Does An Additional Year of Schooling Improve Skills in Reading, Mathematics and Science? Regression Discontinuity due to Imprecise Control over Birthdates

Kaimin Khaw and Wei-Kang Wong[1]

Abstract

This paper estimates how much an additional year of schooling affects skill and knowledge accumulation. We exploit exogenous variation in student birthdates around the school entry cut-off date, causing students of similar age but different grade to take the same international standardized test. The evidence suggests that schooling is not just about signalling. One more year of schooling leads to gains of 0.08 standard deviations for reading, 0.11 standard deviations for mathematics, and 0.18 standard deviations for science in Singapore. Students with more educated parents gain more from schooling, suggesting complementarity between human capital accumulation at home and in school.

Keywords: Regression discontinuity; Education effectiveness; Parental peer effect

JEL codes: I21, J24

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[1] Wong (Corresponding Author): Department of Economics, National University of Singapore, AS2, 1 Arts Link, Singapore 117570, Republic of Singapore. Phone: (65) 65166016. Fax: (65) 67752646. Email: ecswong@nus.edu.sg. We especially thank Jessica Pan for very valuable discussions. The usual disclaimer applies.

Introduction

A large literature investigates the causal effect of education on earnings (for example, Angrist and Krueger (1991), Card (1999) and Oreopoulos (2006)). There is relatively little direct evidence on the effectiveness of schooling on skill improvement because most standardized tests are written by students in the same grade with the same years of schooling. Furthermore, when such tests are taken by students from different grades, the students from different grades are likely to have greater variations in unobservable characteristics, making it difficult to establish the causal effect.

To estimate the causal effect of schooling on skill improvement, this paper uses a regression discontinuity design and the 2009 Singapore data from an international standardised test by the Programme for International Student Assessment (PISA), whereby students from two adjacent grades, aged between 15 years 2 months and 16 years 3 months at the time of the test, were tested in reading, mathematics and science. To identify the causal effect, we use a regression discontinuity (RD) design, exploiting imprecise control over birthdates around the primary school entry cut off date. With an additional year of schooling from secondary 3 to secondary 4, we find a gain of 0.08 standard deviations for the test score in reading, 0.11 standard deviations for mathematics, and 0.18 standard deviations for science. Only the gain for science is statistically significant. Furthermore, the gain depends on the parental education. Specifically, students with more educated parents gain the most from an extra year of school while students with less educated parents do not show any gain from schooling at all. This suggests that the skill and earning gaps between students of different social class widen with more schooling. This has consequences on social mobility.

Background on the Education System in Singapore

Formal schooling in Singapore begins at age 6 where students enrol into primary 1.[2] Students spend 6 years in primary school. At the end of primary 6, students enrol into secondary school where they spend around 4 years. The students from our data set are primarily made up of secondary 3s and 4s. At the end of secondary school, they receive post secondary education at the Junior Colleges (JCs), polytechnics or the Institute of Technical Education (ITEs). The former two types of post secondary institutions prepare students for higher education at the universities. In contrast, the ITEs teach hands-on skills and are for those who are less academically inclined.

The education system is characterised by ability grouping which begins as early as primary school. At the end of primary 4, students are streamed into either the “merged” or “EM3” streams.[3] Students in the “merged” stream are taught at a faster pace and cover more content. At the end of primary 6, students take the high stakes Primary School Leaving Examination (PSLE). This determines which secondary schools they are able to enter.

Secondary school education in Singapore is quite heterogeneous. Most students attend mainstream secondary schools where they work towards the General Certificate of Education (GCE) O-level examinations. Among those who attend mainstream schools, students are broadly split into the “normal” and “express” streams. Students in the former spend 5 years in secondary school as compared to the latter who spend only 4 years.[4] The more gifted students are able to opt for a through train programme offered by selected schools where they by-pass the O-levels and instead spend 6 years working towards either the GCE A-levels or the International Baccalaureate (IB). With the data we have, we are unable to tell which route the students in our sample have taken. Therefore our findings should be interpreted as the reduced form effect of an additional year of schooling.

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[2] This corresponds to grade 1 in the North American context.

[3] This system has since been replaced with subject based banding as of 2008. However, students in our sample were streamed at primary school according to the older system.

[4] Those in “normal” stream are further sub-divided into “normal academic” and “normal technical”. Those in “normal technical” only take the N-levels instead of the O-levels and work towards a technical education at the ITE.

Literature Review

OLS estimates of schooling on test scores are likely to suffer from selection bias as higher ability students are more likely to choose more schooling. Herrnstein and Murray (1994) and Winship and Korenman (1997) use an earlier test score to proxy for unobserved ability. However, this may still yield biased estimates if the prior test score is a poor proxy for ability (Hansen, Heckman and Mullen, 2004).

An alternative approach by Neal and Johnson (1996) and Hansen, Heckman and Mullen (2004) uses birth quarter as instrument for schooling. Angrist and Krueger (1991) argue that quarter of birth is a suitable instrumental variable (IV). First, quarter of birth is related to schooling attainment of students within a particular birth year because of compulsory schooling laws and minimum age regulations on school entry. Second, test scores for students in a particular birth year should be unrelated to their quarter of birth. The second assumption has been challenged because studies have found correlation between test scores and the students' relative age within the same grade (Smith, 2009).

Instead, this paper uses a regression discontinuity (RD) design that exploits exogenous variation in students' date of birth around the primary school entry cut-off date. Two recent papers have also used this approach. Cascio and Lewis (2006) estimate the effect of an extra year of schooling for different ethnic groups in the United States (US) using the Armed Forces Qualifying Test (AFQT) while Frenette (2008) uses data from PISA 2000 to study the effect of an extra year of schooling in Canada.

This paper contributes to the literature in three ways. First, unlike Frenette (2008), we make specific adjustments to take PISA's complex survey design into account. Second, we investigate whether test score gains from additional schooling are affected by parental education. Third, we improve our understanding of whether and how education works in Singapore, a literature with little rigorous empirical research.

Background on PISA

The Programme for International Student Assessment (PISA) is an international standardized assessment developed by the OECD, whereby 15 year old students in participating countries are tested on Reading, Mathematics and Science. The test is conducted once every three years; the first one being conducted in 2000. PISA focuses on how well students are able to apply their knowledge to different situations relevant to daily life. The emphasis is on what students can do with what they have learnt rather than on simple mastery of a particular curriculum. As such, the test is not based on any specific curricula.

This paper uses Singapore data in the 2009 iteration of PISA, the first time Singapore participated in PISA.[5] The test is unique in that students from different grades take the same test as long as they are 15 years of age at the time of the test. Because the testing period was from July – August 2009 which falls around the middle of the school year in Singapore, the sample includes students from adjacent grades from both secondary 3 and secondary 4. This feature allows us to study the effect of an additional year of school from secondary 3 to secondary 4.

The study also collected self-reported background information from the students and school-level variables like percentage of graduate teachers from school principals. The surveys were completely anonymous. As this information is self reported, we acknowledge that there may be some measurement errors.

The data set consists of 5283 students aged between 15 years 3 months and 16 years 2 months. We drop all students who appear to be in the wrong grade for their age.[6] This is around 9.3% of our sample.[7]

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[5] Singapore had previously only taken part in two other international assessments; Trends in International Mathematics and Science Study (TIMSS) and Progress in International Reading Literacy Study (PIRLS). Academic performance of 12 year olds is available via the TIMSS and PIRLS international assessments.

[6] These students are in a grade too low for their age. So these students are most likely to be grade repeaters and their experience from an extra year of schooling would differ markedly from others in the sample. When we include those who repeated secondary 3 into our analysis, we find that repeaters perform much worse than their younger peers in the same grade.

[7] There is only one student that is in a grade too high for his age. In general, children are not allowed to enrol into primary 1 if they are too young. Skipping of grades is also uncommon.

