>
<td>0.03/(0.03)</td>
<td>13544</td>
<td>0.09/0.54</td>
<td>0.00/(0.03)</td>
</tr>
<tr>
<td>1st Grade – Spring Kindergarten</td>
<td>10839</td>
<td>-0.10/0.67</td>
<td>-0.01/(0.04)</td>
<td>10616</td>
<td>-0.04/0.70</td>
<td>0.03/(0.04)</td>
<td>10703</td>
<td>-0.02/0.66</td>
<td>0.06/(0.04)</td>
</tr>
<tr>
<td>3rd Grade – 1st Grade</td>
<td>7814</td>
<td>-0.01/0.65</td>
<td>-0.18*/(0.04)</td>
<td>7657</td>
<td>-0.03/0.70</td>
<td>-0.05/(0.05)</td>
<td>7711</td>
<td>0.01/0.65</td>
<td>-0.09*/(0.04)</td>
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<tr>
<td>5th Grade – 3rd Grade</td>
<td>6764</td>
<td>0.01/0.64</td>
<td>-0.05/(0.04)</td>
<td>6557</td>
<td>0.00/0.69</td>
<td>-0.06/(0.05)</td>
<td>6654</td>
<td>0.03/0.64</td>
<td>-0.06/(0.04)</td>
</tr>
</tbody>
</table>

Notes: All models condition on the covariates described in the text and in the note to Table 2. Actual entry age is instrumented with predicted entry age.
### Table 5b

IV Estimates of the Effect of Entry Age on the Change in Non-cognitive Outcomes

**Early Childhood Longitudinal Study**

<table>
<thead>
<tr>
<th>Change in scores from:</th>
<th>Internalizing Behavior</th>
<th></th>
<th>Externalizing Behavior</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Obs.</td>
<td>Mean/ S. D.</td>
<td>IV</td>
<td>Obs.</td>
</tr>
<tr>
<td>Spring Kindergarten – Fall Kindergarten</td>
<td>13652</td>
<td>0.04</td>
<td>-0.01</td>
<td>13866</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.49</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>1st Grade – Spring Kindergarten</td>
<td>10613</td>
<td>0.04</td>
<td>0.03</td>
<td>10736</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.62</td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>3rd Grade – 1st Grade</td>
<td>7665</td>
<td>0.04</td>
<td>0.01</td>
<td>7756</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.63</td>
<td>(0.04)</td>
<td></td>
</tr>
<tr>
<td>5th Grade – 3rd Grade</td>
<td>6582</td>
<td>0.01</td>
<td>0.01</td>
<td>6699</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.62</td>
<td>(0.04)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: All models condition on the covariates described in the text and in the note to Table 2. Actual entry age is instrumented with predicted entry age.
<table>
<thead>
<tr>
<th>Change in scores from:</th>
<th>Obs.</th>
<th>Mean/ S. D.</th>
<th>IV</th>
<th>Mean/ S. D.</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>2nd Grade – Kindergarten</td>
<td>1555</td>
<td>0.11</td>
<td>0.07</td>
<td>1519</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.69</td>
<td>(0.39)</td>
<td>4.95</td>
<td>(0.74)</td>
</tr>
<tr>
<td>3rd Grade – 1st Grade</td>
<td>1579</td>
<td>-0.10</td>
<td>-0.14</td>
<td>1513</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.77</td>
<td>(0.37)</td>
<td>5.03</td>
<td>(0.69)</td>
</tr>
<tr>
<td>4th Grade – 2nd Grade</td>
<td>1531</td>
<td>-0.18</td>
<td>-0.08</td>
<td>1485</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.74</td>
<td>(0.43)</td>
<td>5.27</td>
<td>(0.84)</td>
</tr>
<tr>
<td>5th Grade – 3rd Grade</td>
<td>1542</td>
<td>-0.35</td>
<td>0.02</td>
<td>1466</td>
<td>-0.14</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.52</td>
<td>(0.32)</td>
<td>4.93</td>
<td>(0.66)</td>
</tr>
<tr>
<td>6th Grade – 4th Grade</td>
<td>1460</td>
<td>-0.94</td>
<td>-0.73*</td>
<td>1400</td>
<td>-0.17</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.54</td>
<td>(0.36)</td>
<td>5.04</td>
<td>(0.74)</td>
</tr>
</tbody>
</table>

Notes: All models condition on the covariates described in the text and in the note to Table 2. Actual entry age is instrumented with predicted entry age.
### Table 7

**IV Estimates of the Effect of Entry Age on Change in Cognitive Outcomes**

*Between-school versus within-school estimates*

*Early Childhood Longitudinal Study Sample*

<table>
<thead>
<tr>
<th></th>
<th>IRT Reading Within School</th>
<th>IRT Reading Between School</th>
<th>IRT Math Within School</th>
<th>IRT Math Between School</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Changes in test scores</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spring Kindergarten – Fall Kindergarten</td>
<td>2.49* (0.38)</td>
<td>5.60* (1.20)</td>
<td>1.82* (0.31)</td>
<td>5.41* (0.90)</td>
</tr>
<tr>
<td>1st Grade – Spring Kindergarten</td>
<td>4.41* (0.83)</td>
<td>3.56* (1.91)</td>
<td>1.21* (0.60)</td>
<td>1.25 (1.44)</td>
</tr>
<tr>
<td>3rd Grade – 1st Grade</td>
<td>-1.38 (1.20)</td>
<td>-3.12 (2.15)</td>
<td>-0.67 (0.92)</td>
<td>-1.43 (1.77)</td>
</tr>
<tr>
<td>5th Grade – 3rd Grade</td>
<td>-2.23* (1.11)</td>
<td>-2.17 (1.59)</td>
<td>-3.02* (0.91)</td>
<td>-1.80 (1.52)</td>
</tr>
</tbody>
</table>

Notes: Sample size is reported below each estimate. The within-school model contains school fixed effects. The between school model is estimated on data aggregated to the school level and weighted by the number of observations per school, as described in the text. All models condition on the covariates described in the text and in the note to Table 2, at either the individual level or averaged to the school level. Actual entry age is instrumented with predicted entry age.
Panel A:

Panel B:

Note: Each figure shows the average percentile score, by survey round, for four non-mutually exclusive groups: children from the bottom quartile of predicted entrance age, children from the top quartile of predicted entrance age, children from the top quartile of current family income, and children from top quartile of current family income.
Appendix 1: Description of Non-cognitive Measures in the ECLS-K

We use five measures of non-cognitive skills that are based on teachers’ reports about children’s behaviors. See text and Tourangeau et al (2009) for details. The following lists the five measures and the associated description taken from the ECLS-K manual:

**Approaches to Learning:** “[M]easures behaviors that affect the ease with which children can benefit from the learning environment. It includes six items that rate the child’s attentiveness, task persistence, eagerness to learn, learning independence, flexibility, and organization.”

**Self-Control:** This scale “has four items that indicate the child’s ability to control behavior by respecting the property rights of others, controlling temper, accepting peer ideas for group activities, and responding appropriately to pressure from peers.”

**Interpersonal Skills:** This scale has five items that “rate the child’s skill in forming and maintaining friendships, getting along with people who are different, comforting or helping other children, expressing feelings, ideas and opinions in positive ways, and showing sensitivity to the feelings of others.”

**Externalizing Problem Behaviors:** Measures “acting out behaviors. Five items on this scale rate the frequency with which a child argues, fights, gets angry, acts impulsively, and disturbs ongoing activities.”

**Internalizing Problem Behavior:** This scale “asks about the apparent presence of anxiety, loneliness, low self-esteem, and sadness. This scale comprises four items.”