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Do ‘Skills Beget Skills’? Evidence on the effect of kindergarten entrance age on the evolution of cognitive and non-cognitive skill gaps 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” in this context. 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. However, after first grade the scores of younger entrants catch up. We find no evidence that the growth in non-cognitive measures differs 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.

1. Introduction

This paper assesses whether children who have a greater stock of cognitive and non-cognitive skills at the beginning of kindergarten experience greater gains in these skills in subsequent years. There is good reason to suspect that they may: A growing literature that posits that the human capital production function is characterized by complementarities within and between skills (Aizer & Cunha, 2012; Cunha & Heckman, 2007; Cunha, Heckman, Masterov, & Lochner, 2006). 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. Despite its importance, the

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[1] See, for example, studies listed at http://www.heckmanequation.org.

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0272-7757/

empirical literature on complementarities in skill production is limited because of the difficulty in identifying exogenous sources of variation in skills and because these effects may be context specific.

We use exogenous variation in cognitive and non-cognitive skills at the beginning of kindergarten that are driven by differences in children's kindergarten entrance age to directly assess whether students who enjoy an initial skill advantage accumulate additional skills at a faster rate. 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 assessments of cognitive and non-cognitive ability at the time of entry.[2] 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 subsequent grade, in which case age-related differences in cognitive skills (and perhaps non-cognitive skills) grow as children progress through school.

Consider estimates in Fig. 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 Study, Kindergarten Class of 1998–99 (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.[3] 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. This 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.

Fig. 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 slightly). The convergence in achievement between older and younger school entrants as children progress through school reflected in Fig. 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 children's developmental processes or 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 & Heckman, 2007). The inclusion of non-cognitive outcomes is a notable contribution of our research.[5] 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 (Heckman, 2007; Heckman, Pinto, & Savelyev, 2013; Kaestner & Callison, 2011). 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.

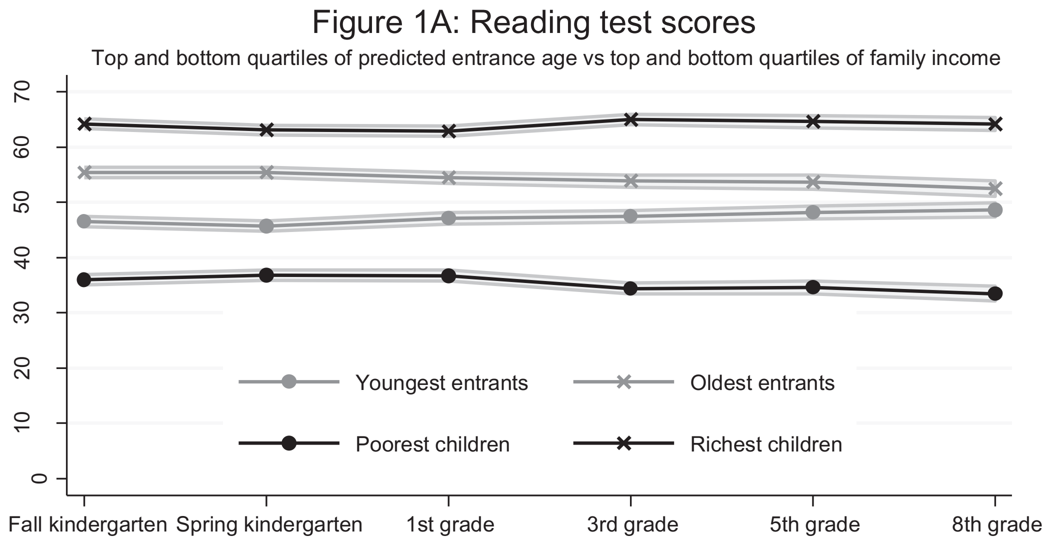
To accomplish the goals of our study, we use data from the Early Childhood Longitudinal Study, Kindergarten Class of 1998–99 (ECLS-K) and the National Longitudinal Survey of Youth (children of 1979 cohort), and a research design that exploits the discontinuity in age at school entry that

[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 cutoff. 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.

[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.

