Alma Mater Studiorum – Università di Bologna

DOTTORATO DI RICERCA IN

ECONOMICS

Ciclo 32

Settore Concorsuale: 13/A1

Settore Scientifico Disciplinare: SECS-P/01

ESSAYS IN ECONOMICS OF EDUCATION

Presentata da: **GIORGIO MONTI**

Coordinatore Dottorato **Supervisore**

PROF.SSA MARIA BIGONI **PROF. PAOLO VANIN**

Esame finale anno 2020

Chapter 1:

The Italian Regional Divide in Education: the Effect of Early Enrollment to Primary School

Giorgio Monti

University of Bologna

Abstract

Italian regional divide is among the widest in western democracies. Northern regions perform better in almost every economic outcomes: GDP per capita, employment rate, health. In this study, I will concentrate on another significant gap between North and South Italy: educational achievement and cognitive skill formation. Students from the North perform systematically better than those from the South, and the gap increases with age. In this paper I will study this difference from an unexplored point of view: difference in school starting age. Italian enrollment system allows parents to enroll children one year earlier to primary school if the pupil was born between the 1st of January and the 30th of April. However, the percentage of parents who enroll their child earlier is much lower in the North than in the South. This generates a significant difference in the average age of students: the average student in the North is 1.5 months older than the average student in the same grade in the South. Given that school starting age has been documented to affect the development of both cognitive and non-cognitive skills, I try to estimate how much of the gap in test scores between Northern and Southern students is due to this heterogeneity in age. Using a large dataset from Standardized test scores (INVALSI) at two different stages of primary school (II and V grade) I estimate that the 60% and 100% of the difference in average test scores in Italian and Mathematics in II grade between the two macro-regions is due to difference in age. The same percentages decrease to 20% in V grade. Moreover, the actual enrollment rules were introduced in 2003, and increased the difference in students' age between the regions. Using Invalsi data from VIII graders I also estimate how much the gap in scores increased because of the reform.

Early enrollment is not exogenous: parents choose when to enroll the child to primary school basing on their beliefs on her skills, on their background, and on social norms. As a results, there is a strong selection in early enrollment which makes the estimation of the effect of this practice more challenging. Whereas to understand the determinants of early enrollment is not the aim of this work, I provide some robustness checks to control for selection. Assuming and testing that scores are linear in age for pupils who are not eligible for early enrollment I was able to check whether being enrolled one year earlier to primary school, has a different effect than the linear effect of age estimated for not eligible students. I found that, even if early starters would have performed much better than regulars, if enrolled one year later, they do not recover better than the average student.

1 Introduction

Enrollment to primary school is based on the date of birth. In most cases, students born in the same calendar year are enrolled to the first grade in the same moment. For example, in England, students born between September 1st and August 31st of the following year start together, whereas in Spain the reference dates are the 1st of January and the 31st of December. This system is aimed to generate the minimum possible differences in age among students in the same class. Differences in outcomes, both cognitive and non-cognitive skills, between students in the same grade, but with different age, is called Relative Age Effect.

However, many primary school systems allow parents to decide about the timing of the enrollment. In particular, in some countries there is the possibility for enrolling the child one year earlier. This is the case of Italy, where children born between January and April may be enrolled at the age of 5 or at the age of 6, whereas all the other children must be enrolled the year they turn 6. I will discuss more in detail the system in section 3 of this paper.

As noticed by several articles in the literature, it is impossible to disentangle school starting age effect from age at the test effect in empirical application like the one in this work. Moreover, in the Italian setting, another issue arises: the selection in age. In fact, as already mentioned, parents of children born between January and April can decide when to enroll the child to primary school. This generates a strong endogeneity in school starting age. Parents will indeed enroll their child earlier because of their beliefs about her ability, for some social interactions effect or for their expectation about the child's future. This amplifies the problem for identification since the difference in score depends on both difference in age and difference in ability and parental background.

In this work I will focus on the results in standardized test score in Italian and Mathematics of students from different grades. Italy presents a significant heterogeneity in terms of several economic and social outputs, and this is also true for results at standardized tests in both Mathematics and Literacy, with students from the North performing constantly better than their peers from the South in both National and International Standardized Test (INVALSI, PISA, TIMSS and PIRLS).

In this paper I will study another unexplored difference between North and South Italy: the age of enrollment at primary school. In fact, even if the Italian education system is almost completely controlled by the central government, and does not present differences in the enrollment rules across the territory, people from different regions follow these rules in different ways. The flexibility left to parents about the timing of enrollment results indeed in a significant difference in the average age of enrollment across macro-area of the country, with parents in the North enrolling their children to primary school older than in the South.

Given this difference in age of enrollment, and therefore in age at the test, between geographic macro-areas, one of the aims of this work is to measure how much of the gap in scores is due to difference in average age of students.

The heterogeneity in early enrollment across regions cannot be considered exogenous. However, to understand the reasons why parents from the North have different preferences than those in the South is out of the aim of this work. Moreover, since schools have some room in deciding the rules of enrollment, and which children have priority over others, it was important to understand whether the heterogeneity lies in parents' preferences or in schools' rules. From interviews made to school administrators in Bologna (North Italy) and in Palermo (South Italy) it seems that most of heterogeneity is in the demand, since in Bologna they declared that almost no parents ask for early enrollment, whereas the opposite is true in Palermo. In addition, administrators in Palermo declared that it is very difficult to refuse the early enrollment mainly for two reasons: parents may appeal to administrative justice, and secondly if they refused all requests, they will have much fewer enrollments with severe consequences on the formation on classes.

Another goal of this paper is to disentangle the effect of the most recent reform of the Primary School Enrollment System in Italy (Moratti Reform, 2003). This reform made it easier to enroll the child earlier if she was born between January and April. Assuming that the timing of the reform was exogenous, I can measure the effect of early enrollment on test scores. I will discuss the reform more in detail in section 3.

This paper proceeds as follows: Section 2 presents a summary of the related literature, Section 3 discuss the Italian enrollment system to primary school and the Moratti Reform, section 4 provides details on the data used in the analysis, section 5 presents the results and section 6 concludes.

2 Related Literature

The North-South divide in Italy has been widely studied from several perspectives. In the country it is called the "Questione Meridionale" (the Southern Question) and has been in the political debate for decades. The gap in education has been the object of several studies, mainly Italian, and an extensive review has been made by Asso et al (2015). Moreover, the Italian Ministry of Education publishes every year a report on the status of the Italian education system, showing the trend in differences among macro-areas in the countries, evidencing how students from the South perform worse in almost every output analyzed, from international test scores (e.g. PISA, TIMSS and PIRLS) to Invalsi scores (Invalsi Report 2012-2017) . However, these studies are mainly descriptive, showing correlations and aggregate data. None of this report studies empirically the effect of age, nor investigates the effect of the differences in early enrollment across the Italian territory.

The effect of age on education has been instead studied for years, by both economists and educational scientists.

School starting age (SSA) effects have been investigated from different perspectives and in different countries. The main problem in the quantitative analysis of such effects is that it is impossible to disentangle the effect of school starting age from the effect of the age of the child the day of the test. As stressed by Black et al. (2011) , the literature on school starting age can be divided into two main categories: the first one is more policy oriented, trying to answer the question on what is the optimal age for starting the primary school, the second one instead is focused on decision process of the parents. My work has the aim to understand what are the consequences of parental decision on when to enroll children to school, given the flexibility allowed by the Italian system. The decision process is out of the purpose of this work, even if I will take into account the selection in age at entrance.

Several articles have been written on the effects of the SSA on different outcomes, from educational attainment to non-cognitive skills. Black et al. (2011) used Norwegian data and was able to separate the effect of SSA from test age effects by using IQ scores taken by students at about 18 years old outside school. They argue that the major effect is given by the age at the test, but also found that children who started school older are less likely to have poor mental health at 18 and teenage pregnancy. Fredriksson and Ockert (2013) used a wide dataset from Sweden and used the school entry cut-off as instrument to find that students who started school older have higher educational attainment and that postponing tracking until age of 16 reduces this effect. In their seminal work, Bedard and Duhey (2006) showed, using data from OECD countries, how younger children in a given cohort score significantly worse than their older peers and are less likely to attend the university in US and Canada, arguing that the effects of the school starting age are very persistent. On the other hand, Elder and Lubotsky (2009) argue that the effect of SSA on academic performance declines as the children grow up. Muhlenweg et al. (2012) focused instead on effects on the development of non-cognitive skills, and, using data from Germany, they found that children who begin primary school older are less often hyperactive and more adaptable to change. Cornelissen and Dustmann (2019) studied the effect of receiving additional schooling before age five on both cognitive and non-cognitive abilities, exploiting variation of age at school entry in England. They found that the effect on cognitive ability disappears by age 11, but that non-cognitive ability is still affected at later stage. Parents who enroll their children earlier are in fact reducing the exposition of the pupil to pre-school programs, which have important effects on skill development, as stressed also by Cunha et. al (2006), Cunha and Heckman (2007), and Heckman (2008). The only recent study on the Italian case has been made by Ponzo and Scoppa (2014) , who used PIRLS, TIMSS and PISA data on Italian students to see how the SSA affects results: students enrolled earlier perform better at tests and are more likely to choose academic high schools rather than vocational schools. Their analysis is focused on a smaller dataset than the one I will use, and used the expected age as instrumental variable for actual age of the pupil, in order to quantify the effect of SSA. They used data from cohorts who started primary school with the old system, when there was small flexibility given to parents on the time of enrollment. Finally, Fenoll et al. (2018) , studied the selection in early enrollment among Italian students born between January and April, showing how early entrants would have scored much better than regular students of the same age if they were enrolled one year later. I will partly use their methodology, but to look into regional differences and to do robustness checks on the main empirical strategy.

