

ECONOMETRIC GAME 2024

TEAM 1

April 18, 2024

## TABLE OF CONTENTS

CHAPTER	
1	Introduction . . . . . 1
2	Literature Review . . . . . 2
2.1	Importance of schools of education . . . . . 2
2.2	School starting age . . . . . 2
3	Descriptive Statistics . . . . . 3
3.1	Comparison between countries . . . . . 3
3.2	Comparison within countries . . . . . 5
3.3	Inter-generational analysis . . . . . 5
4	Empirical Analysis . . . . . 7
4.1	Effect of school starting age on test scores . . . . . 7
4.2	School starting rules and RDD estimates . . . . . 8
4.3	Mechanisms, heterogeneity and robustness . . . . . 12
5	Discussion . . . . . 15
BIBLIOGRAPHY	. . . . . 16

## CHAPTER 1

### INTRODUCTION

Providing good education to children is considered essential for society. Via using the PISA data in 2015, 2018 and 2022, the characteristics of the school performance of 15-year-old students in OECD countries can be drawn as: (1) students from middle and high income countries have better performance than those from low income countries; (2) within the middle income countries, the performance disparity within France is bigger than Japan and Canada; (3) children with parents from the higher educational background perform better in both math and reading.

With more study on different education policies and their effects on school performance of students, school starting age has garnered increased attention from economists. The study of Oosterbeek et al. (2021) compares the students born just before and just after the entry-age cutoff, the latter group scored significantly higher on the primary school exit test. Such finding inspired our study to research on the OECD countries. From which we found that: Lithuania and Czech Republic has the cutting date on the first of January; while Hungary, Austria and South Korea set their cutting date on the first of August. The common finding in these countries is the students born just after the cutting date performs significantly better than those born just before the cutting date.

## CHAPTER 2

### LITERATURE REVIEW

#### 2.1 IMPORTANCE OF SCHOOLS OF EDUCATION

Previous studies have focused on the effects of good schools, including those on academic performance, crime rates and economic growth. Deming (2011) showed that under the lottery system of choosing schools, students who were admitted to their first choice were arrested for fewer serious crimes and spent fewer days in jail. In addition, the "good school" effect can be broken down into different components: better schools may be better in terms of course content, teaching materials and teachers' starting salary, thus making a positive difference for students' academic performance (Fuchs and Wößmann, 2008).

#### 2.2 SCHOOL STARTING AGE

One potential channel through which school starting age affects students' academic performance is relative age in cohort. Overall, existing literature shows that older students in a cohort perform better than younger ones, and that this performance gap closes with age. In the Dutch context, Oosterbeek et al. (2021) found that compared to students born just before the entry-age cutoff and therefore the youngest in their cohorts, students born just after the cutoff scored significantly higher on the primary school exit test and, consequently, were four percentage points more likely to enter college or university education as opposed to vocational education. The authors also conclude that the combined effect of school starting age and relative age in cohort dominates that of age-at-test. Cook and Kang (2020) also showed that after the US state of North Carolina moved its public school entry cutoff date from October to August, children born between the old and new cutoff dates, previously the youngest and now the oldest in their classes, experienced smaller test score gaps between Black and White students, males and females, as well as students from disadvantaged and non-disadvantaged backgrounds. Grade retention was also found to be affected by the change in the school starting rule in this study.

School starting age could determine the amount of time students spend in school, which in turn could influence their educational outcomes. Leuven et al. (2010) utilized the unique school starting rules in the Netherlands and found that one additional month in school had a positive effect on both language and math scores for disadvantaged students, while for non-disadvantaged students no effect was found. These results are in line with those of other studies suggesting heterogeneity in the effects of school starting age. For instance, relative age in cohort may have a longer-lasting impact on students from less advantaged socioeconomic background and those in urban areas (Schneeweis and Zweimüller, 2014).

