

Matta, Rafael; Ribas, Rafael P.; Sampaio, Breno; Sampaio, Gustavo R.

Article

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ORIGINAL ARTICLE

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The effect of age at school entry on college admission and earnings: a regression-discontinuity approach

Rafael Matta¹, Rafael P. Ribas¹, Breno Sampaio^{2*} and Gustavo R. Sampaio²

*Correspondence:

brenorsampaio@gmail.com

²Department of Economics,
Universidade Federal de
Pernambuco, Rua dos Economistas,
Cidade Universitaria, 50740-590
Recife Pernambuco, Brazil
Full list of author information is
available at the end of the article

Abstract

This paper provides evidence of the effect of age at school entry on college admission and earnings. It does so by exploiting a number of features in the application process to one of the major flagship universities in Brazil. By comparing applicants with different ages at school entry depending on whether they were born on December 31 or on January 1, our estimates show that applicants who delayed first-grade enrollment present higher aptitude test scores and probability of admission. Our results further suggest that advantaged applicants also earn more early in their careers.

JEL Classification: I21, J24

Keywords: School starting age, School achievement, College admission, Aptitude test score

1 Introduction

The perception that maturity plays an important role in school learning has encouraged parents and teachers to delay children's first-grade enrollment. As a consequence, there has been a significant increase in the age at school entry in countries such as the USA (Deming and Dynarski 2008). In fact, there is strong evidence that older pupils tend to outperform their younger classmates in early grades (Bedard and Dhuey 2006; Puhani and Weber 2007; McEwan and Shapiro 2008; Justin 2009). However, there is also evidence that this difference declines over time and disappears in the long run, having no positive effect on adult outcomes (Elder and Lubotsky 2009; Mühlenweg and Puhani 2010). Some studies even find that entering school later reduces educational attainment, by increasing high school dropout rates, and decreases lifetime earnings, by reducing experience in the labor market (Angrist and Krueger 1991; 1992; Dobkin and Ferreira 2010; Black et al. 2011).¹ Nonetheless, the positive effects in early grades may be persistent in a system where students are tracked early into different schools or classes (Allen and Barnsley, 1993; Fredriksson and Öckert 2014).

Given the weak and still disputable evidence of its long-term effects, our study presents and discusses the consequences of a delayed school entry on the admission of college applicants and on their subsequent earnings. We exploit the admission process to one of the major flagship universities in Brazil, which selects candidates strictly based on an entrance exam. In addition to its high quality and reputation, *Universidade Federal de*

Pernambuco (UFPE) is a public university and does not charge tuition fees. As a result, practically all high school graduates in the state of Pernambuco apply to this institution as their first choice. This circumstance makes our study unique because candidates who are not accepted by this university cannot easily enroll at another equally good institution.² Moreover, Brazil does not have a tracking system that could explain the persistence of early disadvantages. At the same time, the country also has one of the highest rates of grade retention in the world (Bruns et al. 2012).³ Thus, this system might diminish the disadvantage felt by younger pupils, who are more likely to repeat a grade.

We compare college applicants whose age differences at school entry are exogenously determined by whether they were born on December 31 or on January 1, along with the minimum-age rule enforced by primary schools in Brazil. Our analysis, however, should not be interpreted as the long-term effect on the probability of first graders going to college. Instead, we estimate the effect of delaying school entry on high school graduates aiming to join an elite institution. Our regression-discontinuity (RD) design shows that, among boys, delaying school entry by 1 year increases the admission test score by 0.5 standard deviations (sds) and the probability of college admission by 15 percentage points (p.p.). Importantly, due to the higher repetition rates among early entrants, the age difference between students born on December 31 and those born on January 1 practically disappears by the time they graduate from high school. Therefore, the effect on college admission cannot be attributed to differences in age at the test but rather to learning disadvantages that persist over time. For girls, the effect at early ages is weaker and not persistent on average.⁴

According to Elder and Lubotsky (2009), two potential mechanisms could explain why later entrants outperform their peers. One is that greater maturity at school entry improves children's learning ability at primary school and this effect persists over time. The other is that starting school later implies more human capital accumulated from parenting. To the extent that well-educated parents provide more human capital accumulation at home, the relationship between school-entry age and future outcomes should be weaker for the children of less-educated parents. We find, however, that the effect of delaying school entry on test scores is stronger among candidates with less parental education. If parents do not have a college degree, the enrollment delay increases the admission test score of boys by 0.73–0.86 sds and of girls by 0.14–0.57 sds. These findings imply that the difference in college admission scores comes from candidates' learning ability at primary school, rather than from previously accumulated knowledge. Our findings are consistent with the ideas that learning disadvantages at an early age have a persistent impact on adults (Cunha and Heckman 2007; Cunha et al. 2010) and that grade retention is not an effective way to remedy this distortion (Manacorda 2012).

We also conduct a number of tests to shore up our conclusions. First, we confirm the strength of our instrument by showing that children born on January 1 and on December 31 are indeed more likely to be the oldest and the youngest in the first grade, respectively. Second, our results do not seem to be driven by birthday manipulation. If parents planned ahead so that their children were born after New Year's Eve, then the density of birthdays would be discontinuous around this day. Using the density test proposed by McCrary (2008), however, we show that there is no significant discontinuity between December 31 and January 1. Similarly, parents of children born on New Year's Day have essentially the same income and education levels as parents of children born on New Year's Eve. Thus,

our results are unlikely to be driven by parental background or birthday manipulation; they certainly derive only from the minimum-age rule.

Finally, we verify whether the difference found in college admission rates is carried into the labor market. Unfortunately, we have only data of candidates' employment in their 20s, which are not enough to estimate lifetime earnings. Nevertheless, among poorer candidates, we find that men born on January 1 earn about 20 % more at the age of 25 than if they were born on December 31. For female candidates, the difference in earnings is not significant, but being born a day later increases by 4–14 % the probability of graduating from college and working by the age of 25. These results are consistent with the hypothesis that delaying school entry increases the lifetime earnings of poorer candidates.

The remainder of this paper is organized as follows. Section 2 describes the four sources of data used to estimate the effects on college admission, first-grade enrollment, and adult earnings. Section 3 discusses our empirical strategy based on an RD design. Section 4 presents our main findings, as well as several tests that confirm the consistency of these findings. Our conclusions are presented in Section 5.

2 Data

2.1 College application data

The main source of data used in this study is the admission exam taken by candidates for the *Universidade Federal de Pernambuco* (UFPE), which is a flagship university in the Northeast of Brazil.⁵ The vast majority of its undergraduate students used to be admitted through an exam, called the *vestibular*, which was held only once a year.⁶ This exam has two rounds and evaluates students in the following subjects: mathematics, Portuguese, a foreign language (English, French, or Spanish), literature, history, geography, physics, chemistry, and biology. In the first round, every candidate takes one test per subject and the score is the average of all these tests. The results of this eliminate about 40 % of the candidates, who do not go to the next round. The second-round exam comprises Portuguese, a foreign language, and the three other subjects specifically required for the future program.⁷ The final score is a weighted average of the first- and second-round scores. Finally, each program admits those candidates with the best final scores until all the places are taken. Up to 2013, the final test score was the only admission criterion, so a candidate could not leapfrog others with better scores.⁸ On average, about 10 % of the original candidates per program were admitted.

The dataset consists of the application details of 216,771 candidates between 2002 and 2005. However, most of the candidates take the exam more than once. Apart from not being admitted in previous years, some of them retake the exam because they want to switch majors or even institutions. To analyze high school graduates, our sample is restricted to those who graduated from high school in the year that they took the exam. Although failed candidates can retake the exam, we are interested in the cases in which they are immediately admitted to an elite school. Either delaying college admission or going to another institution is considered costly for candidates because it implies less lifetime earnings. In addition, we exclude all candidates who finished high school on adult education programs and those with a large age-grade distortion.

Because we are interested in the effect of delaying primary school entrance at 6 years of age, we keep only candidates who are 18.5 years or younger—i.e., those who spent at most 12 years at school. These candidates either delayed their school entry for at most 1 year

or repeated at most one grade. Due to this age restriction, we can still separate the reason for delaying high school graduation by using the date of birth as an instrumental variable. For older candidates, their age can be explained by more combinations of entry delay and grade repetition so that the instrument becomes exponentially weaker. The final sample has 45,261 observations, evenly split between 2002 and 2005 and between the various birth cohorts. A birth cohort is defined as a group of candidates born between July 1 and June 30th of the following year.

