Kindergarten Entry Age and Academic Performance

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Abstract

We use instrumental variable estimation strategy to estimate the effect of a one year delay in entering kindergarten on academic outcomes of children. Using data from the Child-NLSY, we present evidence that older entrants perform better in test scores compared to younger entrants in the same grade. The positive effects from being older are statistically significant, at conventional levels of significance, up to grade four. We also find that a one year delay in kindergarten entry reduces the probability of grade retention by 19%. When we compare children at the same age group, older entrants perform worse in test scores. We attribute this to the lesser years of schooling completed by older entrants as compared to children who entered early. The proposed methodology is an improvement from previous literature that tried to deal with the endogeneity of entrance ages. Using our empirical strategy we are able to provide consistent estimates of the Local Average Treatment Effect (LATE) of the group of "compliers" in the spirit of Angrist and Imbens (1994). Our estimates are policy relevant since they capture the effects of a law induced delay in school entry on academic outcomes for children.

1 Introduction

Kindergarten "readiness" is an issue that has perplexed parents and policy makers for many years now. Concerns regarding entrance age exist because of the one year chronological age span between the oldest and youngest kindergartner. The developmental age span is even greater. This correlation between chronological age and mental age has been well established in the literature. It is believed that younger children are not matured enough to handle the pressure of formal schooling. As a result, they may perform worse academically as compared to their older peers. This failure in academic performance could reflect in lower self esteem and may even affect adult outcomes.

Empirically identifying the causal effect of school entrance age on student outcomes is challenging due to the endogeneity of entrance ages. Entrance age is correlated with parental and child unobservable characteristics that may themselves be directly related to student performance. According to the National Center for Education Statistics (NCES), boys are more likely to be redshirted than girls, children from affluent families are more likely to be held back, white and non-Hispanic children are more than twice as likely as black, non-Hispanic children to have entered kindergarten late (West, Meek, & Hurst, 2000). As a result, children whose entry is delayed are not a random sample of the population. Thus, OLS estimates of student academic outcomes on entry age would result in biased estimates. Past studies that have addressed this issue have used, among other methods, instrumental variable estimation strategy to deal with the endogeneity of entrance ages. The most influential of these studies has used quarter of birth or more generally month of birth as an instrument for school entrance ages (Angrist and Krueger, 1991, 1992; Mayer and Knutson, 1999). Recently several researchers have exploited cross state variation in school entrance age laws and variation in date of birth to instrument for actual entry age (Bedard and Dhuey, 2006; Datar, 2005; Elder and Lubotsky, 2006; McCrary and Royer, 2005).

Both the quarter of birth instrument and the permitted entry age instrument does not solve a serious identification problem. With unobservable heterogeneity in treatment effects, traditional IV estimates fail to give an Average Treatment Effect (ATE) for the entire population. Angrist and Imbens (1994) show that with heterogeneous treatment effects, under certain conditions, instrumental variables can still be interpreted as a Local Average Treatment Effect (LATE). Identification of the LATE however hinges on certain key assumptions. As pointed out in Barua and Lang (2008a), the failure to satisfy the monotonicity assumption can lead to severely biased LATE estimates of the effect of school entry age on outcomes.

In this paper we estimate the effect of a one year delay in entering kindergarten on children's academic performance. The contribution of this paper to the school entrance age literature is twofold. First, the estimation strategy provides consistent estimates of the Local Average Treatment Effect (LATE) of entrance age on outcomes even if there is heterogeneity in the entrance age effect. Second, our methodology is very relevant from a policy perspective since we estimate the effect of the law on those children who would have, if not constrained by the law, chosen to enter school before their fifth birthday.

The findings from this paper can be summarized as follows. Using data from the NLSY, we find that older entrants perform better in test scores compared to younger entrants in the same grade and are less likely to repeat grades. The estimates are statistically significant, at conventional levels of significance, up to grade four. In particular, IV estimates for kindergartners suggests that a one year delay in kindergarten entry age causes math test scores to increase by 4.01 points. This is a relatively large effect, roughly two-third of a standard deviation, of delaying school entry age for kindergartners. Conditional on age, older entrants perform worse in test scores because of lesser schooling undertaken. We also find that a one year delay in kindergarten entry reduces the probability of grade retention by 19%.

The next section discusses the identification problem, previous literature, and our empirical approach. Section III describes the data from NLSY79 and NLSY79 child and young adult survey and presents some summary statistics. In section IV we present the main findings from our baseline specifications. Finally, we conclude the discussion in section V.