[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, but not educational attainment. The literature on the effect of entrance age on test scores is large and generally concludes that older children score higher and this effect is particularly large in early grades. See Bedard and Dhuey (2006), Elder and Lubotsky (2009), and Fletcher and Kim (2016).

[5] Coincident with our work, Dee and Sievertsen (2015) also investigate the relationship between school starting age and several mental health measures.



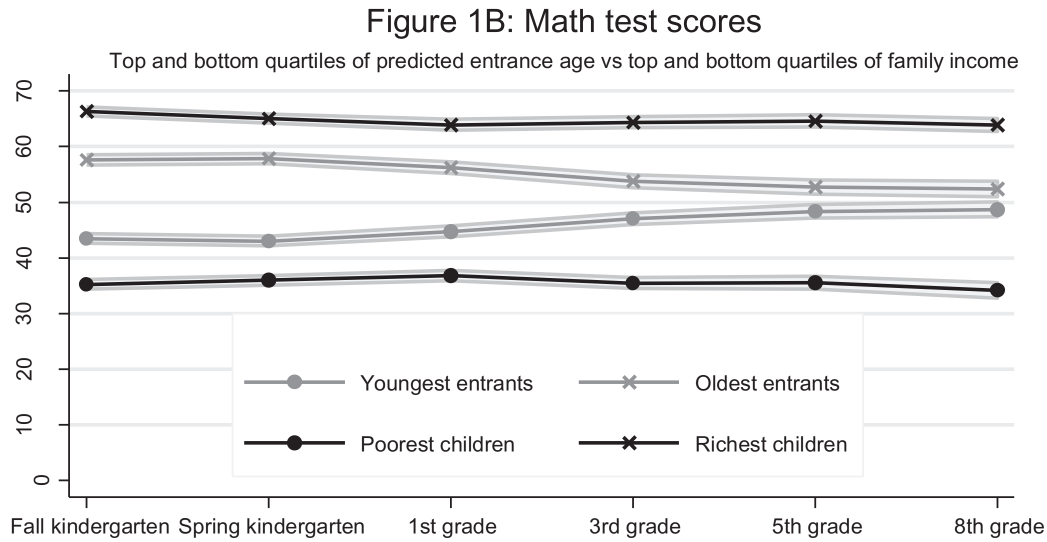


Fig. 1. (a) Reading test scores: Top and bottom quartiles of predicted entrance age vs top and bottom quartiles of family income. (b) Math test scores: Top and bottom quartiles of predicted entrance age vs top and bottom quartiles of family income. Note: The figure shows the average percentile score, 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. Shaded areas indicate 95% confidence intervals.

is created by state kindergarten 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.

We reach the following conclusions: first, we show that children who are older when they begin kindergarten score higher on tests of reading and math ability and also higher on various assessments of non-cognitive ability. We reiterate that while the literature on entrance age and cognitive assessments is fairly deep, there is much less known about the relationship between entry age and non-cognitive skills. Our second conclusion is that, 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 thus at a higher level of both cognitive and non-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. This is important because it suggests that if there are complementarities in the production function for cognitive skills, they are either undone by compensating investments by parents or schools or are not sufficiently strong to counteract an aging effect. In addition, we find no evidence that non-cognitive skills grow faster or slower for older children. Finally, we assess whether there is greater convergence in cognitive scores among children in the same school, which would be expected if convergence was due to compensating investments by schools or teachers in lower-performing students. We find no evidence that this is the case.

2. Conceptual model of cognitive and non-cognitive achievement

The potential effects of age at school entry on 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 and depreciation from past investments. Denote a measure of cognitive or non-cognitive ability for child i at age t as $h_{i,t}$. Ability at age t is a function of a fixed endowment h_0 and the accumulation of investments $\gamma_{i,s}$ made in each prior period, and their returns $\theta_{i,s}$:

$$h_{i,t} = \alpha_t h_{i,0} + \sum_{s=1}^{t} \theta_{i,s}\gamma_{i,s} \tag{1}$$

As Todd and Wolpin (2003) point out, the term $\alpha_t h_0$ can be thought of as a quasi-fixed factor that reflects ability that varies with age or, equivalently, mental capacity that expresses itself differently at different ages. $\gamma_{i,s}$ captures investments in human capital by parents, schools, and others when the child is age s. For notational simplicity we ignore depreciation of human capital.

