The Effects of Kindergarten-Entry Age, Age-at-Evaluation, and Schooling on Educational Achievement

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Abstract

This study separately estimates the effects of kindergarten-entry age, age-at-test, and schooling on cognitive skills using a new identification strategy. These three variables are considered to be perfectly multicollinear in the period of compulsory schooling so that it is deemed that it is not possible to identify their effects separately. I exploit summer break as a period when age increases but schooling does not. The summer break and the variations in survey date in the NLSY79-CS make it possible to resolve the multicollinearity problem. The instrumental variable estimation results show that kindergarten-entry age has a positive effect on math and reading scores. The aging without schooling during the summer break does not improve any test score. Schooling is the most important factor that improves the cognitive skills among the three factors. The IV estimation with sibling fixed effects and the Regression Discontinuity estimation are also conducted as robustness tests and the results are consistent with the IV estimation results.

Keywords: School-entry age; Schooling; Age-at-test; Educational achievement; Multicollinearity

JEL classification: I20, I28, H75

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1 Introduction

This study separately estimates the effects of kindergarten-entry age, schooling, and age-at-test on educational achievement. These three variables are considered to be perfectly multicollinear in the period of compulsory schooling (current age = school starting age + schooling) so that it is deemed that it is not possible to identify their effects on educational achievement separately. For example, Angrist and Pischke (2009) suggest this as an example of a fundamentally unidentified question which cannot be answered even by any ideal experiment: "There is no way to disentangle the effect of start age on learning from maturation and time-in-school effects as long as kids are still in school..." (p. 6). The main goal of this study is to suggest a new identification strategy that resolves the multicollinearity problem and estimate the three effects.

Estimating these three effects separately is important for evaluating kindergarten-entry age policies that have been frequently changed in the United States. 28 states changed their kindergarten-entry cutoff 58 times in total from 1975 to 2008 and most of the changes were to move their cutoffs to earlier dates of the year (Fletcher and Kim, 2016). Moving state kindergarten-entry cutoff to an earlier date of the year increases the minimum permissible age that students can enroll in kindergarten so that the average kindergarten-entry age and the average age of students at times when they take the national assessments increase. For example, children born on September 2, 2000, through September 1, 2001 are supposed to enter kindergarten in 2006 in states with a September 1^{st} cutoff, while children born on December 2, 2000 through December 1, 2001, are expected to enter school in 2006 in states with a December 1^{st} cutoff so that the average age of children in states with a September 1^{st} cutoff is older than that of children in states with a December 1^{st} cutoff at any given point in time.

Bedard and Dhuey (2011) explain that state policymakers may have an incentive to adopt earlier kindergarten-entry cutoffs because (1) it can enhance school readiness rates of children; (2) average school-entry age and age-at-test increase by having an earlier cutoff and this can improve state average scores in the national standardized exams; (3) it also leads to a temporary reduction in education spending because of a reduction in cohort size in the year when the cutoff changes. There are a few studies that show state kindergarten-entry cutoff is related to skill accumulation in childhood. Fletcher and Kim (2016) show that earlier kindergarten-entry cutoff increases state average scores in the NAEP (The National Assessment of Educational Progress) in 4th and 8th grades. Bedard and Dhuey (2011) report that earlier cutoff increases hourly wages of males. The evidence from the literature provides the minimum grounds that validate the state kindergarten-age policies in the U.S. over the past 40 years.

While policy makers might prefer to adopt earlier kindergarten-entry cutoffs if the policy can increase state average scores in the national assessments, it may not be a valid policy if the higher scores are derived mostly from increased age-at-test not from increased kindergarten-entry age by earlier cutoffs. As the real question for policy evaluation is whether children should stay at home longer or should start school earlier, we first need to compare the relative effectiveness for enhancing children's skills between parenting children at home and educating them in school around the period of kindergarten entry.[1] Estimating the three effects separately, therefore, is crucial for evaluating the effects of kindergarten-entry age policies on children's skill development.

There is a wide literature on school-entry age effect. Most of the previous studies, however, do not separately estimate school-entry age effect and age-at-test effect because of the perfect mulicolinearity problem between the three variables. Instead, these studies estimate the combined effect of school-entry age and age-at-test focusing on resolving the endogeneity problem in kindergarten-entry age variable. As parents can make their child enter earlier than the minimum permissible entry age or hold their child out of school for one year, there are students whose actual kindergarten-entry age is different from assigned kindergarten-entry age, which is determined by state kindergarten-entry cutoff and date of birth. This decision for school-entry timing can be correlated with unobservable characteristics of children and parents so that the actual entry age is an endogenous variable. Most of the previous literature uses monthly or daily calculated entry-age predicted by state kindergarten-entry cutoff and date of birth as an instrument for the actual entry age and estimates the combined effect of kindergarten-entry age and age-at-test. This literature commonly finds that the combined effect is significantly positive and the magnitude of the effect decreases over time (Bedard and Dhuey, 2002; Datar, 2006; Elder and Lubotsky, 2008; Fredriksson and Öckert, 2013; McEwan and Shapiro, 2008).

[1] Analyzing monetary benefits and costs of having early kindergarten-entry cutoff is beyond the scope of this study. Cannon and Lipscomb (2008) and Bedard and Dhuey (2011) point out that education cost can be temporarily reduced from change of the cutoff to an earlier date because of the temporary reduction in cohort size. Earlier cutoffs, however, may increase childcare cost for parents and may also affect maternal employment.

To the best of my knowledge, Black, Devereux, and Salvanes (2011) is the only study that separately estimates school-entry age effect and age-at-test effect. Using the variations in age that people are supposed to take an IQ test before entering the military in Norway, they estimate the effects separately. Their estimation results show that age-at-test positively affects the IQ score and the effect of school-entry age is negative. The absolute value of age-at-test effect is greater than that of school-entry age effect so that the combined effect is positive. This raises the possibility that the positive combined effect founded in the previous literature can be mostly from age-at-test effect and provokes the necessity of prudence in interpreting the positive combined effect as a positive school-entry age effect.

These effects, however, are estimated for people at around age 18, and it is not certain that this result holds for students at younger ages. Since many previous studies commonly report that the combined effect is greater at younger ages and it dissipates over time, it is important to estimate kindergarten-entry age effect at younger ages and to figure out changing patterns of the effect over time. I estimate the effects of kindergarten-entry age and age-at-test separately for students from kindergarten to 7th grade and analyze how the effects change over time. More importantly, this study also estimates the effect of schooling and compares the three effects, which are important for policy evaluation as mentioned.

The key idea is to use summer break and variations in survey date in the NLSY79-CS to resolve the multicollinearity problem among the three variables. I consider summer break as a period when age increases but schooling does not change.[2] The variations in survey date and the summer break make it possible to identify the three effects separately. For example, assume that a group of children were one month older at school-entry than the other group of children in the same class. If the first group was surveyed in July, while the second group was surveyed in August in a given year, then children in these groups have the same schooling and age. Any difference in test scores between the two groups can be attributed to the difference in kindergarten-entry age. Age-at-test effect is identified similarly. Consider children in two groups that have the same kindergarten-entry age. If children in the first group who were surveyed in August and those in the second group took tests in July, then children in the first group are one month older at the survey. Any difference

[2]Carlsson et al. (2015) use a similar idea to estimate the effects of schooling and age-at-test on IQ scores in Sweden.

in test scores between the two groups is interpreted as the effect of age-at-test. Schooling effect is identified by changes in test scores during school term excluding age-at-test effect, which is already identified.

In the other aspect, the investigation of changes in educational achievement during the summer break (age-at-test effect) in this study is closely related to a vast literature in sociology and education on skill loss of students during the summer break. The literature mostly reports that educational achievement of children declines during the summer break, especially for children from lower socioeconomic families (Cooper et. al 1996; Alexander, Entwisle, and Olson 2007). One issue in this literature is a measurement problem. One of the ideal analyses is to compare test scores at the beginning and the end of summer break. This exact comparison was not done in the most previous literature (Cooper et. al, 1996) and the estimated summer learning loss was contaminated by schooling effect in part. As there are lots of variations in test dates in summer break in the NLSY79-CS, this study not only improves on the previous literature by resolving the measurement issue but also clearly shows how children's educational achievement evolves over the summer break.

The other issue in estimating the three effects is an endogeneity problem in kindergarten-entry age and schooling. I resolve the endogeneity problem of kindergarten-entry age and schooling by constructing instruments for them. The actual kindergarten-entry age is instrumented by the assigned kindergarten-entry age determined by kindergarten-entry cutoff and date of birth. Schooling is also endogenous by the school-entry timing decision: children who enter kindergarten earlier than the minimum permissible age are supposed to have more schooling and those who enter later are expected to have less schooling at any given point in time. Schooling is instrumented by expected schooling, which is determined by the assigned school-entry age and survey date.

The IV estimation results show that kindergarten-entry age is positively associated with cognitive skill measures. The effect is more substantial in mathematics than reading tests. Schooling has the greatest impacts on all cognitive test scores. For the pooled sample, being one year older at school-entry increases PIAT-Math score by 41.0 percentage of the standard deviation, while an additional year of schooling increases the score by 72.9 percentage of the standard deviation. The analysis by expected grade shows that the effects of kindergarten-entry age and schooling are positive in all grades. For reading tests, the effect of kindergarten-entry age is significant only in earlier grades. Schooling effect is greater than the effect of kindergarten-entry age in all grades for both math and reading tests. Age-at-test effect is negative in most grades for math and negligible for reading tests.

This study conducts several robustness tests. The first test is to include sibling fixed effects as a way of controlling unobservable household characteristics. The second test is to estimate the three effects using the Regression Discontinuity (RD) approach to relieve the concern raised by Barua and Lang (2016) and Aliprantis (2014) that the assigned school-entry age instrument may violate the monotonicity condition. Both estimation results are consistent with the baseline IV estimation results. Finally, I estimate the combined effect of school-entry age and age-at-test and that of schooling and age-at-test to check whether the results of this study are consistent with previous literature or if they are specific to the NLSY79-CS. The results are consistent with previous literature in the sense that the combined effect of school-entry age and age-at-test is greater in earlier grades and the effect tends to decrease over time. Both the combined effects are very precisely estimated in most grades and the results clearly show that the combined effect of schooling and age-at-test is greater than the combined effect of kindergarten-entry age and age-at-test. This confirms again that schooling has a greater effect on test scores than kindergarten-entry age.

This study unfolds as follows. Section 2 explains the empirical strategy for estimating the three effects. Section 3 introduces data. Section 4 conducts graphical analyses. Section 5 discusses the validity of instruments. Section 6 reports the estimation results. Section 7 conducts robustness tests. Section 8 discusses the implications of the results. Section 9 concludes.

2 Empirical Strategy

This study estimates the following equation that describes how school-entry age, age-at-test, and schooling affect educational outcomes.

$$Y_{it} = \beta_0 + \beta_1 EA_i + \beta_2 S_{it} + \beta_3 A_{it} + X_{it}\beta_4 + \epsilon_{it} \tag{1}$$

where Y_{it} is an educational outcome, EA_i is school-entry age, S_{it} is schooling, A_{it} is age-at-test, X_{it} is a vector of other regressors, and ϵ_{it} is an error term of an individual i at time t.

There are two challenging problems in estimating model (1). The first problem is the perfect multicollinearity problem among kindergarten-entry age, age-at-test, and schooling. The multicollinearity problem comes from the fact that current age is perfectly determined by kindergarten-entry age and schooling in general, A_{it}=EA_i+S_{it}. It is regarded that it is impossible to estimate the three effects β_1, β_2, and β_3 separately because of the problem. The second problem is an endogeneity problem in school-entry age (EA_i) and schooling (S_{it}) variables. Both variables are affected by a parents' decision on child's school-entry timing.

In the remaining parts of this section, I first explain the empirical strategy that is commonly employed in previous literature to estimate the combined effect of school-entry age and age-at-test and show that most literature could not estimate the three effects separately because of the multicollinearity problem. I introduce a new identification strategy that can circumvent the multicollinearity problem. I then explain the instrumental variable estimation strategy to resolve the endogeneity problem.