Adjusting for Non-standard Data

The PISA survey involves complex methodology that affects how we analyze the data. In what follows, we briefly discuss the adjustments needed.[8]

Students selected to participate in PISA do not constitute a simple random sample (SRS).[9] Instead, PISA adopts a two stage sampling design. In Singapore, all 171 schools containing 15 year olds were selected with certainty in the first stage.[10] 35 students were then randomly selected from each school in the second stage.[11] As such, students from smaller schools have a higher probability of being included in the sample. Estimating population parameters without taking this two-stage sampling into account would lead to biased estimates. The data thus need to be weighted to make the sample more representative of the population. The weight for each student is simply the inverse of his selection probability.[12] Final student weights provided by PISA are used in all computations.

Furthermore, observations from students in the same school may not be independent because they tend to be more similar across many dimensions. As such, standard errors among observations from the same school tend to be correlated. Formulas to compute standard errors for simple parameters like sample means become very complicated after taking complex sampling design into account. For estimates like regression coefficients, there is simply no formula available to calculate standard errors (Lohr, 1999).

Instead, PISA uses replication methods to estimate standard errors. Replication involves estimating the standard error of a population parameter of interest by using a large number of somewhat different subsamples drawn from the main sample. The variability among the resulting estimates is used to estimate the true standard error of the full-sample

[8] See the appendix for more details.
[9] Samples used in education surveys are typically non-random as constructing a SRS would be costly and impractical. See PISA (2006a).
[10] This is only done in small countries like Singapore. In large countries, schools are randomly selected with probabilities proportional to the size of their intake.
[11] If there are less than 35 15 year olds in the selected school, all of them are invited to participate. Number could also differ slightly from school to school due to student non-response.
[12] Weights could also vary due to oversampling of some strata of the population, inaccuracies in reporting of school intake size or adjustment for non-response bias. See OECD (2006a).

estimate (Rust and Rao, 1996). PISA uses the Balanced Repeated Replication (BRR) method with Fay's modification to estimate standard errors.

Student performance in each area is reported as plausible values. Plausible values are random draws from an estimated distribution of the student's ability in a particular subject. This posterior distribution is imputed based on the students' answers to the test items using item response theory.[13] Such an approach is adopted for two reasons. First, there is some uncertainty involved in estimating a latent construct like students' academic ability. Second, due to time and resource constraints, each student only does a sub-set of the total number of questions. Therefore, some students could end up with items of greater difficulty.

For each subject, a student is assigned five plausible values. To facilitate cross-country comparison, plausible values are standardised to have an international mean of 500 and a standard deviation of 100. PISA recommends that population parameters such as regression coefficients be estimated separately for each of the five plausible values and then averaged in order to minimise imputation bias.[14] This is the approach we take. Imputation bias becomes very large when sample size is small (OECD, 2006a). Thus it is important to use all five plausible values since sample size tends to be small when the RD design is used.

Methodology and Results

We first estimate a standard education production function:

$$StdScore_i = \alpha_0 + F(Age_i) + \beta T_i + \gamma' X_i + \theta' Z_i + \lambda P_{-i} + u_i$$

The dependent variable is the standardised test score (mean 0, standard deviation 1) for student *i*. This shows how a student's test score compares with that of the general population and allows us to interpret regression coefficients in terms of standard deviations. $F(Age_i)$ is a flexible function of students' age. We try different polynomial specifications to determine the best fit. Due to confidentiality issues, we only have students' date of birth to the nearest

[13] For more details see PISA (2006b).
[14] Adjustments need to be made to standard errors of estimated coefficients as well; specifically the addition of an "imputation error" term.

month. Age (measured in months) is calculated as of July 2009.[15] As our sample only includes students born within a one year period, we only have 12 discrete values to describe students' age. T_i is a dummy variable that equals 1 if a student is in secondary 4 (one extra year of schooling) and 0 if a student is in secondary 3. X_i is a vector of student background characteristics. Z_i is a vector of school characteristics. P_{-i} is the average years of parental education among student i's schoolmates. Note that student i's own parent's years of education is not included in this variable.[16] This controls for the school-level peer effect of having schoolmates with highly educated parents. Finally, u_i is an error term.

Regression Results

Table 1 reports our baseline regression results. Gains from an additional year of schooling are smallest for Reading (0.09SD) and largest for Science (0.19SD). The gain for Math is modest at around 0.12SD. The schooling coefficient for Science is highly statistically significant at the 1% level while the coefficient for Math is only significant at the 10% level. The coefficient for reading is not statistically significant at the conventional levels with a p-value of 0.14.

TABLE 1: BASELINE REGRESSION RESULTS

	Dependent Variable		
	(1)	(2)	(3)
Independent Variable	Reading	Math	Science
Dummy for secondary 4	0.0915	0.119*	0.185***
	[0.0608]	[0.0683]	[0.0641]
Age	1.173**	1.281*	0.465
	[0.596]	[0.671]	[0.657]
$(\text{Age})^2$	-0.00308**	-0.00338*	-0.00123
	[0.00157]	[0.00177]	[0.00173]
Dummy for male	-0.315***	0.0637**	0.0226
	[0.0267]	[0.0301]	[0.0271]
Dummy for foreign student	0.0504	0.179***	0.169***
	[0.0534]	[0.0575]	[0.0547]
Dummy for speak Tamil at home	-0.547***	-0.524***	-0.501***
	[0.153]	[0.152]	[0.140]
Dummy for speak Malay at home	-0.468***	-0.525***	-0.420***

[15] The testing period lasted from July 2009 to August 2009. Students from different schools took the test at different times. From our data set we are only able to tell whether students took the test in July or August. Adding a dummy variable to distinguish the two groups in our regressions, We find that the difference in tests scores in negligible and not statistically significant. Therefore, We calculate age as of July 2009 using student's date of birth.

[16] PISA obtains years of parents' education by converting highest qualification into years using the International Standard Classification of Education (ISCED).

	[0.0354]	[0.0401]	[0.0369]
Dummy for speak English at Home	0.0907***	0.0118	0.0654**
	[0.0312]	[0.0314]	[0.0325]
Dummy for speak other language at home	0.00196	0.0797	0.0509
	[0.0881]	[0.107]	[0.0781]
Dummy for single parent family	-0.0745	-0.0757	-0.0809
	[0.0484]	[0.0512]	[0.0514]
Dummy for extended family	-0.252***	-0.176	-0.277***
	[0.0908]	[0.109]	[0.0987]
Number of rooms with bath or shower	0.0895***	0.0940***	0.0807***
	[0.0191]	[0.0232]	[0.0210]
Dummy for parent primary education	0.103	0.186	0.0420
	[0.147]	[0.208]	[0.166]
Dummy for parent lower secondary education	0.171	0.263	0.197
	[0.149]	[0.190]	[0.163]
Dummy for parent upper secondary education	0.406***	0.513***	0.375**
	[0.145]	[0.194]	[0.166]
Dummy for parent A-Level/ITE	0.410***	0.490***	0.365**
	[0.139]	[0.184]	[0.158]
Dummy for parent poly diploma	0.488***	0.600***	0.466***
	[0.141]	[0.193]	[0.161]
Dummy for parent university degree or higher	0.577***	0.591***	0.506***
	[0.141]	[0.191]	[0.157]
Subject Lesson Time (hrs/week)	-0.0380***	0.0183***	0.0476***
	[0.00563]	[0.00480]	[0.00466]
Student-teacher ratio	0.0183***	0.0194***	0.0183***
	[0.00368]	[0.00419]	[0.00381]
Percentage of certified teachers	-0.00239	-0.00135	0.000331
	[0.00175]	[0.00204]	[0.00139]
Percentage of graduate teachers	0.00629***	0.00495***	0.00558***
	[0.00134]	[0.00129]	[0.00125]
Average parental education of peers (yrs)	0.291***	0.321***	0.304***
	[0.0116]	[0.0112]	[0.0136]
Constant	-116.1**	-126.8**	-49.33
	[56.52]	[63.68]	[62.27]
N	4070	3960	3797
R^2	0.35	0.31	0.35

1. Standard errors in brackets and adjusted for clustering at the school level using BRR.
2. Regressions are weighted and all 5 plausible values are used.
* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

In general, older students tend to do better. The effect of age is statistically significant for Reading and Math but not for Science. We find that a quadratic polynomial for age fits the data best.[17] The positive effect of age seems to diminish as students get older. This is implied by the negative sign for the coefficient of the quadratic term for Age.