3 The Italian Enrollment System

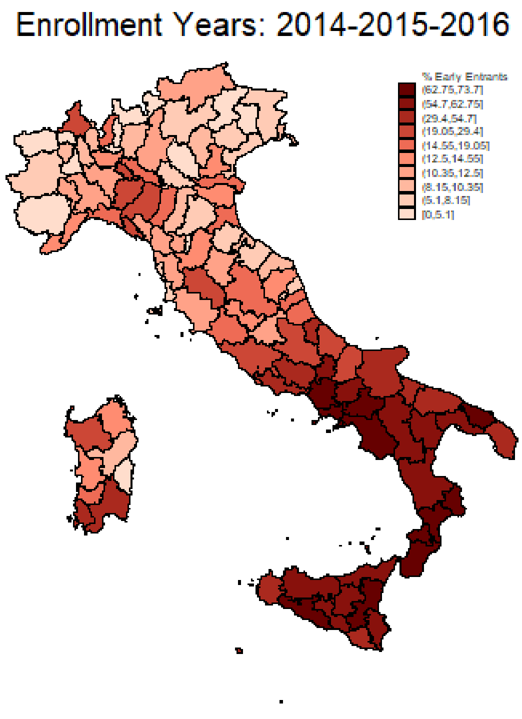
Italian children start the I grade of primary school in September of the year when they turn 6. Only children born from January to April can be enrolled one year before if their parents ask so. The possibility of early enrollment was introduced by the “Moratti reform”, named after the minister of education who signed it in 2003. Before this reform the cut-off date was the 31st of December so that only children who turned 6 in the same year of the beginning of classes could start primary school. The change in the school entry policy was applied gradually: in the first two year after the approval (s.ys. 2003/2004 and 2004/2005), the cut-off was extended to the 28th of February, for the s.y. 2005/2006 it was the 31st of March, and from the s.y. 2006/2007 onwards it has been the 30th of April. In other words, before 2003, if the school started in September of year t, it was mandatory for parents to enroll their child to school if she turned 6 in the same year t, and cannot enroll them if he turned 6 in year t+1. It remains the prohibition, except for healthy issue or language comprehension of the child due to his origins, of the so called "red-shirting", the late enrollment that is becoming popular in other education systems, especially in the United States and Australia. The reform represented an exogenous variation in the enrollment system. However, the possibility of moving up the enrollment of children existed even before the reform, even if it was more costly. In fact, before 2003, and this is still true for children born after the 30th of April, parents can ask to enroll their children directly to the second grade of primary school even if they turn 6 in the same year, instead of 7 as regular students who completed the first grade. In order to do so, children have to pass an exam in September, just before the school year starts. In practice, this is slightly different from early enrollment since it means a "skip" of the first grade, and it is conditional on a test. The reform hence made it easier for children born from January to April to be among the youngest in the class. The writer of this reform justified this choice saying that "parents should have more flexibility in choosing when to enroll their child to primary school". The problem seems to be that no teachers' evaluation is mandatory, and all depends on parents' beliefs about their children readiness and home-made cost-benefit analysis.

Figure 1 shows the heterogeneity of the percentage of early entrants across Italian territory. Darker provinces have a higher percentage of students born between January and April who are early entrants, lighter ones have it lower. The heterogeneity is very strong and follows a clear pattern: provinces in the last decile are all in South Italy and have from 63% to 74% of early entrants, whereas those in the first decile are all in the Center-North and have only 0.5% to 1%.

4 The Invalsi test and Dataset

The Invalsi test is a written standardized exam that every pupil has to do in her II, V, VIII and X grade. It was introduced in the school year 2007/2008 and is divided in two parts, one testing the ability in mathematics while the other the ability in reading and grammar. In the main empirical

Figure 1



analysis, I will use data from the II and V grade from 2012 to 2017 school years, which are likely to be the cleanest. In fact, until the V grade (the primary school in Italy) it is almost impossible for students to fail a year. Since Invalsi data does not say if a student ever repeated a year, data from tests taken in the VIII and in the X grade is less reliable. Moreover, I will also use scores of pupils from a selected sample of classes where external monitors were randomly assigned. Score manipulation is indeed a problem, especially in the South (Bertoni et al., 2013 ; Angrist et al. 2017) and to limit it, the ministry of education selects each year a random sample of class where to send external monitors. In addition, the Invalsi dataset has also a variable for an index of score manipulation, measured by a statistical model that looks for abnormal high average scores, low within-class variability, and implausible missing data patterns. However, cheating seems not to be related to the age of the students and then not to bias results.

Invalsi Data also provide information about family background (index for socio-economic status, parents education and employment, citizenship), gender and date of birth. Actually, only data from a.ys. 2016 and 2017 provide information on the exact date of birth, whereas data from other years only provide the month and the year. I will do an additional analysis using only data with the exact date of birth.

The Moratti Reform, was firstly implemented for students enrolled in the I grade in the academic year 2003/2004 and that were born between the 1st of January and the 28th of February. Due to data availability, I can only study the effect of the last stage of the reform, when the cut-off was moved from the 31st of March to the 30th of April. Hence, I will use data on the tests taken by students in the VIII grade from 2012 to 2018. Data from 2012 and 2013 will be the "pre-reform" data since these students were enrolled to primary school in the s.ys. 2004/2005 and 2005/2006, when the law did not allow to enroll April born children at the age of 5. Data from 2013 onward instead, are considered as "post-reform", when the possibility to be enrolled at 5 years of age was extended to students born in April.

5 Descriptive Statistics

Table 1 reports summary statistics for the whole sample and for the subsample of monitored classes for both II and V grade. The first row shows that the scores decrease dramatically when looking at data from monitored classes. This is an evidence of how severe is the issue of score manipulation, especially in the South. Moreover, we can see that cheating seems to be a bigger issue in II grade than in V. Looking at differences between monitored and not monitored class we can see that it is larger in II grade than in V grade and more in the South than in the North. Table 1 also reports the difference in several outputs among Italian macro-areas. Mothers without a job are more than the 46% in the South and 25% in the North, but also the percentage of mothers with a diploma is higher in the North, and the same is true for the percentage of children who attended nursery schools, and for the ESCS, an index proxying the Socio-Economic Status of the family (available only for V graders). The statistics for background variables do not change significantly when moving to the subsample of monitored classes, confirming the goodness of the randomization made by the INVALSI

5.1 Check for Birth Seasonality

In the whole empirical strategy I use in this work, I always assume that the month of birth is exogenous with respect to other variables that may affect educational outcomes. Bound, Jaeger and Baker (1995) found indeed for the United States that quarter of birth is correlated with other background variables

Table 1. Summary Statistics

Panel A: II Grade								
	Whole Sample				Monitored Class			
Variable:	Italy	North	Center	South	Italy	North	Center	South
Std. Score Ita	0.33	0.22	0.36	0.47	0.00	0.03	0.08	-0.06
Mother Dip	0.71	0.70	0.80	0.66	0.71	0.70	0.79	0.68
Father Dip	0.64	0.62	0.73	0.61	0.64	0.62	0.71	0.62
Mother Grad	0.16	0.13	0.23	0.17	0.15	0.12	0.21	0.16
Father Grad	0.17	0.14	0.25	0.17	0.16	0.13	0.22	0.17
Mother Unemp.	0.32	0.25	0.24	0.46	0.32	0.24	0.24	0.44
Father Unemp.	0.05	0.03	0.04	0.08	0.05	0.04	0.04	0.06
Attended KG	0.90	0.92	0.92	0.87	0.91	0.93	0.93	0.87
Attended Nursery	0.37	0.39	0.45	0.29	0.37	0.39	0.46	0.30
Class Size	20.5	20.8	20.9	19.8	20.8	20.8	21.2	20.4
N	2812686	1313621	530643	968422	150451	59336	29900	61215
Panel B: V Grade								
	Whole Sample				Monitored Class			
Variable:	Italy	North	Center	South	Italy	North	Center	South
Std. Score Ita	0.21	0.20	0.26	0.20	0.01	0.08	0.10	-0.10
Mother Dip	0.67	0.66	0.77	0.62	0.68	0.67	0.76	0.64
Father Dip	0.60	0.59	0.70	0.57	0.61	0.60	0.69	0.59
Mother Grad	0.14	0.12	0.20	0.14	0.13	0.11	0.19	0.14
Father Grad	0.15	0.13	0.21	0.15	0.15	0.12	0.20	0.15
Mother Unemp.	0.34	0.26	0.26	0.49	0.34	0.24	0.25	0.46
Father Unemp.	0.05	0.03	0.03	0.08	0.05	0.03	0.03	0.07
ESCS	0.06	0.15	0.20	-0.13	0.08	0.18	0.19	-0.06
Attended KG	0.89	0.92	0.90	0.84	0.89	0.92	0.92	0.84
Attended Nursery	0.32	0.34	0.40	0.27	0.33	0.35	0.41	0.28
Class Size	20.4	20.6	20.9	19.9	20.8	20.8	21.2	20.8
N	2751867	1245023	506793	1000051	148846	57546	29166	62134

and argued that the date of birth may be an inappropriate instrument in many frameworks. They review the evidence that quarter of birth is correlated with school attendance rate (Carrol 1992), likelihood that a student will be assessed as having behavioral difficulties (Mortimore er al, 1988) and also with mental and physical health (e.g. O'Callaghan et al. 1991, Sham et al. 1992, Gillberg, 1990). To check if Italian students show the same correlation between month of birth and other variables, I check the distribution of many background variables across months of birth. Invalsi provides many background variables for students in V grade. For other grades, data are less comprehensive.