The following econometric model has been used in most previous literature.

$$Y_{it} = \delta_0 + \delta_1 EA_i + X_{it}\delta_2 + \epsilon_{it} \tag{2}$$

where Y_{it} is an educational achievement and X_{it} is a vector of other regressors of an individual i at time t. The main reasons why researchers use this specification are that (1) test scores are not comparable in general if students take different tests; (2) date-at-test information is generally not available in data or there is little variation in test date so that age-at-test variable cannot be calculated or there is little variation in age-at-test among students with the same date of birth. There is also little variation in schooling among students; (3) more fundamentally, there is perfect multicollinearity among school-entry age, age-at-test, and schooling in general even though all the three variables can be acquired.

In most data sets that include test score information, there is no variation in schooling within the same grade, $S_{it} = S_t$. Because of the same schooling among students at survey and the perfect multicollinearity among kindergarten-entry age, age at test, and schooling, we have the following equation, $A_{it} = S_t + EA_i$. If we plug it in equation (1), then we acquire equation (2):

$$\begin{aligned} Y_{it} &= \beta_0 + (\beta_2 + \beta_3)S_t + (\beta_1 + \beta_3)EA_i + X_{it}\beta_4 + \epsilon_{it} \\ &= \delta_0 + \delta_1 EA_i + X_{it}\delta_2 + \epsilon_{it} \end{aligned}$$

where S_t is a period of schooling that students commonly have at survey time t, $\delta_0 = \beta_0 + (\beta_2 + \beta_3)S_t$, $\delta_1 = \beta_1 + \beta_3$, and $\delta_2 = \beta_4$. When δ_1 is estimated using the equation (2) in the previous literature, it is the combined effect of school-entry-age effect and age-at-test effect, $\beta_1 + \beta_3$. The effects of age-at-test and schooling cannot be estimated.

This study estimates the effects of school-entry age, age-at-test, and schooling separately using a new identification strategy. Several characteristics of the NLSY79-CS data give an opportunity to use the new identification strategy and to estimate model (1). First, the raw scores of tests in the NLSY79-CS are comparable regardless of times when students take the tests. Cognitive skill tests conducted in the NLSY79-CS are standardized tests and we can compare test scores even though respondents take the tests at different times. Second, the NLSY79-CS includes the exact interview date information and there are enough variations in interview date. These two characteristics enable us to calculate the exact age-at-test and schooling measured at a daily level and there are sufficient variations in the two variables. After acquiring all the three key variables, I use the summer break to resolve the multicollinearity problem.

Figure 1 describes an example how the utilization of summer break can resolve the multicollinearity problem among school entry age, age-at-test, and schooling. Panel (a) of Figure 1 depicts an example that identifies school-entry age effect. Assume that there is a student who enrolled in kindergarten at 5.2 years old and was interviewed on June 20 when she was a sixth grader. There is another identical student who began school at 5-year-old and was interviewed on August 31 in the sixth grade. This example can be taken from a real-world example that the first student was born on June 20 and the second was born on August 31, and kindergarten-entry cutoff of their state of residence is September 1. In this example, their ages should be approximately the same as 11 years old and have about 4.8 years of school education at the interview.[3] The only

[3] Again, the identification is possible because it is assumed that the period from June 20 to Labor Day is summer break and students do not have school education during this period. Since I assume that the length of summer vacation is two and half months, students have approximately 0.79 years of education in each grade.

difference is their kindergarten-start age. The difference in educational outcomes between these two identical students, therefore, can be thought of as kindergarten-entry age effect.

Panel (b) of Figure 1 presents how the age-at-test effect is identified. Two students started kindergarten at the same age and have the same amount of schooling. They were, however, interviewed at different dates so that their ages at interview are different. The first student is 0.2 years older than the second student since he was interviewed on August 31, while the second student was interviewed on June 20. Comparing educational outcomes of these two students make it possible to identify the age-at-test effect. Using the identified school-entry age effect and age-at-test effect, the schooling effect can be identified. Panel (c) of Figure 1 shows an example how schooling effect is identified using the identified age-at-test effect. The first student has 0.25 years more school education and 0.25 years older than the second student. The gap in educational achievement between these students is from differences in age-at-test and schooling. Since the age-at-test effect is already identified, the schooling effect can be extracted.

In model (1), kindergarten-entry age and schooling are endogenous variables since they are affected by the decision of school-entry timing by parents. To resolve the endogeneity problem, I estimate model (1) using the instrumental variable approach. There are two endogenous variables so that we need to have two instruments for them. I use assigned school-entry age, which is determined by student's date of birth and state-kindergarten-entry cutoff, as an instrument for the actual school-entry age EA_i. The expected schooling, which is determined by kindergarten-entry cutoff, date of birth, and survey date, is used as an instrument for the actual schooling S_{it}. The validity of the instruments is based on the assumption that date of birth for children and survey date are randomly determined, which may be reasonable.[4] Even though these are not directly testable, I conduct several indirect tests for the exogeneity assumption in Section 4. The following equations (3) and (4) describe the first stage regressions in the IV estimation for equation (1).

$$EA_i = \pi_0 + \pi_1 Z_{1i} + \pi_2 Z_{2it} + \pi_3 A_{it} + X_{it}\Pi_4 + \nu_{it} \tag{3}$$

$$S_{it} = \phi_0 + \phi_1 Z_{1i} + \phi_2 Z_{2it} + \phi_3 A_{it} + X_{it}\Phi_4 + \eta_{it} \tag{4}$$

[4] Previous literature reports that season of birth is related to future outcomes (Bound and Jaeger, 1996, Buckles and Hungerman, 2013). Season of birth is controlled in estimations.

where Z_{1i} is an assigned kindergarten-entry age and Z_{2it} is an expected schooling determined by assigned kindergarten-entry age and survey date. ν_{it} and η_{it} are error terms.

3 Data

This study uses the NLSY79 and the NLSY79-CS. The NLSY79 is a nationally representative survey of people who aged 14 to 21 as of January 1, 1979. The NLSY79-CS has surveyed children of females in the sample of the NLSY79 biennially since 1986. I take information on cognitive skill scores, demographics, and schooling of children from the NLSY79-CS and mother's information from the NLSY79.

The NLSY79-CS provides various cognitive skill measurements of children. I use three cognitive skill measurements. They are the Peabody Individual Achievement Test in Mathematics (PIAT-M), the Peabody Individual Achievement Tests in Reading Recognition (PIAT-RR), and Reading Comprehension (PIAT-RC). The PIAT-M measures educational achievement of children in math and it includes 84 multiple-alternative questions of increasing difficulty. The PIAT-RR evaluates word recognition and pronunciation ability of children. It consists of 84 four-alternative questions and includes matching letters, naming names, and reading single words. The PIAT-RC test contains 66 items to measure the ability of a child to draw meaning from sentences. A child reads a sentence once and then chooses one of four pictures that is matched to the meaning of the sentence.[5] I use total raw scores of these tests and these raw scores make it possible to compare cognitive skills of children regardless of times when they took the tests, which is a crucial characteristic to identify the effects of kindergarten-entry age, age-at-test, and schooling separately.

The three key independent variables of interest in this study are kindergarten-entry age, age-at-test, and schooling. These variables are calculated on a daily basis. I calculate the actual age at kindergarten-entry using the date of birth, current grade, and grade repetition information. For example, I can infer that the year of kindergarten entry for a student in the second grade in October 1990 who repeated first grade one time is 1987. I construct assigned school-entry age, which is an instrument for the actual school-entry age, using kindergarten-entry cutoff in the state of residence

[5] Children who score less than 19 on Reading Recognition are assigned their Reading Recognition score as their Reading Comprehension score. If they score at least 19 on the Reading Recognition assessment, their Reading Recognition score determines the entry point to Reading Comprehension. Entering at the correct location is, however, not essential to the scoring.

at kindergarten-entry and date of birth for children. Since there are children who were not surveyed at kindergarten-entry, the exact information on state of residence at kindergarten-entry might not be available for these children. In this case, state of residence at kindergarten-entry is constructed by the state of residence at age that is the closest to age 5. The actual and assigned kindergarten entry ages could be different if a student did not enter kindergarten at the minimum permissible age. Age-at-test is calculated using the date of birth and survey date information in the NLSY79-CS.

I calculate schooling of students using kindergarten-entry year and survey date. There are enough variations in schooling even within the same grade because of variations in survey date. For example, a student who was surveyed in December has three months more education than a student who was surveyed in September in the same grade if all other things are equal. There are, however, issues in calculating schooling. First, the exact start and end dates of schools that students attended are not available. I assume that schools uniformly start at the day after Labor Day and ends on June 15, which means summer break is from June 16 to Labor Day and schooling does not increase during this period. This can bring about measurement error in the schooling variable since school start and end dates can be different by school district. Second, I do not distinguish school days and non-school days during the school year and consider both of them as schooling periods. I also regard holidays other than summer break as schooling period. Therefore, schooling effect in this study is a lower bound for pure schooling effect if schooling effect is greater than age-at-test effect. The expected schooling, which is used as an instrument for the actual schooling, is mechanically calculated using the survey date and expected school-entry date. The actual schooling could be different from the expected schooling because of early or late kindergarten entrance.

Other control variables are gender, race, birth order, mother's years of education, mother's AFQT score, Home Observation Measurement of the Environment-Short Form (HOME-SF), state of residence at survey date, survey year dummies, and kindergarten-entry cohort dummies. Mother's AFQT scores are adjusted for mother's years of education so that residuals from the regression of AFQT on mother's education are used. The HOME-SF variable measures the quality of home environment of a child in the NLSY79-CS, and I use total percentile score of the HOME-SF. School-entry cohorts are grouped into 5-year adjacent kindergarten entry groups.

4 Graphical Analysis

As a preliminary analysis, I investigate the effects of kindergarten-entry age, age-at-test, and schooling on educational achievement graphically, and this motivates the formal analysis of this study. I first show how cognitive skills of students differently evolve during school term and summer break. I then present figures that show that date of birth relative to kindergarten-entry cutoff is related to educational achievement as it is associated with the three key variables.

Figure 2 depicts the distribution of survey date in the sample from the NLSY79-CS for the years 1986-2012. The survey was not conducted evenly over the year, and it was concentrated on the summer. The proportion of surveys conducted in the summer break (June 16-Labor Day) is 56.6% and that in school term is 43.4%. Students are surveyed all over the year even though the amount of observations is relatively small in winter.

Figure 3 shows the average test scores over the year by expected grade. The mean of raw test scores for each date is calculated for each grade. The vertical lines represent the first and last days of school for each grade. The fitted lines of the average scores during school term and summer break are drawn, respectively, for each grade. Figure 3 closely describes how the test scores of students evolve from kindergarten to 7th grade. The graphs consistently show that test scores increase in school term and decrease during the summer break for both math and reading. As the amount of increase during school term is greater than that of reduction during the summer break in all grades, test scores increase as students advance through school. One possible question on the existence of the summer educational loss is whether students actually lose skills during the summer or they just concentrate less on tests during the summer break than during the school term. If the latter is the case, we would see sharp drops in test scores after the last day of school and the scores do not necessarily decline over the summer. The graphs in Figure 3 do not show any sudden change in test scores around the last and first days of school, and the scores gradually decline over the summer.