It is worth stressing that almost half the candidates do not take the second-round exam. Moreover, since some majors are more competitive than others, the second-round exam is different not only in terms of subjects but also in terms of difficulty. Accordingly, we use only the first-round scores to compare the performance of candidates. This score is also standardized every year based on the mean and standard deviation of all candidates. Table 1 presents some descriptive statistics. In our sample, the percentage of admitted candidates is 9.7 %, which is slightly lower than the overall percentage of 10.3 %. However, the average test score of first-time candidates is 0.22 sds greater than the overall mean score. These differences may be explained by the fact that first-time candidates usually apply for more competitive programs, so their probability of admission is lower even though their average score is higher.

2.2 Primary and high school data

To support our evidence and identification strategy, we also use data from PNAD, Brazil's National Household Survey, from 1992 to 2005, and from the 2001 National Basic Education Assessment System (SAEB).

The purpose of the PNAD data is to answer the following questions: (1) Are children born more frequently before or after January 1? (2) Do children born on January 1 have to delay their entrance to primary school? (3) Does the age gap in the first grade remain until they graduate from high school? All these questions are addressed before we move to our main results.

Nonetheless, the PNAD sample cannot be automatically compared to the college application sample, mainly because only 23 % of children in Brazil graduate from high school by the age of 18. If we consider the children of parents who have at least high school education, then this rate jumps to almost 70 %. Accordingly, in addition to restricting the PNAD sample to children in the Northeast region who were born between July 1984 and June 1989, we also reweight it so that it mimics the same parental education as the sample of college candidates above. In practice, we apply the following sample weight in our analyses:

$$w_i^{\text{new}} = w_i^{\text{old}} \frac{\Pr(\text{PE} = pe_i | \text{College Application Data})}{\Pr(\text{PE} = pe_i | \text{PNAD})}$$

where w_i^{old} is the original sample weight from PNAD and pe_i is the parental education value of child i . While the probability on the numerator is estimated using the college application data, the denominator is estimated using PNAD. The new sample weight, w_i^{new} , is also rescaled so that it has the same mean and standard deviation as w_i^{old} , not generating artificial outliers.

Table 1 Descriptive statistics

	All samples		Born in July–Dec.		Born in Jan.–June	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Admitted	0.097	0.296	0.095	0.294	0.099	0.298
First-round score	0.223	0.880	0.186	0.890	0.256	0.878
Age	17.78	0.431	17.91	0.465	17.64	0.341
Born in January–June	0.489	0.500	0.000	0.000	1.000	0.000
Female	0.591	0.492	0.583	0.493	0.599	0.490
Father's education						
Middle school	0.163	0.369	0.163	0.370	0.162	0.369
High school	0.382	0.486	0.378	0.485	0.385	0.487
College	0.351	0.477	0.349	0.477	0.354	0.478
Mother's education						
Middle school	0.140	0.347	0.145	0.352	0.136	0.342
High school	0.393	0.488	0.388	0.487	0.398	0.489
College	0.383	0.486	0.376	0.484	0.389	0.488
Household income						
5–10 MWs	0.294	0.456	0.294	0.456	0.294	0.456
11–15 MWs	0.119	0.323	0.116	0.320	0.121	0.326
16–20 MWs	0.081	0.273	0.081	0.273	0.081	0.273
>20 MWs	0.103	0.304	0.105	0.307	0.101	0.301
Private high school	0.709	0.454	0.700	0.458	0.719	0.450
Private primary/middle school	0.717	0.451	0.704	0.457	0.731	0.444
Living in Pernambuco	0.959	0.197	0.960	0.195	0.958	0.200
Living in the Northeast	0.985	0.122	0.985	0.122	0.985	0.122
Birth cohort						
1985–1986	0.326	0.469	0.326	0.469	0.327	0.469
1986–1987	0.345	0.475	0.348	0.476	0.342	0.474
Year						
2003	0.327	0.469	0.271	0.444	0.258	0.438
2004	0.332	0.471	0.279	0.449	0.258	0.437
2005	0.247	0.431	0.173	0.379	0.227	0.419
Employed at 25 years old	0.488	0.500	0.494	0.500	0.482	0.500
Employed and graduated at 25	0.186	0.389	0.184	0.387	0.187	0.390
Annual earnings (R\$) if employed	19,784	22,026	19,903	22,710	19,655	21,267
Number of observations	45,261		23,133		22,128	

The sample of candidates for undergraduate programs at UFPE is restricted to those who graduated from high school in the year that they took the college entrance exam and were under 18.5 years old. The first-round score is standardized, with mean zero and variance one, with respect to the whole set of candidates taking the exam at the same time. Annual earnings are deflated to December 2006 level using the National Consumer Price Index (INPC)
MW current minimum wage

The purpose of the SAEB data is to verify the positive selection in our sample of college applicants. Its survey asks whether students want to continue or stop studying after graduation. This allows us to look not only at performance but also at high school students' decision to pursue higher education as a function of their month of birth.

2.3 Employment data

To estimate the effect of birthday on candidates' employment and earnings, we match their application to UFPE with employment records from *Relação Anual de Informação Sociais* (RAIS) from the Brazilian Ministry of Labor and Employment, MTE. RAIS

presents comprehensive individual information on occupations, demographic characteristics, and earnings of all registered employees in Brazil. By law, every private or public-sector employer must report this information every year.

When available, the matching is based on the candidate's social security number. Otherwise, it is based on the candidate's name, gender, and date and place of birth. Using RAIS data from 2009 to 2012, when the candidates were 25 years old, we are able to find 49 % of them. That is, at least 49 % of the UFPE first-time candidates in 2002–2005 were formally employed at the age of 25. However, only 19 % (39 % of the employed) had already graduated from college (see Table 1). On average, those who are employed receive almost R\$20,000 a year, which corresponds to 4.7 minimum wages in 2006. Earnings are deflated to the December 2006 level using the National Consumer Price Index (INPC).

3 Empirical strategy

In this section, we explain the empirical strategy we adopt to identify the causal effect of early maturity on test scores after high school, college admission, and adult earnings. In our context, early maturity means delaying the start of primary school and then being one of the oldest pupils in the first grade. Since parents do not randomly take such a decision and we cannot observe when the college candidates started primary school, we use the candidates' birthday as an instrumental variable. In particular, we compare candidates born on December 31 with those born a day later, on January 1, using a regression-discontinuity (RD) design.

In Brazil, the law required children to enroll in first grade in the year they turn seven.⁹ Moreover, most schools did not admit children to the first grade unless they were turning seven that year. Thus, children born on December 31 could start primary school when they are still 6 years old. However, other children born a day later could not start the first grade in the same year because they are still a day away from turning six on December 31.

Let Y_i be student i 's achievement after high school—e.g., as shown in their aptitude test score, college admission, employment, and earnings. Although the minimum-age rule is supposed to affect our outcome of interest through several channels, such as maturity when applying for college and learning ability during primary school, these channels do not offset each other. Thus, consider the following reduced-form model:

$$Y_i = \tau I(B_i \geq 0) + g(B_i) + \varepsilon_i, \quad (1)$$

where B_i is student i 's birthday, which is equal to zero on January 1 and negative (positive) before (after) this date, g is a nonparametric function, and ε_i is a random term. While function g captures the systematic relationship between the birth date and the outcome of interest, coefficient τ represents the discontinuity in this relationship around January 1. That is, τ is the effect of being born on January 1 rather than December 31.

To interpret τ as the effect of the minimum-age policy, first we need the age constraint to be binding—i.e., some parents want their children to start school but they cannot do so due to their age. This condition is verified by estimating the school enrollment rate, E_i , around age six, as follows:

$$E_i = \tau_E I(B_i \geq 0) + g_E(B_i) + \varepsilon_{E,i}. \quad (2)$$

If $\tau_E \neq 0$, then the age constraint makes children born on January 1 delay their school start for a year.

The fundamental assumption in identifying τ and τ_E is that parents do not manipulate their child's birthday. Parents may choose whether their child is born before or after January 1 and this choice could be related to parenting skills. In a RD design, the manipulation of the running variable is an issue only if it happens locally around the cutoff. If parents prefer January 1 to December 31, or vice versa, we should observe a significant difference in birthday densities between these two dates. Accordingly, we verify the assumption of no manipulation using McCrary's (2008) test.

As we estimate Eqs. (1) and (2), the effect of delaying school entry on future outcomes, β , can be calculated using the Wald estimator:

$$\hat{\beta} = \frac{\hat{\tau}}{\hat{\tau}_E}. \quad (3)$$

All equations are estimated using triangular kernel functions. The optimal bandwidth is chosen according to the procedures of Calonico et al. (2014) and Imbens and Kalyanaraman (2012). Robust standard errors are calculated as described by Calonico et al. (2014).

