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School starting age and academic achievement: Evidence from China's junior high schools☆

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ABSTRACT

This paper examines the effect of school starting age on the academic achievement of junior high school students using the newly available data from the China Education Panel Survey. Regression discontinuity design estimation based on an exogenous entrance cutoff date indicates that a one-year delay is associated with a 0.303 decrease in standard deviations of cognitive scores. However, this negative effect is caused by human capital accumulation prior to primary school entry.

1. Introduction

Recently, the question of the optimal age at which a child can join school has generated considerable interest among economists and social scientists. In numerous Western countries, particularly the United States, many parents keep their children out of school even when they are legally eligible to attend because they believe that children who start school later are more physically and mentally mature and thus can do better in school (e.g., Bedard & Dhuey, 2006; Datar, 2006). However, there is no strong causal evidence to support this positive association. In contrast, some studies have found a negative link between age of school entry and education and labor marker outcomes (see a survey by Deming & Dynarski, 2008).

In China, the optimal age at which a child should enter primary school is a widely debated topic. However, unlike Western countries (1), the preprimary education system is not well developed and (2) an early start to primary school is more prevalent in Chinese society. Traditionally, parents have favored an early start as they do not want their children to lose out. Thus, they are more likely to send their children to school early, rather than let them wait an additional year and be part of an older cohort.

Despite being a controversial topic, it is surprising that little research has been conducted on the effect of school starting age (hereafter, SSA) on student outcomes in China. To the best of our knowledge, two previous studies relate to this topic. Liu and Li (2015) examine the relationship between birth months and educational outcomes in middle school. They find indirect evidence

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that show that children born in July and August lag behind more with respect to various outcomes than those born in other months.[1] Chen (2015) estimated the causal impacts of delayed primary school on children's educational outcomes from rural areas in a poor province in Northwestern China. The results suggest that delayed enrollment is negatively associated with middle school enrollment and increases the probabilities of first-grade retention.

However, Liu and Li (2015) could not provide direct evidence of the effect of SSA. More importantly, they could not account for the endogenous entrance age. Although Chen (2015) takes the endogenous problem into account, the results are limited to a special poor rural area in China; therefore, this study also lacks evidence regarding the effect of SSA on the outcomes of children in the population. Moreover, the potential mechanisms between entrance age and educational outcomes were not investigated.

To fill this gap, this paper identifies the causal effect of SSA on cognitive ability test scores by using school entrance cutoff as a quasi-natural experiment to separate the entrance-age effect from other factors, such as parents' decision about the age at which to send their children to school or student ability; as these may be also correlated with student outcomes. We employ a newly available micro data set from the China Education Panel Survey (CEPS), an ongoing nationwide survey of junior high school students. Our regression discontinuity design (RDD) results indicate that a one-year delay is associated with a 0.303 decrease in standard deviation of cognitive scores. Moreover, this result is very robust to numerous specifications. Overall, we do not find any positive association between SSA and test scores.

We further investigate the potential mechanisms between entrance age and cognitive scores. First, heterogeneous results indicate that the negative effects of age of entry are larger and statistically significant for children from rural schools but smaller and statistically insignificant for children from urban schools. Second, we re-estimate the effect of SSA on preschool attendance and find that starting age is negatively associated with the length of preschool participation. Given the lack of preschools in China, these results imply that children with delayed entry are more likely to receive little skills development before they enter primary school. As a result, the late joiners will inevitably experience an academic disadvantage in school.

The remainder of this paper is organized as follows: Section 2 summarizes the existing literature. Section 3 introduces the Compulsory Education Laws and SSA in China. In Section 4, we describe the identification strategy. Section 5 describes data used in this analysis and presents summary statistics by the timing of school entry. Section 6 presents the empirical results. Section 7 discusses the potential mechanisms between SSA and cognitive scores. Section 8 concludes the paper and discusses policy suggestions.

2. Previous studies

In many Western countries, especially the United States, the popular explanation for the optimal age for school entry is that older students benefit academically in subsequent learning because older students acquire greater "readiness" for learning and thus can acquire skills more quickly (see Stipek, 2002). Some studies support this viewpoint such as that by Bedard and Dhuey (2006) who find that children who are relatively older when they enter school have higher test scores in fourth and eighth grade across countries in the Organization for Economic Cooperation and Development (OECD). They use children's predicted school entry age as an instrument for their actual school entry age, thus accounting for the endogenous entrance age. Datar (2006), and McEwan and Shapiro (2008) confirm similar results for the US and Chile, respectively. Note that it is impossible to identify the pure effect of SSA in these studies because of perfect co-linearity between school entrance age and age at test. Therefore, these results should be interpreted as their combined effects.

In addition, some studies suggest that the long-term effects of SSA are very modest. For example, Fertig and Kluve (2005) indicate that there is no effect of age at school entry on educational outcomes both in terms of schooling degree and probability of having to repeat a grade in Germany. Black, Devereux, and Salvanes (2011) also do not find any long-term effects of SSA on education and earnings for boys or girls in Norway. Fredriksson and Ockert (2013) find that school entry age raises educational attainment but has no effect on prime-age earnings in Sweden.

There are also some studies such as that by Elder and Lubotsky (2009) that indicate that older students perform better in school simply because they are older when they take the test (age-at-test effects). Moreover, such effects can fade over time because one year of maturation represents more learning among young children than among adolescents. Black et al. (2011) attempt to distinguish the effects of SSA from pure-age effects by using data for Norway, where at the time of military enrollment, an IQ test is given at age 18. They find that age at the time of taking the test has large positive effects on IQ scores while age at school entry has a small but significant negative effect. They also find that starting school when one is older has a significant negative effect on the probability of teenage pregnancy, but has little effect on educational attainment and long-term earnings.