## CHAPTER 3

### DESCRIPTIVE STATISTICS

#### 3.1 COMPARISON BETWEEN COUNTRIES

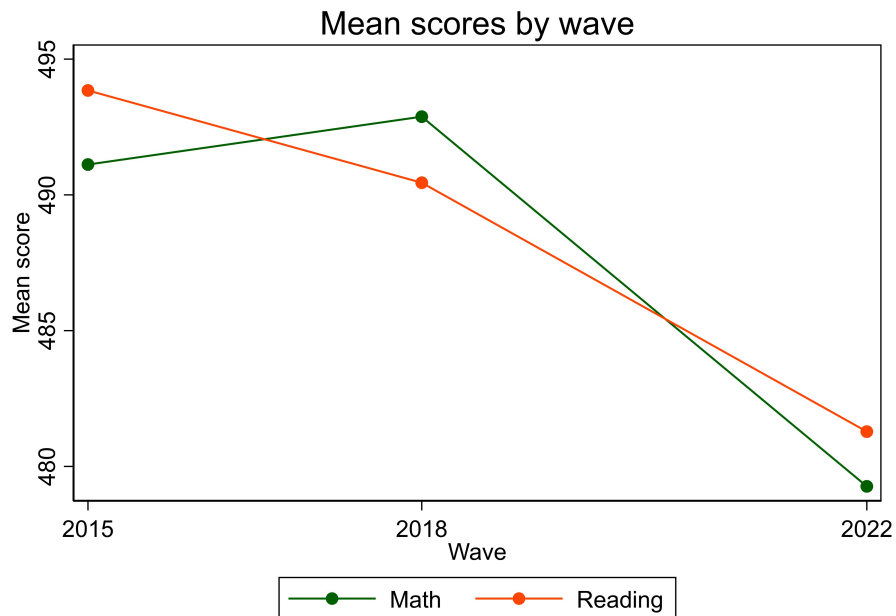
##### 3.1.1 OUR DATA

The analysis of this paper is based upon a dataset comprising the three most recent waves of the Programme for International Student Assessment (PISA) in 2015, 2018, and 2022. The PISA study mainly tests 15-year old students on their math, reading, and science skills. Common student characteristics (such as gender, age, socio-economic status...) are reported as well. After processing the dataset by only focusing on the samples with valid data and deleting those missing values, we will focus on the math and reading section of the test.

##### 3.1.2 DEVELOPMENT OVERTIME

Every student in the dataset has for every category (math and reading) ten so-called plausible values. We use the simple average of these, to create a score in the respective subject for each student. Aggregating this data for every student, allows us to see in Figure 3.1 that there is a substantial variation across time in scores for both subjects.

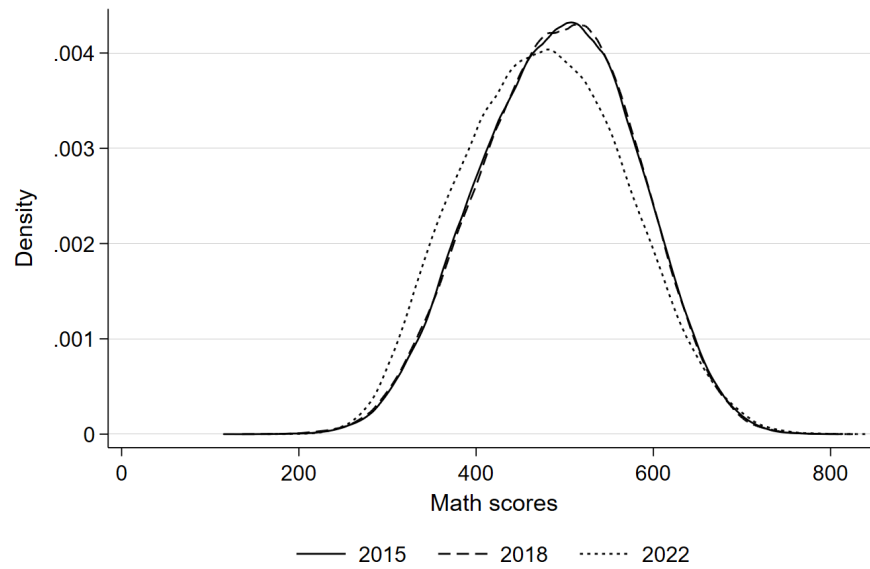
**Figure 3.1:** Average Test Results per Wave