2 Identification Issues

2.1 Identification Problem

Consider the following model of the relation between school entry age and academic achievement:

$$T_i = \alpha E_i + X_i^{'}\beta + \epsilon_i \tag{1}$$

Where, T_i measures test scores of individual i, E_i represents the age of entrance to school. X_i is a vector of observable characteristics such as family background, demographic and school specific measures and ε_i is a vector of unobservable individual characteristics. Since unobserved characteristics are potentially correlated with entrance age, ordinary least square (OLS) estimates of the effect of school entry age on test scores are likely to be biased. For example, affluent parents can afford childcare costs associated with delaying their child's school entry. At the same time, there exists a positive association between parental socioeconomic conditions and student performance. Failure to account for this endogeneity will cause the OLS estimate to be biased towards finding a positive effect of entrance age on academic performance. Similarly the OLS estimate could be downward biased if, for instance, children with developmental difficulties are held back. Since these children are more likely to perform badly in cognitive tests, the OLS estimate would find a negative effect of entrance age on student performance. Depending on the importance of these two factors and the variables for which we control, the overall bias could be positive or negative.

The alternative approach to identifying α_i, employed by existing research, is instrumental variable estimation of the effect of entrance age on test scores in which factors unrelated to parental socioeconomic status or student ability affect the age at which children begin school. The quarter of birth instrument (Angrist and Krueger, 1991) relies on the assumption that quarter of birth or more generally month of birth is independent of student achievement. If everyone follows the law and school starts in September, than someone who is born on December 31^{st} would be four years eight months old when they start school. But someone who is born on the first of January would be approximately five years and eight months old at the beginning of kindergarten. Assuming that month of birth is not correlated with unobservable characteristics, we can use month of birth as a valid instrument for school entrance age (Angrist and Krueger, 1991, Mayer and Knutson, 1999).

Available literature that estimates birth seasonality (Lam and Miron, 1991) finds that births are highly seasonal with great variation in the timing of seasonal patterns across populations. Not only can it be argued that month of birth is directly correlated with student achievements but one can also argue that birth month is correlated with parental socio-economic status. Bound and Jaeger (2000) present evidence in favor of correlations between season of birth and family background, education, and earnings. Moreover, it is possible that the weather during gestation or early childhood affects development.

Recently several researchers have exploited cross state variation in school entrance age laws and variation in date of birth to instrument for actual entry age (Bedard and Dhuey, 2006; Datar, 2005; Elder and Lubotsky, 2006; McCrary and Royer, 2005). Children who begin kindergarten in California, for example, would have a lower average age of entrance to school as compared to children who start kindergarten in Illinois. This is because of different state laws governing kindergarten entrance ages in these two states. In California, children are allowed to enter kindergarten when they are four years and eight months old whereas in Illinois they are allowed to enter when they are five years old. Identification in this example is based on children born between September and December who should be older when entering school in Illinois than if they start school in California.

However, the solution of using state variation in permitted entry age does not solve a crucial problem and may in fact exacerbate it. The IV estimate gives a consistent estimate of the effect of the endogenous explanatory variable on the outcome of interest if the treatment effect is homogeneous for everyone. However with heterogeneous treatment effects, Angrist and Imbens (1994) show that, under certain conditions the instrumental variables estimator can be interpreted as a Local Average Treatment Effect (LATE). LATE is the treatment effect on those who are induced to change their treatment status due to the instrument. These individuals are also known as the "compliers" i.e. those individuals who would have ordinarily not received treatment had they been assigned to the control group. A potentially important condition for the identification of LATE is that the instrument must affect the endogenous explanatory variable monotonically. If the instrument affects the explanatory variable positively in some cases and negatively in others, then the IV estimator may result in an estimate with the wrong sign.

If everyone followed the law, there would be no problem. However, it is precisely because parents sometimes hold their children back a year (also known as "redshirting") that there is a need to instrument. This would be the case, for example, for children who have developmental difficulties. Parents of such children would voluntarily delay entry because these children may not be emotionally and/or mentally prepared to start school at a young age. In addition, some parents are able to obtain exceptions for their children and accelerate their entry. As a result, age of actual entry is not monotonic in month of birth or in the age of permitted entry. It is plausible that the children who are redshirted are disproportionately those who will benefit from delaying. In this scenario, using minimum permitted entry age or month of birth as an instrument will give an estimate with the wrong sign (Barua and Lang, 2008). In the next section we describe our identification strategy that provides consistent estimates of the Local Average Treatment Effect (LATE) of entrance age on academic performance even if there is heterogeneity in the entrance age effect.

2.2 Methods

Consider the following model of the relation between age at enrollment and student test scores:

$$T_{ig} = \alpha_g D_i + X_i^{'} \beta_g + \gamma_g M_i + \delta_g R_i + \epsilon_{ig} \tag{2}$$

Where, T_{ig} is test scores for student i in grade or age g. D_i is the dummy endogenous variable that takes on the value of 1 if the child's school entry is delayed from the year in which he turns five to the year in which he turns six. M_i is a set of dummies indication the month of birth of the child. X_i is a vector of observable individual characteristics and R_i represents a set of demographic controls. We estimate the above equation separately by grade for children in grades kindergarten ($g = 0$) through 8^{th} grade ($g = 8$). In addition, we also do the analysis by age of the child i.e. for children between the ages of 6 ($g = 6$) through 13 ($g = 13$). However, as discussed in the previous section, school entry age is not exogenously determined. As a result OLS estimates of α in the above model would be biased. To control for this endogeneity, we propose an instrumental variable estimation strategy.