In sum, there is no strong evidence to support that delayed enrollment meaningfully improves student outcomes. In their study, Dobkin and Ferreira (2010) have found that parents with high socioeconomic status are more likely to postpone their children's school enrollment. This implies that the effect of age of school entry is mainly relevant to families of low socioeconomic status because they are more likely to comply with the law. Obviously, this effect could be significantly different from the average treatment effect for the population.

The study by Elder and Lubotsky (2009) is among the few that explicitly examines the mechanisms regarding the relationship between entrance age and educational outcomes. They find strong age-at-test effects by observing the difference in test scores in

[1] The enrollment cutoff date is August 31 in China. Therefore, children born in July or August start school at a relatively young age. For further details, see Section 3.

the fall of kindergarten, before the onset of formal schooling could have had much effect. They conclude that older students perform better simply because they have learned more basic skills before entering school, rather than any entrance-age effect, per se. Thus, the advantage in academic achievement only reflects the heterogeneity in children's family background, which, in turn, highlights the important role of preschool educational investments.

Besides the education and labor market outcomes, Dee and Sievertsen (2015) estimate the effect of school starting age on mental health. They find that a one-year delay in the start of school dramatically reduces inattention/hyperactivity at age seven. Moreover, it has a long-lasting effect by age 11. However, they do not find any persistent effect on other mental-health outcomes. Landersø, Nielsen, and Simonsen (2016) find that higher age at school entry lowers the propensity to commit crime, but this reduction is caused by incapacitation while human capital accumulation is unaffected.

In China, there is few study of the effect of school starting age on student outcomes. This is in part because of the lack of suitable micro data, and in part because of defects in the research methodology. For example, Liu and Li (2015) examine the relationship between birth months and educational outcomes, based on a survey from a middle school in Kunming city in Yunnan province. They find that students born in July and August have a 16.7% to 22.8% lower probability of getting into a key senior middle school compared with the rest, because they are relatively younger than their classmates. However, they only focus on a simple correlation analysis, which does not necessarily reflect the causal effect of SSA.

Based on RDD, Chen (2015) estimates the effect of SSA on children's educational outcomes from rural areas in Gansu province. The author finds that a one-year delay in school enrollment increases the incidence of first-grade retention by about 10 percentage points for boys and reduces the probabilities of middle school enrollment by 6 percentage points for both boys and girls. However, these results are limited to a small sample size, which reduces the precision of the RDD estimates. Moreover, the findings only focus on a special poverty area in China. Most importantly, the author does not consider the potential mechanisms between entrance age and educational outcomes. Overall, this paper will aim at contributing empirical evidence through filling these gaps.

3. China's education system and school starting age

China's Compulsory Education Laws (CEL) were passed on April 12, 1986, and went into effect on July 1, 1986. In Chapter 1, Article 1 specifies nine years of compulsory schooling, which comprises six years of primary school and three years of junior high school. As opposed to setting a minimum age for leaving school as in the US (Angrist & Krueger, 1991), the laws in China stipulate the length of compulsory schooling as nine years.

Chapter 2, Article 11 of CEL further requires parents to send their children to primary school once their children reach the age of six before the cutoff date of the school, which is August 31. Thus, children born on August 31 or slightly earlier enter primary school at the earlier stages of the age of six, whereas those born on September 1 or slightly later enter primary school at the later stages of the age of six.

Preprimary education in China is not compulsory for every child. Most preschools are full-time with three age levels, while some also operate on a one- or two-year basis. Newly available statistics from Education Statistics Yearbook show that the participation rate in the three-year program reached 70.5% in 2014. However, the standards in these preschools can be very inconsistent. The attendance rate varies by area and by household income. In general, children from urban or wealthier families are more likely to attend preschool (Gong, Xu, & Han, 2015). Thus, the competition for skills accumulation begins even before the start of primary school.

Every school year, the age of school entry is a controversial topic. Parents and the media debate whether the cutoff dates for enrollment should be adjusted. Many parents seek a relaxing of this restriction, arguing that "being born only one day later means that a child must enroll one year later," which they see as a huge disadvantage for children born in September or October. It is widely believed in Chinese society that a child should not lose time at the start line.[2] Therefore, China's parents care more about whether their children are younger than their peers, rather than their child's age, because earlier school entry means an earlier labor market entry, earlier marriage etc. Based on these cultural preferences, many parents want to send their children born after September, and especially in September and October, to school early, even if they have not reached the age of six for that school year.

It should be noted, though, that CEL Chapter 2, Article 11, does make some exemptions for illness or underdeveloped children. Parents can delay school enrollment for these children if they apply to the local authority. In addition, economically less-developed areas also allow a later start to school enrollment. In reality, in some poor rural countries, children start school at age seven (Brown & Park, 2002; Chen, 2015).

4. Identification strategy

We apply RDD to estimate the effect of school starting age on academic achievement. RDD was firstly developed by Thistlethwaite and Campbell (1960), it estimates treatment effects in a non-experiment setting where treatment is determined by whether an observed assignment variable exceeds a known cutoff point. By comparing the outcomes near the threshold, RDD identify a pure effect of treatment (see Lee and Lemieux (2010) for a review).