Boys perform about 0.32SD lower than girls in reading and this is significant at the 1% level. This performance gap in reading is substantial. By contrast, boys perform only

[17] This is the best we can do given that we only have age to the nearest month.

marginally better than girls in math (about 0.06SD significant at 5% level). There is no evidence to suggest that boys perform significantly better than girls in science.

Foreign students score about 0.18SD higher for both math and science. This is statistically significant at the 1% level. This conforms to the commonly held stereotype among Singaporeans that immigrants excel in math and science. Chinese and Indian nationals make up the bulk of foreigners in Singapore and students from these countries tend to excel in Math and Science (Ng and Tan, 2011).

Students who speak Malay or Tamil at home do worse than students who speak Chinese at home (the omitted dummy). This gap ranges from 0.40SD to 0.55SD depending on the subject tested. This is always statistically significant. Conversely, students who speak English at home perform better than their peers who speak Chinese at home. They perform about 0.1SD better in reading and Science. However, their advantage in Math is smaller at only 0.06SD. There is no significant difference for those who speak another foreign language at home.

It is understandable why students who speak English at home perform better since English is the main language of instruction in Singapore. The poorer performance of those who speak Malay and Tamil at home as compared to those who speak Chinese is harder to account for. While we do not have direct information on students' ethnicity, we find that language spoken at home to be a reasonable proxy for this. According to data from the 2010 Census, 67% of Chinese speak Mandarin at home, 83% of Malays speak Malay at home and 58% of Indians speak Tamil at home. Rather than certain languages being more detrimental to learning than others, what these coefficients actually capture (though imperfectly) is the performance difference between different ethnic groups. Differences in performance for different ethnic groups might in turn be driven the different economic circumstances of each group. Nevertheless, these differences still remain even after we control for parents' education and wealth.

Children from single parent families perform no worse than those from nuclear families. The coefficient on *single* parent is negative across all subjects but is not statistically significant. In contrast, those who live with their extended family perform much poorer than those from nuclear families. For Reading and Science, this gap is around 0.255SD and 0.277SD respectively. These are statistically significant at the 1% level. The gap for Math is 0.23 and not statistically significant. Students living with extended family might perform worse due to lack of study space at home. Parents might also have to spend more time taking care of elderly grandparents, leaving them less time for their child's education.

Number of rooms with a bathroom is a proxy for wealth. It takes on four values; 0-2 corresponds to their numerical values while 3 correspond to 3 or more such rooms. In land scarce Singapore, this variable is highly correlated with the size of dwelling, which is in turn strongly correlated with family wealth. An extra room is associated with an increase of around 0.09SD for each subject. This is always statistically significant at the 1% level.

The dummy variables for parents' education refer to the qualification of the highest educated parent (either the mother or the father). Henceforth, we will use the term "parent's education" to refer to the education level of the highest qualified parent. The excluded dummy is *parent no primary education*.

Across all subjects, parent's education level is positively related to test score. The more highly educated the parent, the higher the test score as compared to student's whose parent did not complete primary education. This gap is highest for reading and lowest for Science. However, the gap is only significant for students whose parents have at least upper secondary education.

There are a number of possible reasons why parent's education is strongly associated with students' academic performance. More educated parents tend to be wealthier which gives them more resources to invest in the child's education. For example, they are able to afford extra private tuition. However after controlling for wealth, we still find that parents' education has a strong effect. Another possible reason is that children of educated parents are genetically endowed with higher natural intelligence. There is no way for us to test this with the data set we have. [18] Lastly, there could be a direct transfer of human capital from parent to child which takes place at home.

Increasing formal lesson time in the subject is associated with higher test scores for Math and Science. Paradoxically, increased lesson time is associated with a decrease in test scores for Reading. This could be due to a possible selection effect where weaker students are the ones who receive the most hours of English lessons. Schools might have an incentive to shift lesson time from other subjects to English for weaker students. This is because passing English in the high stakes O-level exam is a requirement for entry into the Junior Colleges (JCs) and Polytechnics in the next phase of education.[19]

It is puzzling why student-teacher ratio displays a positive sign across all three subjects. This could be due to the way student-teacher ratio as calculated in the PISA data set. PISA calculate student-teacher ratio as total student enrolment of the school divided by total number of staff. This is a relatively crude measure as schools that offer a larger variety of different subjects will have more teachers. However, there would be no change in actual class size since each teacher specialises in a different subject. This reason still fails to explain why the sign is positive and highly statistically significant. A more compelling argument is that the Ministry of Education might intentionally allocate more teachers to the poorer performing schools.

While the percentage of certified teachers does not seem to matter for test scores, the percentage of graduate teachers is positively associated with higher test scores.[20] This result is statistically significant at the 1% level across all 3 subjects. Teachers with a university degree might be more effective as they have stronger content knowledge in their teaching subject as compared to non-graduate teachers. Also, a university degree might be a signal for other unobserved traits like high motivation and ability to handle stress.

[18] A possible way to test for this is to conduct a study using a twins' data set. A good recent example of such a study is the one conducted by Behrman and Rosenzweig (2002).
[19] There are a very limited number of courses in the Polytechnics that accept students who have failed their O-level English.
[20] In Singapore, teachers are "certified" if they are formally trained at the National Institute of Education (NIE), a national teacher training institute.

A one year increase in the average education of schoolmates' parents is associated with an increase of approximately 0.3SD across all subjects. This is statistically significant at the 1% level across all subjects. However, students with better educated parents tend to sort into better schools.[21] Therefore, this is not a treatment effect.

In fact what our peer effect may actually capture is the effect of good schools. In a recent Straits Times article, it was reported that students with graduate parents are disproportionately represented in many of the top schools (Chang, 2011). For example, in the top schools like Raffles Institution, the percentage of students with graduate parents did not dip below 50%. In contrast, the percentage of students with graduate parents did not exceed 13.1% in the 4 mainstream schools for which data were available.

Regression Discontinuity Design

Unfortunately, OLS estimates for an additional year of school suffer from three sources of omitted variable bias. First, Students in secondary 4 could be performing better simply because they are older. Being older confers two advantages. 1) Older students are likely to have greater mental maturity. 2) Older students having lived longer are exposed to more "life experiences" or learning that takes place outside of the classroom. By default, older students will have received more schooling. It is hard to precisely separate these two effects with OLS regression. In principle we could just include some function of age into our OLS regression. However, if the relationship between age and test score is not properly modelled, estimates for schooling will suffer from specification bias.[22]

Second, there might be other variables that are important such as school quality and income level that we do not have information on. Third, OLS estimates are likely to suffer

[21] While entry into good secondary schools is based on merit, entry into good primary schools is determined by home proximity. Therefore, students with better educated parents sort into good primary schools since educated parents are willing and able to pay to locate near good primary schools (Wong, 2010). There are two reasons why being in a good primary school increases one's chances enrolling into a good secondary school. First, being in a good primary school confers some advantage in the Primary School Leaving Examination (PSLE) that determines secondary school placement. Second, some of these good primary schools serve as feeder schools for good secondary schools; this means students from affiliated primary schools can enter with a lower PSLE score.