Tables 2, 3 and 4 show the results for regressions of the dummy for Eligibility for early enrollment (to be born in the first quarter of the year) on several background variables. Since I will use the variation in early enrollment between north and south, I run these regressions also for the two subsamples of

North and South Italy.

Results reported in the tables seem to assure that birth seasonality is not a big issue in this framework. Even if some coefficients many coefficients are statistically significant from zero, and differ across macroareas, their size is negligible, being always less than 0.01. Since all the covariates are dummies (except for the socioeconomic status index, ESCS), this means that differences between eligibles and not eligibles are never bigger than 1%. The statistical significance, in this case, is probably due to the very large sample size (more than 3 million observations for the whole sample and more than 1 million in the subsample).

Table 2. Check for Birth Seasonality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Mother Grad.	Father Grad.	Mother HS	Father HS	Mother Unemp.	Father Unemp.	ESCS
Eligible	0.000	0.001	-0.001**	0.001	-0.002***	-0.001**	0.009***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Constant	0.109***	0.096***	0.648***	0.599***	0.339***	0.050***	0.146***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Observations	3,235,536	3,235,536	3,235,536	3,235,536	3,235,536	3,235,536	3,147,187

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Check for Birth Seasonality - South Italy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Mother Grad.	Father Grad.	Mother HS	Father HS	Mother Unemp.	Father Unemp.	ESCS
Eligible	0.004***	0.003***	0.004***	0.004***	-0.003***	-0.001	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	0.088***	0.078***	0.608***	0.572***	0.481***	0.075***	-0.057***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	1,169,900	1,169,900	1,169,900	1,169,900	1,169,900	1,169,900	1,120,321

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2 Descriptive statistics for Early Entrants

Figure 2 shows the percentage of Early Entrants for each month from January to April and for each Italian Macro-area. This ratio is clearly decreasing when moving from January to April, suggesting that the month of birth is a determinant variable in the choice. This is understandable: parents of

Table 4. Check for Birth Seasonality - North Italy

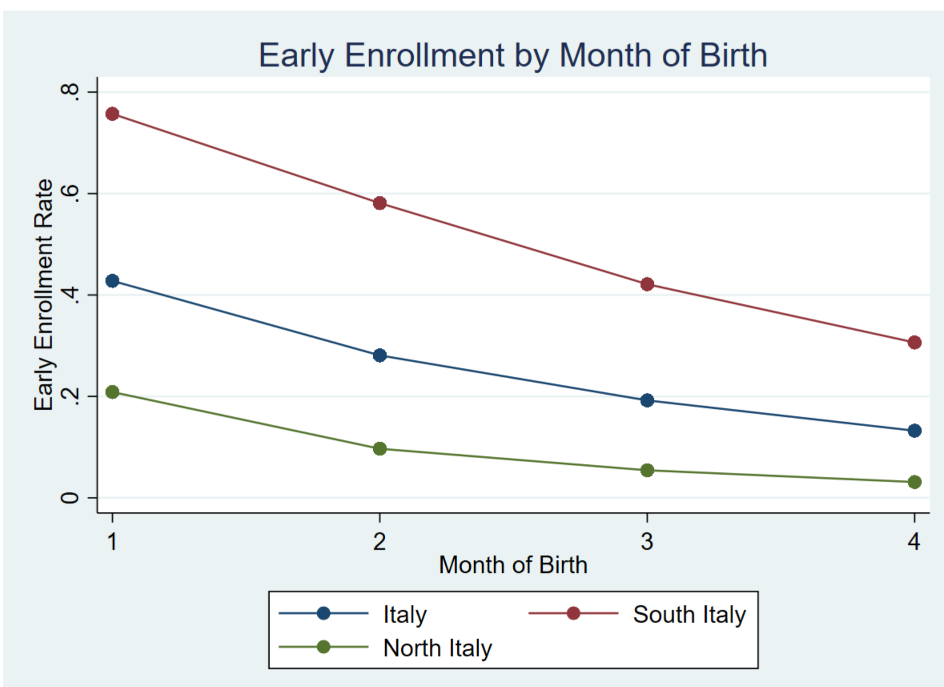
VARIABLES	(1) Mother Grad.	(2) Father Grad.	(3) Mother HS	(4) Father HS	(5) Mother Unemp.	(6) Father Unemp.	(7) ESCS
Eligible	-0.003***	-0.001*	-0.005***	-0.001	-0.002**	-0.000	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)
Constant	0.122***	0.109***	0.637***	0.583***	0.258***	0.039***	0.251***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)
Observations	1,466,267	1,466,267	1,466,267	1,466,267	1,466,267	1,466,267	1,443,218

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

children born in April have more concerns than parents of those born in January in enrolling the child earlier given that they are 3 months younger and are more likely to be perceived as not ready for primary school.

As already mentioned, the fraction of students who were enrolled earlier is much higher in the South: almost the 80% of born students born in January were enrolled earlier, against the 21% in the North. The percentage for born in April goes down to 30% in the South and to 3.5% in the North.

Figure 2



It remains important to see the differences between regular students and early entrants in terms of socio-economic background. Table 5 shows summary statistics for the two groups, dividing also the sample in North and South Italy. Data come from the V grade, when INVALSI administers a survey for students along with the test.

Table 5. Summary Statistics by enrollment status (only pupils born before 30/04)

	Italy			North			South		
	Early	Regular	Diff.	Early	Regular	Diff.	Early	Regular	Diff.
Female	0.54	0.47	0.07***	0.58	0.48	0.10***	0.53	0.45	0.08***
Mother Emp.	0.54	0.63	-0.09***	0.66	0.71	-0.04***	0.47	0.38	0.10***
Father Emp.	0.89	0.91	-0.02***	0.92	0.93	-0.01***	0.88	0.86	0.02***
Mother HS	0.75	0.69	0.06***	0.76	0.69	0.07***	0.73	0.61	0.12***
Father HS	0.70	0.61	0.09***	0.61	0.71	0.10***	0.68	0.55	0.13***
Mother Grad.	0.20	0.15	0.05***	0.26	0.17	0.09***	0.18	0.09	0.08***
Father Grad.	0.16	0.11	0.05***	0.21	0.13	0.09***	0.14	0.07	0.07***
Escs	0.15	0.04	0.11***	0.35	0.14	0.21***	0.02	-0.27	0.29***
Attended Nursery Sc.	0.32	0.33	-0.01***	0.38	0.35	0.04***	0.28	0.25	0.03***
Attended KG	0.85	0.90	-0.04***	0.90	0.92	-0.02***	0.83	0.85	-0.02***
Immigrant	0.07	0.11	-0.04***	0.18	0.13	0.05***	0.04	0.06	-0.02***

Given that the child is born before the 30th of April, the decision of enrolling her one year earlier to primary school is almost completely up to the parents. As reported by table 2 and studied by Fenoll et al. (2018), there is a strong selection in the choice. This is consistent with the hypothesis that the decision depends on how they perceive the ability and the readiness of the child. The table shows indeed significant differences in all the variables considered. Firstly, we can notice that early enrollment is more common among females than among males. This is consistent with the fact that girls mature earlier than boys (Bierman et al., 2009; Son et al., 2013). Moreover, early entrants have on average more educated parents, and a higher index of socioeconomic status (ESCS). In the end, the last row reports that the percentage of immigrants among early enrollers is higher than that among regular in the North, and the opposite is true in the South. The percentage of immigrant students in the North is much higher than in the South, and if immigrants were less inclined to early enrollment, that could have biased the results, since immigrants students perform lower on average. The finding that immigrants are more likely to be early enrolled in the North is surprising, but reassures that estimates will not be amplified by the North-South heterogeneity in the percentage of immigrant students.

To have a better sense of the determinants of early enrollment, I run a multivariate OLS regression of a dummy for early entrants on several background variables. I will use only students eligible for early enrollment (born in the first quarter of the year), and I will present also results for subsamples of South and North Italian students. Table 6 reports the results of these regressions.

Table 6. OLS Regressions of Early Enrollment on Background Characteristics)

VARIABLES	(1) Italy	(2) South Italy	(3) North Italy
Mother Grad.	0.101***	0.135***	0.078***
	(0.002)	(0.004)	(0.002)
Father Grad.	0.055***	0.062***	0.049***
	(0.002)	(0.003)	(0.002)
Mother HS	0.028***	0.047***	0.015***
	(0.001)	(0.002)	(0.001)
Father HS	0.025***	0.029***	0.020***
	(0.001)	(0.002)	(0.001)
ESCS	0.007***	0.028***	-0.008***
	(0.001)	(0.001)	(0.001)
Mother Unemp.	-0.006***	-0.023***	0.017***
	(0.001)	(0.002)	(0.001)
Father Unemp.	-0.006***	-0.005	0.023***
	(0.002)	(0.003)	(0.003)
Feb.	-0.156***	-0.180***	-0.121***
	(0.001)	(0.002)	(0.002)
March	-0.276***	-0.387***	-0.175***
	(0.002)	(0.003)	(0.002)
April	-0.337***	-0.503***	-0.199***
	(0.002)	(0.003)	(0.002)
Constant	0.429***	0.733***	0.204***
	(0.002)	(0.003)	(0.002)
Observations	996,327	350,463	460,141
R-squared	0.127	0.200	0.075
Number of Schools	17,073	6,433	7,511

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results confirm what shown in table 5. All coefficients have the expected signs and are statistically significant. Looking at North-South heterogeneity it is possible to notice that coefficients for parents' education are much larger in the South than in the North, especially looking at mother's education. However, coefficients for parents' employment status have different signs: in the South unemployed mothers are less likely to enroll earlier their children, and the opposite is true in the North. The same is true for unemployed fathers, but the difference is less large. The reasons of this difference is not analyzed in this work, however, it should not drive our results, since parents unemployment is associated with lower scores at standardized test.