We assume that the level of investment at age s depends on the existing level of human capital and the return to investment [*i.e.* $\gamma_{i,s} = \gamma_{i,s}(h_{i,s-1}, \theta_{i,s})$], and the return to investment depends on the child's level of human capital and age [i.e. $\theta_{i,s} = \theta_{i,s}(h_{i,s-1}, s)$]. 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.[6] 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 Eq. (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 $(dh_{i,s})/dh_{i,s-1} > 0$. This complementarity could come about because the returns to investments are higher among higher ability children ($d\theta_{i,s}/dh_{i,s-1} > 0$). A growing, interdisciplinary literature argues that higher-level brain functions depend on lower-level brain functions developed earlier in a child's life (Knudsen, Heckman, Cameron, & Shonkoff, 2007; 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 ($d\gamma_{i,s}/dh_{i,s-1} > 0$), 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 underperforming children, then $d\gamma_{i,s}/dh_{i,s-1}$ could be negative. Thus, whether "skills beget skills" (in a causal sense) 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). Clearly, these are context-specific and depend on the scope that parents, teachers, and others have to react to children's level of development. So these complementarities may exist in some contexts and not others.

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 $h_{i,6} = \alpha_6 h_{i,0} + \sum_{s=1}^{6} \theta_{i,s}\gamma_{i,s}$ Similarly, denote the child who begins at age five as child *j*. Her human capital at the beginning of kindergarten is $h_{j,5} = \alpha_5 h_{j,0} + \sum_{s=1}^{5} \theta_{j,s}\gamma_{j,s}$. For simplicity, assume that these two children had the same investments and returns during the first five years of their lives. Then the difference in human capital between the two children at the very beginning of kindergarten is

$$h_{i,6} - h_{j,5} = \left(\alpha_6 h_{i,0} - \alpha_5 h_{j,0}\right) + \theta_{i,6}\gamma_{i,6} \tag{2}$$

The difference in achievement at the beginning of kindergarten reflects both an age effect and the extra year of investment received by the older entrant. That is, even if these children have the same endowment (i.e. $h_{i,0} = h_{j,0}$), their age differences will contribute to differences in measured achievement.

Empirically, we find this difference to be positive; older entrants have a higher level of cognitive achievement than younger entrants when assessed in the fall of kindergarten. This is consistent with past work by Datar (2006), who was the first to study entrance age effects in kindergarten in the ECLS-K, among others. Note that it is generally not possible to separately identify the age effect in Eq. (2) from the effects of investments and their returns. Elder and Lubotsky (2009) show that entrance age effects in the fall of kindergarten are larger among children from richer families and suggest that this reflects a higher level of investment.

Our principal focus is on differences in the growth of human capital between older and younger school entrants. 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 the beginning of kindergarten to the beginning

[6] See National Scientific Council on the Developing Child [NSCDC] (2007).

of first grade is given by:

$$h_{i,7} - h_{i,6} = \Delta h_{i,7} = (\alpha_7 - \alpha_6)h_{i,0} + \theta_{i,7}\gamma_{i,7} \quad (3)$$

which again is an amalgam of an age effect and investment in the current period. Similarly, child j's growth is given by $(\alpha_6 - \alpha_5)h_{j,0} + \theta_{j,6}\gamma_{j,6}$. The differential growth in human capital between these two children is

$$\Delta h_{i,7} - \Delta h_{j,6} = \left\{(\alpha_7 - \alpha_6)h_{i,0} - (\alpha_6 - \alpha_5)h_{j,0}\right\} + \left\{\theta_{i,7}\gamma_{i,6} - \theta_{j,6}\gamma_{j,6}\right\} \quad (4)$$

The difference in the change in human capital between older and younger school entrants reflects the difference in the aging process, investments, and the returns to these investments. Again, it is generally not possible to separately identify the contributions of the age effects from the contributions of investment and their returns.