Figure 4 and 5 graphically present how the date of birth is related to educational achievement and its possible causes. Figure 4 shows the relationship between date of birth relative to kindergarten-entry cutoff and test scores controlling school-entry cohort and survey year fixed effects. Students in the right of the reference line are expected to be older at kindergarten-entry than those in the left. Those who are closer to the reference line are expected to be older at kindergarten-entry on the right-hand side and younger on the left-hand side. The graphs show that expected kindergarten-entry age is positively associated with both math and reading test scores. Figure 5, however, shows that it may not be a pure kindergarten-entry age effect because other important factors also change along the date of birth relative to cutoff. Panel (b) of Figure 5 shows that age-at-survey is very strongly correlated with kindergarten-entry age as expected. While expected schooling does not vary according to date of birth relative to school-entry cutoff in Panel (c) of Figure 5, the actual schooling substantially changes near the reference line. Within the same expected school cohort, students who were born just before the cutoff date have less schooling than the expected one, while those who were born just after the cutoff date have more schooling. These are related to differential decisions for school-entry timing between people who were born just before and after the kindergarten-entry cutoff as shown in Panel (e) and (f) of Figure 5. Students who were born just after the cutoff are more likely to enter school earlier than their minimum permissible age than others so that they tend to have more schooling at a given point in time. On the contrary, children who were born just before the cutoff are disproportionately more held out of school for one year so that they have less schooling at any given point in time on average. As not only kindergarten-entry age but also schooling and age-at-test vary according to the date of birth relative to cutoff, it is difficult to conclude that there exists a positive relationship between school-entry age and educational achievement. The main object of this study is to provide a way to disentangle the three effects from the combined effect.

5 Validity of Instruments

This section discusses the possible problems in estimating the three effects using the OLS estimation because of the endogeneity problem and suggests evidence from data. This motivates the necessity of using the IV estimation. The validity of the instruments is also discussed in detail.

The timing of kindergarten entry can be endogenously determined. Table 1 shows the effects of children's demographics and mother's characteristics on kindergarten-entry timing. The first column of Table 1 shows the result for early entry decision. The outcome variable is 1 if a child entered kindergarten earlier than she was supposed to enter by school-entry rule, and 0 otherwise.

The most important factor that affects the early entry decision is the expected kindergarten-entry age, which is determined by date of birth and state-kindergarten-entry cutoff. Consistent with the prediction, children who are supposed to enter kindergarten at older ages are more likely to enter kindergarten earlier than the assigned entry date. A year increase in assigned entry age increases the probability of entering kindergarten earlier by 12.2 percentage points. Other demographics and mother's characteristics, however, are not significantly related to early entry decision.

The second column of Table 1 shows the estimation result for late kindergarten entry. I denote that a child chooses a late entry if he enters kindergarten later than when he was supposed to enter. The assigned entry age strongly affects the late entry decision. Having one year older assigned entry age reduces the probability to enter kindergarten one year later by 23.7 percentage points. Children's demographics are also significantly related to the late entry decision. Boys are more likely to be held out of school for one year than girls. White and younger children of the family are more likely to enter kindergarten later. These results are consistent with the previous literature that reports white boys from high socio-economic families are more likely to be held out of school for one year (Bassok and Reardon, 2013). Table 1 shows that school-entry timing may be related to characteristics of children and even the direction of selection is not certain. Since the period of schooling is affected by school-entry timing, schooling can also be related to children's observable and unobservable characteristics. Schooling, therefore, should be thought of as an endogenous variable.

This study uses the instrumental variable approach to resolve the endogeneity problem in kindergarten-entry age and schooling variables. The instruments should be strongly correlated with the endogenous variables and they should not be correlated with unobservables after controlling control variables. The instrument relevance condition can be checked from the first stage regressions. Table 2 shows the estimation results for the two first stage regressions (equations (3) and (4)). All interviewed individuals are included in the regression and I conduct the OLS estimations for the pooled sample and each expected grade from kindergarten to the eighth grade. The reason why I divide group by expected grade, not by the actual grade is that the actual grade of students is affected by school-entry timing so that it is also endogenously determined. Panel (a) of Table 2 shows the estimation results for school-entry age. Kindergarten-entry age is strongly related to assigned kindergarten-entry age. An additional year of assigned school-entry age increases the actual kindergarten-entry age by 0.502 years for the pooled sample. This strong relationship is also observed in the regression by each expected grade.[6] Expected schooling and age-at-survey do not significantly affect kindergarten-entry age in most estimations.

Panel (b) of Table 2 shows the regression results for schooling. Expected schooling is the most important factor that determines actual schooling. An additional year of expected schooling increases the actual schooling by 1.115 years and is statistically significant at 1% for the pooled sample. This strong relationship holds for all grades. An additional year of assigned school-entry age increases schooling by 0.393 years for the pooled sample. Since students with greater assigned entry age are more likely to enter school earlier than the assigned entry date as shown in Table 1, they tend to have longer schooling given the same age and expected schooling. Age-at-survey is not significantly related to schooling in most estimations. The first stage estimation results in Table 2 show that two instruments employed in this study are strongly related to the endogenous variables and they meet the first condition for the validity of the instruments.

The exogeneity of the instruments cannot be directly tested. I indirectly test it by conducting balance tests and placebo tests. The balance test is often used in random experiments to check whether a randomized trial is conducted well by comparing pre-treatment characteristics of treatment and control groups. If the characteristics of treatment and control groups are similar, this can be some evidence of appropriate randomization. Following the idea, I test whether the instruments are related to independent variables including children and family characteristics. This does not need to be held for instruments because the necessary condition is exogeneity conditional on controls, but it may give more confidence for the exogeneity of instruments if the instruments are not related to other exogenous covariates.

Table 3 shows the estimation results for the relationships between the three key variables and other demographic variables. The first column of Table 3 presents the results for expected school-entry age. Except for HOME score, the expected school-entry age is not significantly related to any demographic variable. The second column of Table 3 shows the estimation results for expected schooling. There is no significant relationship between expected schooling and the demographic

[6] As shown in Figure 6, age-at-test is also strongly related to assigned entry age. Controlling age-at-test in the first stage regression substantially increases the standard error of the estimate of the kindergarten-entry age effect. This may be a reason for the weak relationship in some grades such as the fifth grade. When age-at-test is excluded from the regression, expected school-entry is very strongly related to actual school-entry age in all grades.

variables. The estimated relationships between age-at-test and the demographic variables are reported in the third column and it shows that age-at-test is not significantly associated with any demographic variable.

Finally, I estimate the effects of expected school-entry age and age-at-test on test scores before school entrance. Even though these students took tests before kindergarten-entry, their expected kindergarten-entry age can be calculated using information on the date of birth and state of residence. This test can be thought of as a placebo test for the effect of expected school-entry age instrument. Since tests were administered before kindergarten-entry, there is no reason that expected school-entry age is related to test scores if expected school-entry age is exogenously determined. The estimation results in Table 4 show that expected school-entry age is not related to any test score. The results in Table 3 and 4 provide evidence that expected school-entry age is a credible instrument. Table 4 also shows that age-at-test is positively associated with cognitive test scores before school-entry. Being one year older at test increases PIAT-M by 1.464, which 33.8% of the standard deviation. It also increases PIAT-RR and PIAT-RC by 3.071 and 3.184, respectively, which are 61.0 and 69.1% of the standard deviations. This relationship could result from factors such as a longer parental investment for older children and mental and physical maturity by aging. It is conjectured from the results that students who start school later have better test scores at school-start.

6 Result

6.1 The OLS, IV, and Reduced Form Estimation Results

Table 5 shows the OLS, IV, and reduced form estimation results for the effects of kindergarten-entry age, schooling, and age-at-test on PIAT-Math test scores for the pooled sample and each grade. Since the OLS, IV, and reduced form estimates are quite comparable, I discuss the results focusing on the IV estimation results. Panel (b) of Table 5 presents the IV estimation results. The IV estimation results show that being one year older at kindergarten-entry increases PIAT-Math scores by 6.941 points for the pooled sample, which is 41.0% of the standard deviation. An additional year of schooling increases PIAT-Math scores by 12.330, which is 72.9% of the standard deviation. A year increase in age-at-test without schooling decreases PIAT-Math by 4.631 point, which is 25.9% of the standard deviation. The IV estimation results by expected grade show that the effect of kindergarten-entry age on PIAT-Math is positive in all grades. Even though the effect is imprecisely estimated in some grades, the magnitude of the effect is substantial and it is greater than 38% of the standard deviation in all grades. For example, being one year older at kindergarten-entry increases the math score by 14.603 in the first grade, which is 145.3% of the standard deviation. The effect tends to decrease after the third grade. Schooling effect is greater than the effect of kindergarten-entry age in all grades. An additional year of schooling increases the math score by more than 67% of the standard deviation in all grades. In the first grade, one more year of schooling increases the math score by 19.757, which is 196.6% of the standard deviation. The effect of age-at-test is negative in most grades. Being one year older at test decreases the math score by 8.538 in the first grade, which is 81.3% of the standard deviation.

Table 6 presents the estimation results for PIAT-RR. For IV estimation results in Panel (b) of Table 6, the effect of kindergarten-entry age effect is imprecisely estimated except for the first grade. In the first grade, being one year older at kindergarten-entry increases PIAT-RR scores by 8.779, which is 97.7% of the standard deviation. Schooling effect is positive and large in earlier grades from kindergarten to the second grade. An additional year of schooling increases PIAT-RR score by 10.001 and 16.747 in kindergarten and the first grade, which is 164.2% and 186.3% of the standard deviation, respectively. Age-at-test effect by expected grade is imprecisely estimated in most grades because of large standard error. The OLS and reduced form estimates are quite comparable to the corresponding IV estimates.

Table 7 reports estimation results for PIAT-RC. The estimated effect of kindergarten-entry age is positive in all grades. The OLS estimation result in Panel (a) shows that being one year older at school entry increases PIAT-RC by 4.718 for the pooled sample. The corresponding IV estimate in Panel (b) is 2.371, and it is not statistically significant. The reduced form estimate in Panel (c) is 4.127, and it is statistically significant at a 5% level. The IV estimation results by expected grade in Panel (b) show that the effect of kindergarten-entry is positive in all grades, but most of the estimates are imprecise because of large standard error. Being one year older at kindergarten-entry increases PIAT-RC by 7.643 in the first grade, which is 88.5% of the standard deviation, and it is statistically significant at a 10% level. Except this, all estimates are statistically insignificant. The effect of schooling is positive, and it is greater than kindergarten-entry age effect in all grades.

For example, an additional year of schooling increases PIAT-RC by 13.235 in the first grade, which is 153.2% of the standard deviation. The effect of age-at-test on PIAT-RC is not statistically significant in all grades.

The estimation results in Tables 5-7 show that the effect of kindergarten-entry age is positive in most grades for the three tests, and the effect is more evident for PIAT-Math. Schooling strongly affects the test scores, and its effect is greater than kindergarten-entry age effect in all estimations. Age-at-test is negatively associated with PIAT-Math scores, while the effects on reading scores are statistically insignificant in most estimations. This is consistent with the previous literature in the sense that the summer educational loss is greater for math (Cooper et al., 1996).

6.2 Kindergarten-Entry Age and School Readiness

Do older children at school entry learn more in school than younger children? This question is important to understand the changing pattern of kindergarten-entry age effect over time. The results in Table 4 show that age-at-test is positively associated with cognitive test scores before school-entry and this means that older students at school-entry start school with a greater amount of skills. If the greater amount of skills expedite learning in school, the skill gap between older and younger students would expand. On the other hand, if the accumulated human capital depreciates with a low level of complementarity with school education, the skill gap at school-entry would narrow as students advance into higher grades.

I estimate the following model that additionally includes an interaction term between kindergarten-entry and schooling to equation (1) to understand how kindergarten-entry age is related to learning in school and how the relation changes over time.

$$Y_{it} = \beta_0 + \beta_1 EA_i + \beta_2 S_{it} + \beta_3 A_{it} + X_{it}\beta_4 + \beta_5 EA_i S_{it} + \epsilon_{it} \tag{5}$$

The interaction term EA_iS_{it} is another endogenous variable in addition to kindergarten-entry age (EA_i) and schooling (S_{it}) so that it is instrumented by $Z_{1t}Z_{2t}$, which is the interaction between expected kindergarten-entry age and expected schooling.

Table 8 presents the IV estimation results for the pooled sample. The odd columns of Table 8 present the estimation results that include the interaction term between kindergarten-entry age and schooling. This tests whether improvement in educational achievement in school differs by kindergarten-entry age. The estimation results show that the estimates for the interaction term are negative and statistically significant in the three tests. For PIAT-Math, the estimate is -1.239 which means that the growth in PIAT-Math score of students who start school a year later is 1.239 points less as they have a year of schooling than those who start school a year earlier. The estimates are -0.768 and -0.681 for PIAT-RR and PIAT-RC, respectively. The estimates for the interaction term are statistically significant at 1%.