4 Results

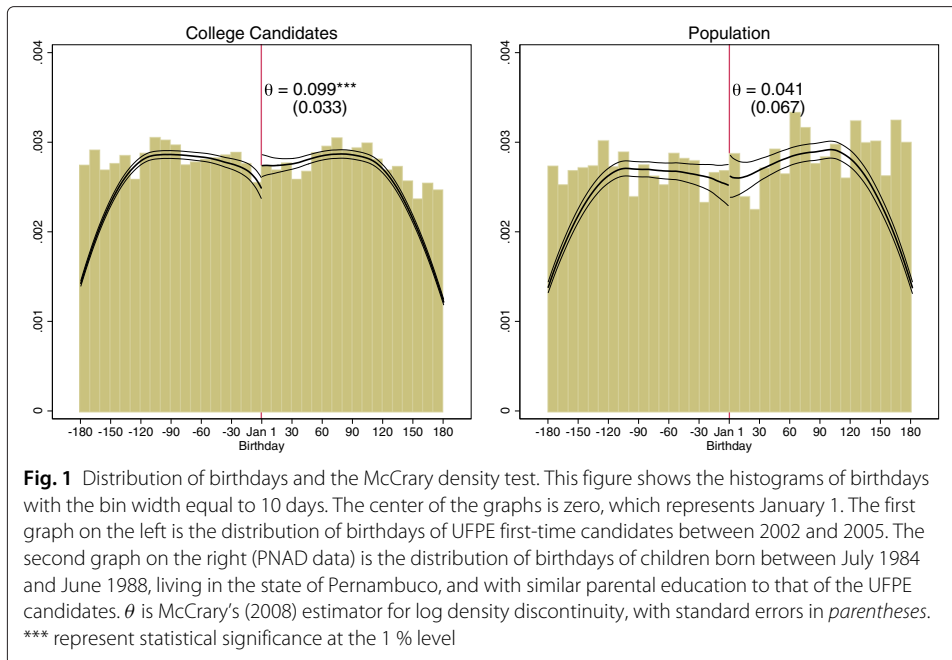
Our results are divided into five parts. First, we show that our instrument (i.e., being born on or after January 1) is indeed exogenous and not subject to parents' choice. Second, we confirm that the minimum-age rule for primary school has been enforced in Brazil and that this instrument is strong enough to predict school-entry age. In Sections 4.3 and 4.4, we present our main results and discuss potential mechanisms through which school-entry age is related to college admission. Finally, we show some evidence for the effect on employment and earnings by the time candidates turn 25.

4.1 Is the date of birth endogenous?

Before we move to the main results, we should check whether parents choose that their child's birthday occurs before or after January 1. If they perceived the child would perform better among younger peers, they might plan her birthday to be after New Year's Eve. In this case, other characteristics related to parenting skills could also drive our results.

To verify this issue, we perform two different tests. First, we test for birthday manipulation using McCrary's test. McCrary (2008) proposes an estimator for the discontinuity in the density function around the cutoff (January 1) of the running variable (the birthday). His test is implemented as a Wald test in which the density is continuous under the null hypothesis. Second, we verify whether being born before or after January 1 is related to parental education. Here we assume that the parent's education is a good proxy for parenting. The more educated parents are, the higher the investment made in their child's education.

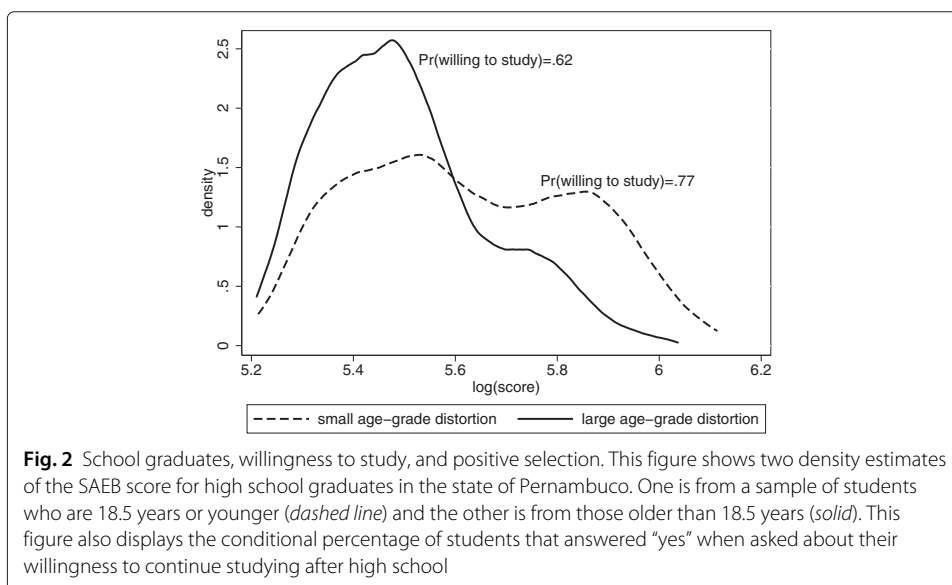
The first graph on the left of Fig. 1 shows that first-time college candidates are more likely to be born on January 1 than on December 31. However, this difference can be the result not only of parental choice but also of performance at school. If students born on December 31 perform worse in school, then they are also less likely to finish high school and apply for college. The second graph on the right confirms that there is no significant difference in the population over the probability of being born before or after January 1. Namely, if we look at the whole cohort of children born at much the same time, living



in the same state, and with similar parental education, there is no evidence of birthday manipulation.

As a result, the discontinuity found among college candidates can be ascribed to school performance, which can potentially lower our causal estimate. That is, if the missing children applied for college at the right age, they would perform worse than those who do actually apply, lowering the average score below the cutoff.

To provide evidence of this positive selection in our sample, we present in Fig. 2 two conditional density estimates of the SAEB score for high school graduates in the state of Pernambuco. One considers the sample of students who are 18.5 years or younger (dashed line)—mimicking our sample—and the other considers those older than 18.5 years (solid line)



line). Note that there is a mass of students with a large age-grade distortion on low scores when compared to those with a small age distortion. That is, the former group performs significantly worse than the sample that we use to obtain our estimates.

Figure 2 also reports the percentage of students who answered *yes* when asked about their willingness to continue studying after graduation. Of the students with a large age-grade distortion, 62 % answered that they wanted to continue studying, whereas 77 % of students with a small distortion gave this answer. These numbers suggest that our sample comes from a highly selected group of high school graduates.

Next, we explore the direction of the bias for high school graduates born around the discontinuity (in January and December) using the SAEB data. We first show in Table 2 that students born in December are more likely to have a large age-grade distortion when compared to those born in January. We then analyze if the (positive) selection bias is stronger for those born in December. This would imply an even lower average score below the cut-off if those excluded from the sample had applied for college at the right age. We observe that the difference in the average test score slightly decreases after we restrict the sample to those who are willing to apply for college. Further restricting the SAEB data to those with a small age-grade distortion, so that it resembles our sample, the average test score becomes slightly higher for those born in December than for those born in January. This evidence reinforces our argument that our sample contains students positively selected from those who would eventually apply for college.¹⁰

Although the probabilities of being born before or after January 1 are similar for the overall cohort, well-educated parents could choose a different birthday than less-educated parents (Buckles and Hungerman 2013). Figure 3 presents the RD estimates for parent's education. The result confirms that parents of candidates born before and after January 1 have a similar probability of holding a college degree.¹¹ Similarly, Fig. 4 shows that there is no significant difference in terms of household income. Candidates' households have nearly the same probability of being poor or rich—i.e., receiving either less than five minimum wages or more than ten minimum wages—regardless of their birth date.