We use 2SLS estimates to identify α in equation (1) above where D_i is instrumented using a dummy variable Z_i that takes on a value of one if the law constrained the child to delay entry into kindergarten. In other words if the child's month of birth lies later than the state kindergarten entrance age cut-off date, Z_i equals one and zero otherwise. More formally, we estimate the parameters of equation (1) using 2SLS based on the following first-stage equation for observed delayed enrollment:

$$D_i = \pi_g Z_i + X_i^{'} \lambda_g + \varphi_g M_i + \theta_g R_i + \upsilon_{ig} \tag{3}$$

Controlling for month of birth, M_i, the relation between school entry and Z_i is monotonic in this specification. Conceptually, we are comparing, for instance, academic performance of children born in October in states where they are allowed to enter early with those of children born in October in states which do not allow them to enter school until they are a year older. Note that the month of birth dummies also capture any biological or sociological relation between month of birth and ability. In addition, we control for state of residence to take into account any difference in school quality across states with early and late cutoffs.

2.3 Instrument Validity

Table 1 shows some direct evidence in favor of the instrument. This table shows that kindergarten entrance age laws have a strong effect on children's entrance age and that compliance rates with state entrance laws are high. For the entire sample, children born in the third quarter have the lowest enrollment age. This is because most of the states in the sample have a September first cut off. The last column shows that children born in the first quarter start school on an average 0.29 years later than children born in the third quarter. Compliance is even more striking when we look at average entrance age by different state cut offs. For example, we would expect that in states with a September cut off, those born in the third quarter would be the youngest and those born in the fourth quarter would be the oldest. The first column verifies this result; children born in the fourth quarter, besides being the oldest, enter kindergarten on an average 0.33 years later than children born in the third quarter. Average entrance age declines, as expected, with quarter of birth among children who go to kindergarten in states with a January first cut off. However, the smaller average age difference between the third and fourth quarter in the January cut off states reflect the large fraction of fourth quarter born children who are redshirted.

Table 1: Entrance Age by QOB and Cut Off Date

	State Cut Off Date			
Birth Quarter	September	December	January	All Cut Offs
First quarter	5.59	5.58	5.71	5.61
second quarter	5.37	5.43	5.52	5.41
Third Quarter	5.36	5.21	5.29	5.32
Fourth Quarter	5.69	5.27	5.14	5.54

A critical identifying assumption of our model is that school entry cut off date does not affect the performance of students who are never constrained by the law. In our sample, the earliest cut off date is in June (Missouri). Children born January through May are never constrained by the school entry law in any state in our sample. The outcomes for these children must not be affected by whether they go to school in a early or late entry age state. There are at least two reasons that this assumption might be false. The first is that if parents want to avoid having their children be among the youngest in the class, they may redshirt their children when the cutoff is early in the year but not when it is late in the year. In other words, those who are constrained by the law may have spillover effects on the unconstrained children. Though such spillover effects are likely to occur, preliminary evidence in Table 1 suggests that this is not a big concern for our data. Table 1 shows that the average entrance age of children born in the first two quarters does not show much variation across states with different cut off dates. The second concern is that the age of the other children in the classroom may directly affect the performance of children who are not affected by the law. If children born in March do worse when children born if October are permitted to start school before age five, we will underestimate the adverse effect of young entry on October children.

To test whether entry laws are independent of other factors affecting student performance, we regress the state cut off dates on student performance for children born between January through May. The results are reported in Table 2 where we have modeled test scores as a quadratic function of state cut off date[1]. Column (1) reports regression results from a model that includes eight census region dummies as additional controls. The main explanatory variable is constructed in units of the number of days till the state cut off date. For example, the cut off date for a December 31st or January 1st cut off would be equal to 365. Similarly, a September1st cut off date would be equal to 244 and so on. The other covariates are the same as in our baseline model namely, month of birth dummies, race, gender, AFQT of mother, mothers grade and marital status, test year dummies and log of family income. Since the cut off date may be related to state differences affecting student

[1] Here we show results from regressions for math test scores conditional on grade of the child. Results for reading test scores and test scores conditional on age are available on request.

performance, we also present results including state fixed effects along with the cutoff. Identification in this version of the regression rely on the relatively small number of states that changed entry date over the period we study. These are reported in the second panel. It is evident from the table that school entry laws do not affect the performance of students who are never constrained by the law. The coefficients on tests score are small and statistically insignificant. The last row in each panel of this table also reports F-test on each of the two cut-off coefficients in table 2. In almost all the cases the joint test for the cut-off coefficient and the square term fails suggesting that cut-offs do not have any externality effects.