The estimation results that additionally include the interaction between kindergarten-entry age and squared schooling are presented in the even columns of Table 8. This allows the possibility that the pattern of differential growth in test scores by kindergarten-entry age while in school can change as students have more schooling. The estimation results for the three tests commonly show that the estimates for the interaction between kindergarten-entry age and schooling are positive in the three tests and those for the interaction between kindergarten-entry age and squared schooling are negative. This means that educational achievement of older students at school-entry is enhanced more as they have more schooling in earlier periods, however, the difference in improvement is getting lower and educational achievement of younger students at school-entry grows faster in later periods. For example, PIAT-Math scores of a year older students at school-entry grow more than younger students in school before 0.79 years of schooling and grow less after it. The turning points are 1.78 and 2.1 years for PIAT-RR and PIAT-RC, respectively. The results that include the interactions of kindergarten-entry age with schooling and squared schooling are consistent with Lubotsky and Kaestner (2016) that show using the ECLS-K and the NLSY-CS data that test scores of older students at school-entry grow faster from kindergarten to the first grade, but test scores of younger students grow faster after the first grade.

7 Robustness Tests

7.1 Sibling Fixed Effects

In this section, I conduct several robustness tests. First, I estimate the effects of kindergarten-entry age, age-at-test, and schooling on educational achievement additionally controlling sibling fixed effects. Even though indirect tests on the exogeneity of the instruments in Section 3 show that the instruments are credible, I further check whether the findings from the baseline IV estimations still hold after controlling sibling fixed effects. This allows us to control unobservable household characteristics and the previous findings will be more credible if the results do not change significantly.

For analysis, I use a sample that only includes students who have other siblings. Table 9 shows the OLS and IV estimation results without and with sibling fixed effects for the pooled sample[7]. All the OLS, IV, and reduced form estimation results produce quite comparable estimates for the three effects. The first column in Panel (b) of Table 9 presents the IV estimation results without sibling fixed effects, and it shows that being one year older at kindergarten-entry increases PIAT-Math by 6.321. When sibling fixed effects are controlled, the estimated effect becomes 6.167. Schooling effect without and with sibling fixed effects is estimated to be 11.476 and 10.548, respectively. The estimates of age-at-test effect without and with sibling fixed effects are -3.636 and -2.779, respectively. The OLS estimates are quite comparable to the IV estimates. The results show that the estimates of the three effects do not change much even though sibling fixed effects are controlled.

The third and fourth columns of Table 9 presents the estimation results for PIAT-RR. The IV estimation results in Panel (b) show that having an additional year of schooling increases PIAT-RR by 5.313 when sibling fixed effects are not controlled and 5.780 when the fixed effects are controlled. Any significant effect on PIAT-RR is not found for kindergarten-entry age and age-at-test.

The fifth and sixth columns show the IV estimation results for PIAT-RC. Being one year older at kindergarten-entry increases PIAT-RC by 2.126 when sibling fixed effects are not included. When the fixed effects are controlled, the effect of kindergarten-entry age is estimated to be 0.315. Both of them are not statistically significant. The IV estimate of schooling effect when sibling fixed effects are not controlled is 7.194, and it is 4.816 when sibling fixed effects are controlled. The effect of age-at-test is statistically insignificant.

All estimation results in Table 9 consistently show that controlling unobservable family characteristics additionally does not change the main results: kindergarten-entry age positively affects PIAT-Math and age-at-test is negatively associated with PIAT-Math. Schooling has the greatest impact on all the cognitive skill test scores.

[7]Because the number of siblings that were surveyed in the same expected grade is small, only the results for the pooled sample are reported.

7.2 Regression Discontinuity Design

Aliprantis (2014) and Barua and Lang (2016) raise a problem in the IV estimation of the combined effect of school-entry age and age-at-test using assigned school entry age as an instrument because it can violate the monotonicity condition. In the presence of heterogeneous treatment effect, the IV estimate is interpreted as the local average treatment effect. The IV estimation, however, does not provide the local average treatment effect when the monotonicity condition is violated. The monotonicity condition required for the instrument of assigned entry age is that higher assigned entry age leads to higher actual entry age for any individual. Barua and Lang (2016) argue that this condition may not hold for the assigned entry age because the degree of conforming school-entry rule can depend on the assigned-entry age. Panel (e) and (f) of Figure 6 show that children born in months right after kindergarten-entry cutoff tend to enter kindergarten earlier and those born in months just before the cutoff tend to enter kindergarten later than the minimum permissible entry age. For example, if a child enters school later if her month of birth is one of two adjacent months just before the kindergarten-entry cutoff, while she enters kindergarten on time otherwise because parents do not want her to be among the youngest in class, then the monotonicity condition is violated. This student enters school at age 5.1 if his birth month is June, while he enters school at about 6.1 if his birth month is August in a state with September cutoff, which is the case that violates the monotonicity condition. The monotonicity condition is not directly testable, but the pattern of average school-entry age by date of birth in Panel (a) of Figure 6 and the ratios of early and late entrances by date of birth relative to cutoff in Panel (e) and (f) of Figure 6 raise a concern related to the issue.

As a robustness test to the possible violation of the monotonicity condition, I estimate the effects of school-entry age, age-at-test, and schooling using the regression discontinuity design. The following equation (6) describes an outcome equation:

$$Y_{it} = \beta_0 + \beta_1 EA_i + \beta_2 S_{it} + \beta_3 A_{it} + X_{it}\beta_4 + f(b_i) + \epsilon_{it} \tag{6}$$

where b_i is a daily measured date of birth relative to cutoff date and function f(b_i) is a polynomial function of b_i.

When the regression discontinuity design is used, the difference in assigned entry age between children born just before and after the kindergarten-entry cutoff is exploited as a source of exogenous variation in the actual school-entry age. Even though a child is held out of school for one year when his date of birth is just before the cutoff and he enters at the minimum permissible entry age when his date of birth is just after the cutoff, his kindergarten-entry age when date of birth is just before the cutoff is about the same with the one when date of birth is just after the cutoff. The monotonicity condition, therefore, is not violated even in the case that there exists a strategic school-entry timing choice according to date of birth.

Table 10 reports the RD estimation results for the effects of kindergarten-entry age, schooling, and age-at-test on the cognitive skill test scores for the pooled sample.[8] Different columns show the estimation results for different polynomial functions of b_i, date of birth relative to cutoff. Following Gelman and Imbens (2016), I report the RD estimation results for linear and quadratic polynomials of the forcing variable. As the estimation results are very comparable regardless of the linear or quadratic specification of forcing variable, I discuss the results focusing on the results for the quadratic specification. Panel (a) of Table 10 shows the estimation results for PIAT-Math score. Schooling is positively associated with the math score. An additional year of schooling increases PIAT-Math by about 9.824. Being one year older at kindergarten entry increases the math score by 5.036. Being one year older at test decreases the score by 2.406. The estimates for kindergarten-entry age effect and age-at-test effect are not statistically significant.

Panel (b) of Table 10 shows the RD estimation results for PIAT-RR. The estimated effect of kindergarten-entry age is 0.545. An additional year of schooling increases PIAT-RR score by 6.163. Age-at-test effect is 1.334 and statistically insignificant. All of them are not statistically significant. Panel (c) of Table 10 reports the estimation results for PIAT-RC. Being one year older at kindergarten-entry increases the PIAT-RC score by 2.634, and it is not statistically significant. An additional year of schooling increases the PIAT-RC score by 7.278, and it is statistically significant at 5%. The effect of being one year older at test decreases the score by 0.520, and it is not statistically significant. The RD estimates in Table 10 are quite comparable to the corresponding IV estimates, while the precision declines. The RD estimation results show that the possible violation of the monotonicity condition of the assigned entry age instrument may not severely

[8]Th RD estimation results by grade are reported in the Appendix. The RD estimates are quite comparable to the corresponding IV estimates in most cases, however most of them are imprecisely estimated.

distort the IV estimation results.[9]

7.3 Conventional Estimation Method of Estimating the Combined Effect of Kindergarten-Entry Age and Age-at-test

Finally, I estimate the combined effect of kindergarten-entry age and age-at-test and that of schooling and age-at-test and compare the results with those in the previous studies to check whether the results in this study are specific to the NLSY79-CS data or can be applied more broadly. The previous studies commonly report that the combined effect of kindergarten-entry age and age-at-test is positive and it decreases as students advance into higher grades. As explained in Section 2, most previous studies estimate model (2).

The regression equation for estimating the combined effects in this study is different from them because the NLSY79-CS is different from data in the most previous literature in the sense that test dates are different even among students in the same grade and this generates variations in age-at-test and schooling. The age-at-test can be represented by the following equation instead of calculating it directly using the date of birth and survey date.

$$A_{it} = EA_i + S_{it} + N_{it} * \tau + \eta_{it} \tag{7}$$

where N_{it} is the number of summer breaks that an individual i had fully spent after kindergarten entry. τ is yearly measured age increase during the summer break which is approximately 0.21 years (the number of days in the summer break divided by 365), η_{it} is an age increment randomly determined by survey date which is zero if an individual i is surveyed in the school term and it has a positive value if the survey was done during the summer break and the magnitude depends on the days spent during the current summer break.

I derive the following equation (8) by putting equation (7) into equation (1) and estimate the

[9] I also conduct the RD estimation by expected grade. The RD estimates are comparable to the IV estimates, but they are imprecisely estimated.

combined effect of kindergarten-entry age and age-at-test and that of schooling and age-at-test.

$$\begin{aligned}
Y_{it} =& \beta_0 + \beta_1 EA_i + \beta_2 S_{it} + \beta_3 A_{it} + X_{it}\beta_4 + \epsilon_{it} \\
=& \beta_0 + (\beta_1 + \beta_3) EA_i + (\beta_2 + \beta_3) S_{it} + \beta_3 \tau N_{it} + X_{it}\beta_4 + \epsilon_{it} + \beta_3 \eta_{it}
\end{aligned} \tag{8}$$

where $\beta_1 + \beta_3$ is the combined effect of kindergarten-entry age and age-at-test and $\beta_2 + \beta_3$ is the combined effect of schooling and age-at-test.

I estimate model (8) using the IV estimation. There are three endogenous variables in the equation, which are EA_i, S_{it}, and N_{it}. N_{it} is additionally instrumented by the expected number of summer breaks, which is determined by the expected school-entry date and survey date.

Table 11 reports the IV estimation results for equation (8) for PIAT-Math, PIAT-RR, and PIAT-RC. Panel (a) of Table 11 shows the IV estimation results for PIAT-Math. The combined effect of kindergarten-entry age and age-at-test is estimated to be 2.529 for the pooled sample, which is the 14.9% of the standard deviation. The estimation results by expected grade show that the combined effect is positive and statistically significant at 1% in all grades before the fifth grade. It tends to decrease as students advance through school after the second grade. The combined effect of schooling and age-at-test is positive and statistically significant in all grades. The combined effect of schooling and age-at-test also tends to decrease as students advance through school. For the pooled sample, the estimated effect is 8.456, which is 50.0% of the standard deviation.

Panel (b) of Table 11 shows the IV estimation results for PIAT-RR. The combined effect of kindergarten-entry age and age-at-test is positive in all grades except for grades 5 and 7. For the pooled sample, the estimated effect is 1.558, which is 8.6% of the standard deviation. The combined effect of schooling and age-at-test on PIAT-RR is positive and statistically significant at 1% in all grades. The estimated effect is 8.511 for the pooled sample, which is 46.8% of the standard deviation.