[2] See website article: http://news.xinhuanet.com/2014-02/18/c_119389811.htm.

Here, we firstly start with the structural equation as follow:

$$y_i = \alpha_0 + \alpha_1 SSA_i + X_i'\beta + \varepsilon_i \tag{1}$$

where y_i denotes the outcome of student i, which in this paper, is cognitive test scores. SSA_i is school starting age. It is calculated as the child's age on September 1 in the school year that he or she entered primary school, based on the retrospective reports on grade progression and months of birth.[3] X is a vector of covariates including student characteristics, family background and county fixed effect. α_1 is our parameter of interest.

Unbiased ordinary least squares (OLS) estimators in Eq. (1) require that SSA and the error term ε are not correlated. In reality, however, this strong assumption is hard to satisfy since some unobserved factors may affect the SSA and outcomes simultaneously. For example, if children who enter school at an older age are those with lower ability or poorer family backgrounds (this is very likely true in China), the OLS estimates will be biased.

To solve the endogenous problem, we exploit exogenous variation in the enrollment age induced by school cutoff date. That is, children who born after the cutoff must delay enrollment by one year. As an administrative regulation, the cutoff should be perceived as reasonable exogenous tools to generate the variation in enrollment age. Therefore, we estimate the following two-stage least squares equations:

$$y_i = \rho_0 + \rho_1 SSA_i + f(\mathrm{M}) + X_i'\pi_1 + \varepsilon_i \tag{2}$$

$$SSA_i = \delta_0 + \delta_1 D_i + f(\mathrm{M}) + X_i'\pi_2 + \upsilon_i \tag{3}$$

Here, D_i is a binary instrument variable equal to 1 if the child born in September or later and 0 otherwise. M denotes month of birth, and $f(\mathrm{M})$ is a control function of the assignment variable M, and is allowed to be different on each side of the cutoff. As Fredriksson and Ockert (2013), we normalize month of birth to zero at the school entry cutoff, so children born in September are assigned a month of birth of 0.5 and thus $\mathrm{M} = (-5.5, \ldots 5.5)$.

Following Lee and Card (2008), we adopt a parametric rather than a nonparametric approach to approximate $f(\mathrm{M})$ since the assignment variable is discrete. In the main results given below, we specify it as a quadratic polynomial upon visual assessment and on the basis of the Akaike information criterion (AIC). We also perform sensitive analysis for various specifications of $f(\mathrm{M})$ and for different bandwidth. Following Lee and Card (2008), the standard errors are adjusted by clustering the discrete value of the assignment variable.

Note that substituting the Eq. (3) into the outcome Eq. (2) could generate the reduced form equation:

$$y_i = \gamma_0 + \gamma_1 D_i + f(\mathrm{M}) + X_i'\tau + \eta_i \tag{4}$$

where γ_1 can be interpreted as an intent-to-treat (ITT) effect. Since the model is exactly identified, 2SLS estimates are equal to $^{\gamma_1}/_{\delta_1}$, given that the same bandwidth is used for Eqs. (3) and (4).

As a key assumption, RDD requires that $Cov(D,\varepsilon) = 0$. However, if parents give birth exactly around the cutoff date and these unobserved parents' attributes are also correlated with the children's outcome, the 2SLS estimates will be biased. As given below, we will address these concerns by (1) testing the distribution of month of birth and (2) regressing each of the X variables on D. Given these necessary conditions for $Cov(D,\varepsilon) = 0$, we conclude that parental manipulation cannot influence our results.

Another important assumption of RDD is the requirement that there are no “defiers” in the sample. However, it indeed allows some parents to manipulate their children's actual school entry age. In reality, those children born just after the cutoff date are very likely to enroll early by one year. Likewise, those children born just before the cutoff date are more likely to delay enrollment by one year.

In Table 1, we present the compliance rate for age of school entry by month of birth. We find that around 76% of children complied with the entry age law. The percentage of early entry (defined as children who started school before they turned six years old) jumped from 3% for children born in August to 41% for those born in September. Likewise, the percentage of delayed school entry (defined as children who started school after they turned six years old) was relatively high for children who were born in July and August, with 23% and 25%, respectively. However, for example, it seems to be reasonable to assume that no one starts at late ages if born in August instead of September for these early enrollees. There should be no “defiers” in the sample. Therefore, our 2SLS estimates explain a local average treatment effect (LATE) that applies to children whose school entry is influenced by entrance cutoffs (see Imbens & Angrist, 1994).

[3] Although the question C2 on student questionnaire asks the school starting age, we doubt that some Chinese students are accustomed to answer the nominal age, but not years old. In this paper, we follow previous studies (e.g., Elder & Lubotsky, 2009) to compute school starting age using detailed information on grade retention and skipping. The actual SSA can be defined as: $SSA = (\text{year of enrollment} - \text{year of birth}) + (8 - \text{month of birth}) / 12$. We also check the distribution of SSA based on the two methods and indeed find notable differences.

Table 1
Compliance rate by month of birth.Source: CEPS 2013–2014.

Month of birth	Early	On time	Late
January	0.10	0.75	0.15
February	0.08	0.73	0.19
March	0.08	0.77	0.15
April	0.06	0.77	0.17
May	0.04	0.77	0.19
June	0.05	0.74	0.21
July	0.03	0.74	0.23
August	0.03	0.72	0.25
September	0.41	0.51	0.08
October	0.32	0.61	0.07
November	0.30	0.63	0.07
December	0.23	0.69	0.08

Notes: Early refers to children who started school before they turned the age of six. On time refers to children who started school once they turned the age of six. Late refers to children who started school after they turned the age of six.