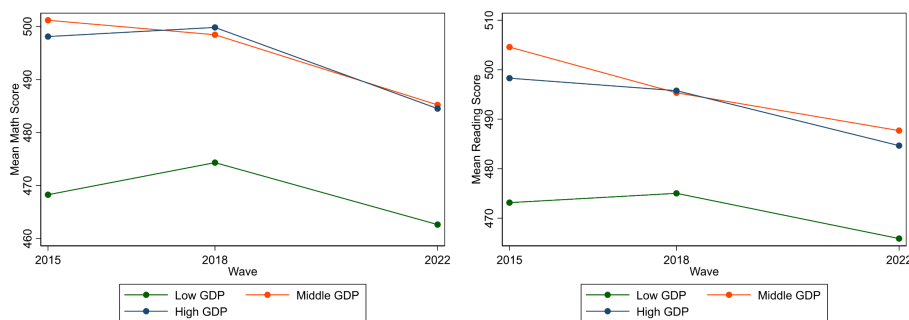
To be more specific, as for the reading performance, student's average performance shows a downward trend while math performance has increased between 2015 and 2018 and decreased from 2018 to 2022.

Moreover, as we can see in Figure 3.2, the second phase (2018-2022) witnessed a more prominent decline for math scores. Taking into account the actual situation, schools will adopt more methods such as suspending classes or online teaching to educate students during the epidemic, which is consistent with the trend we have observed.

**Figure 3.2:** Math Score Density per Wave



**Figure 3.3:** Average Reading and Math Results per Wave and per GDP Group



We then focus on comparisons between countries. We divided the related countries into three groups based on the 2018 GDP level in \$ disclosed by the OECD.

As we can see in 3.3, there is a difference of student's performance among countries of different GDP levels. The students from countries of middle and high GDP level show a

better performance both in reading and math than students from countries of low GDP level by 18 scores in reading and 25 points in math.

### 3.2 COMPARISON WITHIN COUNTRIES

Looking at differences within countries, we chose for North America, Europe, and Asia from the middle GDP group the countries with the biggest population for our further analysis. This is Canada (CAN), France (FRA), and Japan (JPN) respectively.

**Table 3.1:** Average Math and Reading Test Scores per Percentile

Math				Reading			
%	CAN	FRA	JPN	%	CAN	FRA	JPN
10%	386	357	418	10	377	338	388
50%	498	489	535	50	509	492	520
90%	606	600	637	90	624	616	623

If we divide the students by the percentile of 10%, 50% and 90% from low to high in each country, we can see France has the biggest disparity of student performance in both math and reading within the country itself.

On the other hand, the relatively concentrated levels of achievement observed in Japan and Canada may indicate that educational practices or cultures place a more uniform emphasis on academic achievement, which is also in line with the better average performance in these two countries, leading to a narrowing of the achievement gap between students.

### 3.3 INTER-GENERATIONAL ANALYSIS

To take a closer look at inter-generational mobility, we use a variable that provides us with the highest education in years of schooling of the parents of the student. As 12 years of schooling is the median, we split it into a low-education group with zero to 12 years of parental education and a high-education group with more than 12 years of education of the parents.

From the table 3.2 we can see that in all these three countries selected, children of parents with higher education have better academic performance, in both reading and math and in each student percentile. As better-educated parents tend to have more resources and opportunities to support their children's education, including access to better schools, educational materials and extracurricular activities.

Compared to Canada, the inter-generational effect is more obvious in France and Japan, which means the difference of the education level from parents would lead to a greater divergence of the school performance of children.

We can conclude this descriptive section by emphasizing the motivating character of these findings. First, as figure 3.1 illustrates, the score is not fixed. As the score differed over these last years, the possibility is given to achieve a better result through improved public policy. Furthermore, as the diverging results between countries highlight, there is room for differentiation and improvement between the countries. The contrast between Japan and

**Table 3.2:** Math Test Scores for Low and High Education of Parents

	CAN		FRA		JPN	
	L	H	L	H	L	H
10%	365	396	338	376	396	437
50%	468	508	453	510	500	554
90%	575	613	566	611	599	650

This table shows the test scores in the math assignment at the 10th, 50th and 90th percentile. It is split into children with parents with a low education background (L) and with a high education background (H).