[22] Furthermore, when we perform OLS, we implicitly assume that there is no discontinuity at the cut-off since the estimated age function is plotted smoothly through the cut-off.

from selection bias. Higher ability students will self select into the higher grade since they are less likely to repeat a grade or drop out.

We reduce these biases by using a regression discontinuity (RD) design. The RD design was first introduced by Thistlethwaite and Campbell (1960) as a way to estimate treatment effects in a non-experimental setting. Treatment is determined by whether an observed assignment variable exceeds a known cut-off point. In the context of our paper, the assignment variable is students' date of birth, the cut-off is the 2nd January primary one registration cut-off date and the treatment is an extra year of schooling. Students born before 2nd January 1994 have to register for the year 2000 primary 1 intake while those born after 2nd January 1994 can only register for the year 2001 intake.[23]

Our identification strategy is simple: we restrict our sample to those born just before and just after the 2nd January cut-off date. Those born just before the cut-off date join the earlier intake while those born just after the cut-off only enrol into primary one the following year. This results in a sample where students of approximately equal age receive different amounts of schooling (some receive an extra year and others don't) simply because they were born on different sides of the cut-off date. Since students born around the cut-off are of approximately equal age, there is no need include age in the regression. This allows us to side step the issue of specifying a correct model for age thus eliminating specification bias.

Another compelling implication of the RD design is the following. As long as there is no sorting around the cut-off date, a plausible assumption since precise manipulation of date of birth around the cut-off date (especially as a function of unobservable characteristics such as abilities) is either impossible or unlikely, the students can be thought of as being randomly assigned into treatment and control groups (Lee, 2008).[24] If random assignment

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[23] The cut-off rule is strictly enforced for those who are deemed too young to enter primary one. However there are some who enrol late due to family circumstances. This number is small. Another exception to the cut-off rule is foreigners who typically start a few grades lower than their peers of the same age if they come from non-English speaking countries.

[24] If possible, one may argue that parents might prefer to have their children born just after the cut-off date so that they enrol one year later and end up being the oldest in their cohort. There is some evidence that being the oldest in the cohort is associated with better academic and sporting performance in the lower school grades (Blatchford et al, 2002, Smith, 2009). However, it is unlikely that mothers are able to precisely plan their child's birth date. Because most women are unaware of when they ovulate, the due date is typically calculated by counting 280 days

holds, individuals born in a narrow window on both sides of the cut-off should have the same average characteristics (both observed and unobserved). This randomisation allows us to control for omitted variable bias. In principle, this means that we can drop all control variables in our regression and still obtain the treatment effect. However, we continue to control for other characteristics because this improves the precision of our estimates.

It is important to note that even if random assignment holds, we are unable to remove selection bias completely. Students who manage to make it to secondary 4 might be of higher average ability than those in secondary three.[25] This is because there is a chance that those in secondary three might either drop out or not get promoted to secondary 4. Ex ante, it is impossible for us to know which secondary three students will fail to make it to next grade. This generates some upward bias in estimates for the gains from an extra year of school.

However, it seems unlikely that many secondary 3s will drop out. Singapore's dropout rate from primary school all the way up to secondary four is a mere 1.6% (Ministry of Education, 2008). The bigger problem is the likelihood that some students get retained. Retention is normally a decision left to the discretion of the school. Estimates from our sample show that the retention rate among secondary 3s is only 3%.[26] This implies that most secondary 3 students end up getting promoted to secondary 4 and that selection bias is likely to be small. Furthermore, among the few get retained, some may have got retained not because of lower ability, but because of random shocks that turn out to be negative.

If the assumption that students born close to the cut-off date are randomly assigned is true, then average characteristics of those on the left and right of the cut-off should be similar. A natural way to check for this would be to examine if the control variables on each side of the cut-off are similar to each other. If observed covariates do not differ significantly

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from the first day of the last menstrual period. As such, only 5% deliver on the due date, although most deliver within two weeks of the due date (Bennett, 2004).

[25] Here we are referring to those that are rightfully in secondary three as their age would suggest.

[26] This percentage is calculated as follows. We count the number of secondary 3s who should be in secondary 4 given their age and divide this number by the total number of secondary 4s in our sample. We include only those who answered yes to the question *Have you ever repeated a grade in upper secondary.* This helps us exclude those who repeated a grade earlier on in their education career and also foreigners who are normally placed in a grade too low for their age.

across the cut-off, we can be reasonably confident that unobserved characteristics do not as well. For each control variable, we take the difference in mean between those born on the left and right of the cut-off date. We report p-values to show if the difference (if any) between the two means is statistically significant. We do this for different bandwidths. Table 2 reports the results.

As we reduce the bandwidth, the difference in means of most control variables becomes less statistically significant. For most covariates in the narrowest one month band, the difference in means is not statistically significant. However, the difference in means for some controls is still significantly different from 0 even in the narrowest bands. These differences merit some discussion.

TABLE 2: DIFFERENCE IN MEANS BETWEEN SECONDARY 3 AND 4 STUDENTS

Bandwidth	±1 month		±2 months		±3 months	
	Diff in means	P-value	Diff in means	P-value	Diff in means	P-value
Male	-0.053	0.14	-0.020	0.43	0.012	0.54
Immigrant	-0.044	0.03	-0.028	0.04	-0.030	0.00
Speak Tamil at home	-0.006	0.50	-0.007	0.17	-0.004	0.42
Speak Malay at home	-0.056	0.04	-0.027	0.17	-0.029	0.08
Speak English at Home	0.035	0.34	-0.003	0.92	-0.012	0.55
Speak Chinese at home	0.041	0.26	0.042	0.10	0.051	0.01
Speak other language at home	-0.014	0.19	-0.005	0.50	-0.006	0.30
Nuclear family	0.003	0.91	0.027	0.20	0.023	0.14
Single parent family	-0.013	0.61	-0.032	0.10	-0.020	0.16
Mixed family	0.009	0.26	0.008	0.31	0.002	0.78
Number of rooms with bath	0.011	0.80	0.019	0.61	0.004	0.88
Parent no primary education	0.003	0.73	0.006	0.30	0.004	0.40
Parent primary education	0.005	0.80	-0.002	0.90	0.000	0.98
Parent lower secondary	-0.018	0.31	-0.005	0.66	0.005	0.57
Parent upper secondary	0.023	0.28	0.018	0.19	0.021	0.04
Parent A-Level/ITE	-0.056	0.09	-0.013	0.63	-0.006	0.78
Parent poly diploma	0.076	0.01	0.017	0.46	0.009	0.57
Parent university degree or	-0.032	0.25	-0.021	0.33	-0.034	0.04
Reading Lesson Time	0.228	0.13	0.317	0.01	0.256	0.01
Math Lesson Time (hrs/week)	0.237	0.22	0.344	0.02	0.170	0.17
Science Lesson Time	-0.143	0.14	-0.020	0.43	0.012	0.54
Student-teacher ratio	0.219	0.03	-0.028	0.04	-0.030	0.00
Percentage of certified	0.320	0.50	-0.007	0.17	-0.004	0.42
Percentage of graduate	-0.705	0.04	-0.027	0.17	-0.029	0.08
Av. Peers' parents' education	-0.193	0.34	-0.003	0.92	-0.012	0.55

1. Difference in means refers to the mean value for students in secondary 4 minus the mean value for students in secondary 3.
2. P-values are for the null hypothesis that the difference in mean across grades equals zero.
3. All computations are weighted.
4. Standard errors computed using BRR to adjust for clustering at the school level.