Given this strong selection and the consequent differences between regulars and early entrants, to identify the effect of moving the enrollment of one year is a challenging task. In the next sections, I will propose a methodology to quantify how much of the gap in scores between North and South is due to the difference in average age, and some robustness checks to validate the results.

6 North vs South Italy Analysis

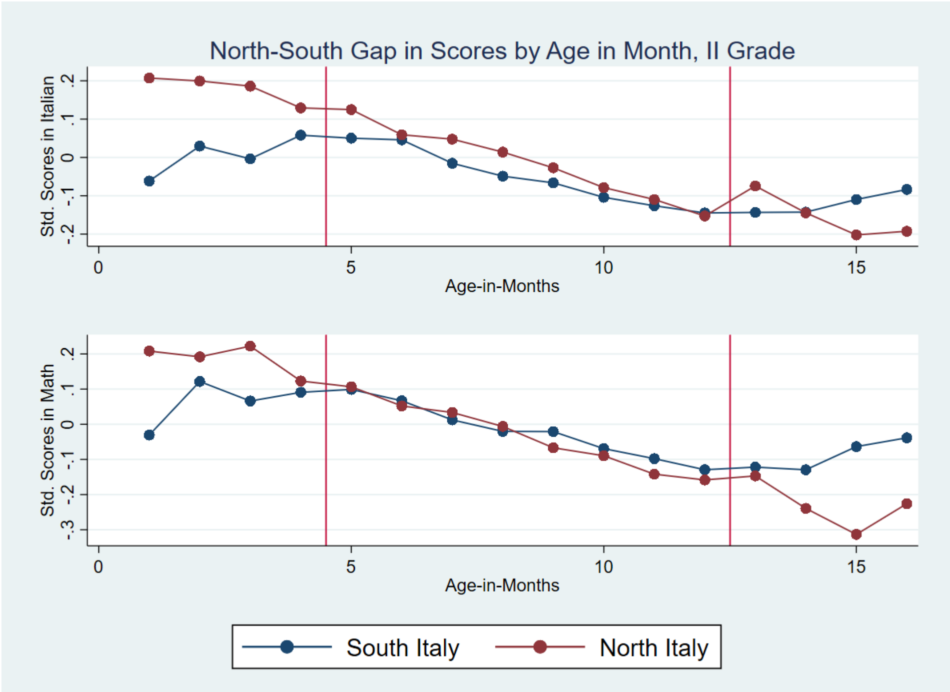
Descriptive statistics presented in the previous sections show both the gap in scores and the gap in the number of early entrants between North and South Italy. Moreover, they evidence how early entrants come, on average, from families with a higher socio-economic background. As noticed in the section about the literature, several studies have shown the effect of age on scores, and Fenoll and coauthors show how this effect is linear when there is no choice about the timing of enrollment, with younger students performing worse. Given the selection in the early entrance, would this effect be lower for early starters? First of all we can look at Figure 3 and Figure 4.

The graphs are obtained by pooling together data from all the school years available. In appendix A graphs for each year are presented. The graphs in the top panel shows the average score for each month in South and North Italy. The variable on the horizontal axis represents the age-in-months, with 1 being students born in January who are regularly enrolled and 13 students born in January who are early starters. The area between the two vertical red lines includes the months of birth for which parents cannot choose about the enrollment. It is evident that selection is in place: for those months of birth not eligible for early enrollment, the relation between age and scores looks linear and negative. On the other hand, the graph shows how this trend change when looking at born between January and April. The graph on the lower panel instead pools together regular and early entrants, showing the scores on the month of birth, independently of the year of birth. Hence, those on the right of the vertical red line are born in the same year, whereas those on the left may be either regulars or early enrollers.

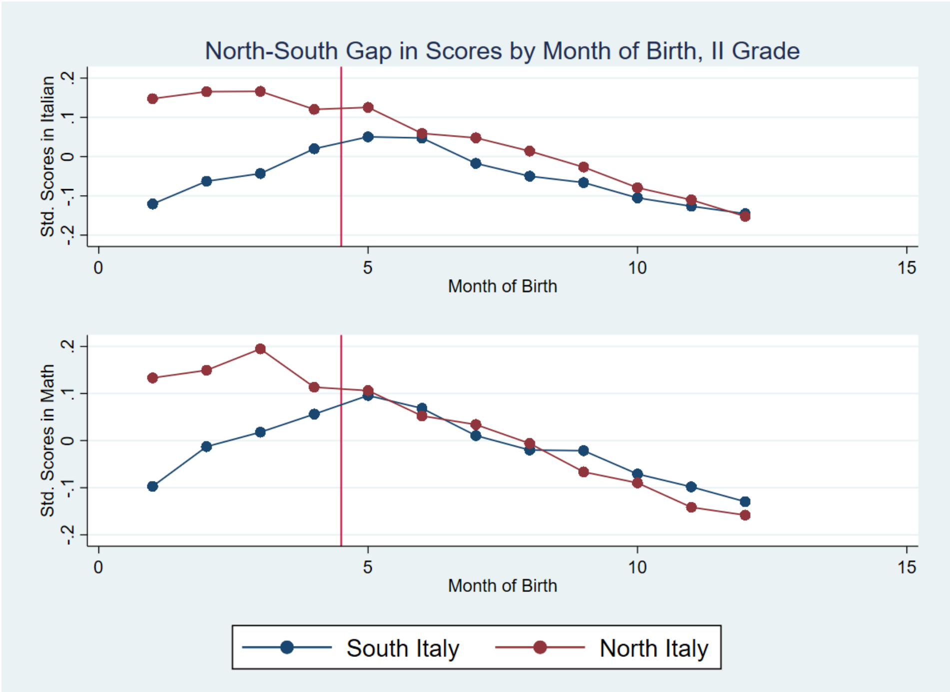
The main message coming from these graphs is that the North-South gap in scores increases dramatically when looking at students born between January and April. Moreover, in the second grade, there is almost no gap in scores between Northern and Southern students born between May and December. The main hypothesis I want to test is that this is due to the difference in age, being the rate of early entrants much higher in the South.

To measure how much of the difference in scores is due to the difference in age, I used a difference-