**Table 3.3:** Reading Test Scores for Low and High Education of Parents

	CAN		FRA		JPN	
	L	H	L	H	L	H
10%	354	386	320	358	366	406
50%	481	519	458	513	486	537
90%	597	632	588	628	590	633

This table shows the test scores in the reading assignment at the 10th, 50th and 90th percentile. It is split into children with parents with a low education background (L) and with a high education background (H).

France - two economically similar countries - is a prime example for the potential that could be revealed. Thirdly, the disparity in outcomes depending on the education of the parent is a call to action. While it is visible across all countries, it is prominent in varying degrees. Thus an ameliorated education policy could not only increase the overall performance, but as well decrease social inequality. The next chapters will look in closer detail at such a policy.



## CHAPTER 4

### EMPIRICAL ANALYSIS

#### 4.1 EFFECT OF SCHOOL STARTING AGE ON TEST SCORES

To show the correlation between school starting age and test scores across countries, we first estimate the following regression specification:

$$Score_{scwi} = \beta_0 + \beta_1 StartAge_c + \epsilon_{scwi} \quad (4.1)$$

Where

- $Score_{scwi}$ : test score of student  $i$  in country  $c$  on subject  $s$  (math or reading) in Wave  $w$
- $StartAge_c$ : mean school starting age in country  $c$  across waves

The results of this specification are summarized in columns (1) and (2) of Table 4.1. Without any controls, on average, a one-year increase in the country mean school starting age is associated with a 6.6 point decrease in math scores and a 9.5 point decrease in reading scores on the PISA test.

We then control for certain student characteristics and the results are summarized in columns (3) and (4) of Table 4.1. After including these controls, the coefficients on school starting age change drastically, but are still statistically significant. This indicates that the control variables play an important role and should be carefully considered in further analysis.

We do not include country fixed effects in the regression specifications. Since all students in a country have the same value for mean school starting age, if we included country fixed effects, any correlation between school starting age and test scores would be absorbed by the country fixed effects and we would not be able to obtain a coefficient estimate for the starting age variable.

**Table 4.1:** Correlation Between Country-Wave-Average School Starting Age and Individual Test Scores

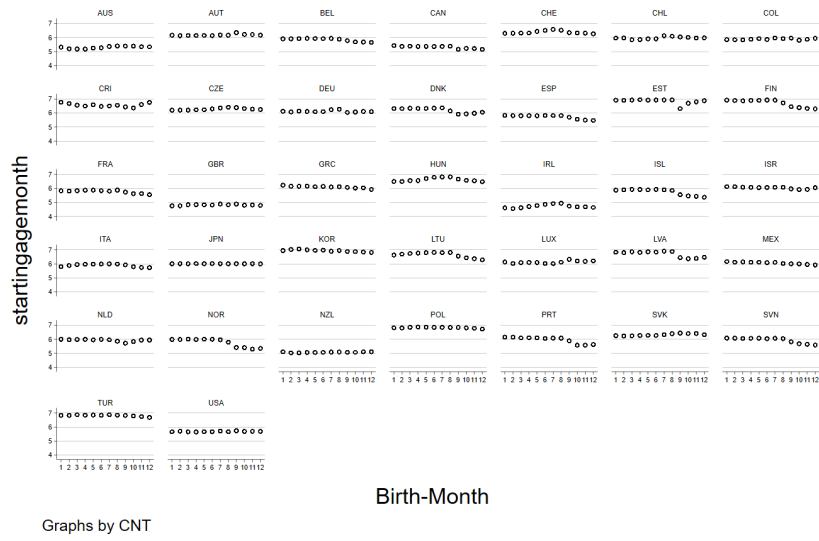
	(1)	(2)	(3)	(4)
	Math Score	Reading Score	Math Score	Reading Score
Starting Age	-6.624*** (0.108)	-9.492*** (0.119)	1.364*** (0.170)	-1.708*** (0.186)
Age			1.697** (0.584)	5.218*** (0.627)
Grade Compared to Modal Grade			28.564*** (0.329)	26.985*** (0.360)
Immigration Background			3.205*** (0.478)	6.092*** (0.531)
Socio-Economic Factors			73.932*** (0.548)	64.629*** (0.577)
Parent's Occupation			-0.696*** (0.016)	-0.489*** (0.017)
Parent's Education			-11.859*** (0.135)	-10.338*** (0.144)
Gender			15.140*** (0.330)	-19.075*** (0.354)
Siblings			-5.629*** (0.172)	-5.419*** (0.183)
_cons	526.404*** (0.651)	545.226*** (0.717)	641.792*** (9.550)	621.236*** (10.259)
<i>N</i>	785101	785101	213877	213877