The proportion of foreign students in secondary 4 is 0.04 lower than those in secondary 3. This is probably because Ministry of Education strongly discourages new foreigners from enrolling into secondary 4 straight away. Since students in secondary 4 sit for the high stakes O-level exams at the end of the year, new immigrants might not have enough time to adapt and prepare if they enrol into secondary 4 immediately. The proportion of students who speak Malay at home in secondary 4 is 0.056 lower than those in secondary 4. This might reflect a higher rate of retention among this group. The proportion of students whose parents have A-Level/ITE qualifications is lower for those in secondary 4. On the other hand, the proportion of students whose parents have a Poly diploma is higher for those in secondary 4. While the difference in means for the *student-teacher ratio* and *percentage of graduate teachers* is statistically significant, the size of this difference is probably too small to be of any economic significance. The percentage of graduate teachers in secondary 4 is lower by 0.7% as compared to secondary 3. Student-teacher ratio for secondary 4 students is 0.22 higher than those in secondary 3.

Since we use quite a sizable number of covariates, it is possible that some of their discontinuities will be statistically significant purely due to random chance (Lee and Lemieux, 2009). In general, most covariates are largely similar for those born around the cut-off and this validates our RD design. However, we continue to control for all observed characteristics since some differ in an economically significant way.

RD Results

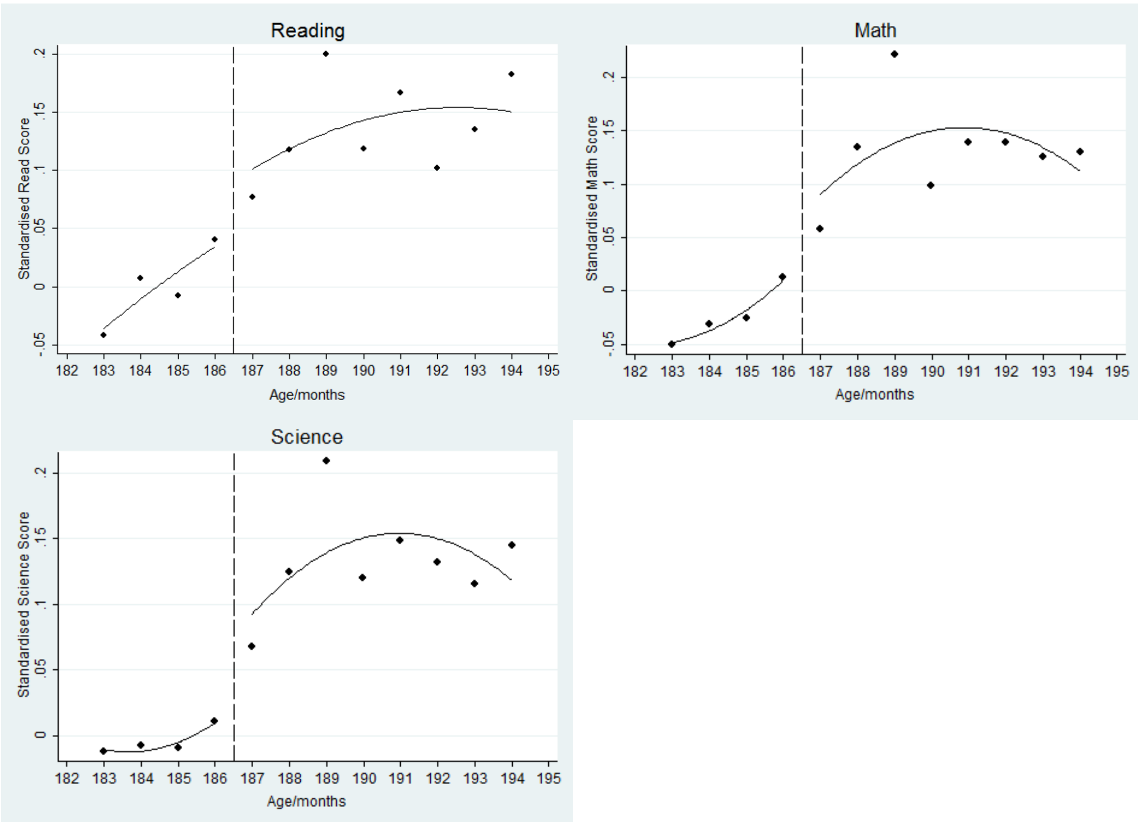
Figure 1 shows scatter plots of the outcome variable (test scores) against the assignment variable (age).[27] The y axis is standardised test score for each subject while the x axis is age in months. Because we only have the months of birthdates but not the days, we have only 12 distinct points for the scatter plot. Each point corresponds to the weighted mean

[27] It makes no difference whether we use age or date of birth as the x axis since age (to the nearest month) is calculated using date of birth (information only available to the nearest month).

score for students born within a particular month.[28] The dotted line corresponds to the school-entry cut-off date. We fit separate curves on the left and right hand side of the cut-off. The scatter plots show a large jump for Science scores and relatively smaller jumps for Math and Reading around the cut-off date due to the treatment effect of an extra year of schooling.

Disturbingly, the average test scores across all subjects for those born in October 1993 (corresponding to 189 months of age on the graph) are unusually high. The reasons remain unclear. Students in the sample are evenly distributed across each birth month so this rules out small sample size for October. All schools are evenly represented across each birth month so this rules out the case that October students are over represented by students from a particularly good school. Finally, there were no relevant legislative changes that could have affected those born during this period.

FIGURE 1: SCATTER PLOTS AND FITTED CURVES BY SUBJECT



[28] As such, having a discrete assignment variable simplifies the problem of choosing an optimal bin width for the graph.

Table 3 shows our regression results using the RD design using all possible bandwidths around the school entry cut-off date. In the narrowest bandwidth, we include only those born within a month of the school entry-cut off date. The widest bandwidth contains those born within 4 months of the school-entry cut off date. There are 2 key differences between the baseline regression and the RD regression. First, we restrict our sample to only those born near the school entry cut-off date. Second, we exclude age from the regression since age is more or less constant in the narrow window around the cut-off.[29]

In general, standard errors become smaller when we widen the bandwidth. This increased precision is due to the increased sample size. However, coefficients increase in size as well due to the upward trending effect of age. This reflects the precision bias trade-off inherent in any RD study.

TABLE 3: RD RESULTS WITH INCREASING BANDWITH BY SUBJECT

	(1) Dec 93 – Jan 94	(2) Nov 93 – Feb 94	(3) Oct 93 – Mar 94	(4) Sep 93 – Apr 94
Bandwidth	±1 month	±2 months	±3 months	±4 months
Reading				
Secondary 4	0.0800	0.135***	0.168***	0.200***
	[0.0609]	[0.0461]	[0.0354]	[0.0304]
N	709	1360	2059	2737
Math				
Secondary 4	0.112	0.169***	0.191***	0.217***
	[0.0722]	[0.0488]	[0.0358]	[0.0292]
N	689	1329	2002	2661
Science				
Secondary 4	0.182***	0.189***	0.204***	0.221***
	[0.0622]	[0.0522]	[0.0380]	[0.0310]
N	655	1269	1920	2557

1. Apart from age being excluded from all regressions other controls same as baseline regression.
2. Standard errors are in brackets and adjusted for clustering at the school level using BRR.
3. Regressions are weighted and all 5 plausible values are used in estimation.
* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

In the narrowest 1 month window, the gains for Reading are only 0.08SD and this effect is not statistically significant. The gains for Math are 0.11SD. Though this coefficient

[29] Given the discrete nature of our age variable, it is also not feasible to do so. Inclusion of the age variable in the narrower windows would lead to high multi-collinearity since age is perfectly correlated with whether the student receives an extra year of schooling.

is not significant at even the 10% level, its p-value of 0.13 is still relatively low. The gain for Science is 0.182 which is large and statistically significant at the 1% level. These represent our most robust findings for test score gains from an additional year of schooling using an RD design. Interestingly, the coefficient sizes are very similar to the OLS estimates.[30]

As we widen the bandwidth, the gains for all subjects increase and become statistically significant at the 1% level. The increase in coefficient size when we widen the bandwidth from 1 to 2 months is 0.055 for Reading and 0.057 for Math. By contrast, the coefficient on Science only increases by 0.007. This corroborates the earlier finding in our baseline regression that age does not seem to affect Science scores.