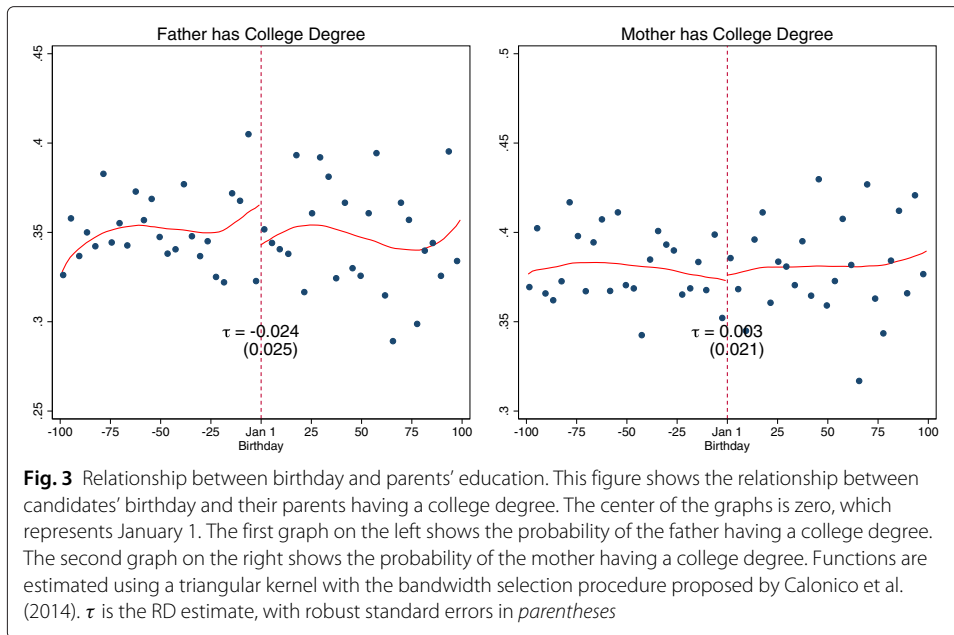
4.2 Does their birth date make children delay school entry?

In this section, we present and discuss our “first-stage” estimates. In other words, we verify if children born on January 1 are indeed more likely to be the oldest student in class

Table 2 Descriptive statistics: selected sample

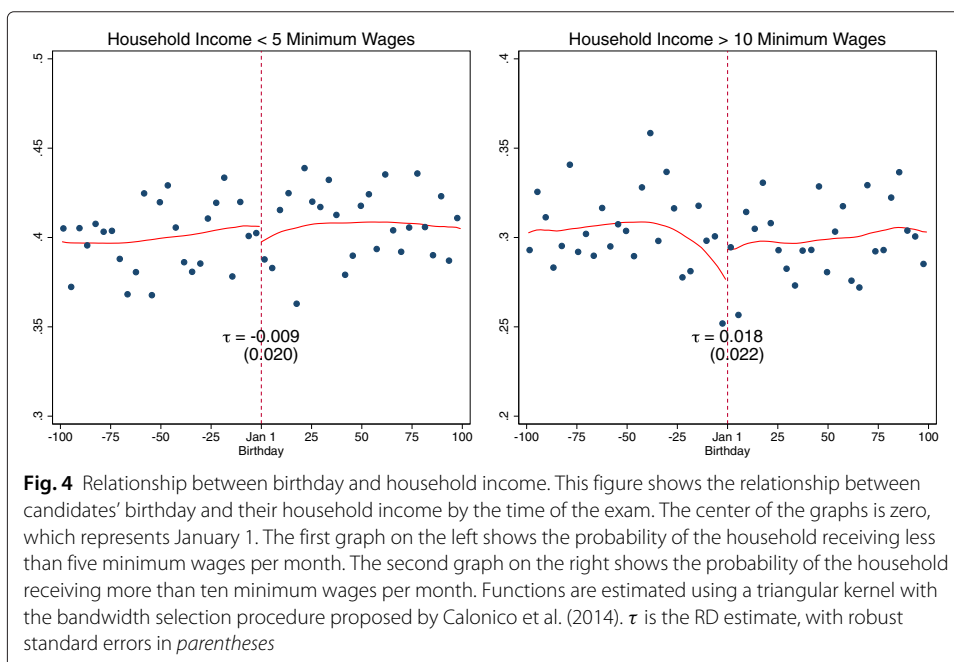
	Born in December	Born in January	Difference
Large age-grade distortion	0.235 (0.426)	0.186 (0.391)	−0.049 (.052)
Log (score)	5.586 (0.196)	5.594 (0.213)	0.008 (0.026)
Log (score) for students willing to keep studying	5.601 (0.204)	5.603 (0.214)	0.001 (0.032)
Log (score) for students willing to study with small age-grade distortion	5.634 (0.206)	5.616 (0.221)	−0.019 (0.037)

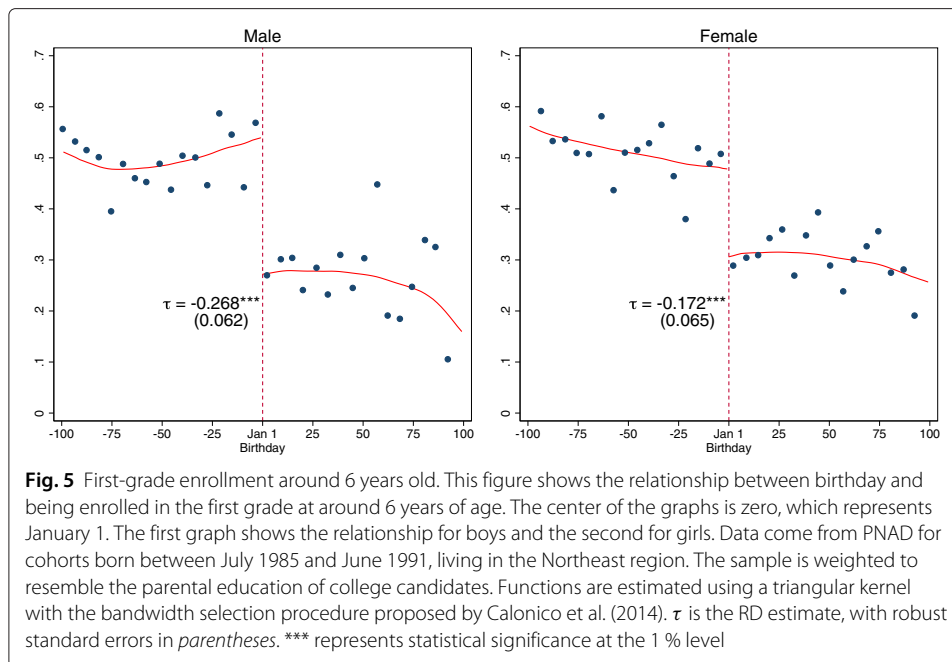
Summary statistics for high school graduates born in January and December come from SAEB in 2001. The large age-grade distortion group comprises students older than 18.5 years. A student is “willing to keep studying” if she wants to continue studying after high school



during their primary school years, while those born on December 31 are more likely to be the youngest. Using data from PNAD, we investigate what happened to those cohorts of college candidates when they were 6 years old.

Close to 6 years of age, children born on January 1 are in fact less likely to be enrolled in the first grade than those born just a day earlier. Figure 5 shows that the difference for boys is almost 27 p.p., while for girls it is 17 p.p. These estimates indicate that being even one day short of turning six can make both boys and girls delay their school start in the





Northeast region of Brazil. This rule causes the children born on December 31 more likely to be younger than their classmates than those born on January 1, who start a year later.

If older students perform better than their peers, as presumed, we should expect that the repetition rate for children born on December 31 will be higher than for the ones born on January 1. In this case, the age gap created by the minimum-age rule should narrow over time as the former repeat a grade and turn into one of the oldest in their class.¹² Similarly, the grade gap—i.e., being at least a year behind where the rest of the cohort should be—must narrow at the same rate. Table 3 presents the RD estimates for the grade gap. For boys, it practically disappears at age nine, when they were supposed to be in the fourth grade. For girls, it vanishes in the second grade.

Table 3 RD estimates of the grade gap by age

Age	Male		Female	
	τ	z-stat	τ	z-stat
6	0.268***	4.581	0.172***	2.794
7	0.095*	1.867	-0.002	-0.349
8	0.135***	4.098	0.029	0.998
9	0.031	0.69	0.042*	1.893
10	0.008	0.389	-0.011	-0.803
11	-0.005	-0.419	-0.010	-0.903
12	0.002	0.082	0.001	0.046
13	-0.004	-0.395	0.024**	1.974
14	0.014	1.264	0.023**	2.256
15	-0.014	-1.192	0.001	0.015
16	-0.013	-0.558	0.015	1.565

This table shows the difference between children born on January 1 and on December 31. The dependent variable is equal to one if the student is in the wrong grade for his age and zero otherwise. The first columns show the difference for males, while the last columns show the difference for females. Data come from PNAD for cohorts born between July 1985 and June 1991, living in the Northeast region. The sample is weighted to resemble the parental education of the college candidates. Functions are estimated using a triangular kernel with the bandwidth selection procedure proposed by Calonico et al. (2014). τ is the robust RD estimate. ***, **, * represent statistical significance at the 1, 5, and 10 % levels, respectively