The IV estimation results for PIAT-RC are presented in Panel (c) of Table 11. The combined effect of kindergarten-entry age and age-at-test is positive before the seventh grade. The estimated effect is 1.886 for the pooled sample, which is 12.2% of the standard deviation. The combined effect of schooling and age-at-test effect on PIAT-RC is positive and statistically significant at 1% in all grades. For the pooled sample, the effect is 7.081, which is 45.7% of the standard deviation. The estimation results for the three tests commonly show that the magnitude of the combined effect of schooling and age-at-test is greater than the combined effect of school-entry age and age-at-test in all grades. The effects also tend to decrease as students advance through school.

Table 12 presents the RD estimation results for the combined effects. The RD estimates are comparable to the IV estimates. The RD estimation results show that the combined effect of kindergarten-entry age and age-at-test is positively associated with PIAT-Math until 4th grade, and the relationship is statistically significant at 1%. The combined effect of schooling and age-at-test is positive and statistically significant at 1% in all grades. For PIAT-RR, the combined effect of kindergarten-entry age and age-at-test is positive except for grade 5. The combined effect of schooling and age-at-test is positive and statistically significant at 1% in all grades. For PIAT-RC, the combined effect of kindergarten-entry age and age-at-test is positive in all grades. For all test scores, the magnitude of the combined effect of schooling and age-at-test is greater than that of the combined effect of kindergarten-entry age and age-at-test.

The estimated combined effects in Tables 11 and 12 are precise in most estimations, and this compliments the estimation results for the three effects in Section 6.2 which are less precisely estimated. The results in this section are consistent to those in the previous studies. The estimate of the combined effect is positive and the effect tends to decrease after earlier grades in elementary school. The estimation results also show that the combined effect of schooling and age-at-test is greater than that of kindergarten-entry age and age-at-test in all grades in the sample, which implies schooling is more effective in improving cognitive skills of children than educating children at home.

8 Discussion

This section discusses implications of the estimation results. First, increasing the length of the school year may be able to improve cognitive skills of children. The estimation results consistently show that schooling increases cognitive test scores more than spending time during the summer break. It is inferred from the results that lengthening the school year can improve cognitive skills. This is consistent with recent studies that report that additional schooling improves cognitive test scores and other educational outcomes (Carlsson et al., 2015, Fitzpatrick et al., 2011, Hansen, 2011, Parinduri, 2014).

Second, maturation itself without intensive human capital investment may not improve cognitive skills. The estimation results show that the effect of age-at-test is negative for math and insignificant for reading tests in most grades. The effect of age-at-test is identified from aging without schooling during the summer break. Human capital accumulation does not exceed its depreciation during the summer break possibly because of less self- and parental-investments in human capital during the period. It is shown from the sluggish improvement or reduction in test scores during the period. In contrast, the results show that age-at-test is positively associated with cognitive test scores before kindergarten entry. Parents may actively invest in human capital for their children before school entry. This implies that maturation itself does not lead to improvement in skills, but it enhances skills when intensive human capital investment is accompanied.

Third, providing school education to children earlier than current school start age may be able to improve cognitive skills. The results show that the effect of schooling on cognitive test scores is greater than kindergarten-entry age effect in all grades, which implies that school education is more effective than educating children at home. Expanding early childhood education such as universal preschool can be beneficial for development of children's cognitive skills.

9 Conclusion

Estimating the effects of kindergarten-entry age, schooling, and age-at-test separately is important for the evaluation of kindergarten-entry age policies that have been frequently changed in the U.S. over the past 40 years. Comparing relative effectiveness for improving children's skills between staying at home and having education in school is crucial. These three variables, however, are considered to be perfectly multicollinear in the period of compulsory schooling so that it is deemed that it is impossible to identify the three effects separately. The main contribution of this study is to suggest a new identification strategy that resolves the multicollinearity problem. The identification strategy is to use summer break as a period when age increases but schooling does not change. The variations in survey date in the NLSY79-CS and the summer break allow to resolve the multicollinearity problem and to identify the three effects separately. In addition, enough variations in test date of the NLSY79-CS during the summer break allow us to improve on measurement problem in the previous literature on the summer educational loss and to estimate the age-at-test effect. The endogeneity problems in kindergarten-entry age and schooling are handled by using the instrumental variable approach.

The OLS and IV estimations provide comparable results and they show that kindergarten-entry age is positively associated with PIAT-Math scores in all grades and PIAT-RR and PIAT-RC scores in earlier grades. Age-at-test is negatively associated with PIAT-Math score in most grades, while it is not significantly related to the reading test scores. Schooling is the most important factor that increases all the three cognitive test scores.

This study conducts three robustness tests. First, I estimate the three effects using the IV estimation with sibling fixed effects to control unobservable household characteristics. Second, this study estimates the three effects using the fuzzy regression discontinuity regression to relieve the concern raised by Barua and Lang (2016) that the assigned kindergarten age instrument may not satisfy the monotonicity condition. The IV estimation with sibling fixed effects and the RD estimation results are comparable to the baseline IV estimation results. Third, I estimate the combined effect of kindergarten-entry age and age-at-test and compare the estimate with the results in the previous literature. The results are consistent with the previous literature in the sense that kindergarten-entry age effect is positive and its magnitude tends to decrease as students advance into higher grades. It also more precisely shows that the effect of schooling on cognitive test scores is greater than the effect of kindergarten-entry in all grades.

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Figure 1: Identification of Kindergarten-entry Age Effect, Age-at-test Effect, and Schooling Effect: An Example

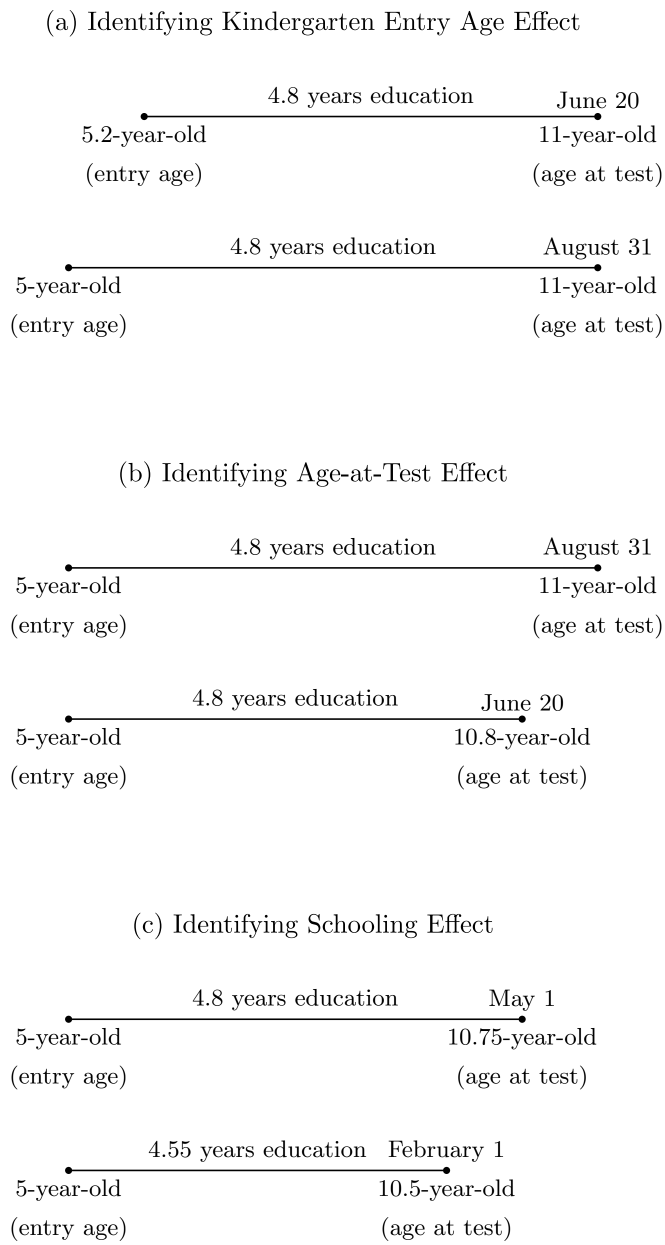


Figure 2: Distribution of Survey Date in the NLSY79 Children and Young Adults

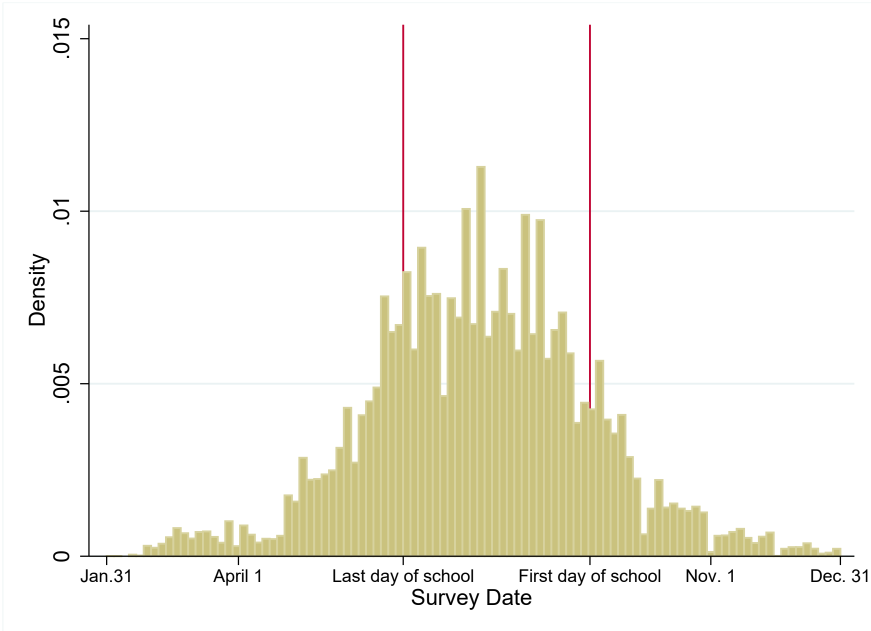
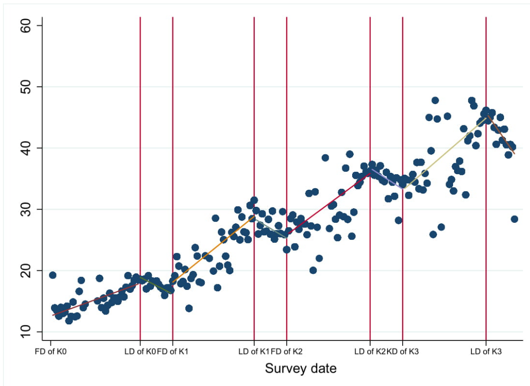
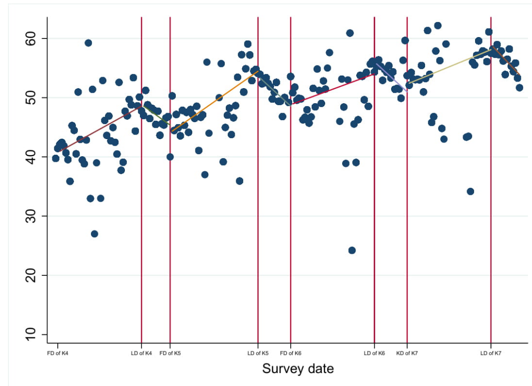


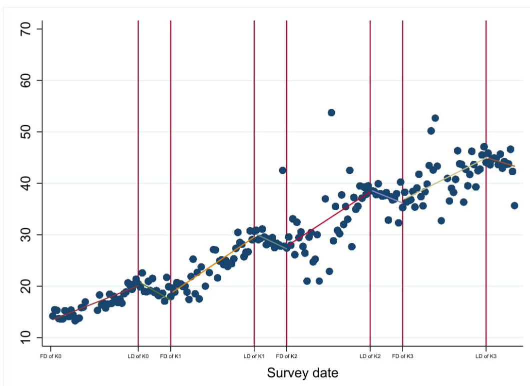
Figure 3: The Relationship Between Survey Date and Average Test Score by Expected Grade