5. Data and descriptive analysis

We used data from the CEPS conducted by the National Survey Research Center at Renmin University. The CEPS is a school-based nationally representative survey with a multi-stage stratified probability proportional to size (PPS) sampling design that focuses on junior high school students. The first wave of data survey begins at 7th and 9th graders in the 2013–2014 academic year. It includes 19,487 students in 438 classrooms of 112 schools in 28 county-level units in China.

The dependent variable in our analysis is cognitive ability test scores. The CEPS administers internationally standardized cognitive ability tests, derived from 15-minute in-class assessment. These tests are unrelated to the content of school curricula and measure students' reasoning abilities in three dimensions: Chinese language, graphical interpretation, and calculation and logic. To facilitate comparisons of scores across students, the CEPS extracts three parameter item response theory scores, and we use their *Z*-scores.

We now describe the sample selection criteria. First, we exclude 9208 students in the 9th grade. The CEPS includes retrospective reports on grade progression for grades 1–6, which are used to calculate the year of primary school entry. Therefore, we can only judge the school enrollment year for 7th graders.

Second, we exclude some counties with weak enforcement of the school enrollment rule. Given our identification strategy, we focus on counties in which there is strong evidence that the threshold is used to determine the school entry age. To verify whether the cutoff date is strictly enforced, we regress the actual school entry age on an indicator to be born in September or later and a polynomial function of birth months relative to cutoff. According to the results, 20 of the 28 counties strictly enforce the school entry cutoff, meaning that being born after the cutoff significantly increases the school entry age.[4] This selection rule excludes 2956 students.

Given the sample selection criteria, our results capture the effect of school starting age in counties with strict enforcement. Parents who decided to send their children to school early may be systematically different from those who send their children late, and their children's ability can itself influence parental decisions. In China, the disadvantaged students are more likely to delay enrollment. Therefore, we think of RDD estimates as providing an upper bound of the causal effects. Table A in the Appendix provides sensitivity analysis when including the eight counties.

Control variables contain gender, parental education in years, subjective family income level (low = 1, fair = 2, high = 3), books at home (very few = 1, few = 2, fair = 3, many = 4, a lot = 5), number of siblings, parental attitudes toward child's future education (stop going to school now = 1, junior high school graduation is ok = 2, … Ph.D graduation = 9) and county dummies. After taking into account missing information on some of the variables, we are left with 6866 observations of students in our final sample.

Table 2 presents descriptive statistics by the timing of school entry. We find that children who attend primary school late achieve the lowest cognitive test scores (−0.475), compared with the early enrollees (−0.003) and on-time enrollees (0.103). They also tend to have parents with lower education and restricted attitudes toward education, lower family income and books at home, and more number of siblings. Interestingly, as compared with the on-time enrollees, the early enrollees also face disadvantages on both family background and cognitive scores. This should be consistent with the prevalent cultural preference in Chinese society for an early start, even if the children have not acquired greater "readiness" for learning in primary school.

Children who enter late are associated with the most disadvantaged family backgrounds. Although the compulsory education is tuition-free in China, parents need to pay fees for book and in-school activities. They therefore have to face heavy burden for financing their children's schooling (Brown & Park, 2002; Chen & Jin, 2012). Given the lacks of preschools, those delayed children

[4] Among the eight counties with weak enforcement, in five counties (ID: 6, 17, 21, 22, and 27), being born after the cutoff decreases the school starting age in children (most of them are statistically insignificant); and in three counties (ID: 2, 18, and 23), being born after the cutoff slightly increases the school starting age in children (statistically insignificant).

Table 2
Descriptive statistics by the timing of primary school enrollment.Source: China Education Panel Survey 2013–2014.

	All	Early	On time	Late
Dependent variables				
Cognitive scores	0.000	−0.003	0.103	−0.475
	(1.000)	(0.968)	(0.983)	(0.972)
Explanatory variables				
Father's education in years	10.53	10.00	10.96	9.11
	(3.22)	(2.98)	(3.24)	(2.88)
Mother's education in years	9.72	9.13	10.32	7.53
	(3.68)	(3.26)	(3.49)	(3.98)
Number of siblings	0.729	0.880	0.597	1.19
	(0.851)	(0.862)	(0.774)	(0.99)
Family income level	1.87	1.79	1.93	1.69
	(0.49)	(0.50)	(0.47)	(0.54)
Books at home	3.30	3.06	3.47	2.77
	(1.24)	(1.27)	(1.18)	(1.28)
Parental attitudes toward child's future education	6.92	6.93	7.02	6.47
	(1.64)	(1.62)	(1.56)	(1.96)
Gender (1 if girl)	0.477	0.519	0.482	0.413
Sample size	6866	1049	4787	1030

are very likely to stay at home before entering primary school. As a result, they may receive less human capital accumulation than children from wealthy families. In the next section, we will also empirically test these notations.

6. Empirical results

This section presents the empirical results. We first show the first-stage estimates. Then we confirm the validity of the instrument. Finally, we report the baseline results derived by OLS and 2SLS and estimate the heterogeneity of treatment effects by different groups.

6.1. First-stage estimates

We first show that school starting age significantly increases for children born in September or later. Fig. 1 illustrates this visual evidence. The graph shows that school entry age jumps from 6.2 to 6.5 for children born around the cutoff date. Interestingly, this pattern implies that children born before the cutoff date are more likely to comply with the law. However, the non-compliance among children born after the cutoff is relatively high.