Figure 3

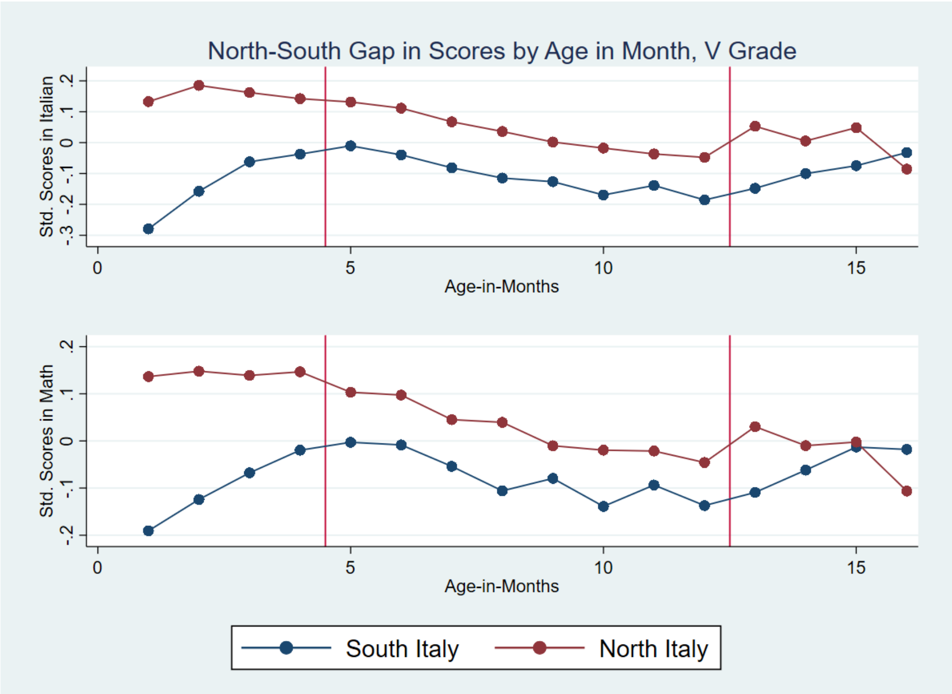


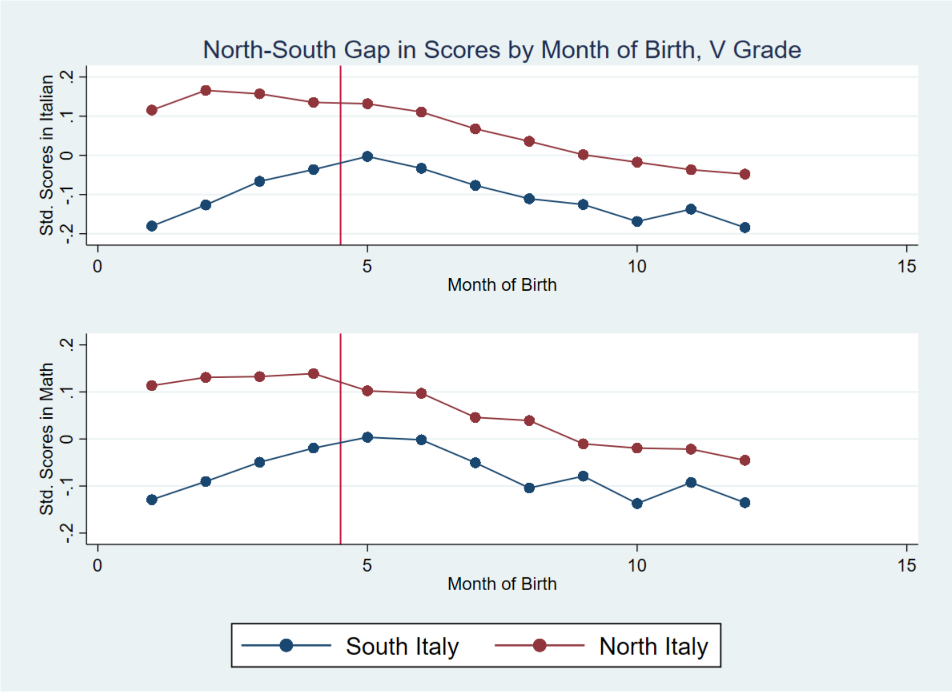
North-South Gap in Scores by Age in Month, II Grade
Std. Scores in Italian
-.2
-.1
0
.1
.2
0
5
10
15
Age-in-Months
Std. Scores in Math
-.3
-.2
-.1
0
.1
.2
0
5
10
15
Age-in-Months
South Italy
North Italy



North-South Gap in Scores by Month of Birth, II Grade
Std. Scores in Italian
-.2
-.1
0
.1
.2
0
5
10
15
Month of Birth
Std. Scores in Math
-.2
-.1
0
.1
.2
0
5
10
15
Month of Birth
South Italy
North Italy

Figure 4


North-South Gap in Scores by Age in Month, V Grade
Std. Scores in Italian
-.3 -.2 -.1 0 .1 .2
0 5 10 15
Age-in-Months
Std. Scores in Math
-.2 -.1 0 .1 .2
0 5 10 15
Age-in-Months
South Italy
North Italy


North-South Gap in Scores by Month of Birth, V Grade
Std. Scores in Italian
-.2 -.1 0 .1 .2
0 5 10 15
Month of Birth
Std. Scores in Math
-.2 -.1 0 .1 .2
0 5 10 15
Month of Birth
South Italy
North Italy

in-difference strategy, comparing the North-South difference in scores between not eligible and that between eligible to early enrollment.

To do so I have to control that the effect of age on scores of not eligible is the same for South and North, in other words, I will assume that the relationship between month of birth and scores would be the same also for months between January and April if early enrollment was not allowed.

I then run 3 different regressions, using only data from students not eligible to early enrollment (born between May and December), for South and North separately and then pooling data together and adding an interaction term (*South*Month*). Tables 7 and 8 show the results from regression made by using data pooled from all school years in the dataset.

Tables 7 and 8 show that the coefficients in North and South for months of birth on scores in Italian Invalsi test at the II grade are slightly different for both subjects, whereas they are not for scores in V grade. Overall, in V grade the coefficient is smaller than in II, and this is consistent with other results from the literature that show how the effect of age at test and age at the enrollment on scores decreases with the age of the student. The coefficient for II grade is indeed around 0.035 s.d. whereas in V grade it is about 0.025 s.d.. This means that on average, to be born one month later decreases the score of about 0.035 s.d. in grade II and of 0.025 in grade V. This is true for all school years, and all the coefficients remain quite stable over time. Moreover, results are similar also across subjects.

6.1 The Difference-in-Difference Approach

In order to estimate how much the North-South gap in scores increase when moving from not eligible to eligible students I used pooled data from every school year 2012-2017 to estimate two different equations, using as dependent variables age in month and score at the Invalsi Italian test for II and V graders:

$$AgeinMonth_i = \alpha + \beta South_i + \gamma Eligible_i + \delta South_i * Eligible_i + \varepsilon_i$$

$$Score = \eta + \lambda South_i + \theta Eligible_i + \rho South_i * Eligible_i + \epsilon_i$$

From the first equation, I would expect that the coefficient β is not significantly different from 0 since it represents the difference in the average age of not eligible between students in the North and in the South. Since their parents do not have a choice about the enrollment, I expect this difference to be null. On the other hand coefficient γ is negative by construction: the variable *Eligible* is indeed a dummy equal to 1 if the student is born between January and April and 0 otherwise, whereas the

Table 7. Coefficients for linear effect of age on Invalsi Scores in Italian, North vs South Italy

Panel A: II Grade				
	(1)	(2)	(3)	(4)
VARIABLES	Italy	South-Italy	North-Italy	Interaction
Month of Birth	-0.035***	-0.030***	-0.037***	-0.037***
	(0.002)	(0.003)	(0.003)	(0.003)
				-0.096***
				(0.034)
Interaction				0.007*
				(0.004)
Constant	0.254***	0.150***	0.293***	0.271***
	(0.017)	(0.027)	(0.026)	(0.026)
Observations	89,617	36,768	35,151	71,919
R-squared	0.005	0.005	0.007	0.005
Panel B: V Grade				
	(1)	(2)	(3)	(4)
VARIABLES	Italy	South-Italy	North-Italy	Interaction
Month of Birth	-0.024***	-0.022***	-0.027***	-0.027***
	(0.002)	(0.003)	(0.003)	(0.003)
South				-0.182***
				(0.035)
Interaction				0.005
				(0.004)
Constant	0.170***	0.080***	0.236***	0.248***
	(0.017)	(0.028)	(0.026)	(0.025)
Observations	88,338	37,015	34,013	71,028
R-squared	0.002	0.002	0.004	0.007
School FE	Yes	Yes	Yes	Yes
year FE	yes	yes	yes	yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

variable *AgeinMonth* is built such that for regular students it has value of 1 if born in January and 12 if born in December and has value from 13 (born in January) to 16 (born in April) for early starters. The coefficient δ for the interaction terms should be instead positive: given the higher number of early enrollers in the south, this coefficient measure how much the gap in age between North and South increases when looking at eligibles.

The second equation is the same as the first but with Invalsi Score as the dependent variable. Then, the coefficient λ represents the gap in scores between not eligible in the South and in the North. The

Table 8. Coefficients for linear effect of age on Invalsi Scores in Math, North vs South Italy

Panel A: II Grade				
	(1)	(2)	(3)	(4)
VARIABLES	Italy	South-Italy	North-Italy	Interaction
Month of Birth	-0.035***	-0.031***	-0.038***	-0.038***
	(0.002)	(0.003)	(0.003)	(0.003)
South				-0.053
				(0.035)
Interaction				0.008**
				(0.004)
Constant	0.254***	0.218***	0.253***	0.261***
	(0.017)	(0.029)	(0.026)	(0.025)
Observations	86,933	35,399	34,318	69,717
R-squared	0.005	0.005	0.008	0.005

Panel B: V Grade				
	(1)	(2)	(3)	(4)
VARIABLES	Italy	South-Italy	North-Italy	Interaction
Month of Birth	-0.021***	-0.018***	-0.022***	-0.022***
	(0.002)	(0.003)	(0.003)	(0.003)
South				-0.140***
				(0.035)
Interaction				0.004
				(0.004)
Constant	0.147***	0.111***	0.163***	0.205***
	(0.017)	(0.028)	(0.026)	(0.026)
Observations	85,729	35,684	33,243	68,927
R-squared	0.002	0.003	0.004	0.004
School FE	Yes	Yes	Yes	Yes
year FE	yes	yes	yes	yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

coefficient θ is instead the gap in scores between eligible and not eligibles in the North Italy, and ρ is the main coefficient of interest, measuring how much the North-South gap in scores increase when moving from not-eligibles to eligible students.

Tables 9 and 10 presents the results for II and V grade respectively.