Table 2: Effect of cut off date on test scores of unconstrained children (Born between January and May)
(Analysis by Grade)

Model with region dummies	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Kindergarten	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6	Grade 7	Grade 8
Cut-off Date in Days	-0.0502	-0.1875	-0.1386	-0.0827	-0.0384	-0.1081	0.0024	-0.0613	0.0294
	(0.0527)	(0.0728)**	(0.0893)	(0.0825)	(0.0996)	(0.0923)	(0.1082)	(0.1128)	(0.1263)
Cut-off Date Square	0.0001	0.0004	0.0002	0.0001	0.0001	0.0002	-0.0000	0.0001	-0.0000
	(0.0001)	(0.0001)***	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	993	910	926	877	779	825	674	649	512
R-squared	0.24	0.23	0.23	0.23	0.22	0.24	0.21	0.30	0.27
Prob > F	0.4107	0.0109	0.1638	0.6039	0.9165	0.1047	0.8214	0.6160	0.2557
Model with state dummies									
Cut-off Date in Days	-0.2158	0.2259	-0.3344	0.0387	-0.2098	-0.0154	0.1885	-0.0063	0.1136
	(0.1699)	(0.2739)	(0.2405)	(0.2735)	(0.2235)	(0.1716)	(0.2667)	(0.2244)	(0.2679)
Cut-off Date Square	0.0005	-0.0004	0.0006	-0.0001	0.0004	0.0000	-0.0004	-0.0000	-0.0001
	(0.0003)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0005)	(0.0004)	(0.0005)
Observations	993	910	926	877	779	825	674	649	512
R-squared	0.27	0.26	0.27	0.25	0.24	0.27	0.26	0.34	0.33
Prob > F	0.1740	0.7085	0.3794	0.9723	0.6437	0.9919	0.7442	0.9765	0.4374

*** significant at 10%; ** significant at 5%; *** significant at 1%**

3 Data

3.1 NLSY

The data used in this paper are drawn from the NLSY79 cohort and the NLSY79 Child and Young Adult Survey data. The NLSY contains extensive information on the labor market experience, education, family, and habits of the respondents. In addition to the public use files of the NLSY we obtained information about exact date of births and state of residence from the NLSY Geocode files.

The primary advantage of this dataset is the longitudinal nature of the data that allows us to compare cognitive scores by age and by grade. The main variable of interest in our analysis is measures of academic performance of children. The NLSY includes two measures of young children's cognitive skills, the Peabody Individual Achievement Tests (PIAT) and Peabody Picture Vocabulary Test Revised (PPVT). The PIAT measures academic achievement of children between the ages of 5 to 18. It is designed for children in grades K-12.

The data also allows us to identify the state of residence of the child from the original NLSY79 information about the mothers' state of residence. This information together with the information on exact date of birth was crucial for our empirical exercise. In addition, the data allowed us to include a rich set of controls for the analysis because it has extensive information on family background, demographics and schooling.

The main explanatory variable in this paper is kindergarten entrance age. The NLSY does not have data on the exact age of entrance. We, therefore, computed this variable using data on last grade attended, interview dates and grades repeated or skipped. The survey contains several questions pertaining to grade attended and grades completed. We used this information combined with information on grades skipped or repeated to compute the age at which the child entered kindergarten. However, in computing this variable we faced another potential problem. The NLSY asked the respondents questions about the "last grade attended or attending". One problem with the way the question is framed is that a respondent who answered the question in January of this year, for instance, would be referring to the grade that he entered in the previous year. To address this problem, we used interview dates to verify the exact age of entrance. To be consistent, any respondent who was asked about his last grade attended before July was assumed to have started that grade in the previous year. On the other hand any respondent who was interviewed in August or later would have referred to his grade in the present year. We used this technique to identify kindergarten entrance age for every child in the sample. Observations that did not have sufficient information to compute the entrance age were deleted from the sample. This left us with a sample size of 7448 children and young adults.

The NLSY data provides the 1989 AFQT scores for the mothers. Following Lang and Manove (2004), we computed and included adjusted AFQT scores in the regressions[2]. All regressions include control for month of birth, gender, race, standardized AFQT of the mother, test year dummies, state dummies, mothers' grade, marital status of the mother, whether the child attended preschool, controls for the month when the test was taken and log of family income.