Next, we present the regression results of this first-stage relationship on the basis of Eq. (3). In the first specification, we control for a linear function of the assignment variable that is allowed to vary on either side of the cutoff. In specifications (2) and (3), we replace the linear trend with quadratic trend. Finally, we use a narrower sample around the threshold (born in the two or three months before and after the cutoff date, respectively) as well as linear trend of the assignment variable. These results are shown in Table 3.

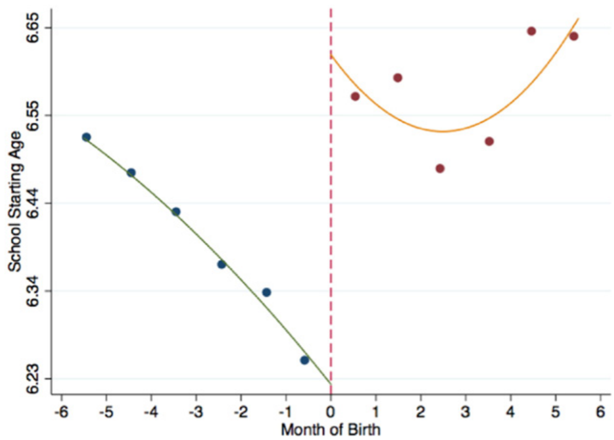

Fig. 1. School starting age and birth months. Notes: regression lines are quadratic polynomials of the assignment variable fitted separately on each side of the cutoff date. The dashed line indicates the school entry cutoff.

Table 3
First-stage regressions: effect of being born after the cutoff date on school starting age.

	Dependent variable: School starting age					
	(1)	(2)	(3)	(4)	(5)	(6)
$D = 1$	0.290	0.394	0.403	0.383	0.398	0.363
	(0.028)***	(0.050)***	(0.044)***	(0.048)***	(0.042)***	(0.054)***
Linear in f(M)	Yes	No	No	Yes	Yes	Yes
Quadratic in f(M)	No	Yes	Yes	No	No	No
Covariates	Yes	No	Yes	No	Yes	Yes
Bandwidth	Full	Full	Full	Jun-Nov	Jun-Nov	Jul-Oct
Sample size	6866	6866	6866	3533	3533	2424

Notes: Covariates include gender, number of siblings, parental education, family income, books at home, parental attitudes toward child's education and county fixed effects. Standard errors shown in parentheses are adjusted by clustering the assignment variable.
* indicates the coefficient is significant at 10% level, ** at 5% and *** at 1%.

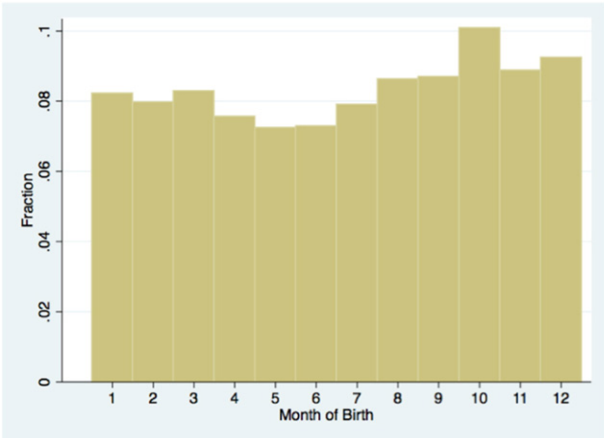

Fig. 2. Distribution of birth months in the CEPS.

All the estimates across these specifications provide strong evidence that school starting age undergoes large jumps and is statistically significant. However, the jump of SSA conditional on the linear trend of assignment variable is 0.29, smaller than other specifications. It jumps by 0.394 and 0.403 after controlling for quadratic terms of assignment variable, without and with covariates respectively. Interestingly, local regression results show very similar results (0.363 to 0.398). Arbitrary choice on the order of polynomial may lead to biased estimates. In this paper, we prefer to employ the quadratic functional form of the assignment variable from both visual inspection and the AIC across specifications.[5] As a robust check of the functional form, we also report the estimates on the basis of narrower samples around the threshold.

6.2. Validity of the instrument variable

For RDD, the main concern is that parents may give births exactly around the threshold. To address this concern, we first illustrate the distribution of birth months. From Fig. 2, we can see that the birth months are almost uniformly distributed, and there is no clear sign of parental manipulation of birth month around August and September.

Second, we regress each of the covariates X on D. If the month of birth is not subjected to parental manipulation, we would expect little correlation between X and D. Table 4A shows these results. None of the covariates are statistically significant in either the local sample or full sample specification. As an additional check, we also regress the cognitive scores on all covariates. Then, using the predicted values (the weighted average of the covariates), regress on D as well as the control function. As Table 4B shows, all the coefficients are not statistically significant. In sum, the continuity of covariates suggests that parental manipulation cannot influence our results.

[5] The AIC is given by: $AIC = N^* \ln(SSE_k) + 2^* N_k$, where N is the number of observations, SSE_k is the mean square error of the regression, and N_k is the number of parameters with k order polynomial in the regression model. In practice, I find that the AIC procedure prefers to $k = 2$, and higher order did not improve the fit of the model.

Table 4A
Covariate continuity tests.