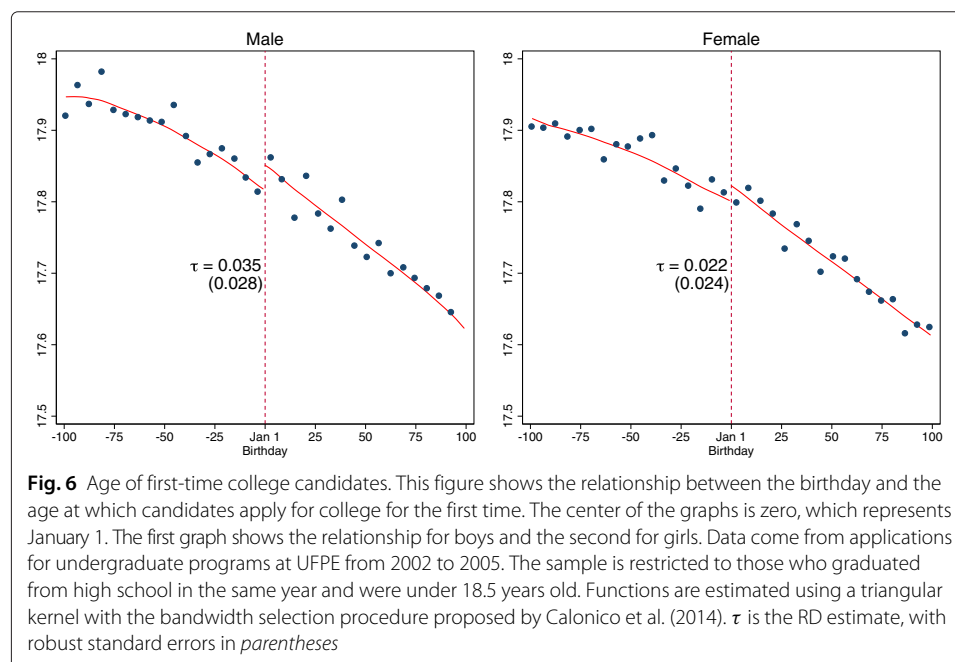
When they graduate from high school and apply for college, the age gap is almost zero, as seen in Fig. 6. Therefore, any difference between college candidates born before and after January 1 cannot be attributed to differences in their current age. The difference between these two groups lies in their learning ability in primary school, which results in a greater repetition rate for one of them. Whereas students born on January 1 tend to outperform their classmates in primary school, students born on December 31 tend to fall behind the class. We discuss next how those two different experiences affect the probability of their admission to college. Later, we examine whether this differentiation emerges in school or at home.

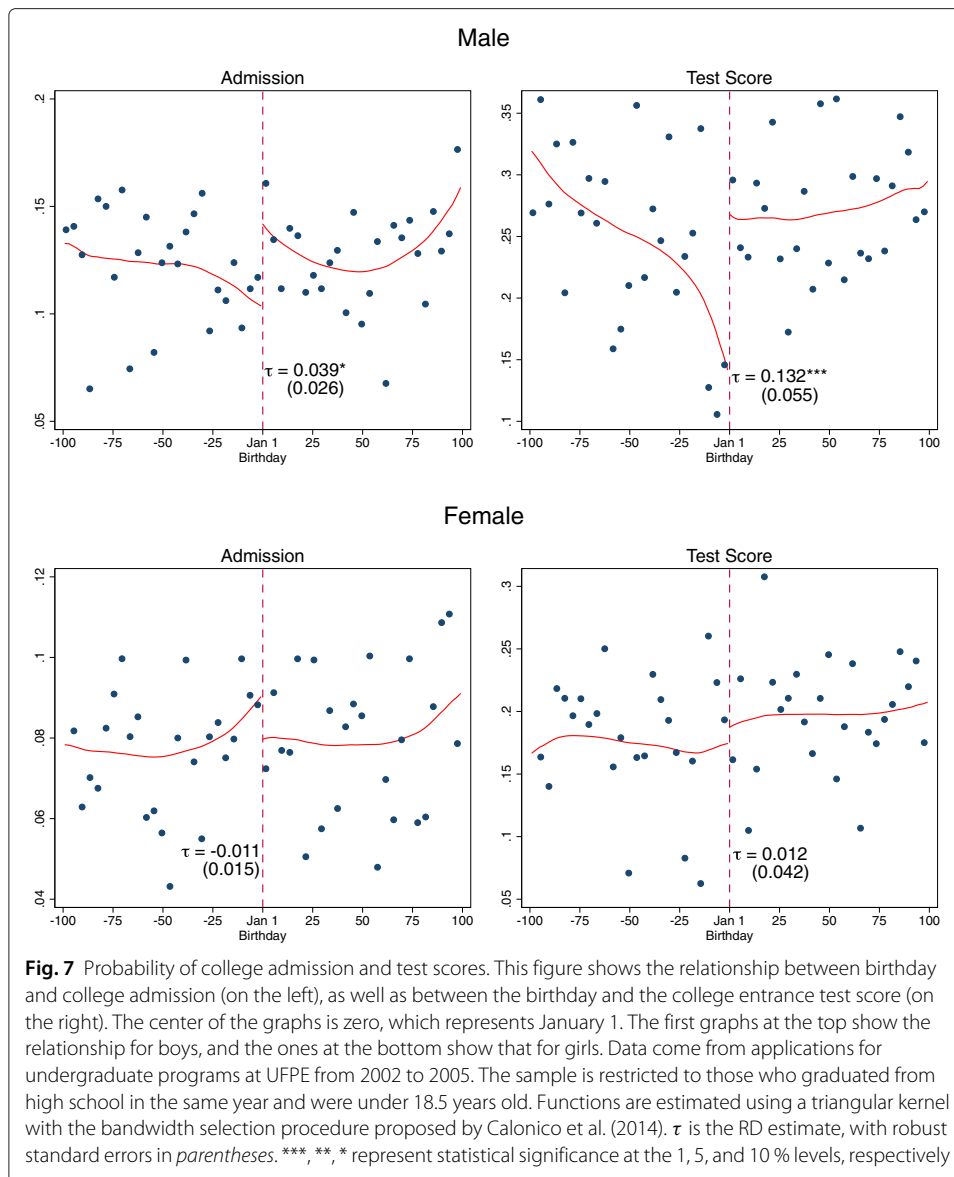
4.3 Main results—the effect on college admission

Even though there is no age gap between college candidates of the same cohort when they apply to college for the first time, they can still have different outcomes. Figure 7 confirms this prediction, at least for males. The average score of all those born on December 31 is 0.13 sds less than the average of those born on January 1. This difference in the score affects the probability of college admission in about 4 p.p.

To calculate the effect of delaying school entry on college admission and test scores, we simply have to divide the estimates in Fig. 7 by those in Fig. 5—i.e., by applying the Wald estimator. For boys, we find that delaying a year of school increases by 0.5 sds their aptitude test score and by 15 p.p. their probability of college admission. These effects are greater than the ones found by Bedard and Dhuey (2006) for eighth graders in OECD countries and by Justin (2009) for tenth graders in Canada but similar to the ones found by McEwan and Shapiro (2008) for eighth graders in Chile and by Crawford et al. (2010) for high school graduates in England.

For girls, no significant difference is found, at least on average. McEwan and Shapiro (2008) also find that delaying primary school enrollment affects more boys than girls in





the long run. A possible explanation is that boys mature later than girls, so their gap in terms of learning ability tends to persist longer over the primary school period.

Table 4 presents similar RD estimates but using different local-polynomial degrees and different bandwidth selection procedures. Our results look robust whatever procedure we apply.

4.4 The effect by parental education and school choice

Elder and Lubotsky (2009) point out two potential mechanisms that make older students better than their classmates. On the one hand, maturity may affect children’s learning ability in primary school and this effect continues over time. On the other hand, starting school a year later means more time spent at home, so more human capital accumulation from parenting. If we assume that well-educated parents provide more human capital accumulation at home than less-educated parents, the relationship between school-entry

Table 4 RD estimates of college admission and test scores

Polyn. degree	Admission						Test score					
	CCT procedure			IW procedure			CCT procedure			IW procedure		
	τ	z-stat	Bandwidth	τ	z-stat	Bandwidth	τ	z-stat	Bandwidth	τ	z-stat	Bandwidth
Male												
0	0.026*	1.741	23.26	0.005*	1.918	110.00	0.087**	2.554	31.72	0.066**	2.341	43.20
1	0.039*	1.749	46.85	0.032*	1.905	65.48	0.132***	2.696	53.71	0.091**	2.275	83.79
2	0.042*	1.660	86.43	0.037*	1.848	117.89	0.185***	2.751	59.66	0.096**	2.525	160.87
Female												
0	-0.008	-0.954	26.06	-0.001	-0.493	75.72	0.022	0.735	51.65	0.026	0.868	64.13
1	-0.011	-0.960	69.12	-0.003	-1.309	129.29	0.012	0.165	76.14	0.013*	1.647	164.55
2	-0.017	-0.962	72.30	-0.010	0.176	111.32	-0.065	-1.117	54.92	0.004	0.878	109.72

This table shows the RD estimates of college admission and test scores using different local-polynomial degrees (per row) and different bandwidth selection procedures (per column). The CCT procedure is proposed by Calonico et al. (2014). The IW procedure is proposed by Imbens and Kalyanaraman (2012). All functions are estimated using a triangular kernel. Data come from applications for undergraduate programs at UFPE from 2002 to 2005. The sample is restricted to those who graduated from high school in the same year and were under 18.5 years old. τ is the robust RD estimate
 ***, **, * represent statistical significance at the 1, 5, and 10 % levels, respectively

age and future outcomes should be stronger for the former's children. Namely, the effect on aptitude test scores would be proportional to parental education. Nevertheless, we find the opposite. The gap between candidates born in late December and early January is higher among those with less parental education.