3.2 State Kindergarten Entrance Age Policies

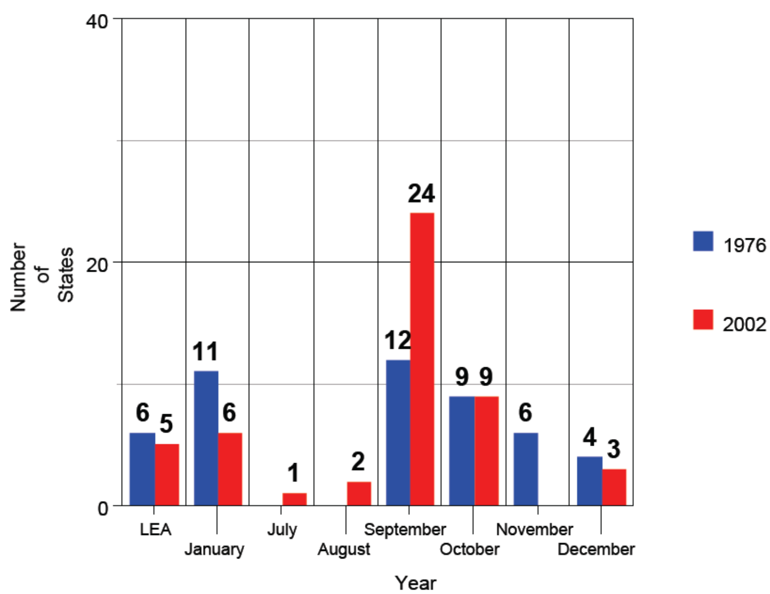
Our identification strategy required knowledge of exact kindergarten entry cutoff dates for every child in the sample. Data on state laws regarding kindergarten entrance ages were gathered from various sources to get accurate information. We gathered information on school cut off dates for several years from the Education Commission of the States. We

[2] AFQT scores were normalized to have mean zero and variance one. Using 1981 weights, the scores were regressed on age. Than the adjusted AFQT scores were computed by subtracting age time the coefficient on age.

verified these laws by looking at the US historical state statutes. If the history of the statute indicated a change in the state law at any given year, we examined the relevant state session law to determine the exact form of the change. In this way we computed kindergarten entrance age cut off dates for all 51 states for the period 1976 to 2002. Figure 1 compares the proportion of states with different kindergarten entrance age cut off dates in 1976 to the corresponding proportions in 2002.

Children who went to kindergarten in states that had given Local Education Authorities (LEA) the power to set the entrance age law were deleted from the sample. The states of Colorado, Massachusetts, New Jersey, New Hampshire and Pennsylvania were thus deleted from the sample. Other states such as Indiana and Louisiana had similar laws, but, for a shorter period of time. Children who went to kindergarten in these two states within that period were also deleted from the sample.

Figure 1: State Kindergarten Entrance Age Laws: 1976-2002



3.3 Summary Statistics

Table 3 shows unweighted means and standard deviations of some of the variables used in our regressions. The mean kindergarten entrance age for children in our sample is 5.46 years with a standard deviation of 0.46.

Table 3: Variable Means

Entrance Age	5.46 (0.56)
Boys	0.51
Girls	0.49
Black	0.32
White	0.47
Hispanics	0.21
Standardized AFQT of mother	-0.24 (0.96)
Quarter of Birth	
Quarter 1 (Jan-march)	0.23
Quarter 2 (April-June)	0.25
Quarter 3 (July-Sept)	0.27
Quarter 4 (Oct-Dec)	0.25
Total Observations	7448

Table 4 presents mean math test scores by grade and quarter of birth. This table shows that children born in the first and the fourth quarter perform better in test scores relative to children born in the second and third quarter. These children continue to have better test scores till the fourth grade after which the gains from being older starts to decline.

Table 4: Descriptive Statistics By Grade and QOB (PIAT Math)

Grade / Quarter	First quarter	Second quarter	Third quarter	Fourth quarter
Kindergarten	15.62	15.37	14.92	16.06
	(6.05)	(5.93)	(5.93)	(6.50)
First Grade	23.32	22.61	22.69	23.72
	(8.70)	(8.42)	(8.41)	(8.83)
Second Grade	31.24	31.09	30.3	31.59
	(9.80)	(9.50)	(9.25)	(9.98)
Third Grade	38.91	38.4	38.67	39.12
	(9.76)	(9.88)	(9.98)	(9.88)
Fourth Grade	44.15	43.54	44.08	44.15
	(9.14)	(9.75)	(8.55)	(9.64)
Fifth Grade	47.55	47.59	47.57	48.4
	(10.56)	(9.35)	(9.27)	(9.57)
Sixth Grade	50.09	51.02	50.3	50.72
	(9.43)	(9.78)	(9.38)	(10.00)
Seventh Grade	52.29	53.12	52.48	53.77
	(10.52)	(9.95)	(9.59)	(11.28)
Eight Grade	55.71	56.07	55.24	53.33
	(11.26)	(10.37)	(10.23)	(10.96)

Table 5 and Table 6 reports means and standard deviation of raw test scores by grade and age of the child respectively. Data has been pooled across time and individuals between the period 1976 to 2002.