Dependent Variable	(1)	(2)	(3)
Mother's education	0.066	−0.438	−0.372
	(0.337)	(0.223)	(0.238)
Father's education	0.092	−0.414	−0.409
	(0.293)	(0.223)	(0.255)
Number of siblings	0.082	0.016	0.039
	(0.079)	(0.036)	(0.040)
Family income level	0.008	−0.042	−0.014
	(0.045)	(0.028)	(0.032)
Books at home	0.128	0.011	0.039
	(0.113)	(0.052)	(0.051)
Parental attitudes toward child's future education	0.064	−0.008	−0.131
	(0.150)	(0.032)	(0.087)
Gender	−0.019	−0.003	−0.012
	(0.046)	(0.006)	(0.009)
Bandwidth	Jul-Oct sample	Jun-Nov sample	Full sample
Linear trend in $f(M)$	Yes	Yes	No
Quadratic trend in $f(M)$	No	No	Yes

Note: Each coefficient was estimated separately based on Eq. (4) in the text but not include covariates.

Table 4B
Covariate continuity tests.

	(1)	(2)	(3)
Y (predicted cognitive scores)	0.016	−0.022	−0.029
	(0.033)	(0.016)	(0.021)
Bandwidth	Jul-Oct sample	Jun-Nov sample	Full sample
Linear trend in $f(M)$	Yes	Yes	No
Quadratic trend in $f(M)$	No	No	Yes

Note: We first regress the cognitive scores on the covariates: gender, number of siblings, parental education, family income, books at home and parental attitudes toward child's education. Then we regress the predicted scores on the indicator for being born on September or later and quadratic trend in $f(M)$.

In a recent study, Shigeoka (2015) finds that more than 1800 births a year are shifted from one week before the school entry cutoff to one week following the cutoff date in Japan, where the school entry rule is strictly enforced (almost 100% of children comply with the law). Therefore, the birth months fully determine when children start primary school. However, in other countries with weak enforcement of the school entry cutoff, such as the US and Chile, such behavioral responses of parents were absent. Obviously, China's school entry rule is also relatively weak. Our RDD results should have internal validity.

6.3. Main estimates

In Table 5, we first report the reduced-form estimates across six different specifications. All the specifications indicate that cognitive scores exhibit a statistically significant decline around the cutoff. The visual result in Fig. 3 also confirms this finding.

Table 6 reports 2SLS estimates of the effects of school starting age on cognitive scores. In specification (1), an OLS estimate with no covariates suggests that delaying entry by one year decreases the cognitive scores by a statistically significant 0.221 standard deviation. Specification (2) confirms this negative result (with −0.115), even controlling for covariates. Of course, the OLS estimates may be subject to selection bias, and the disadvantaged children are more likely to enter school late.

Specifications (3) and (4) present 2SLS estimates without and with control variables, respectively. Both of the specifications show larger size estimates of SSA than OLS, and a one-year delay in school entry is associated with 0.331 and 0.303 decreases in standard deviation of test scores, respectively. The magnitude of 2SLS estimates are stable across specifications (3) and (4), which implies that the RDD should satisfy the “as good as randomly assigned” condition. That is, the discontinuity of test scores is solely through the assignment variable and not the other control variables. Therefore, our 2SLS estimation results reflect a true effect of SSA on test scores.

The negative effect of SSA on our analysis is consistent with the results presented by Chen (2015), who finds that delayed school enrollment has a significantly negative impact on children's educational outcomes in rural China. This finding is not consistent with many findings from developed countries (such as Bedard & Dhuey, 2006). As noted by Chen (2015), the different effects are very likely to reflect the differences in their preprimary education, though the author does not provide any empirical evidences.

In Table 7, we present the heterogeneous effect of SSA on cognitive scores. The results indicate that SSA has statistically insignificant effects for boys. Delayed school entry seems to be uniquely relevant and more harmful for girls.

Table 5
Effect of school starting age on cognitive scores (reduced-form regressions).

	Dependent variable: Cognitive scores					
	(1)	(2)	(3)	(4)	(5)	(6)
$D=1$	−0.051	−0.130	−0.122	−0.089	−0.096	−0.051
	(0.027)*	(0.053)**	(0.039)***	(0.035)**	(0.031)**	(0.013)***
Linear in f(M)	Yes	No	No	Yes	Yes	Yes
Quadratic in f(M)	No	Yes	Yes	No	No	No
Covariates	No	No	Yes	No	Yes	Yes
Bandwidth	Full	Full	Full	Jun-Nov	Jun-Nov	Jul-Oct
Sample size	6866	6866	6866	3533	3533	2424

Notes: Covariates include gender, number of siblings, parental education, family income, books at home, parental attitudes toward child's education and county fixed effects.
Standard errors shown in parentheses are adjusted by clustering the assignment variable.
* indicates the coefficient is significant at 10% level, ** at 5% and *** at 1%.

Interestingly, we find that the negative effects for children in rural junior high schools are larger and statistically significant, but it is smaller and statistically insignificant for children in urban schools.[6] It should be recalled that the preschool attendance rate in China is relatively low, especially in rural areas. As shown in Table 2, the delayed children are associated with disadvantaged family background; therefore, they may have lower chances than children from rich families to attend preschool and develop less basic skills before school entry.

Also note that holding back children from school entry in China is rare. In contrast, parents are more likely to send their children to school early. In the next section, we will further discuss the mechanism of interactions between entrance age and test scores.