Table 5 shows that the birthday effect on the test scores of boys is between 0.16 and 0.21 sds if their parents do not have a college degree and between 0.04 and 0.19 sds if at least one of them does. If we divide these estimates by the effect on first-grade enrollment, we find that delaying the school start increases by 0.73–0.86 sds the average test scores in the former group. Even for girls, the effect becomes significant if we look only at the group with less parental education. In this group, being born on January 1 increases by 0.08–0.11 sds the average test score. As a consequence, delaying school entry increases their average test score by 0.14–0.57 sds. For both boys and girls with well-educated parents, the difference is insignificant and very close to zero.¹³

There are several reasons why the effect varies with parental education. To begin with, education is closely related to wealth and wealthier parents can afford additional support for their children (e.g., by hiring private tutors), and this may compensate for any disadvantage.¹⁴ Table 6 confirms that similar results are found if we split the sample by household income. That is, the effect on both boys and girls is stronger and significant if they come from poor households, but it is very close to zero if they come from households that receive more than five minimum wages per month.¹⁵

Moreover, wealthier parents can send their children to better schools, which may give special attention to the youngest pupils. Table 7 confirms that the birthday effect is significant for candidates from public high schools but insignificant for candidates from private institutions. If parents assumed that private schools are better for disadvantaged students, candidates' birthday might be correlated with private school enrollment. We observe in the first graph of Fig. 8 that there is no significant relationship between birthday and attendance at a private institution at early ages. However, candidates born on or after January 1 are more likely to come from private high schools (second graph at the top).

The difference between the two graphs at the top of Fig. 8 suggests that children are not initially sorted into primary schools on the basis of their birthday. But after then, advantaged students who were born in January are more likely to be in private high schools. The graphs in the bottom row reveal that this difference is not due to the movement of disadvantaged students from private to public schools but rather to the movement of advantaged students from public to private institutions. That is, parents of older (and better) students in public schools are more willing to pay the cost of a private high school.

This result has two potential implications. First, the movement of better students from public primary/middle schools to private high schools may lower the average above the cutoff point in both public and private high schools. As a result, the effects presented in Table 7 would be underestimated—i.e., they represent lower bounds. Second, this movement also represents a self-tracking mechanism that keeps disadvantaged students in public schools and moves advantaged students to private schools. Although Brazil does not have a formal tracking system, sorting of this kind may explain why early disadvantages have persistent effects.

According to Hsieh and Urquiola (2006) and Muralidharan and Sundararaman (2015), however, private schools do not necessarily improve students' test scores in developing countries. A back-of-the-envelope calculation using estimates from Figs. 7 and 8 and

Table 5 RD estimates of test scores by parental education

Polyn. degree	Less-educated parents						Well-educated parents					
	CCT procedure			IW procedure			CCT procedure			IW procedure		
	τ	z-stat	Bandwidth	τ	z-stat	Bandwidth	τ	z-stat	Bandwidth	τ	z-stat	Bandwidth
Male												
0	0.177**	2.447	23.28	0.159***	2.639	33.51	0.046	1.482	44.83	0.035	1.322	60.86
1	0.205**	2.149	48.14	0.217***	2.845	76.23	0.149**	2.374	37.33	0.060	1.429	88.54
2	0.209**	1.962	83.50	0.213**	2.085	91.51	0.190**	2.518	56.81	0.102*	1.853	105.42
Female												
0	0.09**	2.220	45.63	0.082***	2.604	76.65	-0.004	-0.160	40.91	0.001	0.055	61.08
1	0.107*	1.825	80.29	0.110**	2.059	96.40	-0.014	-0.354	78.42	-0.011	-0.392	134.77
2	0.030	0.282	60.86	0.106	1.511	125.08	-0.083	-1.207	55.88	-0.028	-0.571	105.52

This table shows the RD estimates of test scores using different local-polynomial degrees (per row) and different bandwidth selection procedures (per column). The first panel on the left has the results for candidates whose parents have no college degree and at least one has no high school education. The second panel on the right has the results for candidates whose either both parents have a high school diploma or at least one has a college degree. The CCT procedure is proposed by Calonico et al. (2014). The IW procedure is proposed by Imbens and Kalyanaraman (2012). All functions are estimated using a triangular kernel. Data come from applications for undergraduate programs at UFPE from 2002 to 2005. The sample is restricted to those who graduated from high school in the same year and were under 18.5 years old. τ is the robust RD estimate

***, **, * represent statistical significance at the 1, 5, and 10 % levels, respectively

Table 6 RD estimates of test scores by household income

Polyn. degree	<5 MWs				5–10 MWs				>10 MWs			
	CCT procedure		IW procedure		CCT procedure		IW procedure		CCT procedure		IW procedure	
	τ	z-stat	τ	z-stat	τ	z-stat	τ	z-stat	τ	z-stat	τ	z-stat
	Male											
0	0.220***	2.808	0.040	1.188	0.075	1.430	0.074	1.626	0.033	0.668	0.025	0.717
1	0.257***	2.826	0.216***	2.877	0.067	0.870	0.096*	1.791	0.013	0.210	0.044	1.026
2	0.280***	2.928	0.246***	2.924	0.063	0.633	0.083	1.133	0.078	0.805	0.006	0.080
	Female											
0	0.094**	2.314	0.061**	2.568	0.050	1.222	0.055	1.517	−0.063	−1.356	−0.007	−0.285
1	0.108**	2.036	0.109**	2.277	−0.028	−0.370	0.067	1.328	−0.088	−1.458	−0.078	−1.558
2	0.100	1.197	0.123**	2.013	−0.057	−0.625	0.005	0.076	−0.119	−1.338	−0.103*	−1.875

This table shows the RD estimates of test scores using different local-polynomial degrees (per row) and different bandwidth selection procedures (per column). The first panel on the left has the results for candidates from households that receive less than five minimum wages (<5 MWs) per month. The second panel in the center has the results for candidates from households that receive between five and ten minimum wages (5–10 MWs) per month. The third panel on the right has the results for candidates from households that receive more than ten minimum wages (>10 MWs) per month. The CCT procedure is proposed by Calonico et al. (2014). The IW procedure is proposed by Imbens and Kalyanaraman (2012). All functions are estimated using a triangular kernel. Data come from applications for undergraduate programs at UFPE from 2002 to 2005. The sample is restricted to those who graduated from high school in the same year and were under 18.5 years old. τ is the robust RD estimate

***, **, * represent statistical significance at the 1, 5, and 10 % levels, respectively

Table 7 RD estimates of test scores by school choice

Polyn. degree	Public high school						Private high school					
	CCT procedure			IW procedure			CCT procedure			IW procedure		
	τ	z-stat	Bandwidth	τ	z-stat	Bandwidth	τ	z-stat	Bandwidth	τ	z-stat	Bandwidth
Male												
0	0.184**	2.225	24.65	0.090*	1.787	64.52	0.036	1.166	45.04	0.031	1.073	53.11
1	0.211**	2.185	64.14	0.181**	2.095	79.54	0.081	1.513	52.60	0.044	1.120	99.72
2	0.296**	2.091	65.62	0.230**	2.061	102.88	0.089	1.404	78.92	0.048	1.095	171.98
Female												
0	0.082	1.477	32.86	0.076**	2.002	76.17	-0.029	-0.904	29.33	0.001	0.057	60.36
1	0.041	0.429	42.69	0.089*	1.697	144.49	-0.038	-0.977	72.78	-0.020	-0.630	107.40
2	0.001	0.005	59.70	0.149**	1.983	143.90	-0.136**	-1.981	53.75	-0.043	-1.012	130.34