The difference in human capital between older and younger entrants could grow or shrink as children age and progress through school. Even if the children have the same endowment or mental capacity ($h_{i,0} = h_{j,0}$), the age effects could lead achievement to diverge or converge (or diverge and then converge). One would presume that these effects generally converge to a constant as children age. So as children age, differences in achievement growth are more reflections of differences in investment.

The investment terms could also lead to either divergence or convergence. If the return to investment is higher among older (and more-skilled) children ($\theta_{i,s} > \theta_{j,s}$) and older children have more investments made in them ($\gamma_{i,s} > \gamma_{j,s}$), then $\theta_{i,s}\gamma_{i,s} - \theta_{j,s}\gamma_{j,s} > 0$ and the gap in skills between older and younger children may diverge. More generally, if the complementarity between the existing stock of skills and future investments or returns is sufficiently high, the gap in scores between older and younger children will tend to grow. There may be convergence in scores if parents or teachers make compensating investments in younger (and less-skilled) children ($\gamma_{i,s} < \gamma_{j,s}$) with a goal of catching them up to their more advanced peers. It could be the case that older or more-skilled children have higher returns, but because of a compensating motive receive fewer investments than their less-skilled peers.

The model of human capital investment above speaks to both cognitive and non-cognitive skill formation. Non-cognitive, or 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, Center for the Developing Child at Harvard 2011; Heckman, 2007). 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 may 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. 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.

3. Empirical models

We use our 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 estimate the model:

$$Y_{ik} = \alpha_k EA_i + \beta_k X_{ik} + \varepsilon_{ik} \quad (5)$$

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, urbanicity, parents' log income and education, the log of family size, children's quarter of birth, and fixed effects for the child's state of residence when he or she began kindergarten. 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. The effect of entrance age on outcomes is given by β_k. As described above, in the context of our model, the coefficient on entry age, β_k, is $(\alpha_6 h_{i,0} - \alpha_5 h_{j,0}) + \theta_{i,6}\gamma_{i,6}$.

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 to 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 in the year proscribed by the state entrance law. We refer to this as the predicted entrance age, PEA_i. Our model includes fixed effects for the state in which the child began kindergarten, so variation in predicted entrance age comes from variation in birthdates relative to the state cutoff.[7] Note, however, that our model includes quarter of birth fixed effects, so our estimates are

[7] Estimates without state fixed effects are nearly identical. These estimates include variation in entrance age based on variation across states in the cutoff. 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 (2015) discuss the relationship between these various estimators and alternative policy effects of interest.

not affected by unobserved or unmeasured differences between children born in different seasons.[8]

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

$$\Delta Y_{it} = \alpha_t' EA_i + \beta_t' X_{it} + e_{it} \tag{6}$$

In the context our model, the coefficient on entrance age, α_t', is described in Eq. (4). Again, we instrument actual entrance age with predicted entrance age.

4. 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 1999, 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 live in any of the seven states that did not have a uniform statewide cutoff.[9] 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.[10] 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 A 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 "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 and 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 22–29) and 2010 (when mothers were aged 46–53).

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 & 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 level and ceiling level are established for each child and scores are calculated as the ceiling minus the number of incorrect answers between the basal and ceiling levels. 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 & Zill, 1986). The BPI questions are used to create two sepa-

[8] 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.

[9] These states are Colorado, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, and Vermont.

[10] 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).

Table 1
Sample means and proportions of selected variables by predicted entry age Kindergarten sample.