Does Parents' Education Level Affect Gains from Extra Schooling?

To answer this question, we split our sample into three different subgroups and applying the RD design separately for each sub group. The three sub groups are: those whose parents have at most upper secondary education, those whose parents have post-secondary education (ITE, Polytechnic Diploma or A-Level) and those who have graduate parents. We split the sample this way so that we have a sizable number of observations in each subgroup. Furthermore, our baseline regression results show that performance differences within each subgroup are either small or not statistically significant.

Figure 2 shows the scatter plots of test scores against age for each different subgroup. The graphs reveal that for each subgroup, the jump in test score is smallest for Reading and largest for Science. Comparing across subgroups, we find that the jump is largest for students with graduate parents. There is a modest jump for students whose parents have post secondary education. Surprisingly, there is no discontinuity for those whose parents have only secondary education and below. This suggests that students with parents of lower educational level do not gain at all from an additional year of schooling.

To investigate how the gain from an additional year of school is affected by parents' education, we make three changes to the RD regression. First, we replace the full set of

[30] Note that due to the discontinuous jump in test score at the cut-off, OLS estimation using a smooth function through the cut-off is wrong. Instead the correct approach would be to estimate separate age functions on the left and right of the cut-off (Imbens and Lemieux, 2008).

parental dummies with *parent secondary & below*, *parent post secondary* and *parent university graduate*. The omitted dummy in this case is *parent secondary & below.* Second, we include the interaction terms *secondary 4* parent post secondary* and *secondary 4*parent university graduate*. This allows the gain from an extra year to vary across the three subgroups.

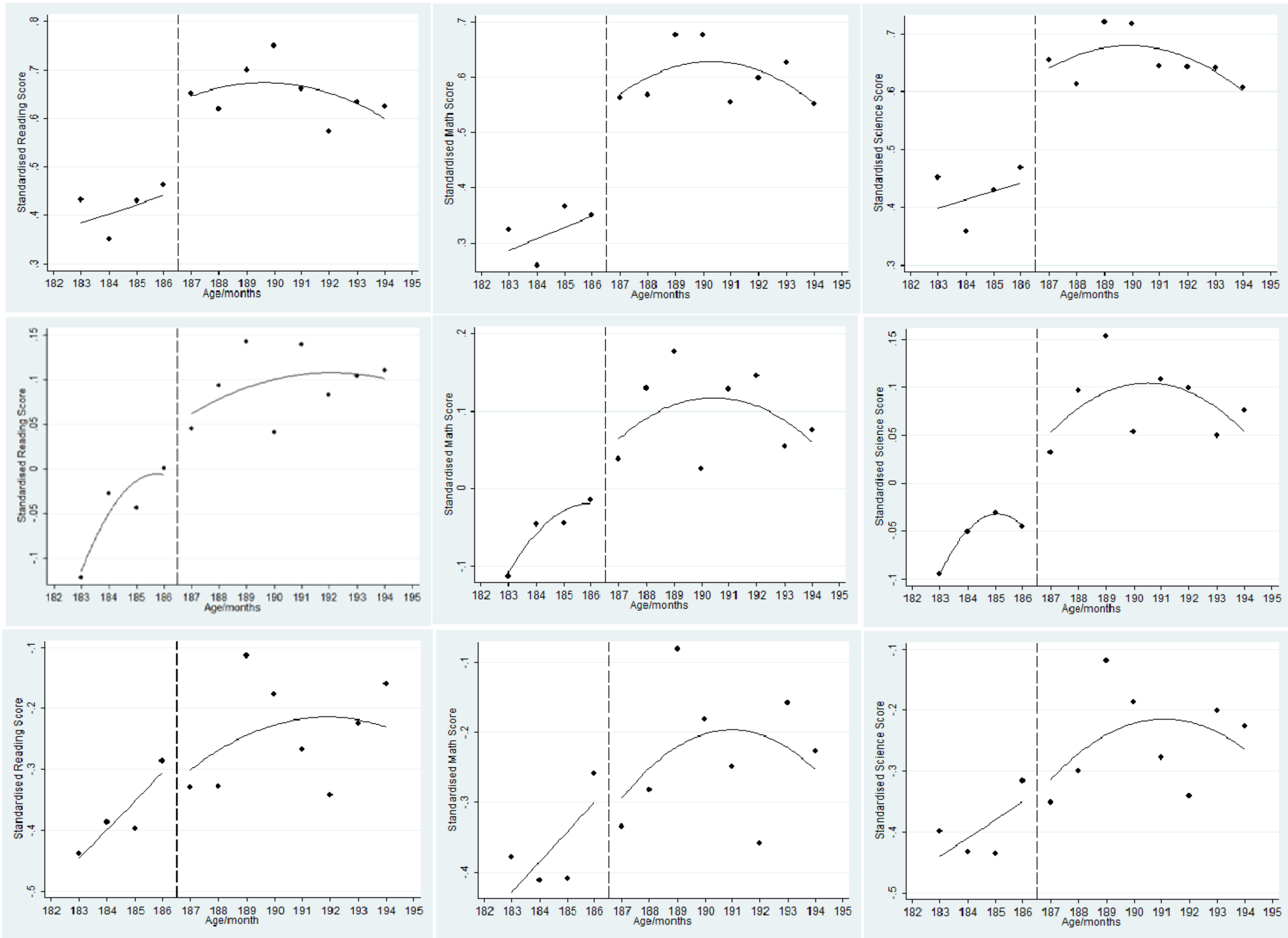
FIGURE 6.1: SCATTER PLOTS AND FITTED CURVES BY PARENTS' EDUCATION

Reading **Math** **Science**

Parent graduate

Parent post secondary

Parent secondary and below



Finally, we include interaction terms for all other control variables with the subgroup dummies. This more flexible specification allows for the possibility that the effect of other covariates differs between the three subgroups. We estimate

$$StdScore_i = \beta_0 + \beta_1 sec4 + \beta_2 sec4 \times postsec + \beta_3 sec4 \times graduate + \pi' Z_i \ + v_i$$

where Z_i here denotes a vector of all other covariates.

The advantages of using a pooled regression versus separately estimating regressions for each subgroup are two-fold. First, we can conveniently tell if one subgroup's test score gain is statistically different from another subgroup's by observing the significance level of the coefficient on the interaction term.[31] Second, there is an efficiency gain as sample size is larger in the pooled regression.

Table 4 reports the results for the narrowest 1 month window. Turning first to Reading scores, we see that the test score gain for students whose parents are secondary educated and below is -0.126SD. This is negative but not statistically significant. Test score gain for students with post secondary educated parents is 0.139 and this is statistically significant at the 10% level. Test score gain for students with graduate parents is largest at 0.229 (p-value=0.14). The difference in test score gain between students with post secondary educated parents and students with secondary educated parents is 0.264SD (p-value=0.13). Students with graduate parents gain 0.355SD more than students with secondary educated parents. This is statistically significant at the 10% level.

We find similar results for Math. Test score gain for the group with the lowest educated parents is -0.126 but this is not statistically significant. Students with post secondary educated parents gain 0.17SD while those with graduate parents gain 0.29SD; these gains are both statistically significant at the 10% level. Students with post secondary educated parents gain about 0.296SD more than students whose parents are secondary educated and below (p-value=0.12). Students with graduate parents gain 0.419SD more than

[31] If we ran separate regressions; comparison would require the use of the chow test.

students whose parents are secondary educated and below. This is statistically significant at the 10% level.