7. Understanding the mechanisms between SSA and test scores

The estimation results indicate that children with delayed school entry seem to fare worse, even controlling for endogenous entrance age. However, the negative effect between entrance age and cognitive scores may be attributed to the causal effect of school starting age or skill accumulations prior to school entry. It is well known that human capital accumulation is a sequential process; the educational attainment at any stage is the outcome of previous schooling choices (Cameron & Heckman, 1998, 2001). If the traditional views on children's education in China push more parents, especially the wealthy ones, to invest in their children in an earlier age, it is very likely that the school entry has no effect on children's eventual school performance.

Given the lack of preschools in China, a child with delayed entry is more likely to stay at home. On the other hand, wealthier families may be able to better offset any negative effect from being young in school by investing more in children before they enter primary school, either by high-quality preschool or by their parents.[7]

To test this directly, we estimate the effect of SSA on preschool attendance through the same model specification in Section 6. If the data support our prediction, we expect the starting age to be negatively associated with the length of preschool participation. Unfortunately, the sample data contain no information about the intensity of participation. To compensate, we estimate using students' age upon entering preschool. Children who started preschool at a late age are very likely to have experienced shorter exposure and are, thus, less likely to learn basic skills before entering primary school.

In our sample, 19.8% of the children had never attended preschool. Among the participants, 46.4% of the children start preschool at age four or later and 20.6% at age five or later. In China, the formal entry age of preschool is three years old, which means that considerable proportion of students did not receive three years of preschool education.[8] In a recent study, Zhang (2017) examines whether attending preschool enhances the cognitive abilities, health and socialization of junior high school students in China. The author's results indicate that attending preschool significantly increases students' cognition. Moreover, the cognitive benefits are larger among children who enter preschool earlier.

Table 8 presents these results. The three outcomes are dummy variables, which are equal to one if the student started preschool at certain ages and zero otherwise. Because we drop children who did not attend preschool, the zero indicates that children started at an earlier age for a given outcome.[9]

In column 1, we can see that the school starting age increases the probability of attending preschool at age three or later by only 0.1 percentage points, and it is not significant. Furthermore, the magnitude of positive effects of starting age is larger for

[6] We treat school's location as school-level variable and do not include baseline model. Although prior research also mainly adds child and family characteristics, we still test the robustness of our results when including school's location as control variables. However, we found no change in the estimates. Results available upon request.

[7] Using China Health and Nutrition Survey 1991–2006, Gong et al. (2015) explores the role of household income on preschool attendance in China. They find a positive association between household income per capital and preschool attendance in both rural and urban areas.

[8] Some preschool programs (e.g., *tuo er suo*, child-care center) have even started accepting younger children due to parental demand.

[9] Note that we also construct a binary variable, which is equal to one if the student did not attend preschool and zero if they have attended. We find that the sign of school starting age is positive but insignificant. Thus, we do not report in the table.

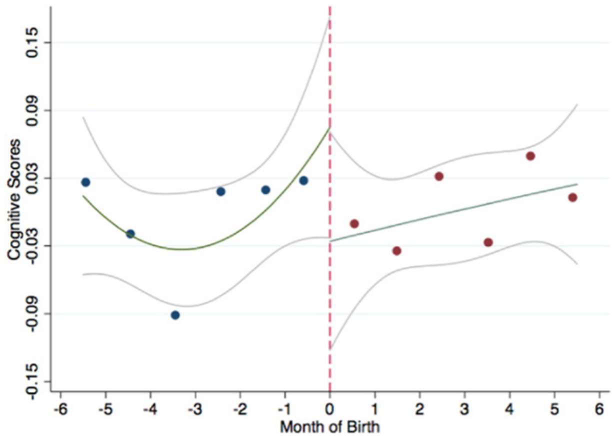

Fig. 3. Reduced-form relationship between SSA and cognitive scores. Notes: Regression lines are quadratic polynomials of the assignment variable fitted separately on each side of the cutoff date. The dashed line indicates the school entry cutoff.

Table 6
Effect of school starting age on cognitive scores (OLS versus 2SLS).

	OLS		2SLS	
	(1)	(2)	(3)	(4)
School starting age	−0.221	−0.115	−0.331	−0.303
	(0.031)***	(0.019)***	(0.131)**	(0.097)***
Quadratic in *f*(M)	No	No	Yes	Yes
Covariates	No	Yes	No	Yes

Notes: The sample size in each regression is 6866. Covariates include gender, number of siblings, parental education, family income, books at home, parental and attitudes toward child's education and county fixed effects. Standard errors shown in parentheses are adjusted by clustering the assignment variable.
* indicates the coefficient is significant at 10% level, ** at 5% and *** at 1%.

children who start preschool at age five or later: delaying entry by one year significantly increases the probability by 27.6 percentage points. For children who start preschool at age four or later, this estimation effect weakens but is still statistically significant with 8.2 percentage points. Overall, these results imply that entrance age and the length of preschool attendance is negative association. Thus, it is consistent with the idea that older students perform worse in school only because they are less likely to build skills prior to primary school entry.

From these results, one should interpret the negative entrance-age effects in China with caution, because the entrance age is likely to have not much of an effect on academic achievement, as it is human capital accumulation before primary school that is more likely to explain the subsequent outcomes in school. As shown by Cunha and Heckman (2007), skills developed in earlier stages promote the development of skills in later stages, so skills acquired before a given investment increases the productivity of that investment. Although many evidences from developed countries show that older students do better in school, they usually also have well developed preschool education systems. Even children delay enrollment, they could still require the skills through preschool. However, China's preschool participation rate is low, receiving high-quality preprimary education for poorer families is still difficult. Given that in China, parents feel that a child should not lose time at the starting line, the late enrollees will inevitably experience an academic disadvantage in school.