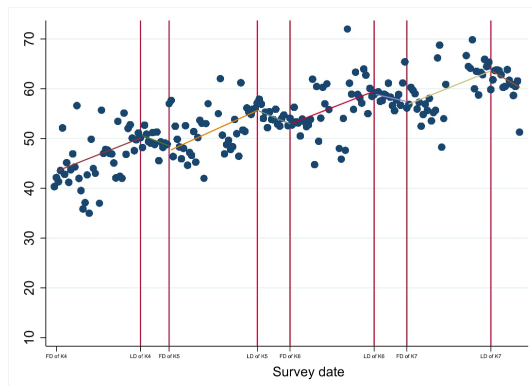
(a) PIAT-Math: Grade 0-3



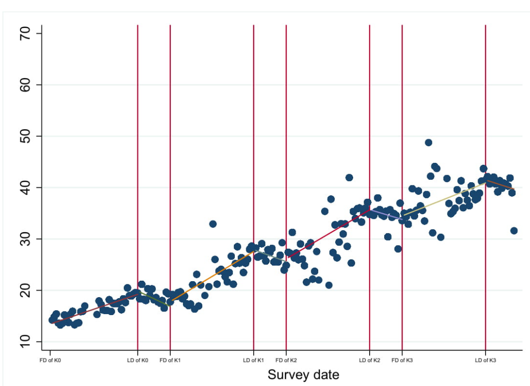
(b) PIAT-Math: Grade 4-7



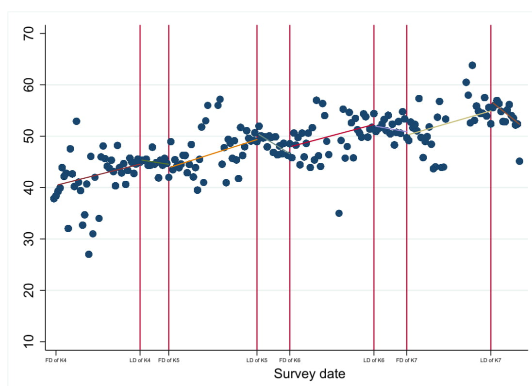
(c) PIAT-RR: Grade 0-3



(d) PIAT-RR: Grade 4-7



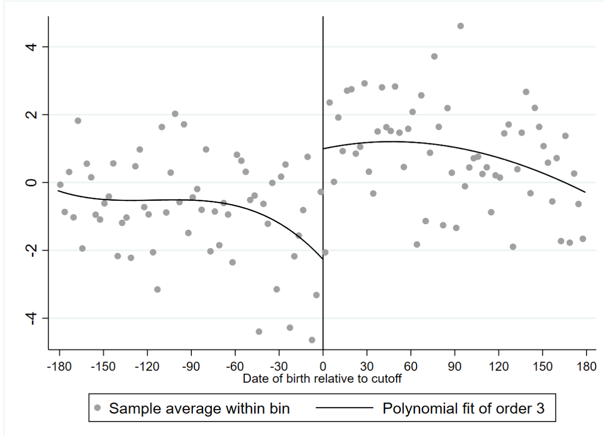
(e) PIAT-RC: Grade 0-3



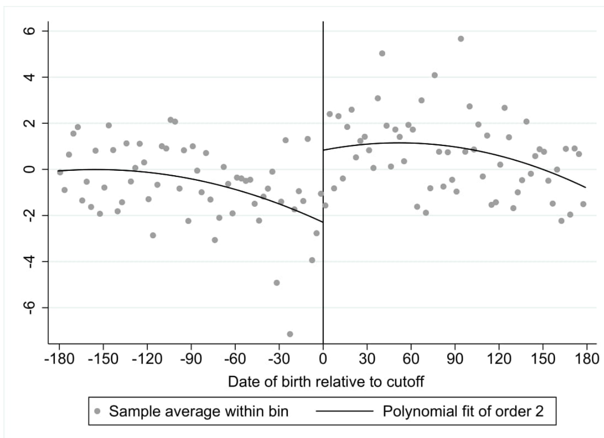
(f) PIAT-RC: Grade 4-7

Note: 1. Abbreviation. FD: First day of school, LD: Last day of school. 2. The average score for each survey date is the average of raw test scores for each date.

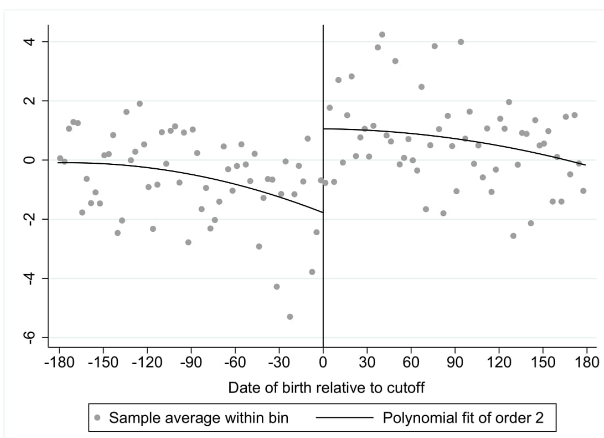
Figure 4: Date of Birth Relative to School-Entry Cutoff and Average Test Scores



(a) PIAT-Math Score



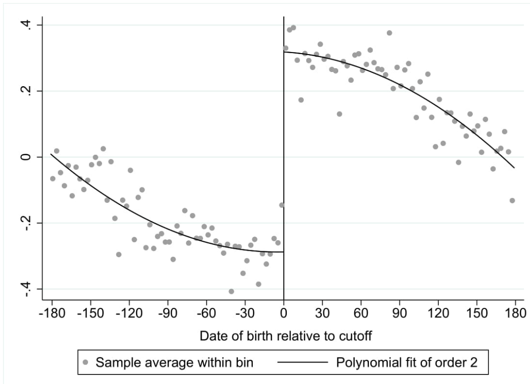
(b) PIAT-R-Recognition Score



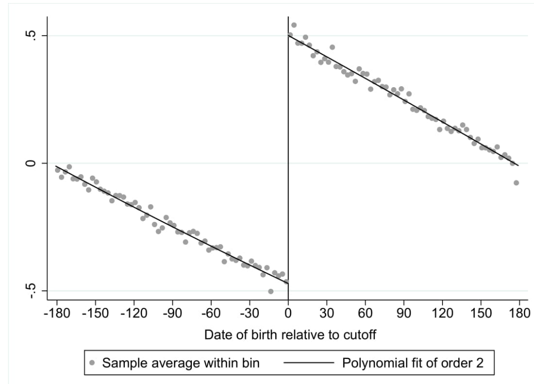
(c) PIAT-R-Comprehension Score

Note: The average score for each bin is an average of residuals from a regression of the raw score on dummies of expected school-entry year and survey year dummies for each bin.

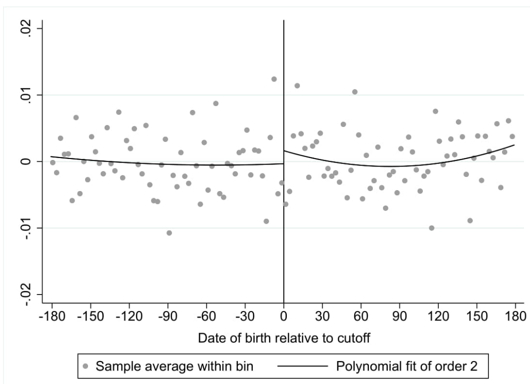
Figure 5: Date of Birth Relative to School-Entry Cutoff and Kindergarten-Entry Age, Age-at-test and Schooling Variables



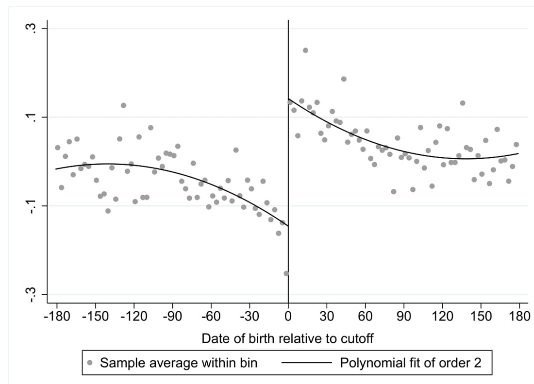
(a) Kindergarten-entry age



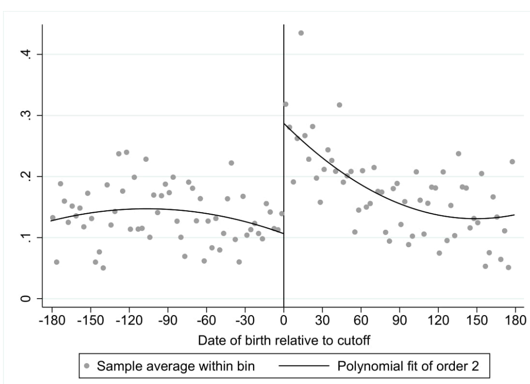
(b) Age-at-survey



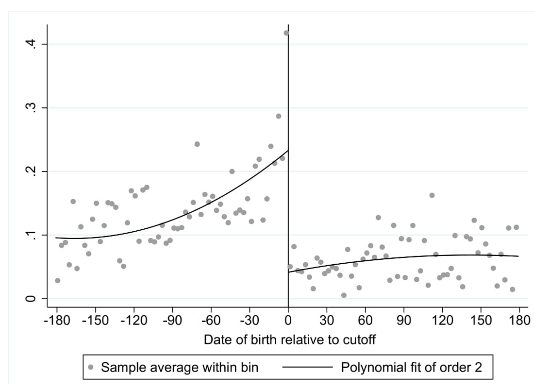
(c) Expected schooling



(d) Schooling



(e) Early entry



(f) Late entry

Note: For graphs in (a)-(d), the average value of each variable for each bin is an average of residuals from a regression of the variable on dummies of expected school-entry year and survey year dummies for each bin.

Table 1: The Decision for Kindergarten Entry Timing: Early and Late Entry

	(1) Early entry	(2) Delayed entry
Expected entry age	0.122***	-0.237***
	(0.020)	(0.049)
Gender (Boy=1)	-0.007	0.056***
	(0.010)	(0.009)
Black	0.009	-0.008
	(0.017)	(0.017)
White	-0.007	0.026**
	(0.017)	(0.011)
Birth order	0.008	0.011***
	(0.005)	(0.002)
Mother's years	0.003	-0.002
	(0.002)	(0.001)
Mother's AFQT	0.005	-0.026
	(0.028)	(0.019)
HOME	-0.023	-0.010
	(0.019)	(0.015)
Observations	7,110	7,110

Notes: 1. *** p<0.01, ** p<0.05, * p<0.10. 2. Standard errors are clustered by state of residence and survey year.

Table 2: The First Stage Regressions: the Effects of Expected Entry Age, Expected Schooling, and Age-at-test on Actual Entry Age and Schooling by Expected Grade

	(1) All	(2) grade 0	(3) grade 1	(4) grade 2	(5) grade 3	(6) grade 4	(7) grade 5	(8) grade 6	(9) grade 7
Entry Age									
Expected entry age	0.502***	0.847***	1.325***	0.600***	0.590**	0.455**	0.415	0.416*	0.653**
	(0.083)	(0.226)	(0.262)	(0.197)	(0.234)	(0.231)	(0.255)	(0.214)	(0.271)
Expected schooling	-0.146	0.401	0.474	-0.257	-0.149	-0.166	-0.256	-0.300	0.022
	(0.101)	(0.274)	(0.301)	(0.226)	(0.262)	(0.259)	(0.288)	(0.239)	(0.318)
Age-at-test	0.141*	-0.014	-0.815***	0.110	0.057	0.205	0.199	0.281	-0.095
	(0.080)	(0.230)	(0.257)	(0.188)	(0.224)	(0.227)	(0.246)	(0.204)	(0.270)
Schooling									
Expected entry age	0.393***	0.121	-0.257	0.315**	0.324*	0.430**	0.461**	0.461***	0.274
	(0.066)	(0.178)	(0.207)	(0.156)	(0.185)	(0.182)	(0.201)	(0.169)	(0.214)
Expected schooling	1.115***	0.683***	0.626***	1.203***	1.118***	1.131***	1.202***	1.237***	0.982***
	(0.080)	(0.217)	(0.238)	(0.178)	(0.207)	(0.205)	(0.227)	(0.189)	(0.251)
Age-at-test	-0.111*	0.011	0.643***	-0.087	-0.045	-0.162	-0.157	-0.221	0.075
	(0.063)	(0.181)	(0.203)	(0.149)	(0.177)	(0.179)	(0.194)	(0.161)	(0.213)
Observations	22,221	2,750	2,593	2,620	2,621	2,548	2,517	2,407	2,308

Notes: 1. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. 2. Standard errors are clustered by state of residence and survey year. 3. Gender, race, birth order, mother's years of education, mother's AFQT score, HOME score, season of birth, state of residence, five year adjacent cohorts and survey year are controlled.