TABLE 4: RD RESULTS BY PARENTS' EDUCATION

	Dependent Variable		
	(1) Reading	(2) Math	(3) Science
Secondary below gain (β_1)	-0.126	-0.126	0.0338
	[0.138]	[0.149]	[0.130]
Post secondary gain ($\beta_1 + \beta_2$)	0.139*	0.170*	0.235**
	[0.082]	[0.093]	[0.088]
Graduate gain ($\beta_1 + \beta_3$)	0.229	0.292*	0.248
	[0.155]	[0.160]	[0.158]
Post secondary gain – secondary below gain (β_2)	0.264	0.296	0.201
	[0.171]	[0.186]	[0.169]
Graduate gain – secondary below gain (β_3)	0.355*	0.419*	0.214
	[0.213]	[0.226]	[0.221]
N	709	689	655

1. Reported results are for narrowest 1 month bandwidth.
2. Full set of parental education dummies replaced with *parent secondary & below*, *parent post secondary* and *parent university graduate*. Omitted dummy is *parent secondary & below*.
3. Full set of interaction terms for 3 subgroups included.
4. Age is excluded from all regressions. Other controls are the same as baseline regression.
5. Standard errors in brackets and adjusted for clustering at the school level using BRR.
6. Regressions are weighted and all 5 plausible values are used in estimation.
* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

For Science, test score gain for students whose parents are secondary educated and below is 0.034SD. This is positive but not statistically significant. Students with post secondary educated parents gain 0.235SD and this is statistically significant at the 5% level. Students with graduate parents gain 0.248SD (p-value=0.12). For the two subgroups whose parents are higher educated, the difference in test score gain as compared to students with the lowest educated parents is not statistically significant Interestingly, differences in test score gain among the three subgroups are smallest for Science.

Though not statistically significant, it is puzzling why test score gains for students whose parents are secondary educated and below are negative for both Reading and Math.[32]. If randomisation around the cut-off holds, then students on the left and right of the cut-off should be similar in terms of all average characteristics. In fact, if there is any sorting, those on the right of the cut-off should have slightly higher unobserved ability as a small number

[32] P-value is very high at 0.37 and 0.40 for Math and Reading respectively.

of low ability students might get retained or and drop out before reaching secondary 4. Therefore any bias in the effect of schooling on test score ought to be upwards rather than downwards.

Nevertheless, our findings indicate that students from more educated backgrounds gain more from an additional year of schooling compared to those from less educated backgrounds. These differences are statistically significant for Math and Reading but not for Science.

Why do students with more educated parents gain more from schooling? Perhaps for many of the same reasons they tend to score better in the first place. They could be blessed with more natural intelligence which would allow them to learn more from an extra year of school. It is also likely that more educated parents pass on other unobserved character traits. For example students from more educated backgrounds might be more motivated to excel in school which would in turn cause them to adopt positive learning habits like paying attention in class and handing up homework on time. Therefore schooling might be more effective for this group simply because they make the most of it. In addition, students from more educated backgrounds are able to afford expensive private tuition if needed. If such out-of-school lessons are taken into account, these students actually receive a higher quantity of education within a year as compared to their counterparts with less educated parents. Finally, students from more educated backgrounds are over represented in the top schools. It is possible that they gain more from an additional year of schooling simply because good schools provide better education.

How Does Parental Education Matter?

In what follows, we briefly explore some mechanisms in which parents' education level might affect test score. We do so by making some modifications to our baseline regression model. Understanding how parents' education affects test score helps shed some light on why students from more educated backgrounds gain more from school.

Fathers' education, mothers' education and occupational status

We consider whether the effect of parents' education differs between fathers and mothers. We also explore whether there is any test score gain if either the mother or the father stays home. We remove the dummies for highest parental education and replace them with years of education for mothers and fathers. We also include two dummy variables, each indicating whether the father or mother is working.[33] Other controls used are identical to those in our baseline regression. Panel A of table 5 reports the results.

We can see that the effect of an extra year of parents' education on Math and Reading scores is the same for both mothers and fathers. This is around 0.02SD per year. Students' score in Science improves more from one year of mothers' education (0.026SD) as compared to fathers (0.019SD).

There is a statistically significant improvement in test scores for Reading if either the mother or the father does not work. Students whose mothers do not work perform 0.07 SD higher than students whose mothers work while students whose fathers do not work perform about 0.15SD higher than students whose fathers work. For Math, students whose fathers are not working score better than those whose fathers work. The effect for mothers is not statistically significant. The reverse is true for Science, students with stay-home mothers perform better than those with working mothers while the effect for fathers is not statistically significant.

TABLE 5: REGRESSION RESULTS USING MOTHER'S AND FATHER'S EDUCATION

Panel A: Without interaction terms	Dependent Variable		
Independent Variable	(1) Reading	(2) Math	(3) Science
Mother's education (yrs)	0.0251***	0.0205***	0.0256***
	[0.00544]	[0.00605]	[0.00615]
Father's education (yrs)	0.0247***	0.0210***	0.0193***
	[0.00493]	[0.00577]	[0.00478]
Mother does not work	0.0696***	0.0462	0.0716***
	[0.0269]	[0.0308]	[0.0254]
Father does not work	0.149***	0.124**	0.0672
	[0.0525]	[0.0602]	[0.0557]

[33] We consider those who work part time or are actively seeking employment to be working as well.

Panel B: With interaction terms			
Mother's education (yrs)	0.0254***	0.0224***	0.0287***
	[0.00624]	[0.00704]	[0.00703]
Father's education (yrs)	0.0253***	0.0207***	0.0200***
	[0.00521]	[0.00592]	[0.00501]
Mother doesn't work	0.0790	0.0972	0.157
	[0.0940]	[0.111]	[0.102]
Father doesn't work	0.253	0.0877	0.189
	[0.193]	[0.206]	[0.206]
Mother's education * mother doesn't work	-0.000868	-0.00467	-0.00785
	[0.00788]	[0.00954]	[0.00860]
Father's education * father doesn't work	-0.00937	0.00326	-0.0109
	[0.0164]	[0.0170]	[0.0178]
F Statistic Mother	6.77	2.36	8.08
P-value	0.0338	0.3074	0.0176
F Statistic Father	8.25	4.48	1.81
P-value	0.0162	0.1067	0.4047
N	3966	3861	3704

1. Apart from dummies for highest parental education, other controls exactly the same as table 1.
2. F statistic is for the joint test that work dummy and interaction term for each parent are not both equal to zero.
3. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.
4. Standard errors are in brackets and are adjusted for clustering at the school level using BRR.
5. Regressions are weighted and all 5 plausible values are used in estimation.

In panel B, we investigate whether students actually gain more from having an educated parent stay home. If so, this implies that part of the academic advantage enjoyed by students with more educated parents is due to transmission of human capital in the home environment. For example, stay home parents might coach the child in his daily schoolwork. To study this effect, we interact the dummy for not working with years of education for mothers and fathers respectively.

The results in panel B show that the coefficients on the interaction terms mostly have a negative sign. However their magnitude is too small to be of any economic significance. There are no additional gains to having an educated parent stay home. This implies that higher test scores enjoyed by students from more educated backgrounds are not a result of direct human capital transmission at home.

<u>Externalities from schoolmates' parental education</u>

It is possible that there is some positive externality associated with being surrounded by students that come from more educated backgrounds. Conversely, there might be negative externality associated with being surrounded by students from less educated backgrounds. To explore this, we replace *average parental education of peers* with the following two variables:

$$Peer\ parental\ education\ lower\ than\ yours = \begin{cases} |parental\ education\ gap| \text{ if gap} < 0 \\ 0 \text{ otherwise} \end{cases}$$

$$Peer\ parental\ education\ higher\ than\ yours = \begin{cases} |parental\ education\ gap| \text{ if gap} > 0 \\ 0 \text{ otherwise} \end{cases}$$

$$where\ parental\ education\ gap$$

$$= average\ parental\ education\ of\ peers - own\ parent's\ education$$

This more general specification allows for the possibility that the effect of peers' parental education has different magnitude depending on whether the student's own parents' level of education is higher (or lower) than that of his peers. Table 6 reports the results.