Standard errors in parentheses

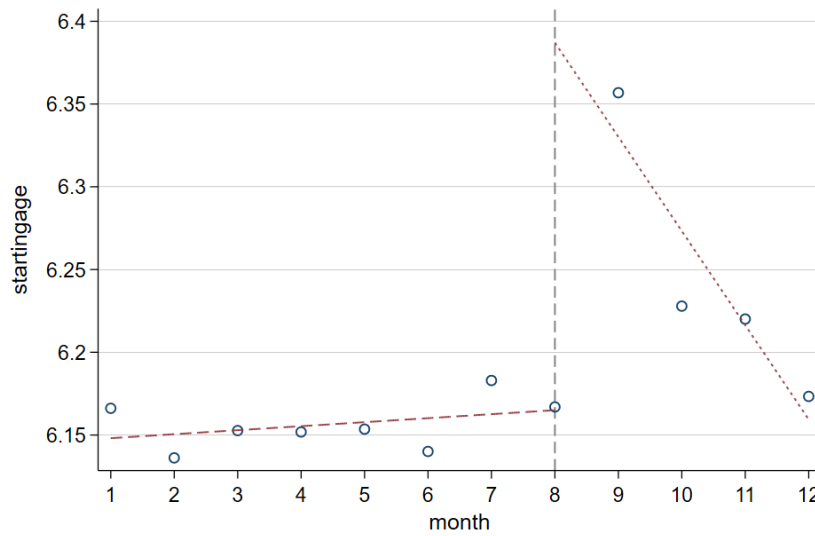
\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ 

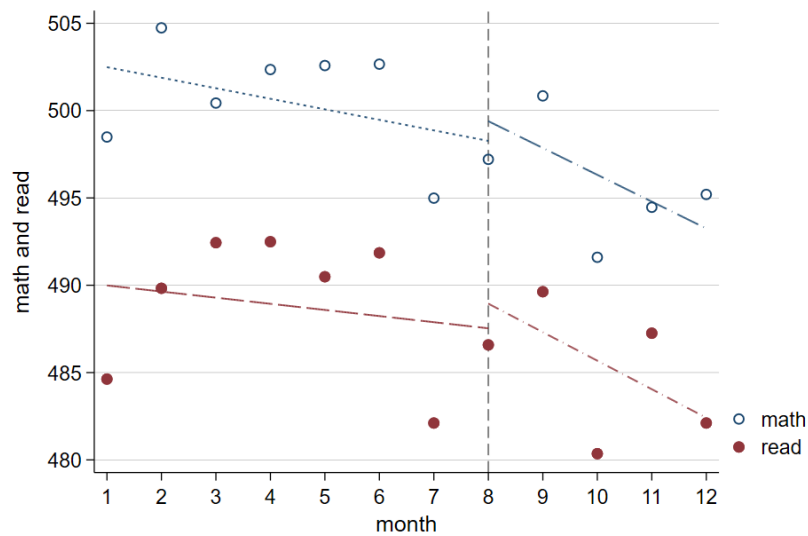
## 4.2 SCHOOL STARTING RULES AND RDD ESTIMATES

School starting age varies across countries, as shown in 4.1. This figure plots the average school starting age for each birth-month. An upward jump may thus indicate an entry age cutoff, as students born just after the cutoff can only start school in the following year.