ECLS-K				NLSY			
	Below median predicted entry age	Above median predicted entry age	Difference		Below median predicted entry age	Above median predicted entry age	Difference
Predicted entry age	5.1	5.7	0.5*	Predicted entry age	5.2	5.7	0.5*
Actual entry age	5.2	5.6	0.4*	Actual entry age	5.3	5.6	0.3*
Math IRT score	25.0	27.7	2.7*	PIAT Math	15.1	16.1	0.9*
Reading IRT score	34.3	36.1	1.8*	PIAT Read. Rec.	17.1	17.7	0.6*
				PIAT Read. Comp.	16.4	17.1	0.7*
App. to learning	2.9	3.1	0.2*				
Interpersonal skills	2.9	3.0	0.1*				
Self-control	3.0	3.1	0.1*				
Internalizing Beh.	1.6	1.5	−0.1*	Internalizing Beh.	3.0	2.9	−0.0
Externalizing Beh.	1.7	1.6	−0.0*	Externalizing Beh.	7.3	7.3	−0.0
Mother HS+	89.0%	87.9%	−1.2*	Mother HS+	74.3%	74.3%	−0.0
Mother college+	24.6%	23.0%	−1.6*	Mother college+	14.8%	13.3%	−1.5
Parents married	65.3%	63.5%	−1.9*	Parents married	63.9%	65.9%	1.9
Family income	$55,036	$50,785	−$4251*	Family Income	$42,130	$41,396	−$734
				Mother's AFQT	35.6	34.9	−0.7
Number of Obs.	7142	6897	245	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 median predicted entrance age is 5.3 years old in the ECLS-K and is 5.4 years old in the NLSY. Asterisk indicates differences are statistically significant at the five percent level.

rate scales that measure internalizing and externalizing behaviors. The same questions are also grouped into six subscales 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.[11]

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 would be on September 1 of the year she began kindergarten 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% of the standard deviation. The differences in the PIAT scores in the NLSY range from 0.6 to 0.9 points, or 10–15% 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 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% of the standard deviation in scores. We find no differences in average scores

[11] See https://www.nlsinfo.org/content/cohorts/nlsy79-children/other-documentation/researchtechnical-reports.

Table 2
OLS and IV estimates of the effect of entry age on cognitive and non-cognitive outcomes Kindergarten sample.

ECLS-K (Fall kindergarten)					NLSY				
	Obs.	Mean/S. D.	OLS	IV		Obs.	Mean/S. D.	OLS	IV
Math IRT	14,887	25.83	4.90*	7.58*	PIAT Math	2975	15.60	1.09**	2.69**
		9.09	(0.27)	(0.39)			6.19	(0.19)	(0.91)
Reading IRT	14,039	35.15	3.41*	5.16*	PIAT Read. Recognition.	2929	17.42	0.98**	2.47**
		10.21	(0.33)	(0.46)			5.92	(0.19)	(0.89)
Approach to learning	15,262	2.96	0.28*	0.49*	PIAT Read. Comp.	2805	16.78	0.76**	2.44**
		0.68	(0.02)	(0.03)			5.25	(0.17)	(0.81)
Interpersonal skills	14,540	2.96	0.12*	0.20*					
		0.63	(0.02)	(0.03)					
Self-control	14,703	3.06	0.10*	0.13*					
		0.62	(0.02)	(0.03)					
Internalizing behavior	14,892	1.55	−0.07*	−0.13*	Internalizing Behavior	3127	2.95	0.22**	0.23
		0.53	(0.01)	(0.02)			2.81	(0.09)	(0.40)
Externalizing behavior	15,075	1.65	−0.08*	−0.13*	Externalizing Behavior	3090	7.25	0.39**	−0.27
		0.65	(0.02)	(0.03)			5.62	(0.18)	(0.80)

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, state, 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. Asterisk indicates that a coefficient is statistically significant at the five percent level.

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 are small (and not statistically significant in the NLSY) and reflect the well-known seasonal pattern in births. Although we control for these and other covariates in our models, the estimates are virtually unchanged if we omit these controls. Thus, we are not concerned about omitted variables bias.

5. 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 (Eq. 5). 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.

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.[12] The IV estimates from the ECLS data indicate that being a year older at the start of kindergarten is associated with scoring 7.58 points higher on the math test and 5.16 points higher on the reading test. These differences are large and reflect 83% and 51% of the standard deviation of scores. The results from the NLSY are quite similar: being a year older at entry is associated with a score 2.80 points higher on the PIAT Math test, 2.57 points higher on the reading recognition test, and 2.41 points higher on the reading comprehension test. These effects represent 45%, 43%, and 46% 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 0.43 points higher on the Approach to Learning scale, which is 63% 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% (for Interpersonal skills) to 18% (for Externalizing behavior). In the NLSY, however, we find no meaningful relationship between the internalizing and externalizing scores and entrance age.