Table 7
Heterogeneous effects of SSA on cognitive scores.

	School's location		Gender	
	Rural	Urban	Girls	Boys
School starting age	−0.355	−0.166	−0.764	0.040
	(0.115)***	(0.128)	(0.193)***	(0.104)

Notes: Covariates include number of siblings, family income, parental attitudes toward child's education and county fixed effects. Urban is defined as school's geographic location in the downtown or suburbs. All results are using quadratic trend in *f*(M). Standard errors shown in parentheses are adjusted by clustering the assignment variable.
*** indicates the coefficient is significant at 1% level.

Table 8
Potential mechanisms (effects of SSA on preschool attendance).

	Outcomes		
	(1)	(2)	(3)
	Attended preschool at age 3 or later	Attended preschool at age 4 or later	Attended preschool at age 5 or later
SSA	0.001	0.082	0.276
	(0.018)	(0.050)*	(0.043)***
Sample size	5145	5145	5145

Note: Covariates include gender, number of siblings, parental education, family income, books at home, parental attitudes child's education and county fixed effects. All results are using quadratic trend in $f(M)$. Standard errors shown in parentheses are adjusted by clustering the assignment variable.
* indicates the coefficient is significant at 10% level, ** at 5% and *** at 1%.

8. Conclusion and policy implications

Traditionally, Chinese parents believe that a child should not lose time at the starting line. Many parents do not want their children to wait an additional year just because they were born after the entrance cutoff date, although there is no explicit evidence to support early entry behavior.

This paper aims at contributing empirical evidence on the effect of school starting age on cognitive test scores in China, using newly available nationwide data from the CEPS. The RDD identification strategy relies on school entry cutoff, which generates a specific entrance age among compliers that are arguably exogenous with respect to academic achievement in school. In contrast with previous findings in many Western countries, the 2SLS estimation results in this paper indicate that a one-year delay in school entry is associated with a 0.303 decrease in standard deviation of test scores.

The mechanisms underlying the relationship between entrance age and educational outcomes were investigated. First, we find a larger negative effect for children from rural schools and a small effect for those from urban schools. Second, the school starting age is negatively associated with the length of preschool participation. These results imply that wealthier families may be able to better offset any negative effects from being young in school by investing more in children before they enter primary school.

Given the lack of preschools in China, poor families are very likely to keep their children at home before they can enter primary school. In contrast, wealthier families not only provide their children with a better home environment but can also afford to send them to a high-quality preschool. Combined with the preference for early school enrollment, the entrance cutoff only exacerbates socioeconomic differences in school performance.

Therefore, we provide the following suggestions for the government and policy makers. First, to play fair, the government should strictly enforce the age for school entry policy. Since better-off families can always provide their children with more human capital investment to offset the negative effects of being young in a school cohort, an earlier entry means that they have additional earnings from the labor market, further expanding the income inequality among adults. Alternatively, the government should refine the selection process; for example, by conducting individual schooling tests before primary school.

Second, government should provide a universal and high-quality preschool education for each child in the future. It is obvious that children from poor families are very likely to stay at home or receive little by way of skills development before they can enter primary school. Especially, many previous studies have shown the benefits of attending high-quality preschools on child well-being (see a recent survey by Elango, Garcia, Heckman, and Hojman (2015)). Therefore, universal preschool education can guarantee a fair education before a child enters primary school.

Recently, the Chinese government has begun to focus more on preschool education. Following the *outline of National Medium- and Long-Term Program for Education Reform and Development 2010–2020*, the government has mandated net enrollment in one-year preschool to reach 95% by 2020 and that specified economically developed areas provide universal three-year preschool education. We believe these early education investments can benefit more children especially economically disadvantaged children, and alleviate educational inequality in China.

Appendix A. Including the eight counties

In the text, we exclude eight counties whose cutoff dates do not significantly increase the school starting age. As a robustness check, we re-estimate the effect of school starting age on cognitive scores when including the eight counties. Specification (1) is the baseline estimation. Specifications (2) and (3) show the results without and with control variables, respectively. Specification (2) allows for the inclusion of students for whom some family background data was missing. As expected in the text, we see the following: first, the results are not sensitive to the missing background variable values because the estimates between specification (2) and (3) are almost unchanged. Second, the effect of being born after the cutoff date is smaller than the baseline estimates without including the eight counties; also, the negative entrance age effect is larger for specifications (2) and (3) than specification (1).

Table A
Sensitivity analysis.

	Baseline estimates	Including the eight counties	Including the eight counties
	(1)	(2)	(3)
First stage			
$D=1$	0.403	0.256	0.266
	(0.044)***	(0.042)***	(0.038)***
Second stage			
School starting age	−0.303	−0.469	−0.476
	(0.097)***	(0.125)***	(0.116)***
Quadratic in f(M)	Yes	Yes	Yes
Covariates	Yes	No	Yes
Observations	6866	9917	9768

Notes: The eight counties with ID number 2, 6, 17, 18, 21, 22, 23, and 27 do not strictly enforce the school entry rule. Covariates include gender, number of siblings, parental education, family income, books at home, parental attitudes toward child's education and county fixed effects. Standard errors shown in parentheses are adjusted by clustering the assignment variable.
* indicates the coefficient is significant at 10% level, ** at 5% and *** at 1%.

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