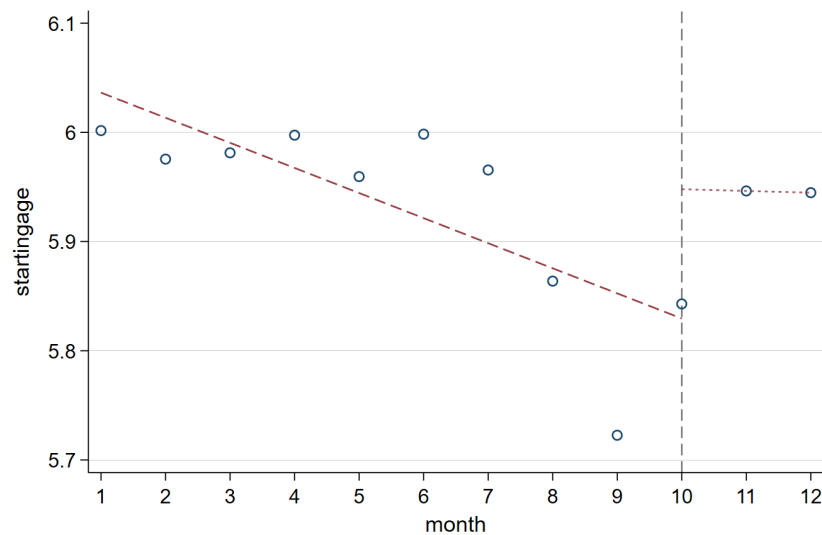
**Figure 4.1:** Visualization of Starting Rule per Country

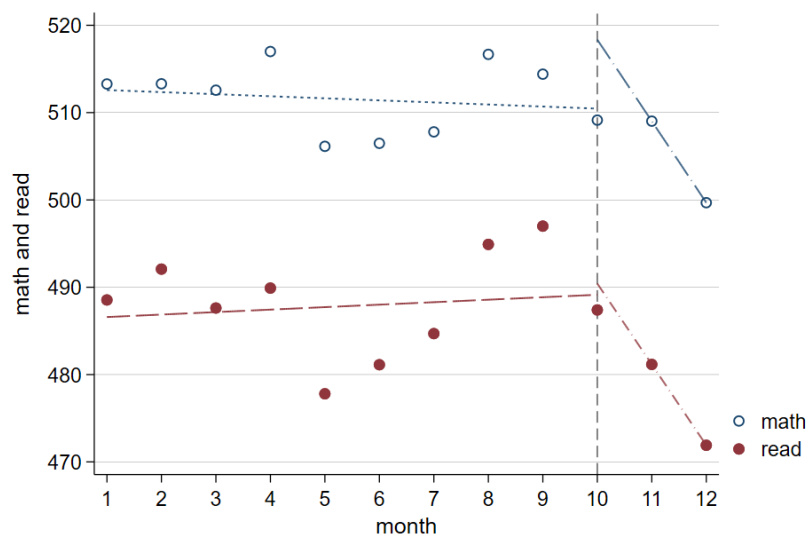
We have thus identified a possible birth month cutoff in August for Austria and an October cutoff for the Netherlands. As can be seen in Figure 4.3 and Figure 4.5, there appear to be visible upward jumps in test scores at the cutoff for both countries.

**Figure 4.2:** Visualization of Birth Month Cutoff for Austria

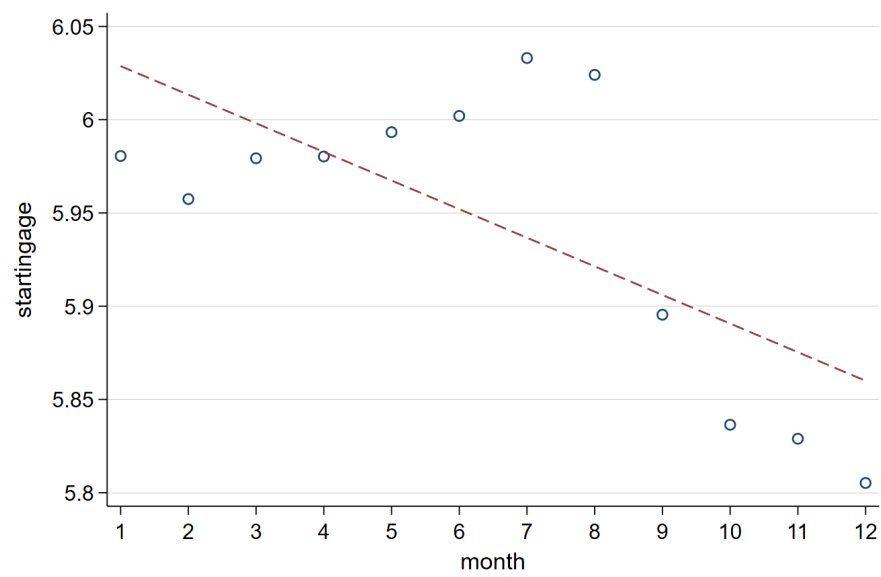
**Figure 4.3:** Visualization of Birth Month Cutoff and Test Scores for Austria