Overall, the estimates in Table 2 confirm the descriptive evidence presented in Fig. 1 and are consistent with the previous literature that found substantial differences in cognitive achievement between older and younger school entrants (Datar 2006; Elder & Lubotsky, 2009; Cornelissen, Dustmann, & Trentini, 2013). 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 (Cornelissen et al., 2013) and Denmark (Dee & Sievertsen, 2015). It is worth emphasizing 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.

[12] The first-stage F-statistic for the instruments are about 2600 in the ECLS and about 130 in the NLSY.

Table 3
IV estimates of the effect of entry age on the change in cognitive outcomes Early childhood longitudinal study.

Change in scores from:	IRT math			IRT reading		
	Obs.	Mean/S. D.	IV	Obs.	Mean/S. D.	IV
Spring kindergarten – Fall kindergarten	14,175	10.45	1.89*	13,363	11.48	2.81*
		6.81	(0.31)		8.00	(0.41)
1st grade – Spring kindergarten	12,037	24.94	1.26*	11,562	31.24	3.89*
		11.61	(0.52)		15.76	(0.72)
3rd grade – 1st grade	10,199	37.04	−1.31	9936	49.06	−1.02
		15.41	(0.76)		19.18	(1.04)
5th grade – 3rd grade	8147	24.03	−2.36*	8095	22.84	−2.05*
		12.68	(0.75)		14.72	(0.88)
8th grade – 5th grade	6565	16.87	−3.44*	6513	18.49	−3.19*
		13.09	(0.80)		17.77	(1.18)

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. Asterisks indicate that a coefficient is statistically significant at the five percent level.

6. 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. 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 (Eq. 5 above).[13] 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 1.9 point faster growth in math test scores, or 28% 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% 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 2.8 points faster growth in scores, or 35% of the standard deviation, between the fall and spring of kindergarten. Being a year older is also associated with 3.9 points faster growth in reading test scores between the spring of kindergarten and first grade. This represents 25% 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 2.4 points slower growth in math scores and 2.1 points slower growth in reading scores between third and fifth grade; these represent 19% and 14% of the standard deviations in the growth of scores. Being a year older is associated with 3.4 and 3.2 points slower growth in math and reading scores between fifth and eighth grade – 26% and 18% of the standard deviations in the growth of scores. The convergence in scores between older and younger entrants is consistent with other evidence by Bedard and Dhuey (2006) and Fletcher and Kim (2016) who study 4th and 8th grade NAEP test scores and show that effects are larger in 4th grade than 8th grade in the United States.

Table 4 shows analogous results for the NLSY sample.[14] Estimates indicate that being a year older is associated with faster growth (31% 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 indicates 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 0.2 points, or 31% of the standard deviation of the change in this score, with a further decline of 0.06 points from third to fifth grade. Table 2 also indicated smaller effects of entrance age on Interpersonal Skills and Self-Control scores in the fall of kindergarten. 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

[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.

[14] In the NLSY, we first observe children in either Kindergarten or 1st grade, so on-track children will be in 2nd (3rd), 4th (5th), and 6th grade.

Table 4
IV estimates of the effect of entry age on the change in cognitive outcomes National longitudinal survey of youth.

Change in scores from:	PIAT math			PIAT reading recognition			PIAT reading comprehension		
	Obs.	Mean/S. D.	IV	Obs.	Mean/S. D.	IV	Obs.	Mean/S. D.	IV
2nd Grade – kindergarten	1479	16.24	2.14	1460	17.25	0.36	1349	15.25	0.84
		8.37	(1.70)		8.46	(1.61)		8.65	(1.69)
3rd grade – 1st grade	1560	16.04	−3.15**	1559	14.73	0.36	1450	13.19	−0.71
		8.29	(1.28)		7.98	(1.25)		(8.27)	(1.36)
4th grade – 2nd grade	1502	12.44	−3.07	1498	11.85	2.25	1450	9.75	0.47
		8.41	(1.90)		7.70	(1.72)		8.76	(2.00)
5th grade – 3rd grade	1515	9.12	−3.32**	1517	10.02	0.17	1482	8.29	0.59
		8.12	(1.36)		7.64	(1.30)		8.49	(1.43)
6th grade – 4th grade	1440	6.96	−1.66	1443	9.21	−0.04	1422	6.68	−0.65
		7.55	(1.61)		8.45	(1.82)		9.02	(1.98)

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.