This table shows the RD estimates of test scores using different local-polynomial degrees (per row) and different bandwidth selection procedures (per column). The first panel on the left has the results for candidates who graduated from a public high school. The second panel on the right has the results for candidates who graduated from a private high school. The CCT procedure is proposed by Calonico et al. (2014). The IW procedure is proposed by Imbens and Kalyanaraman (2012). All functions are estimated using a triangular kernel. Data come from applications for undergraduate programs at UFPE from 2002 to 2005. The sample is restricted to those who graduated from high school in the same year and were under 18.5 years old. τ is the robust RD estimate

** and * represent statistical significance at the 5 and 10 % levels, respectively

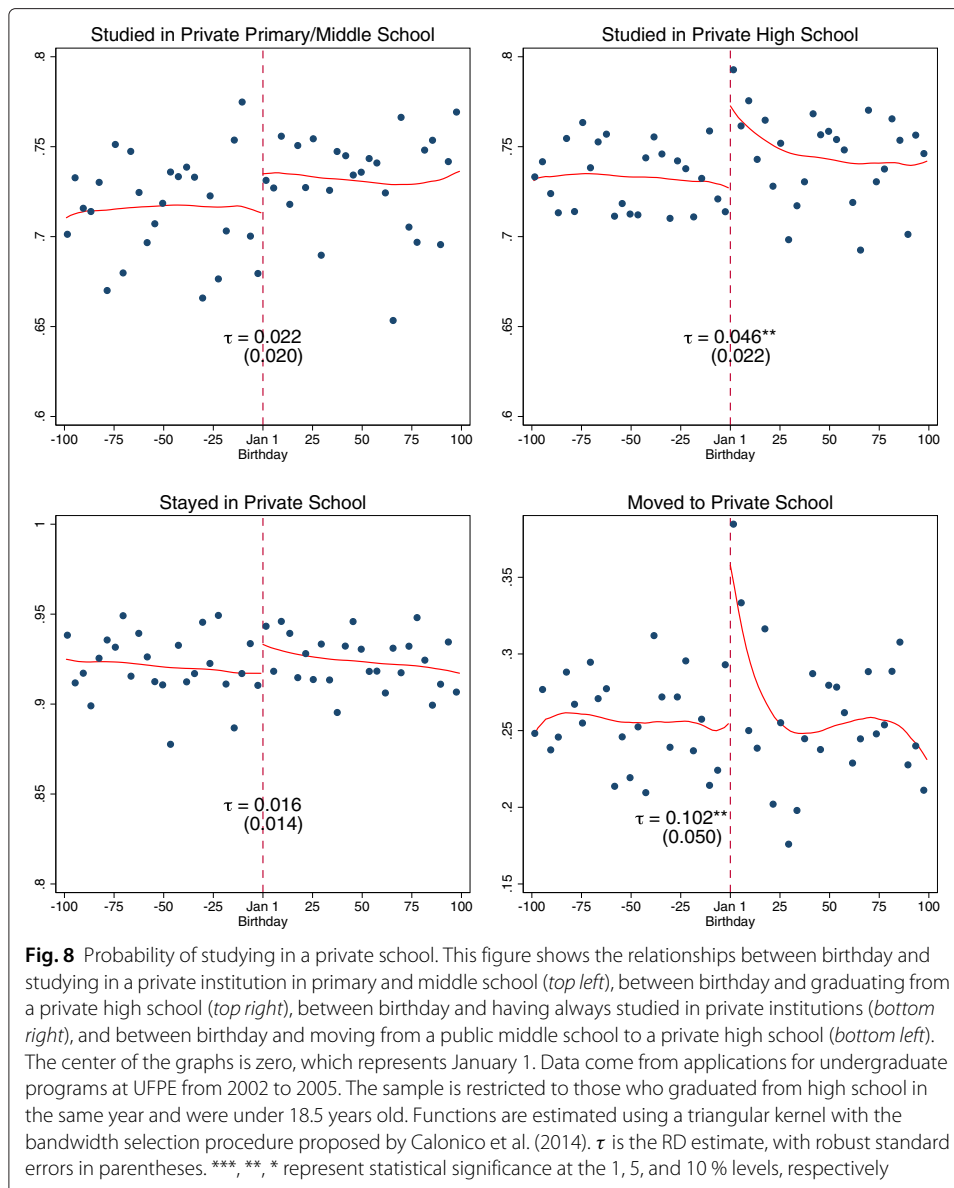


Table 7 tells that attending private school is responsible for 9 % of the average effect on boys and 267 % on girls (not significant).¹⁶

4.5 The effect on early employment and earnings

Since our sample is from college candidates who have recently entered the labor market, we cannot estimate the effect on lifetime earnings. Nonetheless, we can verify whether these candidates have gains/losses related to their birth date in the early stages of their career. Table 8 presents the estimated effect of birthday on employment, college graduation, and earnings at the age of 25 for UFPE candidates from poor households.¹⁷

For male candidates, being born on or after January 1 has no significant effect on the probability of graduating from college or being employed, but it increases earnings by 15–22 %. Namely, the difference in admission test scores found earlier does not imply that male candidates born in January will graduate and be in the market sooner than their

Table 8 RD estimates of employment and earnings at 25 years old

	Less-educated parents				HH income <5 MWs				Less-educated parents and HH income <10 MWs			
	CCT procedure		IW procedure		CCT procedure		IW procedure		CCT procedure		IW procedure	
	τ	z-stat	τ	z-stat	τ	z-stat	τ	z-stat	τ	z-stat	τ	z-stat
	Male											
Employed	-0.024	-0.465	-0.025	-0.505	-0.012	-0.259	-0.017	-0.384	-0.010	-0.193	-0.013	-0.261
Employed and graduated	0.024	0.366	0.045	0.969	-0.020	-0.336	0.015	0.362	-0.002	-0.025	0.031	0.694
Log earnings	0.189*	1.949	0.162*	1.874	0.194*	1.873	0.150*	1.943	0.224**	2.222	0.210**	2.259
	Female											
Employed	-0.054	-1.216	-0.044	-1.416	-0.042	-0.982	-0.015	-0.569	-0.055	-1.268	-0.045	-1.430
Employed and graduated	0.136**	2.172	0.077*	1.692	0.053	1.100	0.043	1.400	0.136**	2.159	0.094*	1.859
Log earnings	0.125	1.445	0.050	0.801	0.051	0.854	0.033	0.657	0.138	1.566	0.057	0.904

This table shows the RD estimates of employment outcomes at the age of 25 (per row) and different bandwidth selection procedures (per column). The outcomes are as follows: being employed, having graduated from college and being employed, and log of earnings. The first panel on the left has the results for candidates whose parents have no college degree and at least one has no high school education. The second panel in the center has the results for candidates from households that receive less than five minimum wages (<5 MWs). The third panel on the right has the results for candidates from households that receive less than ten minimum wages (<10 MWs) and where parents have no college degree and at least one has no high school education. The CCT procedure is proposed by Calonico et al. (2014). The IW procedure is proposed by Imbens and Kalyanaraman (2012). All functions are estimated using a triangular kernel. Data come from applications for undergraduate programs at UFPE from 2002 to 2005. The sample is restricted to those who graduated from high school in the same year and were under 18.5 years old. τ is the robust RD estimate

** and * represent statistical significance at the 5 and 10 % levels, respectively

counterparts born the previous December. However, the ability gap continues in the labor market and is reflected in earnings.

For female candidates, the effect on earnings is not as strong and significant as it is for men. Yet the probability of graduating from college and being employed by the age of 25 is 4–14 % higher if they were born on or after January 1. Unlike men, women who are born in January do graduate sooner than women born in the previous December. This means that the potential return for a college degree emerges earlier in their life cycle, which probably increases their lifetime earnings.

5 Conclusions

Delaying primary school entry tends to affect students' outcomes not merely in the early grades. We reach this conclusion by exploiting an exogenous variation in birthdays between late December and early January and the minimum-age rule enforced by primary schools in Brazil. In particular, we find that college applicants who were older than their classmates in the first grade are more likely to be admitted to a flagship university right after high school. On the one hand, the age difference created by the minimum-age rule disappears over time because younger students are more likely to repeat grades. Once they have to repeat a grade, they become one of the oldest in their class. On the other hand, candidates born on January 1 still outperform those born on December 31, even though they are the same age when they apply for college. Thus, it is not necessarily the current maturity gap that affects their test scores but the difference in their learning abilities at school.