Table 5: Means and Standard Deviation of Raw Test Score by Grade

Grade / Variable	PIAT Math	Observations	PIAT Reading	Observations
Kindergarten	15.48	3016	17.36	3009
	(6.12)		(5.92)	
First Grade	23.08	2909	25.59	2898
	(8.60)		(8.20)	
Second Grade	31.04	2866	34.35	2861
	(9.63)		(10.41)	
Third Grade	38.78	2811	40.86	2800
	(9.88)		(10.94)	
Fourth Grade	43.98	2553	46.5	2552
	(9.27)		(11.75)	
Fifth Grade	47.77	2485	50.73	2476
	(9.70)		(12.83)	
Sixth Grade	50.53	2240	54.83	2241
	(9.64)		(13.41)	
Seventh Grade	52.88	1999	58.67	1995
	(10.34)		(13.56)	
Eight Grade	55.31	1365	62.17	1371
	(10.71)		(13.16)	

Table 6: Means and Standard Deviation of Raw Test Score by Age

Age / Variable	PIAT Math	Observations	PIAT Reading	Observations
5 Years	12.62	2672	13.84	2607
	(4.66)		(5.36)	
6 Years	17.95	2864	20.11	2821
	(8.60)		(6.83)	
7 Years	25.96	2849	28.74	2850
	(6.97)		(9.27)	
8 Years	33.5	2814	36.61	2804
	(8.97)		(10.75)	
9 Years	40.42	2759	42.36	2758
	(10.32)		(11.94)	
10 Years	44.9	2604	47.6	2604
	(9.80)		(12.66)	
11 Years	48.43	2429	51.61	2412
	(10.00)		(13.38)	
12 Years	51.1	2247	55.83	2248
	(10.23)		(13.91)	
13 Years	53.15	2029	58.64	2027
	(11.02)		(14.25)	

4 Results

4.1 Analysis by Grade

Table 7 presents the first stage results from the reduced form regression of the instrument on the endogenous delay variable. The first stage results show that the instrument is a very good predictor of delayed entry and the coefficients are statistically significant for all the grades. The first stage F-statistics range between 150 and 200.

Table 7: First Stage Results

Grade	(1) Math	(2) Reading	Age	(3) Math	(4) Reading
Kindergarten	0.4740	0.4692	Five Years	0.5367	0.5327
	(0.0301)	(0.0301)		(0.0307)	(0.0311)
First Grade	0.4863	0.4879	Six Years	0.4596	0.4583
	(0.0297)	(0.0296)		(0.0289)	(0.0288)
Second Grade	0.5458	0.5464	Seven years	0.4823	0.4809
	(0.0298)	(0.0299)		(0.0319)	(0.0319)
Third Grade	0.5060	0.5079	Eight Years	0.5319	0.5291
	(0.0312)	(0.0313)		(0.0284)	(0.0285)
Fourth Grade	0.4992	0.4899	Nine Years	0.5058	0.5083
	(0.0315)	(0.0314)		(0.0323)	(0.0322)
Fifth Grade	0.4924	0.4913	Ten Years	0.4705	0.4699
	(0.0319)	(0.0320)		(0.0301)	(0.0301)
Sixth Grade	0.5796	0.5822	Eleven Years	0.5102	0.5078
	(0.0337)	(0.0338)		(0.0346)	(0.0348)
Seventh Grade	0.4749	0.4691	Twelve Years	0.5111	0.5071
	(0.0382)	(0.0382)		(0.0335)	(0.0335)
Eight Grade	0.4938	0.4946	Thirteen years	0.5107	0.5138
	(0.0425)	(0.0419)		(0.0374)	(0.0374)

We begin by estimating the OLS regression given in equation (2). Table 8, column (1) and column (3) show the OLS estimates from regressions of delayed enrollment on math test score for children in kindergarten and grade 1. All regressions include control for month of birth, gender, race, standardized AFQT of the mother, test year dummies, state dummies, mothers' grade, marital status of the mother and log of family income. Regressions are clustered by state times month of birth to generate heteroskedacticity robust standard errors. Being a year older at kindergarten entry raises test scores by 2.66 points. The mean test score for kindergartners is 15.48 with a standard deviation of 6.12, this implies that being a year older leads to 0.43 of a standard deviation increase in mean kindergarten test scores. Similarly, for children in first grade, one year delay in entry age causes math test scores to increase by 2.85.

Referring to the IV estimates in columns (2) and (4) of table 8, we find that PIAT math IV estimates are larger than corresponding OLS estimates. The larger IV estimates imply a downward bias in the OLS estimates. This could be driven by red shirting among children who are less precocious intellectually and/or emotionally. IV estimates for kindergartners suggests that a one year delay in kindergarten entry age causes test scores to increase by 4.01 points. This is a relatively large effect, roughly two-third of a standard deviation, of delaying school entry age for kindergartners.