Change in scores from:	Approach to learning			Interpersonal skills			Self-control		
	Obs.	Mean/S. D.	IV	Obs.	Mean/S. D.	IV	Obs.	Mean/S. D.	IV
Spring kindergarten – Fall kindergarten	14,079	0.13	−0.03	13,349	0.15	−0.04	13,544	0.09	−0.00
		0.53	(0.03)		0.56	(0.03)		0.54	(0.03)
1st grade – Spring kindergarten	10,839	−0.10	−0.01	10,616	−0.04	0.03	10,703	−0.02	0.09*
		0.67	(0.03)		0.70	(0.04)		0.66	(0.04)
3rd grade – 1st grade	7814	−0.01	−0.20*	7657	−0.03	−0.07	7711	0.01	−0.09*
		0.65	(0.04)		0.70	(0.05)		0.65	(0.04)
5th grade – 3rd grade	6764	0.01	−0.06	6557	0.00	−0.04	6654	0.03	−0.06
		0.64	(0.04)		0.69	(0.05)		0.64	(0.04)

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. Asterisks indicate that a coefficient is statistically significant at the five percent level.

Table 5b
IV estimates of the effect of entry age on the change in non-cognitive outcomes Early childhood longitudinal study.

Change in scores from:	Internalizing behavior			Externalizing behavior		
	Obs.	Mean/S. D.	IV	Obs.	Mean/S. D.	IV
Spring Kindergarten – Fall kindergarten	13,652	0.04	−0.01	13,866	0.05	0.00
		0.49	(0.02)		0.48	(0.02)
1st grade – Spring kindergarten	10,613	0.04	0.05	10,736	0.01	−0.05
		0.62	(0.03)		0.60	(0.03)
3rd grade – 1st grade	7665	0.04	0.02	7756	0.06	0.05
		0.63	(0.04)		0.58	(0.04)
5th grade – 3rd grade	6582	0.01	−0.04	6699	−0.05	0.08*
		0.62	(0.04)		0.56	(0.04)

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. Asterisks indicate that a coefficient is statistically significant at the five percent level.

Table 6
IV estimates of the effect of entry age on the change in non-cognitive outcomes National longitudinal survey of youth.

Change in scores from:	Internalizing behavior			Externalizing behavior		
	Obs.	Mean/S. D.	IV	Obs.	Mean/S. D.	IV
2nd grade – kindergarten	1555	0.11	0.21	1519	0.53	1.20
		2.69	(0.51)		4.95	(0.98)
3rd grade – 1st grade	1577	−0.10	−0.47	1511	0.09	0.36
		2.77	(0.46)		4.99	(0.85)
4th grade – 2nd grade	1531	−0.18	−0.05	1485	0.19	0.04
		2.74	(0.58)		5.27	(1.15)
5th grade – 3rd grade	1542	−0.35	0.37	1466	−0.14	0.70
		2.52	(0.43)		4.93	(0.89)
6th grade – 4th grade	1460	−0.94	−0.32	1400	−0.17	0.43
		2.54	(0.55)		5.04	(1.16)

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. Asterisks indicate that a coefficient is statistically significant at the five percent level.

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 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.

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

Much of children's human capital development takes place within schools and so a natural question is whether schools and teachers act to compress or exacerbate entrance age skill differentials. 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.[15] 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. Or, if schools track students based on their relative performance, initial skill differences may be more likely to persist or grow.[16] 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 from the ECLS because schools are not identified in the NLSY and there are likely not multiple children per school in the data.

The effect of entrance age on the level and change in outcomes can be decomposed into an effect of the child's age relative to average entrance age in a school and the effect of the school average entrance age. That is, $EA_i = (EA_i - \overline{EA_s}) + \overline{EA_s}$. These two sources of variation in entrance age may reflect different underlying factors. For example, if teachers target their time and resources towards low-achieving students within a classroom, initial skill differences may be more likely to fade away and $(EA_i - \overline{EA_i})$ may have a negative effect on the growth in scores.