Columns 1 and 3 of tables 9 and 10 present the overall North-South gap in age and in scores respectively. The coefficient for age says that on average, II and V graders from the south are respectively 1.5 and 1.4 months younger than those from the North, score 0.09 and 0.17 standard deviation less at

Table 9. Diff-in-Diff. II Grade, 2012-2017

VARIABLES	(1) Age-in-Months	(2) Age-in-Months	(3) Score ITA	(4) Score ITA	(5) Score MAT	(6) Score MAT
South	1.487***	0.044***	-0.092***	-0.039***	-0.044***	0.011
	(0.021)	(0.016)	(0.006)	(0.007)	(0.006)	(0.007)
Eligible		-4.781***		0.164***		0.180***
		(0.028)		(0.009)		(0.009)
South*Eligible		4.489***		-0.164***		-0.170***
		(0.051)		(0.012)		(0.013)
Constant	6.966***	8.463***	0.018**	-0.033***	0.003	-0.054***
	(0.025)	(0.021)	(0.007)	(0.008)	(0.007)	(0.007)
Observations	120,058	120,058	120,369	119,886	116,713	116,250
R-squared	0.041	0.223	0.002	0.005	0.000	0.004
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10. Diff-in-Diff. V Grade, 2012-2017

VARIABLES	(1) Age-in-Months	(2) Age-in-Months	(3) Score ITA	(4) Score ITA	(5) Score MAT	(6) Score MAT
South	1.394***	0.003	-0.171***	-0.141***	-0.132***	-0.102***
	(0.021)	(0.016)	(0.006)	(0.007)	(0.006)	(0.007)
Eligible		-4.724***		0.110***		0.104***
		(0.028)		(0.009)		(0.009)
South*Eligible		4.332***		-0.105***		-0.099***
		(0.051)		(0.012)		(0.013)
Constant	6.893***	8.394***	0.068***	0.034***	0.056***	0.023***
	(0.025)	(0.022)	(0.007)	(0.008)	(0.007)	(0.008)
Observations	119,081	119,081	119,678	119,081	116,119	115,539
R-squared	0.036	0.213	0.007	0.009	0.004	0.006
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

the Italian Invalsi test and 0.04 and 0.14 s.d. less in the Mathematics test. Columns 2 show instead the results for the equation of age defined above: as expected θ is very close to 0 (the coefficient for II graders is positive and significant but its magnitude is negligible), and that $\gamma = -4.7$ in both grades, meaning that in the North, Eligible students are on average 4.7 months older that not eligible. The coefficient δ for the interaction term is instead positive: it says that looking only at students born between January and April, the average age in the South II grade cohort is 4.5 (4.3 in V grade) months less than in the North. This difference simply reflects the fact that in the South early enrollment is far more common. Finally, column 4 presents the results of main interest. From the coefficient λ for the dummy variable *South,* the regression estimates for scores in Italian are $\hat{\lambda} = -0.039$ for II Graders and $\hat{\lambda} = -0.141$ for V Graders. For scores in Mathematics, they are $\hat{\lambda} = 0.011$ (not statistically different from zero) and $\hat{\lambda} = -0.102$ for II and V graders respectively. These values reflect the North-South gap in scores for not eligibles. The results for the Diff-in-Diff estimators are very impressive, especially for II graders. In fact, for scores in Italian it is $\hat{\rho} = -0.164$ and it measures how much the North-South difference in average score increases when looking at eligible students. This means that the total gap in scores for students born between January and April is: $\hat{\lambda} + \hat{\rho} = -0.203$. This result is dramatic: if we look at column 3 of table 9, we see that the overall gap in scores between the two macro-region is 0.092, but when we look at not eligible it decreases to only 0.039. This means that almost 60% $((0.092-0.039)/0.092)$ of the gap is due to the difference in age among eligible students: in other words to the difference in early enrollment. Looking at the results in Mathematics, the difference in scores explained by the difference in age is even larger: among not eligible there is no significant difference in scores. This means that all the difference in average test scores in mathematics between North and South Italy comes from the difference in average age. When looking at the results for V grade, we see that the overall gap increase, and that the effect of the difference in early enrollment is less intense. This is consistent with the fact that the effect of age in school scores decrease with the student growing up. The estimate for $\hat{\rho}$ for scores in Italian is -0.105 and $\hat{\lambda} + \hat{\rho} = -0.246$. Given that the overall North-South difference in scores is 0.171 and the one for not eligibles is $\hat{\lambda} = -0.141$, this means that still in V grade, almost the 20% of the gap in scores between Northern and Southern students is due to difference in the enrollment. For scores in mathematics, the percentage of the gap explained by the difference in age is larger also in V grade, being around 23%: $(-0.132 - 0.102)/(-0.132)$.

If we look better at the magnitude of the Diff-in-Diff estimator, we can notice that it is very close to the linear coefficient estimated by running the regression of score on age-in-month for not eligibles. In fact, from that regression, the estimate says that on average, both in the North and in the South, being one month younger leads to a decrease in Italian Invalsi Score of around 0.035 s.d. in II grade and of around 0.025 s.d. in V grade. Given that the increase in the difference in age (δ), is equal to 4.5 months and 4.3 months in the II and V grade respectively, we can see that multiplying this coefficient to the corresponding estimate for the linear effect of age on scores, we get 0.157 for II grade and 0.108 for the V grade, which are very similar to the estimates of the diff-in-diff coefficients which are $\hat{\rho} = -0.164$ for the grade II and $\hat{\rho} = -0.107$ for grade V. The very same results hold also for scores in mathematics.

However, this estimate can be biased and deeper checks are required. For example, we are assuming that not-eligible are not affected by the number of early entrants. In the South, in fact, not eligibles would be relatively older within a class than in the North, since they will have more early entrants as classmates. To be older in the distribution of age in the class can have different effects: it can lower your results because the teacher has to "slow down" and to flatten the learning curve in order to help younger students. On the other hand, to be older can also have some positive effects on cognitive ability. Even if, at a first glance, I would expect that the negative effect of having younger peers prevails, and then that the estimates from the diff-in-diff analysis can be seen as a lower bound for the true effect, in the next sections I will propose some robustness checks that will improve the reliability of the results.

6.2 Robustness Checks

6.2.1 Month by Month analysis

In this section, I will use the same diff-in-diff strategy but using as eligible group students born in one of the first four months of the year. In other words, I will run the same regression as before four times, one for each month, dropping observation of born in other months that are also eligible. Hence, I want to estimate 4 different equations, one for each month of birth of eligible (January-April):

$$ScoreITA_i = \alpha + \lambda South_i + \theta Jan_i + \rho South_i * Jan_i + \epsilon_i$$

Where Jan_i is a dummy equal to 1 if student i was born in January and 0 otherwise, and observation of student born from February to April are dropped. I do the same for each month until April, and see if the effect for each month is related to the change in the percentage of early starters. We would expect higher estimates for January than for April since the difference in number of early entrants is much bigger for born in the first month of the year.

Tables 11 reports the estimation for each month of eligibility and for the diff-in-diff estimation for both age-in-months and score in Italian and Mathematics.

Table 11. Diff-in-Diff, Month by Month Analysis

Panel A: II Grade

VARIABLES	(1) Jan Age-in-Months	(2) Jan ITA	(3) Jan MATH	(4) Feb Age-in-Months	(5) Feb ITA	(6) Feb MATH	(7) Mar Age-in-Months	(8) Mar ITA	(9) Mar MATH	(10) Apr Age-in-Months	(11) Apr ITA	(12) Apr MATH
South	0.046***	-0.040***	0.010	0.047***	-0.040***	0.010	0.044***	-0.039***	0.010	0.045***	-0.040***	0.010
	(2.923)	(-5.707)	(1.439)	(2.988)	(-5.732)	(1.432)	(2.765)	(-5.628)	(1.469)	(2.843)	(-5.726)	(1.396)
Eligible	-4.910***	0.161***	0.165***	-5.261***	0.179***	0.182***	-4.835***	0.180***	0.227***	-4.115***	0.134***	0.145***
	(-70.207)	(10.714)	(11.243)	(-96.159)	(11.216)	(11.890)	(-122.005)	(11.778)	(15.176)	(-131.455)	(8.598)	(9.527)
South*Eligible	6.103***	-0.231***	-0.242***	5.199***	-0.190***	-0.174***	3.802***	-0.172***	-0.189***	2.849***	-0.062***	-0.069***
	(58.381)	(-10.830)	(-11.072)	(49.280)	(-8.391)	(-7.545)	(41.460)	(-7.976)	(-8.584)	(33.696)	(-2.860)	(-3.067)
Constant	8.514***	-0.038***	-0.058***	8.526***	-0.041***	-0.060***	8.471***	-0.035***	-0.055***	8.483***	-0.035***	-0.054***
	(412.206)	(-4.744)	(-7.231)	(420.704)	(-5.062)	(-7.358)	(430.359)	(-4.389)	(-6.827)	(440.533)	(-4.304)	(-6.681)
Observations	91,978	92,332	89,469	91,015	91,371	88,553	91,912	92,258	89,463	91,342	91,698	88,877
R-squared	0.157	0.003	0.002	0.158	0.002	0.002	0.152	0.002	0.003	0.123	0.002	0.001

Panel B: V Grade

VARIABLES	Jan Age-in-Months	Jan ITA	Jan MATH	Feb Age-in-Months	Feb ITA	Feb MATH	Mar Age-in-Months	Mar ITA	Mar MATH	Apr Age-in-Months	Apr ITA	Apr MATH
South	0.003	-0.137***	-0.099***	0.006	-0.137***	-0.100***	0.005	-0.137***	-0.099***	0.004	-0.137***	-0.099***
	(0.188)	(-19.573)	(-13.935)	(0.359)	(-19.567)	(-13.971)	(0.298)	(-19.560)	(-13.927)	(0.258)	(-19.568)	(-13.926)
Eligible	-4.817***	0.083***	0.089***	-5.134***	0.133***	0.106***	-4.892***	0.124***	0.108***	-4.056***	0.102***	0.114***
	(-66.279)	(5.590)	(5.918)	(-88.949)	(8.492)	(6.542)	(-129.423)	(8.465)	(7.132)	(-122.988)	(6.757)	(7.365)
South*Eligible	6.417***	-0.160***	-0.144***	5.183***	-0.157***	-0.123***	3.457***	-0.087***	-0.084***	2.286***	-0.035	-0.059***
	(61.969)	(-7.502)	(-6.684)	(48.409)	(-6.948)	(-5.271)	(38.728)	(-4.098)	(-3.810)	(28.890)	(-1.619)	(-2.690)
Constant	8.364***	0.029***	0.021**	8.386***	0.030***	0.019**	8.393***	0.031***	0.023***	8.372***	0.028***	0.021**
	(392.369)	(3.540)	(2.561)	(398.453)	(3.618)	(2.291)	(409.171)	(3.843)	(2.761)	(420.882)	(3.431)	(2.561)
Observations	91,084	91,681	88,950	90,089	90,686	87,984	91,022	91,619	88,858	90,741	91,338	88,632
R-squared	0.154	0.006	0.004	0.147	0.007	0.004	0.159	0.006	0.003	0.129	0.006	0.004
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As expected, the table shows that the diff-in-diff estimator for test scores decrease togeteher with the one for age-in-month, when moving from January to April. It is interesting to notice that for each month, the diff-in-diff estimator for scores is close to the product of the linear effect of being one month younger and the North-South difference in age-in-months. This relationship holds for both II graders and V graders. One of the main questions this paper wants to investigate is indeed whether to be enrolled earlier gives a disadvantage to the pupils which is bigger (or lower) than the normal linear effect of age on scores which affects also not eligible students. The month by month analysis gives further evidence that this is not the case.