The difference in aptitude test scores, as well as in the likelihood of college admission, created by the minimum-age rule is much greater for boys than for girls. This indicates that the maturity gap in primary school, which affects long-run outcomes, tends to close faster for girls, who usually mature earlier than boys. Moreover, this rule affects mainly college candidates whose parents are poorer and less educated. In this group, delaying primary school for a year increases by 0.73–0.86 sds the college admission test score of boys and by 0.14–0.57 sds the score of girls. As long as human capital accumulation before primary school is related to parents' education and wealth, this finding suggests that differences in aptitude test scores are mostly created at primary school.

We also observe that students born in January tend to move from public to private schools some time after their advantage with respect to their classmates is revealed. Although Brazil has no tracking system, this sorting mechanism may be a reason why the effect of age at school entry persists among poor students. The persistence of this effect is reflected not only in the test scores but also in the early gains in the labor market. These gains happen either directly through earnings (for men) or indirectly by graduating and entering the market sooner (for women).

Our findings reinforce the need for change in the inflexible age-grade system that puts children with disparate learning abilities in the same class. Since children are assessed at times dictated by a fixed school calendar, younger pupils have a natural disadvantage that may continue to their adulthood. Although grade retention tends to adjust the age difference in the early grades, this is not an effective way of narrowing the learning gap (e.g., Manacorda 2012). To assess students' actual ability, the school system should apply age-normalized exams, which ensure that they are compared to peers at exactly the same age.

One important caveat in interpreting the results of our study is their external validity. In fact, we cannot claim that our findings result from the long-term effects of age at school entry on the entire population of first graders. Given our setting and the available data, we have instead focused on their interval validity by selecting a very specific sample. Namely, our inferences are for a population of high school graduates with little age-grade distortion, aiming to join an elite institution. In that sense, our study differs, for instance, from Crawford et al. (2010), who estimates the likelihood of a first grader going to college, despite the quality of the institution. However, we still believe that our study contributes to the debate about school-entry age by showing estimated effects on students who are probably at the top of the distribution of skills.

Endnotes

¹Effects on labor market outcomes in the USA are in part explained by the compulsory laws that specify a minimum school leaving age.

²See Brewer et al. (1999) and Dale and Krueger (2002) on the returns of attending an elite institution.

³According to PREAL (2009), almost 25 % of first-grade students repeat the year and more than 40 % of high school students have fallen two or more years behind.

⁴This difference between genders is in line with McEwan and Shapiro (2008), who find that the effect of delaying school entry on test scores at the fourth grade is one third higher for boys than for girls.

⁵According to the Ministry of Education, UFPE is the largest and most selective university in the North and Northeast regions of Brazil. It has 62 undergraduate programs and 108 graduate programs. In 2004, the university had 25,000 enrolled students (20,500 in undergraduate programs and 4500 in graduate programs) and 1647 faculty members.

⁶Since 2010, the admission score has been composed of the *vestibular* and the National High School Exam (similar to the American SAT test).

⁷In Brazil, universities require candidates to choose their major when they apply for an undergraduate program.

⁸A law approved in 2012 requires that all federal universities implement quotas by 2016 on the basis of attendance at a public high school, family income, or qualifying as indigenous or an afrodescendant.

⁹This law changed in 2010. The new law added one more grade to primary education and now requires children to turn six by March 31 in the year of the first grade.

¹⁰We have two additional remarks regarding our sample. The first relates to the possibility of students being grade advanced. The implication for our estimates would be severe, because the selection bias would be negative instead of positive. In Brazil, however, the percentage of pupils skipping at least one grade has been close to zero. According to the National Institute for Educational Studies and Research (INEP), this number was 682 (around 31 students in the state of Pernambuco) in 2000. This situation started to change in 2005, when the Government launched a program to identify gifted students. In 2010, for example, the number of kids that skipped a grade in the country reached 8851, which still represents a small percentage. Nevertheless, acceleration should not affect our results given our sample period. The second remark is with regard to excluding those

taking the exam for at least the second time. These candidates are either high school graduates not accepted in the previous years, adults seeking professional training, or college students aiming to switch majors and/or institutions. We consider that this pool of candidates is very heterogeneous and it is not necessarily comparable to high school graduates.

¹¹We also estimate the difference in terms of high school education and find a similar magnitude. This result is available upon request.

¹²Differently from the USA, the numbers of kids moving a grade ahead in Brazil has been historically close to zero. According to the National Institute for Educational Studies and Research (INEP), the number of kids that moved ahead a grade in Brazil in 2000 was 682 (around 31 students in the State of Pernambuco). This situation however started to change after 2005, when the Government launched a program to train professors in identifying gifted students. In 2010, for example, the number of kids that moved ahead a grade in the country reached 8,851, still small but 62 % larger than that observed in 2009 (5478 students).

¹³The estimated effect on first-grade enrollment by parents' education is available upon request.

¹⁴Sampaio et al. (2011), using similar data, show that wealthier parents are more likely to pay for private tutoring classes for children graduating from high school in the state of Pernambuco. They also provide evidence that tutoring classes increase scores significantly.

¹⁵We report differences in RD estimates presented in Tables 5 and 6 in the Appendix (see, respectively, Appendix: Tables 9 and 10).

¹⁶The effect through private school by gender is obtained by $\{ \text{average effect} - [p * (\text{effect on public students}) + (1 - p) * (\text{effect on private students})] \} / (\text{average effect})$, where p is the proportion of candidates attending public schools.

¹⁷For wealthier candidates, no effect is significant.

Appendix

Table 9 Differences in RD estimates of test scores by parental education

Polyn. degree	Less-educated vs. well-educated parents			
	CCT procedure		IW procedure	
	Diff.	z-stat	Diff.	z-stat
	Male			
0	0.131*	1.664	0.124*	1.884
1	0.056	0.490	0.157*	1.803
2	0.019	0.146	0.111	0.957
	Female			
0	0.094**	1.974	0.081**	2.228
1	0.121*	1.711	0.121**	2.005
2	0.113	0.892	0.134	1.566

This table shows the differences in RD estimates of test scores between well-educated parents and less-educated parents using different local-polynomial degrees (per row) and different bandwidth selection procedures (per column). The CCT procedure is proposed by Calonico et al. (2014). The IW procedure is proposed by Imbens and Kalyanaraman (2012). All functions are estimated using a triangular kernel. Data come from applications for undergraduate programs at UFPE from 2002 to 2005. The sample is restricted to those who graduated from high school in the same year and were under 18.5 years old

** and * represent statistical significance at the 5 and 10 % levels, respectively

Table 10 Differences in RD estimates of test scores by household income

Polyn. degree	(<5 MWs)–(5–10 MWs)				(5–10 MWs)–(>10 MWs)				(<5 MWs)–(>10 MWs)			
	CCT procedure		IW procedure		CCT procedure		IW procedure		CCT procedure		IW procedure	
	Diff.	z-stat	Diff.	z-stat	Diff.	z-stat	Diff.	z-stat	Diff.	z-stat	Diff.	z-stat
Male												
0	0.145	1.538	–0.034	–0.601	0.042	0.583	0.049	0.855	0.187**	2.019	0.015	0.309
1	0.190	1.594	0.120	1.301	0.054	0.547	0.052	0.758	0.244**	2.218	0.172**	1.989
2	0.217	1.572	0.163	1.461	–0.015	–0.108	0.077	0.734	0.202	1.484	0.240**	2.129
Female												
0	0.044	0.763	0.006	0.138	0.113*	1.825	0.062	1.416	0.157**	2.544	0.068**	1.990
1	0.136	1.472	0.042	0.604	0.060	0.620	0.145**	2.040	0.196**	2.439	0.187***	2.700
2	0.157	1.269	0.118	1.314	0.062	0.487	0.108	1.260	0.219*	1.795	0.226***	2.751

This table shows the differences in RD estimates of test scores between household income ranges using different local-polynomial degrees (per row) and different bandwidth selection procedures (per column). The first panel on the left shows differences in estimates between candidates from households that receive less than five minimum wages (<5 MWs) per month and candidates from households that receive between five and ten minimum wages (5–10 MWs) per month. The second panel in the center shows differences in estimates between candidates from households that receive between five and ten minimum wages (5–10 MWs) per month and candidates from households that receive more than ten minimum wages (>10 MWs) per month. The third panel on the right shows differences in estimates between candidates from households that receive less than five minimum wages (<5 MWs) per month and candidates from households that receive more than ten minimum wages (>10 MWs) per month. The CCT procedure is proposed by Calonico et al. (2014). The IW procedure is proposed by Imbens and Kalyanaraman (2012). All functions are estimated using a triangular kernel. Data come from applications for undergraduate programs at UFPE from 2002 to 2005. The sample is restricted to those who graduated from high school in the same year and were under 18.5 years old

***, **, * represent statistical significance at the 1, 5, and 10 % levels, respectively

Competing interests

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