However, looking at the above-mentioned clear cut-off in the Netherlands, we can see in Figure 4.5 that despite the cut-off, there is not a remarkable difference in math in test-performance, but in reading a slight difference. Thus, it seems to be a strong correlation in some countries, while less prominent in others. And we can see slightly differing effect and effect size for reading or math.

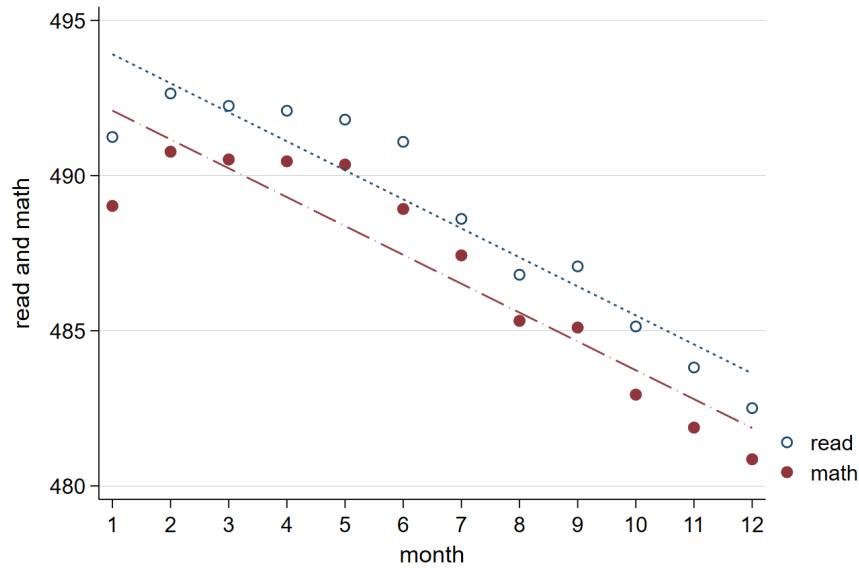
**Figure 4.4:** Netherlands: Starting Date Cut-off

**Figure 4.5:** Netherlands: Starting Date Cut-off

Pooling every observation we get the following graph, Figure 4.6 for the relationship between the starting and the birth-month

**Figure 4.6:** Starting Age Cut-off with Month

This leads us directly to the following Figure 4.7

**Figure 4.7:** Birth-month related to Test Performance

### 4.3 MECHANISMS, HETEROGENEITY AND ROBUSTNESS

There are many possible mechanisms through which the school starting age can affect test scores of teenage students. To exploit exogenous variation in starting age, we consider a regression discontinuity IV approach using Austrian data and a cutoff point corresponding to the month of August:

For Math

First-stage regressions

---

Number of obs = 756,262  
 F(3, 756258) = 1475.95  
 Prob > F = 0.0000  
 R-squared = 0.0060  
 Adj R-squared = 0.0060  
 Root MSE = 0.9766

---

startingage	Coefficient	Robus std. err.	t
month_centered	.0090706	.0005895	15.39

old#c.month_centered				
1		−.0371096	.0018762	−19.78
old		−.1512848	.0043572	−34.72
_cons		6.034834	.0029182	2067.98

---

Instrumental variables 2SLS regression

Number of obs = 756,262  
Wald chi2(3) = 997.89  
Prob > chi2 = 0.0000  
Root MSE = 90.191