Table 3: Balance Test

	(1) Expected entry-age	(2) Expected schooling	(3) Age-at-test
Gender	0.004	-0.002	0.003
	(0.005)	(0.027)	(0.035)
Black	0.005	0.009	0.027
	(0.008)	(0.044)	(0.055)
White	0.011	0.014	0.017
	(0.008)	(0.039)	(0.050)
Birth order	0.005*	-0.014	-0.018
	(0.003)	(0.019)	(0.024)
Mother's years of	0.00001	0.006	0.003
education	(0.001)	(0.009)	(0.012)
Mother's AFQT	0.012	0.015	0.005
	(0.011)	(0.072)	(0.091)
HOME	-0.038***	0.057	0.031
	(0.011)	(0.061)	(0.077)
Observations	20,364	20,364	20,364

Notes: 1. *** p<0.01, ** p<0.05, * p<0.10. 2. Standard errors are clustered by state of residence and survey year.

Table 4: The Effects of Expected School-Entry Age and Age-at-test on Test Scores Before School Entrance

	(1) PIAT-Math	(2) PIAT-Reading Recognition	(3) PIAT-Reading Comprehension
Mean	12.66	13.57	13.40
(SD)	(4.33)	(5.03)	(4.61)
Expected entry age	0.335	-0.306	-0.089
	(1.171)	(1.158)	(1.076)
Age-at-test	1.464	3.071**	3.184***
	(1.131)	(1.261)	(1.079)
Observations	1,121	1,093	1,086

Notes: 1. *** p<0.01, ** p<0.05, * p<0.10. 2. Standard errors are clustered by state of residence and survey year. 3. Gender, race, birth order, mother's years of education, mother's AFQT score, HOME score, season of birth, state of residence, five year adjacent cohorts and survey year are controlled.

Table 5: The Effects of School-Entry Age, Schooling, and Age-at-Test by Expected Grade: PIAT-Math

	(1) All	(2) grade 0	(3) grade 1	(4) grade 2	(5) grade 3	(6) grade 4	(7) grade 5	(8) grade 6	(9) grade 7
Mean (SD)									
	40.64	16.95	26.04	33.78	41.47	46.43	51.18	53.19	56.50
	(16.92)	(6.12)	(10.05)	(10.54)	(11.18)	(10.86)	(11.34)	(12.41)	(12.59)
(a) OLS									
Entry age	8.594***	3.864	12.545***	5.280	14.403***	9.692**	10.627**	7.246	5.980
	(1.702)	(2.380)	(4.053)	(3.914)	(5.006)	(3.878)	(4.459)	(5.102)	(5.178)
Schooling	12.566***	5.836**	19.294***	8.802*	20.281***	13.327***	15.813***	9.992	8.839
	(2.174)	(2.949)	(5.051)	(4.898)	(6.232)	(4.926)	(5.615)	(6.375)	(6.522)
Age-at-test	-4.631***	0.527	-8.054*	0.733	-10.378**	-6.380	-9.692**	-4.996	-6.915
	(1.714)	(2.442)	(4.119)	(4.031)	(5.149)	(3.937)	(4.629)	(5.187)	(5.373)
(b) IV									
Entry age	6.941***	3.635	14.603***	4.991	17.285***	11.578**	9.444*	10.435	4.837
	(1.799)	(2.564)	(4.514)	(4.772)	(5.944)	(5.085)	(5.531)	(6.410)	(6.285)
Schooling	12.330***	5.876**	19.757***	8.650*	21.567***	14.062***	15.346***	11.437*	8.495
	(2.189)	(2.950)	(5.235)	(5.226)	(6.548)	(5.187)	(5.855)	(6.673)	(01)
Age-at-test	-4.381**	0.616	-8.538**	0.907	-11.960**	-7.522*	-9.057*	-6.992	-6.420
	(1.727)	(2.474)	(4.271)	(4.440)	(5.584)	(4.454)	(4.998)	(5.789)	(5.697)
(b) Reduced form									
Expected entry age	8.346***	3.627	14.380***	5.735	17.170***	11.344**	10.863**	9.647*	5.642
	(1.722)	(2.564)	(4.712)	(4.449)	(5.575)	(4.495)	(5.069)	(5.706)	(5.727)
Expected schooling	12.715***	5.271*	19.372***	9.140*	21.520***	14.016***	15.759***	11.107*	8.626
	(2.167)	(3.023)	(5.457)	(5.089)	(6.445)	(5.114)	(5.870)	(6.540)	(6.625)
Age-at-test	-4.752***	0.812	-7.826*	0.708	-11.943**	-7.449*	-9.428*	-6.648	-6.379
	(1.708)	(2.517)	(4.598)	(4.349)	(5.537)	(4.306)	(4.988)	(5.574)	(5.651)
Observations	19,413	2,572	2,472	2,504	2,513	2,434	2,425	2,312	2,181

Notes: 1. *** p<0.01, ** p<0.05, * p<0.10. 2. Standard errors are clustered by state of residence and survey year. 3. Gender, race, birth order, mother's years of education, mother's AFQT score, HOME score, season of birth, state of residence, five year adjacent cohorts and survey year are controlled.

Table 6: The Effects of School-Entry Age, Schooling, and Age-at-Test by Expected Grade: PIAT-Reading-Recognition

	(1) All	(2) grade 0	(3) grade 1	(4) grade 2	(5) grade 3	(6) grade 4	(7) grade 5	(8) grade 6	(9) grade 7
Mean (SD)									
	43.38	18.45	27.44	36.15	43.08	48.70	53.80	57.84	61.88
	(18.19)	(6.09)	(8.99)	(11.24)	(11.44)	(12.40)	(13.00)	(13.64)	(13.31)
(a) OLS									
Entry age	2.573	6.619**	10.180***	7.713	-2.970	4.524	-8.918	1.164	6.268
	(1.679)	(2.716)	(3.631)	(4.740)	(4.762)	(5.071)	(6.143)	(6.013)	(5.627)
Schooling	5.552**	9.615***	17.035***	12.498**	-1.313	7.945	-8.644	3.050	9.875
	(2.373)	(3.399)	(4.618)	(5.940)	(5.981)	(6.349)	(7.738)	(7.625)	(7.073)
Age-at-test	1.701	-2.558	-6.590*	-2.181	7.578	-0.815	11.050*	2.227	-5.889
	(1.879)	(2.790)	(3.801)	(4.916)	(4.870)	(5.084)	(6.337)	(6.220)	(5.745)
(b) IV									
Entry age	-0.618	4.280	8.779**	3.759	-5.362	3.029	-12.145	0.946	2.497
	(2.008)	(2.916)	(4.041)	(5.581)	(6.203)	(6.103)	(7.448)	(7.282)	(6.611)
Schooling	5.091**	10.001***	16.747***	10.479*	-2.410	7.383	-9.946	2.950	8.756
	(2.429)	(3.381)	(4.689)	(6.260)	(6.468)	(6.471)	(8.034)	(7.889)	(7.216)
Age-at-test	2.189	-1.640	-6.281	0.169	8.914	0.078	12.804*	2.363	-4.271
	(1.924)	(2.801)	(3.869)	(5.284)	(5.527)	(5.490)	(6.813)	(6.731)	(6.018)
(b) Reduced form									
Expected entry age	1.734	4.333	7.697*	5.476	-3.792	4.325	-9.772	1.725	4.389
	(1.886)	(3.027)	(4.309)	(5.258)	(5.579)	(5.597)	(6.787)	(6.557)	(6.112)
Expected schooling	5.748**	7.906**	14.928***	11.541*	-1.694	7.565	-9.201	3.292	9.033
	(2.356)	(3.544)	(4.938)	(6.098)	(6.242)	(6.467)	(7.961)	(7.712)	(7.194)
Age-at-test	1.558	-1.006	-2.999	-0.212	8.576	-0.271	12.123*	2.017	-4.147
	(1.866)	(2.953)	(4.234)	(5.173)	(5.367)	(5.442)	(6.736)	(6.483)	(6.006)
Observations	19,336	2,536	2,465	2,504	2,504	2,432	2,412	2,301	2,182

Notes: 1. *** p<0.01, ** p<0.05, * p<0.10. 2. Standard errors are clustered by state of residence and survey year. 3. Gender, race, birth order, mother's years of education, mother's AFQT score, HOME score, season of birth, state of residence, five year adjacent cohorts and survey year are controlled.

Table 7: The Effects of School-Entry Age, Schooling, and Age-at-Test by Expected Grade: PIAT-Reading-Comprehension

	(1) All	(2) grade 0	(3) grade 1	(4) grade 2	(5) grade 3	(6) grade 4	(7) grade 5	(8) grade 6	(9) grade 7
Mean (SD)									
	39.49	17.77	25.67	33.61	39.66	44.09	48.27	51.21	54.21
	(15.50)	(5.51)	(8.64)	(10.03)	(10.05)	(10.46)	(10.84)	(11.39)	(11.74)
(a) OLS									
Entry age	4.718***	4.115*	8.060**	6.944*	2.030	2.520	-0.128	3.956	8.256
	(1.679)	(2.208)	(3.874)	(3.857)	(4.337)	(4.694)	(4.843)	(4.569)	(5.044)
Schooling	7.604***	6.053**	13.335***	11.146**	4.344	4.821	1.598	5.760	12.306*
	(2.122)	(2.829)	(4.891)	(4.806)	(5.398)	(5.883)	(6.102)	(5.792)	(6.296)
Age-at-test	-0.860	-0.136	-4.115	-0.943	1.331	0.005	2.272	-0.786	-8.198
	(1.670)	(2.343)	(4.003)	(3.940)	(4.365)	(4.741)	(4.975)	(4.768)	(5.155)
(b) IV									
Entry age	2.371	2.248	7.643*	7.314	0.525	0.134	1.875	4.887	3.163
	(1.871)	(2.389)	(4.298)	(4.537)	(5.461)	(5.661)	(6.089)	(5.983)	(6.021)
Schooling	7.223***	6.333**	13.235***	11.332**	3.662	3.926	2.496	6.196	10.820
	(2.184)	(2.905)	(4.961)	(4.969)	(5.675)	(5.972)	(6.279)	(6.030)	(6.563)
Age-at-test	-0.469	0.598	-4.012	-1.160	2.169	1.429	1.130	-1.373	-6.025
	(1.721)	(2.346)	(4.073)	(4.167)	(4.798)	(5.094)	(5.414)	(5.328)	(5.503)
(c) Reduced form									
Expected entry age	4.127**	2.306	7.187	7.943*	1.579	1.523	1.935	4.888	5.416
	(1.718)	(2.421)	(4.554)	(4.245)	(4.925)	(5.266)	(5.255)	(5.143)	(5.356)
Expected schooling	7.768***	4.769*	12.279**	11.728**	4.135	4.126	2.522	6.197	11.119*
	(2.106)	(2.830)	(5.221)	(4.877)	(5.549)	(6.065)	(6.152)	(5.880)	(6.332)
Age-at-test	-0.982	1.066	-2.149	-1.294	1.958	1.046	1.107	-1.373	-5.833
	(1.658)	(2.363)	(4.448)	(4.113)	(4.711)	(5.136)	(5.205)	(5.064)	(5.301)
Observations	18,896	2,431	2,329	2,421	2,459	2,402	2,395	2,285	2,174

Notes: 1. *** p<0.01, ** p<0.05, * p<0.10. 2. Standard errors are clustered by state of residence and survey year. 3. Gender, race, birth order, mother's years of education, mother's AFQT score, HOME score, season of birth, state of residence, five year adjacent cohorts and survey year are controlled.