6.3 The Penalty for Early Enrollment

Fenoll and coauthors (2018) proposed another way for looking at the effect of early enrollment. In their work, the authors propose a method to estimate counterfactual scores for early entrants, having they started regularly. In this section, I will replicate their results but focusing on the North-South difference in this penalty and on how this penalty is related to the linear effect of age.

In the baseline analysis, I will use again data from monitored students in V grade from 2012 to 2017.

The methodology relies on the assumption that, if there is not selection and early enrollment is not possible, average test scores in the population are linear in age.

The first step is then to estimate the linear effect of age in months on test scores in Italian, for regular students born between May and December. For this subsample, parents have no choice about early enrollment.

$$T_i^{st} = \alpha^{st} + \beta^{st} m_i^t + \varepsilon_i^{st} \tag{1}$$

where T is the standardized test score of student i in subject s in year t. m is the variable for age-in-months. The estimates for β are then those shown before in tables 7 and 8 for Italian and Mathematics scores respectively.

They then divide the students into 3 groups G:

1. S: Selected in Early Enrollment. Students born between January and April who are enrolled earlier;

2. NS: Not Selected in Early Enrollment: Students born between January and April who are enrolled

regularly;

3. U: $S \cup NS$ denoting all students

Treatment status variable $T = E$, R tells if the student is regular or early entrants. Therefore, we can call average scores as $A(G, T, m)$, where G is one of the three groups described above, T is the treatment status and m is the month of birth.

In the second step, they measured the predicted average test scores of students born between January and April, had all students started regularly. To do so, they use the estimates for the coefficients $\hat{\alpha}$ and $\hat{\beta}$ from equation (1) and compute $\hat{A}(U, R, m) = \hat{\alpha} + \hat{\beta}m$, for $m \leq 4$.

To calculate the counterfactual scores for early entrants they assume that the weighted average between actual scores of not selected student and counterfactual scores of early entrants is equal to the predicted average scores. Notationally:

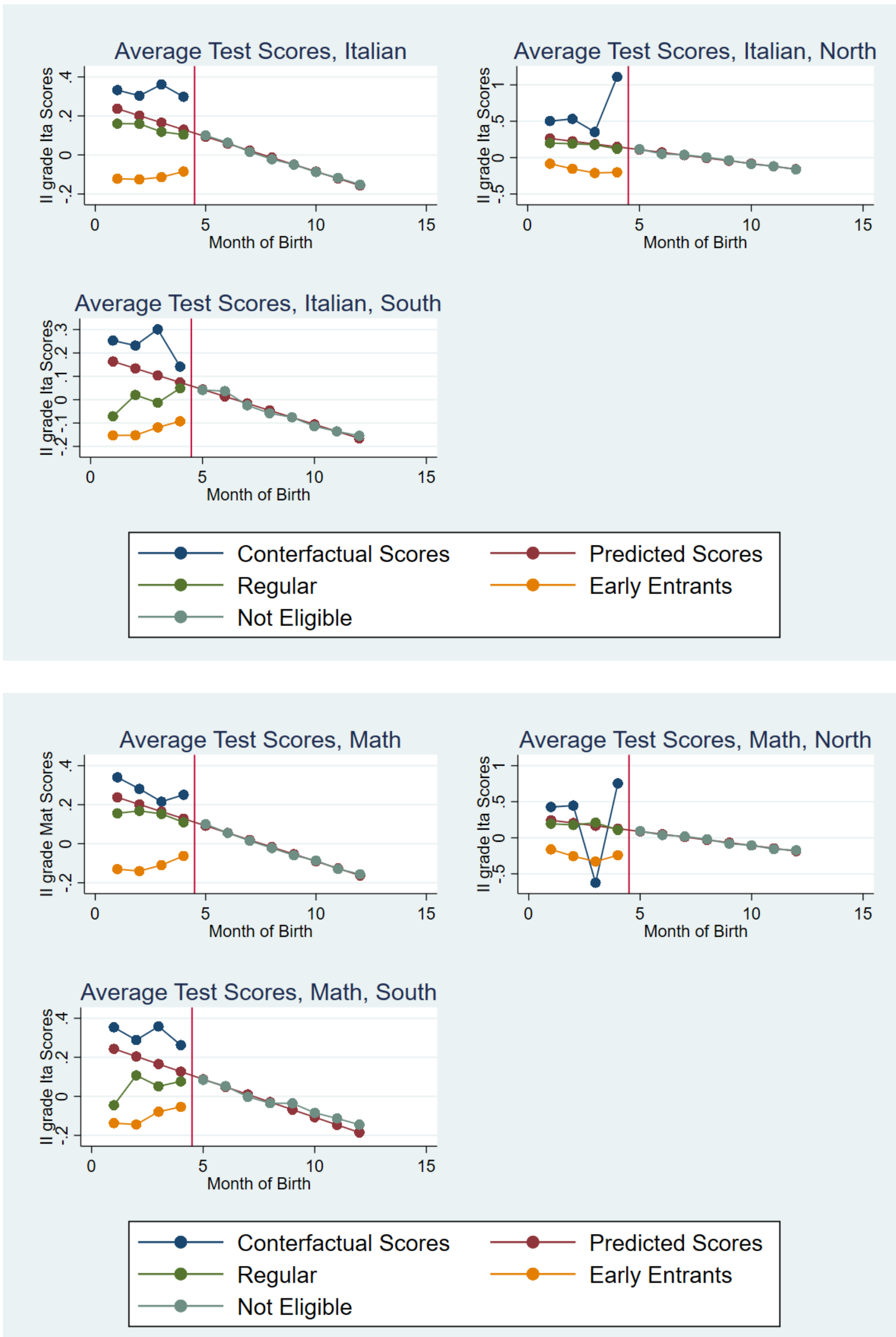
$$A(U, R, m) = P_S(m)A(S, R, m) + [1 - P_S(m)]A(NS, R, m)$$

where $P_S(m)$ is the fraction of students born in month m who are Early Entrants, $A(S, R, m)$ is the average counterfactual scores of Early Starters, had they started regularly and $A(NS, R, m)$ is the observed average scores of regular students. Hence, the average counterfactual score for early entrants having they started regularly will be:

$$A(S, R, m) = \{A(U, R, m) - [1 - P_S(m)]A(NS, R, m)\}/P_S(m)$$

Figure 5 presents graphically the results from this computation for the whole sample of II graders and for subsamples of North and South Italy.

Figure 5. II Grade, Invalsi Test 2012-2017



The blue line represents the counterfactual scores for early starters, had they started regularly, the red line contains fitted values from equation (1), whereas the green and the yellow lines are the actual average scores for regular and early entrants respectively.

This methodology allows to estimate the strength of selection as the difference between counterfactual scores of student selected into early enrollment and the average test score in the population having all students started regularly: $A(S, R, m) - A(U, R, m)$. It allows also to estimate the penalty associated with the early enrollment, which can be identified as $A(S, R, m) - A(S, E, m)$: the difference between average counterfactual score and average actual scores of early entrants.

Whereas Fenoll and her coauthors focus more on the selection, in this work I focus on the penalty associated with the early enrollment. More specifically I will use their technique to check whether the penalty is different from the linear effect of age on scores, or if, due to selection, the effect of being one year younger is either weaker or stronger.

Tables 12 and 13 show a comparison between the penalty for early enrollment measured as in Fenoll and the linear effect of age measured as the coefficient for the linear effect of being one month younger multiplied by 12. Results in tables 12 and 13 referred to scores in Italian test for II and V grade respectively. Looking at scores in mathematics, results do not change significantly.

These results come from data of all school years available and year fixed effect are included in the regressions. The year by year analysis is more appropriate in this case since the "Over-Penalty" is made by comparing the penalty estimated with data from each year and the linear coefficient for age-in-month coming from regression made using data from the following school year. In fact, early entrants if entered regularly would have been enrolled one year later. Since results are very similar for each year I show here estimates from pooled data, for exposition purpose.

Tables 12 and 13 give two important insights: first, all the estimates for the "Over-Penalty" are not significantly different from zero. Secondly, whereas in the North the over-penalty has high variance and does not seem to have a trend, in the South it seems to decrease with month of birth and then with the number of early starters, especially in V grade (a negative value for "Over-Penalty" means that the penalty measured with the Fenoll method is bigger than the linear effect of age).