Table 8: OLS and IV estimates of the effect of delayed school enrollment on math test scores (Analysis by Grade)

	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
	Kindergarten	Kindergarten	Grade 1	Grade 1
Delayed School Entry	2.661***	4.013***	2.856***	3.082**
	(0.341)	(0.868)	(0.483)	(1.301)
Black	-1.279***	-1.224***	-2.522***	-2.511***
	(0.317)	(0.321)	(0.487)	(0.487)
Hispanic	-1.715***	-1.662***	-2.927***	-2.928***
	(0.380)	(0.387)	(0.503)	(0.503)
Standardized AFQT	1.275***	1.282***	2.289***	2.288***
	(0.180)	(0.180)	(0.234)	(0.236)
Mother's Grade	0.269***	0.274***	0.293***	0.295***
	(0.066)	(0.064)	(0.091)	(0.092)
Marital Status of Mother	0.830***	0.814***	0.210	0.215
	(0.302)	(0.300)	(0.425)	(0.424)
Income	0.211	0.219	0.228	0.224
	(0.148)	(0.146)	(0.246)	(0.247)
Observations	2469	2469	2347	2347
R-squared	0.27	0.27	0.25	0.25

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Regressions also include month of birth dummies, state of residence dummies and test year dummies

In table 9, we show additional OLS and IV estimates conditional on grade. Panel A shows OLS and IV estimates for math test scores for children in grade 2 through grade 8. Panel B presents similar regression estimates for reading test scores.

For math scores, the estimates are statistically significant up to grade four. For fourth graders, a year's delay in entering kindergarten raises math test scores by 2.61 points. These results suggest that children who enter late perform better in test scores compared to early entrants. However, the benefits are large for kindergartners and decline thereafter. In panel B, OLS estimates suggest that being a year older at kindergarten entry raises the reading test score by 2.38. The IV estimates are smaller in magnitude and, unlike math scores, are not statistically different for later grades. The huge standard errors for older children make it difficult to draw any strong conclusions. This could be driven by the lack of variation within state in laws for the older children. We have tried estimating all regression with regional dummies instead of state dummies. However, we do not report them here because the estimates with regional dummies do not yield significantly different results from the estimates with state dummies. In effect, the results show that older entrants do not gain much in terms of reading skills even though they perform better in mathematics.

Table 9: OLS and IV estimates of the effect of delayed school enrollment on test scores

	(Analysis by Grade)		
	Panel A: Math Test Scores		
	(1)	(2)	(3)
Grade Attending	OLS	IV	Observations
2nd Grade	1.837***	1.925	2302
	(0.559)	(1.187)	
3rd Grade	1.183**	4.354***	2247
	(0.560)	(1.373)	
4th Grade	0.133	2.614*	2030
	(0.487)	(1.400)	
5th Grade	-0.522	-0.844	1970
	(0.557)	(1.466)	
6th Grade	0.198	2.111	1757
	(0.685)	(1.525)	
7th Grade	-0.361	0.680	1583
	(0.633)	(1.761)	
8th Grade	0.327	-0.337	1084
	(1.100)	(2.803)	
	Panel B: Reading Test Scores		
Kindergarten	2.378***	1.974**	2457
	(0.331)	(0.864)	
1st Grade	2.618***	0.004	2344
	(0.512)	(1.351)	
2nd Grade	0.564	0.186	2297
	(0.588)	(1.544)	
3rd Grade	0.274	0.720	2241
	(0.577)	(1.582)	
4th Grade	-0.310	-0.417	2028
	(0.703)	(1.812)	
5th Grade	0.091	3.423	1960
	(0.701)	(2.168)	
6th Grade	-0.585	4.211**	1759
	(0.985)	(1.877)	
7th Grade	-0.634	1.405	1583
	(0.862)	(2.620)	
8th Grade	-2.651**	-0.947	1091
	(1.258)	(3.760)	

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
Main explanatory variable is delayed school enrollment dummy
Full set of controls included

4.2 Analysis by Age

Next, we estimate the baseline model for children in the same age group. Most of the previous studies on entrance age effects have studied the effect of school entry age on outcomes for children in the same grade. When tested at the same age, however, children who enter late would have smaller years of schooling as compared to children who entered early. As a consequence we would expect test scores to be higher for those who have more schooling. This would imply a negative coefficient on the entrance age variable. This is confirmed by our results presented in table 10. Consistent with results presented earlier, we find the IV estimates to yield much larger effects of delayed enrollment on test scores. Results for the 2SLS estimates for math and reading are statistically significant up to age ten and age nine respectively even though the negative effect does not dissipate with age. Among nine year olds, for example, a one year delay in entering kindergarten is associated with a lower test score of the magnitude of 2.89 points for PIAT math and 7.04 points for PIAT reading (the mean test scores for nine year olds has a standard deviation of 10.32 and 11.94 respectively).