Table 8: The Effects of School-Entry Age, Schooling, Age-at-Test and Interaction of School-Entry Age and Schooling on Cognitive Skills: IV Estimation

	(1) PIAT-M	(2) PIAT-M	(3) PIAT-RR	(4) PIAT-RR	(5) PIAT-RC	(6) PIAT-RC
Entry age	11.307***	7.717***	2.102	-0.993	4.817**	1.699
	(1.966)	(1.825)	(2.108)	(1.990)	(2.010)	(1.856)
Schooling	18.844***	15.161***	9.140***	5.967**	10.826***	7.610***
	(2.692)	(2.486)	(2.743)	(2.591)	(2.498)	(2.328)
Age-at-test	-4.344**	-2.788*	2.202	3.528*	-0.469	0.883
	(1.738)	(1.607)	(1.929)	(1.825)	(1.722)	(1.597)
Entry age×	-1.239***	0.276	-0.768***	0.533**	-0.681***	0.610***
Schooling	(0.254)	(0.260)	(0.247)	(0.259)	(0.226)	(0.226)
Entry age×		-0.175***		-0.150***		-0.148***
Schooling^2		(0.006)		(0.006)		(0.005)
Observations	19,413	19,413	19,336	19,336	18,896	18,896

Notes: 1. *** p<0.01, ** p<0.05, * p<0.10. 2. Standard errors are clustered by state of residence and survey year. 3. Gender, race, birth order, mother's years of education, mother's AFQT score, HOME score, season of birth, state of residence, five year adjacent cohorts and survey year are controlled.

Table 9: The Effects of School-Entry Age, Schooling, and Age-at-Test on Cognitive Skills: OLS, IV and Reduced Form Estimations with Sibling Fixed Effects

	(1) PIAT-Math	(2) PIAT-Math	(3) PIAT-RR	(4) PIAT-RR	(5) PIAT-RC	(6) PIAT-RC
(a) OLS						
Entry age	7.888***	6.756***	2.597	2.172*	4.610**	2.037*
	(1.756)	(1.267)	(2.070)	(1.261)	(1.822)	(1.236)
Schooling	11.667***	10.448***	5.727**	5.384***	7.554***	4.525***
	(2.250)	(1.618)	(2.618)	(1.645)	(2.296)	(1.565)
Age-at-Test	-3.852**	-2.727**	1.600	1.785	-0.773	1.600
	(1.769)	(1.281)	(2.069)	(1.277)	(1.804)	(1.226)
(b) IV						
Entry age	6.321***	6.167***	-0.811	0.061	2.126	0.315
	(1.848)	(1.421)	(2.164)	(1.373)	(1.973)	(1.384)
Schooling	11.476***	10.548***	5.313**	5.780***	7.194***	4.816***
	(2.273)	(1.628)	(2.687)	(1.683)	(2.361)	(1.574)
Age-at-Test	-3.636**	-2.779**	2.069	1.568	-0.387	1.447
	(1.788)	(1.287)	(2.122)	(1.305)	(1.856)	(1.233)
Observations	18,589	18,589	18,525	18,525	18,131	18,131
Sibling fixed effects	N	Y	N	Y	N	Y

Notes: 1. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. 2. Standard errors are clustered by state of residence and survey year. 3. Gender, race, birth order, mother's years of education, mother's AFQT score, HOME score, season of birth, state of residence, five year adjacent cohorts and survey year are controlled.

Table 10: The Effects of Kindergarten-Entry Age, Schooling, and Age-at-Test: Regression Discontinuity Design

	(1)	(2)
(a) PIAT-Math		
Entry age	5.027	5.036
	(3.216)	(3.210)
Schooling	9.813***	9.824***
	(3.763)	(3.754)
Age-at-test	-2.397	-2.406
	(2.983)	(2.976)
(b) PIAT-RR		
Entry age	0.560	0.545
	(3.682)	(3.682)
Schooling	6.182	6.163
	(4.335)	(4.333)
Age-at-test	1.319	1.334
	(3.438)	(3.437)
(c) PIAT-RC		
Entry age	2.641	2.634
	(3.084)	(3.081)
Schooling	7.287**	7.278**
	(3.602)	(3.597)
Age-at-test	-0.526	-0.520
	(2.857)	(2.854)
Polynomial	Linear	Quadratic

Notes: 1. *** p<0.01, ** p<0.05, * p<0.10. 2. Standard errors are clustered by state of residence and survey year. 3. Gender, race, birth order, mother's years of education, mother's AFQT score, HOME score, season of birth, state of residence, five year adjacent cohorts and survey year are controlled.

Table 11: The Effects of School-Entry Age, and Schooling on Cognitive Skills by Expected Grade: IV Estimation

	(1) All	(2) grade 0	(3) grade 1	(4) grade 2	(5) grade 3	(6) grade 4	(7) grade 5	(8) grade 6	(9) grade 7
(a) PIAT-M									
Entry age +	2.529***	4.095***	6.502***	7.052***	5.822***	2.899**	-0.706	2.846*	-2.396
Age-at-test	(0.561)	(0.828)	(1.239)	(1.202)	(1.186)	(1.464)	(2.175)	(1.590)	(1.832)
Schooling +	6.061***	6.303***	10.304***	10.469***	7.911***	5.679***	4.832***	3.468**	0.788
Age-at-test	(0.370)	(0.486)	(0.887)	(0.811)	(0.848)	(1.222)	(0.816)	(1.346)	(1.015)
(b) PIAT-RR									
Entry age +	1.558***	1.952*	2.296*	4.220***	3.868**	1.749	-0.045	2.771	-0.664
Age-at-test	(0.571)	(1.043)	(1.201)	(1.325)	(1.548)	(1.696)	(3.710)	(1.847)	(2.050)
Schooling +	6.846***	6.901***	9.253***	10.863***	8.044***	7.707***	4.841***	5.655***	4.134***
Age-at-test	(0.411)	(0.673)	(0.854)	(0.983)	(1.015)	(1.679)	(1.230)	(1.515)	(1.267)
(b) PIAT-RC									
Entry age +	1.886***	2.283*	3.439***	7.266***	3.112**	0.539	3.746	3.063	-2.071
Age-at-test	(0.559)	(1.217)	(1.126)	(1.353)	(1.430)	(1.619)	(3.133)	(1.892)	(1.785)
Schooling +	6.030***	6.002***	8.391***	10.716***	6.348***	5.744***	3.818***	4.618***	4.069***
Age-at-test	(0.389)	(0.567)	(0.815)	(0.945)	(0.968)	(1.464)	(1.250)	(1.446)	(1.108)

Notes: 1. *** p<0.01, ** p<0.05, * p<0.10. 2. Standard errors are clustered by state of residence and survey year. 3. Gender, race, birth order, mother's years of education, mother's AFQT score, HOME score, season of birth, state of residence, five year adjacent cohorts and survey year are controlled.

Table 12: The Effects of School-Entry Age, and Schooling on Cognitive Skills by Expected Grade: RD Estimation

	(1) All	(2) grade 0	(3) grade 1	(4) grade 2	(5) grade 3	(6) grade 4	(7) grade 5	(8) grade 6	(9) grade 7
(a) PIAT-M									
Entry age +	2.587***	3.546***	7.702***	6.176***	5.524***	4.270***	-2.760	0.881	-0.593
Age-at-test	(0.669)	(0.945)	(1.339)	(1.201)	(1.529)	(1.483)	(2.444)	(1.821)	(2.076)
Schooling +	8.456***	6.916***	12.372***	12.099***	11.462***	7.899***	7.861***	5.082***	4.094***
Age-at-test	(0.393)	(0.508)	(0.801)	(0.751)	(0.851)	(0.920)	(0.952)	(1.100)	(1.106)
(b) PIAT-RR									
Entry age +	2.043***	3.119***	3.302**	3.745***	3.857**	3.539**	-1.523	1.337	1.453
Age-at-test	(0.614)	(1.047)	(1.352)	(1.264)	(1.772)	(1.613)	(3.658)	(2.044)	(2.178)
Schooling +	8.511***	8.036***	11.555***	11.791***	9.067***	8.356***	7.443***	6.266***	6.221***
Age-at-test	(0.435)	(0.562)	(0.781)	(0.849)	(0.919)	(1.139)	(1.248)	(1.331)	(1.327)
(b) PIAT-RC									
Entry age +	2.220***	2.957***	4.710***	5.812***	2.544	3.322**	1.491	0.374	0.339
Age-at-test	(0.535)	(1.080)	(1.250)	(1.205)	(1.699)	(1.403)	(2.816)	(1.951)	(1.937)
Schooling +	7.081***	6.919***	10.573***	11.181***	7.393***	6.263***	5.669***	4.396***	5.135***
Age-at-test	(0.364)	(0.489)	(0.756)	(0.759)	(0.852)	(0.934)	(1.096)	(1.125)	(1.076)

Notes: 1. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. 2. Standard errors are clustered by state of residence and survey year. 3. Gender, race, birth order, mother's years of education, mother's AFQT score, HOME score, season of birth, state of residence, five year adjacent cohorts and survey year are controlled.

Appendices

Table A1: The Effects of Kindergarten-Entry Age, Schooling, and Age-at-Test by Expected Grade: Regression Discontinuity Design

	(1) grade 0	(2) grade 1	(3) grade 2	(4) grade 3	(5) grade 4	(6) grade 5	(7) grade 6	(8) grade 7
(a) PIAT-Math								
Entry age	-5.047	5.823	10.535	5.807	17.151	6.687	6.059	6.021
	(6.590)	(5.942)	(10.989)	(9.224)	(11.089)	(7.866)	(11.293)	(12.660)
Schooling	-2.727	9.262	14.486	8.731	19.128*	12.919	6.898	9.906
	(7.284)	(6.819)	(12.301)	(9.913)	(11.515)	(8.225)	(11.936)	(13.797)
Age-at-test	8.340	0.204	-3.987	-1.063	-12.034	-6.974	-2.990	-7.667
	(6.250)	(5.601)	(10.444)	(8.356)	(10.016)	(6.965)	(10.337)	(11.455)
(b) PIAT-RR								
Entry age	4.944	5.573	7.390	-13.211	17.170	-15.052	3.860	5.511
	(4.338)	(5.440)	(7.270)	(9.718)	(11.216)	(11.873)	(12.895)	(12.425)
Schooling	10.285**	12.598**	14.297*	-11.511	22.043*	-13.032	6.042	11.870
	(4.845)	(6.132)	(8.150)	(10.248)	(11.752)	(12.295)	(13.902)	(13.631)
Age-at-test	-1.982	-2.724	-3.059	16.612*	-12.866	15.471	-0.327	-6.907
	(4.061)	(5.032)	(6.876)	(8.642)	(10.154)	(10.516)	(11.840)	(11.287)
(c) PIAT-RC								
Entry age	3.818	2.535	11.235*	-8.787	14.824	-0.414	-4.432	6.228
	(3.997)	(5.634)	(6.728)	(8.989)	(10.886)	(9.184)	(11.753)	(11.408)
Schooling	7.785*	6.920	15.363**	-6.649	17.853	0.535	-2.907	14.026
	(4.511)	(6.306)	(7.439)	(9.253)	(11.536)	(9.389)	(12.523)	(12.315)
Age-at-test	-0.703	1.314	-4.524	10.889	-10.969	2.818	6.630	-8.742
	(3.768)	(5.152)	(6.207)	(7.812)	(9.959)	(8.103)	(10.853)	(10.277)

Notes: 1. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. 2. Standard errors are clustered by state of residence and survey year. 3. Gender, race, birth order, mother's years of education, mother's AFQT score, HOME score, season of birth, state of residence, five year adjacent cohorts and survey year are controlled.