TABLE 6: REGRESSION RESULTS FOR EXTERNALITY FROM PEERS' PARENTS

	Dependent Variable		
	(1) Reading	(2) Math	(3) Science
Peers' parental education lower than yours	-0.257***	-0.290***	-0.276***
	[0.0177]	[0.0182]	[0.0198]
Peers' parental education higher than yours	0.339***	0.363***	0.343***
	[0.0200]	[0.0203]	[0.0209]
N	4070	3960	3797

1. Apart from *Average parental education of peers*, other controls exactly the same as table 1.
2.* Significant at 10%. ** Significant at 5%. *** Significant at 1%.
3. Standard errors are in brackets and are adjusted for clustering at the school level using BRR
4. Regressions are weighted and all 5 plausible values are used in estimation

Having schoolmates whose parents have one more year of education than your own parents is associated with an increase of between 0.34SD to 0.36SD depending on subject. By contrast, having schoolmates whose parents have one less year of education is associated with a decrease of between 0.26SD to 0.29SD. The test score gain from having peers with higher parental education exceeds the loss associated with having peers with lower parental education. This asymmetric externality suggests that suggests that there might be some pareto improvement to having students from more diversified backgrounds in the same school.[34]

Conclusion

This paper found modest gains in skill arising from an additional year of schooling for Reading, Math and Science. Using a RD design, our most conservative estimates show that the gains for Science are the largest while the gains for reading are small and not statistically significant. Gains for Math are modest and marginally significant.

Nevertheless, these gains are not evenly distributed across different groups. Students with the most educated parents gain the most from an additional year of school while students with the least educated parents do not gain at all from schooling. The difference is quite substantial. For example students with graduate parents gain between 0.2-0.3SD more than students with parents who have secondary education and below. Why do students with more educated parents gain more from schooling? There are a number of possible reasons that we have not been able to explore in depth in this paper.

We have only managed to estimate gains in skill between secondary 3s and secondary 4s. These estimates should not be generalised to other grades. However, if skill gains between other grades conform to a similar pattern (children from less educated backgrounds gaining less than children with more educated parents); it could imply that skill gaps between different social classes might actually be increasing with more years of schooling. Pre-existing test score gaps that arise from differences in parents' education could have begun early on in childhood and gradually widened as the child experienced more years of schooling. This suggests that any intervention to help disadvantaged children close the skill gap ought to come sooner rather than later.

[34] There is no way to know for sure since peer groups are not formed randomly.

References

Angrist, Joshua. D., and Krueger, Alan. B. (1991). Does Compulsory School Attendance Affect Schooling and Earnings? *The Quarterly Journal of Economics, 106*(4), 979-1014.

Angrist, Joshua D., and Pischke, Jorn-Steffen. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. New Jersey: Princeton University Press.

Behrman, Jere. R., and Rosenzweig, Mark. R. (2002). Does Increasing Women's Schooling Raise the Schooling of The Next Generation? *The American Economic Review, 92*(1), 323-334.

Blatchford, Peter., Goldstein, Harvey., Martin, Claire., and Browne, William. (2002). A Study of Class Size Effects in English School Reception Year Classes, *British Educational Research Journal,* 28(2), 169-185.

Card, David E. (1999). The Causal Effect of Education on Earnings. *Handbook of Labor Economics, 3*, 1801-1863.

Cascio, Elizabeth. U., and Lewis, Ethan. G. (2006). Schooling and the Armed Forces Qualifying Test: Evidence from School-Entry Laws. *The Journal of Human Resources, 41*(2), 294-318.

Chang, Rachel. (2011). Parents' Background The Edge for Students at Top Schools: MM. *The Straits Times*, p.A3.

Frenette, Marc. (2008). The Returns to Schooling on Academic Performance: Evidence from Large Samples Around School Entry Cut-off Dates. *Statistics Canada: Analytical Studies Branch Research Paper Series*. No. 317.

Hansen, Karsten T., Heckman, James J., and Mullen, Kathleen J. (2004). The Effect of Schooling and Ability on Achievement Test Scores. *Journal of Econometrics, 121*(1-2), 39-98.

Herrnstein, Richard J., and Murray, Charles. A. (1996). *The Bell Curve: Intelligence and Class Structure in American life*. New York: Free Press.

Imbens, Guido. W., and Lemieux, Thomas. (2008). Regression Discontinuity Designs: A Guide to Practice. *Journal of Econometrics, 142*(2), 615-635.

Lee, David. S. 2008. Randomized Experiments from Non-random Selection in U.S. House Elections. *Journal of Econometrics*, 142(2), 675-97.

Lee, David. S., and Lemieux, Thomas. (2010). Regression Discontinuity Designs in Economics. *Journal of Economic Literature, 48*(2), 281-355.

Lohr, Sharon L. (1999). *Sampling Design and Analysis*. Pacific Grove, CA: Duxbury Press.

McEwan, Patrick., and Shapiro, Joseph. (2008). The Benefits of Delayed Primary School Enrollment: Discontinuity Estimates Using Exact Birth Dates. *The Journal Of Human Resources*, 93(1), 1-29.

Ministry of Education. (2008). *Helping Students who are At-Risk of Dropping-Out Stay in School.* Retrieved from http://www.moe.gov.sg/media/press/2008/03/helping-students-who-are-atris.ph

Neal, Derek A., and Johnson, William. R. (1996). The Role of Premarket Factors in Black-White Wage Differences. *The Journal of Political Economy, 104*(5), 869-895.

Ng, Jane. and Tan, Amelia. (2011). In Two Years their English Grades Leapt from F9 to A1. *The Straits Times*, p.H1.

Oreopoulos, Phillip. (2006). Estimating Average and Local Average Treatment Effects of Education when Compulsory Schooling Laws Really Matter. *American Economic Review, 96*(1), 152-175.

Organisation for Economic Co-operation and Development. (2006a). *PISA 2006 Data Analysis Manual*. Paris: OECD.

Organisation for Economic Co-operation and Development. (2006b), *PISA 2006 Technical Report*. Paris: OECD.

Rust, Keith. F., and Rao, Jonnagadda. N.K. (1996). Variance Estimation for Complex Surveys Using Replication Techniques. *Statistical Methods in Medical Research, 5*(3), 283-310.

Singapore Department of Statistics. *Census of Population 2010: Statistical Release 1 on Demographic Characteristics, Education, Language and Religion.* Retrieved from http://www.singstat.gov.sg/pubn/popn/c2010sr1.html

Smith, Justin. (2009). Can Regression Discontinuity Help Answer an Age-Old Question in Education? The Effect of Age on Elementary and Secondary School Achievement. *The B.E. Journal of Economic Analysis and Policy,* 9(1), Article 48.

Thistlethwaite, Donald L., and Campbell, Donald. T. (1960). Regression Discontinuity Analysis: An Alternative to The Ex Post Facto Experiment. *Journal of Educational Psychology, 51*(6), 309-317.

Winship, Christopher., and Korenman, Sanders. D. (1997). Does Staying in School Make You Smarter? The Effect of Education on IQ in The Bell Curve. In *Intelligence, Genes, and Success: Scientists Respond to The Bell Curve* (pp. 215-234). New York: Springer-Verlag.

Wong, Wei-Kang. (2010). *Parental Valuation of Priority Admission to Primary Schools: The Effects of Academic Reputation and Choices.* National University of Singapore, Department of Economics. Working paper.