Table 10: OLS and IV estimates of the effect of delayed school enrollment on test scores

(Analysis by Age)

	(1)	(2)	(3)
Grade Attending	OLS	IV	Observations
Panel A: Math Test Scores			
Age 6	-2.490***	-3.014***	2333
	(0.427)	(1.080)	
Age 7	-2.549***	-6.213***	2309
	(0.507)	(1.286)	
Age 8	-2.987***	-3.041**	2235
	(0.582)	(1.398)	
Age 9	-1.783***	-2.900**	2222
	(0.604)	(1.403)	
Age 10	-2.333***	-3.748**	2080
	(0.524)	(1.691)	
Age 11	-2.284***	-1.211	1899
	(0.607)	(1.479)	
Age 12	-1.425**	-0.470	1770
	(0.689)	(1.858)	
Age 13	-0.632	-0.955	1626
	(0.666)	(1.815)	
Panel B: Reading Test Scores			
Age 6	-3.700***	-6.677***	2301
	(0.473)	(1.320)	
Age 7	-3.494***	-11.386***	2312
	(0.571)	(1.685)	
Age 8	-3.354***	-4.072***	2227
	(0.578)	(1.545)	
Age 9	-2.462***	-7.042***	2222
	(0.699)	(1.841)	
Age 10	-1.944***	-0.718	2082
	(0.624)	(2.168)	
Age 11	-2.329***	-0.603	1883
	(0.761)	(1.960)	
Age 12	-2.639***	1.059	1773
	(0.995)	(2.086)	
Age 13	-1.996**	-2.108	1625
	(0.866)	(2.421)	

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Main explanatory variable is delayed school enrollment dummy

Includes the entire set of controls

4.3 Probability of Repeating a Grade

Table 11 presents marginal probit estimates of the effect of delaying kindergarten entry on the probability of repeating a grade in school. The repeated grade variable takes on a value of one if a child has repeated a grade between kindergarten and $8th$ grade. The IV estimates show that children who delay entry are less likely to have repeated a grade compared to an otherwise identical child who entered kindergarten a year earlier. A one year delay in kindergarten entry reduces the probability of grade retention by 19%. A boy is about 10% more likely to repeat a grade, than a girl, controlling for everything else. Children of mothers with high AFQT scores are less likely to repeat a grade. Blacks are more likely to repeat a grade compared to otherwise identical whites.

Table 11: Probability of Repeating a Grade

	(1) OLS	(2) IV
Delayed School Entry	-0.032	-0.195
	(0.017)*	(0.039)***
Male	0.098	0.104
	(0.014)***	(0.014)***
Black	0.028	0.019
	(0.018)	(0.018)
Hispanic	-0.007	-0.013
	(0.024)	(0.024)
Standardized AFQT	-0.172	-0.172
	(0.008)***	(0.008)***
Attended Preschool	-0.041	-0.040
	(0.012)***	(0.012)***
Observations	5519	5519

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Also includes controls for state and month of birth dummies

5 Conclusion

We present an instrumental variable strategy to estimate the effect of kindergarten entrance age on academic outcomes. Using our empirical strategy, we are able to identify and estimate the Local Average Treatment Effect (LATE) in the spirit of Angrist and Imbens (1994). Our methodology is an improvement upon earlier studies that tried to estimate similar effects but failed to account for heterogeneity in treatment effects. Our results suggest that older children perform better in measures of test scores as compared to otherwise identical children who enter a year earlier. Delaying school entry also decreases the likelihood of repeating a grade. IV estimates for kindergartners suggests that a one year delay in kindergarten entry age causes test scores to increase by 4.01. This is a relatively large effect, roughly two-third of a standard deviation, of delaying school entry age for kindergartners. The estimates are statistically significant up to grade four.

The results are different when we compare children of the same age group. When tested at the same age, children who enter late would have lesser years of schooling as compared to children who entered early. As a consequence we would expect test scores to be higher for those who have more schooling. We find negative effects of entrance age on PIAT math and reading test scores for children belonging to the same age group.

We also find that a one year delay in kindergarten entry reduces the probability of grade retention by 19%. Girls, whites and children of mothers with high AFQT scores are less likely to repeat a grade than otherwise comparable boys, blacks and children whose mothers have lower AFQT scores.

Our estimates and estimation strategy are both relevant from a policy perspective. Even though several papers have documented the association between entrance age and academic performance, most of these studies have not been able to provide consistent IV estimates. In comparison, our study provides a clean estimate of the effect of delaying kindergarten entry on those children who would have chosen not to delay had they not been constrained by the law. For some policies, the Average Treatment Effect (ATE) may be important, but in the US the relevant policy is permissive rather than prescriptive. Our results are therefore policy relevant and shed some light on the issue of kindergarten readiness that has perplexed parents and policy makers for several decades. The policy conclusions that we can draw from this study would depend on the long run effect of delayed enrollment on ultimate educational attainment. In a complementary working paper (Barua and Lang, 2008), we study the effect of school entry age on educational attainment.

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