While there is of course a lot of variation in $(EA_i - \overline{EA_s})$, there is also variation across schools in the average entrance age because of differences in states' school entry 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. These differences across schools may be too small to generate any behavioral responses by teachers and schools.

In this subsection we separately estimate the effects of these sources of variation in entrance age on the change in cognitive achievement. The effect of $(EA_i - \overline{EA_s})$ on outcomes is measured by including school fixed effects in IV models that are otherwise similar to those in Eq. (6). The effect of $\overline{EA_s}$ is estimated by aggregating the data to the school level and estimating the model:

$$\Delta\overline{Y_{st}} = a_t\overline{EA_s} + b_t\bar{X}_{st} + \overline{\varepsilon_{st}} \quad (7)$$

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 is 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% 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, $\overline{PEA_s}$. Finally, the between-school models omit state fixed effects since we rely on across-state variation in average entrance age to identify these models.

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 4.6 point increase in reading scores and a 5.5 point increase in math scores. The larger estimates from the between-school model are consistent with schools targeting resources towards younger entrants.

Beginning in first grade, the estimates from the two models are largely similar. 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 2.6 and 3.3 points in the between-school

[15] Neal and Schanzenbach (2010) show that accountability programs lead teachers to shift effort towards children who are on the margin of passing.

[16] Mühlenweg and Puhani (2010) demonstrate that younger children within a grade in Germany are less likely to be placed into a more academically rigorous track.

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				
	IRT reading Within school	Between school	IRT math Within school	Between school
Changes in test scores				
Spring kindergarten – Fall kindergarten	2.49*	4.62*	1.82*	5.55*
	(0.38)	(1.05)	(0.31)	(0.79)
	13,056	788	13,845	791
1st grade – Spring kindergarten	4.41*	2.56	1.21*	3.29*
	(0.83)	(1.70)	(0.60)	(1.30)
	10,486	827	10,929	830
3rd grade – 1st grade	−1.38	−0.39	−0.67	−1.44
	(1.20)	(1.91)	(0.92)	(1.56)
	8238	1130	8441	1138
5th grade – 3rd grade	−2.23*	−2.04	−3.02*	−2.26
	(1.11)	(1.40)	(0.91)	(1.34)
	6547	1139	6583	1142

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. Asterisks indicate that a coefficient is statistically significant at the five percent level.

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 similarity in the estimates from the two models suggests that the factors that lead to the convergence in test scores between older and younger entrants are at work both within and across schools. It still may be the case that teachers focus resources on younger entrants, though it may also be the case that schools with younger average ages adjust their curriculum slightly to better match the average skills of the students. These estimates are also consistent with convergence in scores reflecting a general aging effect whereby differences in human capital acquired early in life fade away and overwhelm any complementarities in the human capital production process.

8. 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.

We have made three contributions to the growing body of evidence on early childhood skill formation. First, we have shown that older children in a kindergarten class perform better on both cognitive and non-cognitive assessments. The existing literature has focused on cognitive skills. Our inclusion of non-cognitive skills is important because of the growing body of evidence that non-cognitive skills are important determinants of later childhood and adult outcomes. Second, we exploited the large and plausibly exogenous difference in skills at the time of entry to school to directly assess whether initial skill advantages lead to faster accumulation of new skills. 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 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 & Thomas, 1995) or attending a small class in kindergarten (Krueger & Whitmore, 2001) fade as children age. Our final contribution is to assess whether there is relatively more convergence between older and younger entrants within schools than across then. This would be the case if teachers or schools acted to offset the skill advantages of older students by, for example, focusing more attention on younger or less-able students. Our evidence indicates that there is not disproportionately more convergence within schools, which suggests that the convergence in scores may reflect offsetting investments by parents or a natural aging process in which skills acquired earlier in life are less relevant for later achievement.

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Appendix A. 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, Nord, Lê, Sorongon, and Najarian (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."

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