---

	math		Coefficient	Robus std. err.	z
startingage			11.53599	2.666882	4.33
month_centered			−.6755506	.0449906	−15.02
old#c.month_centered					
1		−.3869214	.2239054	−1.73	
_cons		416.9023	15.90644	26.21	

---

Endogenous: startingage

Exogenous: month\_centered 1.old#c.month\_centered old

We obtain a positive coefficient estimate of 11.536

For reading:

First-stage regressions

---

Number of obs = 756,262  
F(3, 756258) = 1475.95  
Prob > F = 0.0000  
R-squared = 0.0060  
Adj R-squared = 0.0060  
Root MSE = 0.9766

---

startingage		Coefficient	Robus std. err.	t
month_centered		.0090706	.0005895	15.39
old#c.month_centered				
1		−.0371096	.0018762	−19.78

	old		-.1512848	.0043572	-34.72
	_cons		6.034834	.0029182	2067.98
<hr/>					
Instrumental variables 2SLS regression					
Number of obs	=		756,262		
Wald chi2(3)	=		878.43		
Prob > chi2	=		0.0000		
R-squared	=		.		
Root MSE	=		95.709		
<hr/>					
	read		Coefficient	Robus std. err.	z
	startingage		6.17074	2.833121	2.18
	month_centered		-.7175957	.0477535	-15.03
<hr/>					
old#c.month_centered					
	1		-.6146713	.2378078	-2.58
	_cons		450.5861	16.89804	26.66

Endogenous: startingage

Exogenous: month\_centered 1.old#c.month\_centered old

For the math score, we obtain a coefficient estimate of 11.53 and for the reading score we obtain a positive coefficient estimate of 6.17074. This indicates to us that the starting age has a positive effect on the test performance both in math tests and in reading tests. As one can assume that both coefficients correlate, it is a sign of internal validity that they both have the same sign.



## CHAPTER 5

### DISCUSSION

Based on the descriptive and empirical analysis we conducted above, here is some discussion about (1) our contribution; (2) policy suggestions; and (3) future research.

As for the first part, we have described the variation of student performance from the perspective of between countries of different levels of income, within typical countries in the middle income countries and inter-generational between parents and children. Moreover, we have collected the different policies for cutting-off date for school starting age in the majority of the OECD countries and measured the effect of school starting age on the school performance in different countries. Notably, from the potential mechanism, we compared children from different families background and captured that children whose parents attended university are less affected by the school starting age.

For policy suggestions, it shows in the mechanisms that the poor performance of the students born just before the cutting-off date have a higher tendency to retake a year alongside their study before 15 years old compared to other students. Thus, the settings of the school starting age should be reconsidered. To be more specific, the composition of the education system, including teaching qualities, school starting age, skill expectations should be in line with each other to provide students the most suitable study experience.

As for the future research, the long-term effect is always important to figure out. Also, more details about the education system should be looked into, for instance, the textbook, years for each stage of study journey, family attendance for students of different stages. Furthermore, the socio-economic norms, which are underrated in the previous study, should be measured in the upcoming researches.

## BIBLIOGRAPHY

- Cook, P. J. and Kang, S. (2020). Girls to the front: How redshirting and test-score gaps are affected by a change in the school-entry cut date. *Economics of Education Review*, 76:101968.
- Deming, D. J. (2011). Better schools, less crime? *The Quarterly Journal of Economics*, 126(4):2063–2115.
- Fuchs, T. and Wößmann, L. (2008). *What accounts for international differences in student performance? A re-examination using PISA data.*
- Leuven, E., Lindahl, M., Oosterbeek, H., and Webbink, D. (2010). Expanding schooling opportunities for 4-year-olds. *Economics of Education Review*, 29(3):319–328.
- Oosterbeek, H., ter Meulen, S., and van Der Klaauw, B. (2021). Long-term effects of school-starting-age rules. *Economics of Education Review*, 84:102144.
- Schneeweis, N. and Zweimüller, M. (2014). Early tracking and the misfortune of being young. *The Scandinavian Journal of Economics*, 116(2):394–428.