6.3.1 Penalty by Week

For School Years 2015/2016 and 2016/2017, Invalsi provides also data about the exact date of birth, instead of providing only the month of birth as for other years. For those cohorts of V graders, I can then use the same methodology as before, but with age-in-weeks instead of age-in-months as the main

Table 12. Early Enrollment Penalty and Linear effect of age by Month of Birth. II Grade - ITA

Month of Birth:		January	February	March	April
Italy	Penalty	-0.505	-0.487	-0.552	-0.448
	Linear Effect	-0.478	-0.478	-0.478	-0.478
	Over-Pen.	-0.027	-0.009	-0.074	0.030
	N	5502	3246	2369	1527
North	Penalty	-0.646	-0.802	-0.530	-1.166
	Linear Effect	-0.511	-0.511	-0.511	-0.511
	Over-Pen.	-0.135	-0.291	-0.019	-0.655
	N	1070	445	249	129
South	Penalty	-0.451	-0.436	-0.502	-0.301
	Linear Effect	-0.401	-0.401	-0.401	-0.401
	Over-Pen.	-0.050	-0.036	-0.101	0.100
	N	3513	2389	1849	1255

Table 13. Early Enrollment Penalty and Linear effect of age by Month of Birth. V Grade - ITA

Month of Birth:		January	February	March	April
Italy	Penalty	-0.399	-0.337	-0.307	-0.194
	Linear Effect	-0.307	-0.307	-0.307	-0.307
	Over-Pen.	-0.092	-0.030	0.000	0.113
	N	5808	3329	2136	1394
North	Penalty	-0.546	-0.397	-0.433	-0.739
	Linear Effect	-0.324	-0.324	-0.324	-0.324
	Over-Pen.	-0.221	-0.073	-0.109	-0.414
	N	1038	469	213	141
South	Penalty	-0.340	-0.325	-0.281	-0.158
	Linear Effect	-0.288	-0.288	-0.288	-0.288
	Over-Pen.	-0.051	-0.036	0.008	0.130
	N	3765	2401	1654	1086

variable of interest. Hence, I can calculate the penalty for students born in each week in the period January-April.

Figures 6 and 7 present the difference between the Over-Penalty measured as $A(S,R,w)-A(S,E,w)$, where w is the week of birth, for Italian and Mathematics test score respectively. Red dots are for students in South Italy and blue ones are for the Northerners. It is possible to notice that in the South the over-penalty for both Italian and Math scores stays close to zero and does not have a clear pattern with respect to the week of birth. This is true also for the over-penalty in the North for II graders, even if it presents a much higher variance. On the other hand, in the North the over-penalty in the V grade for early entrants seem to increase dramatically in the last weeks before the cut-off. However, any of the estimates is significantly different from zero, and this result probably come from the fact that there are very few early entrants in the North born in the last weeks of April. In fact, remembering that the formula to calculate the counterfactual scores for early entrants born in the week w is:

$A(S, R, w) = \{A(U, R, w) - [1 - P_S(w)]A(NS, R, w)\}/P_S(w)$

we can see that, being $P_S(w)$ in the North around 0.03 for weeks from 10 to 16, if regulars born in that week have an average score $(A(NS, R, w))$ slightly lower than the counterfactual score of students born in that week, having everybody started regularly $(A(U, R, w))$, the counterfactual score of early entrants $A(S, R, w)$, will be incredibly high. In fact, the value for over-penalty in the North, are totally non-realistic being in some cases higher than 2 s.d..

These results give more confidence to the hypothesis that the effect of being enrolled earlier is not different from the linear effect of age, meaning that, even if there is a strong selection, the early entrants do not recover faster, and are still strongly penalized when looking at the Invalsi Scores in Italian in grade V.

Figure 6. Std. Score, II grade

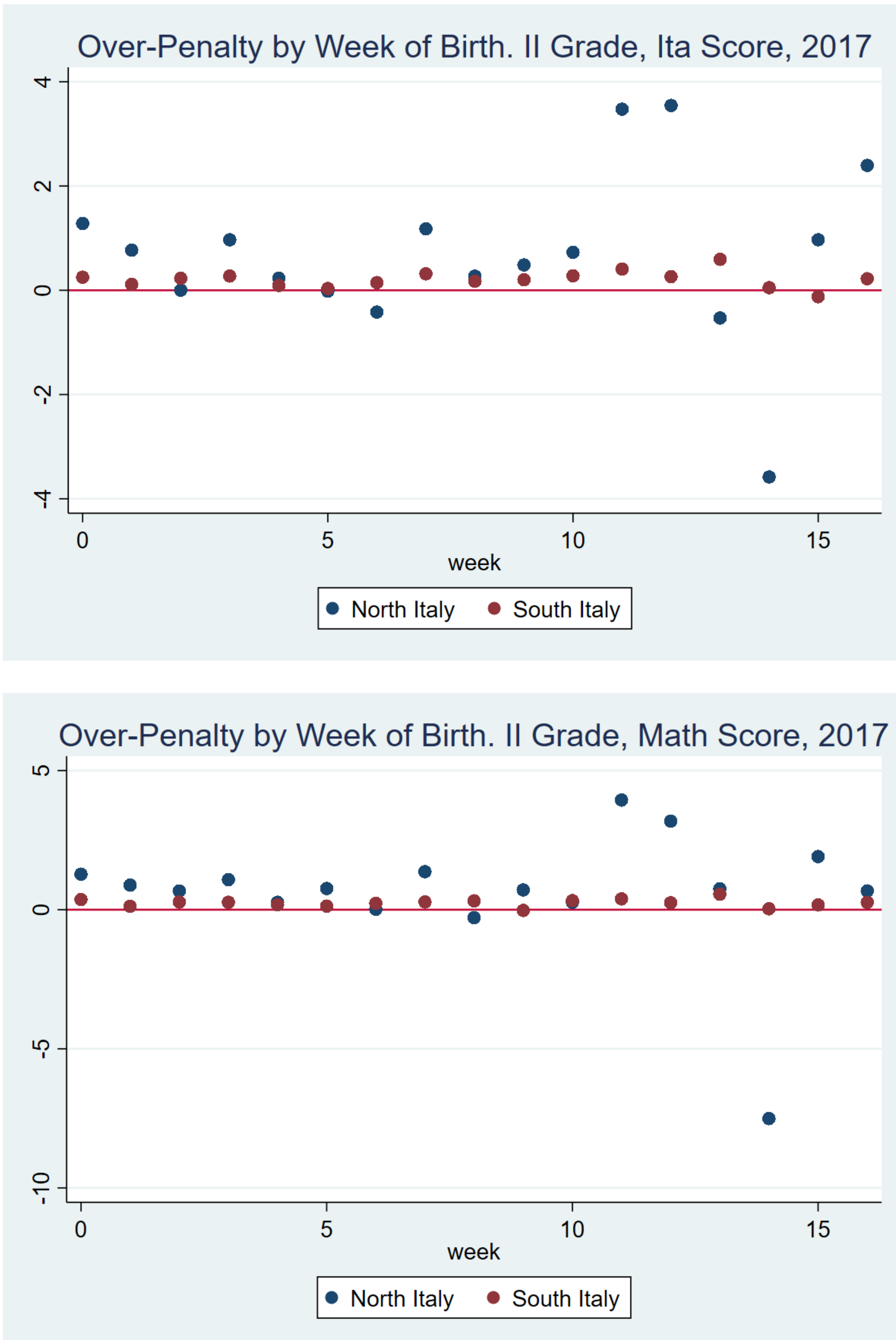
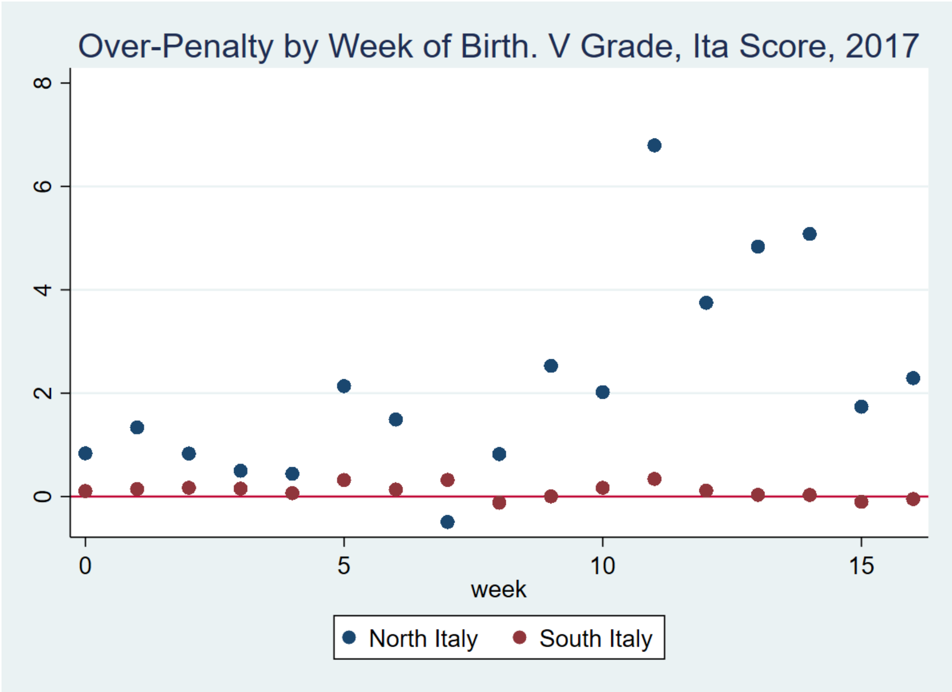
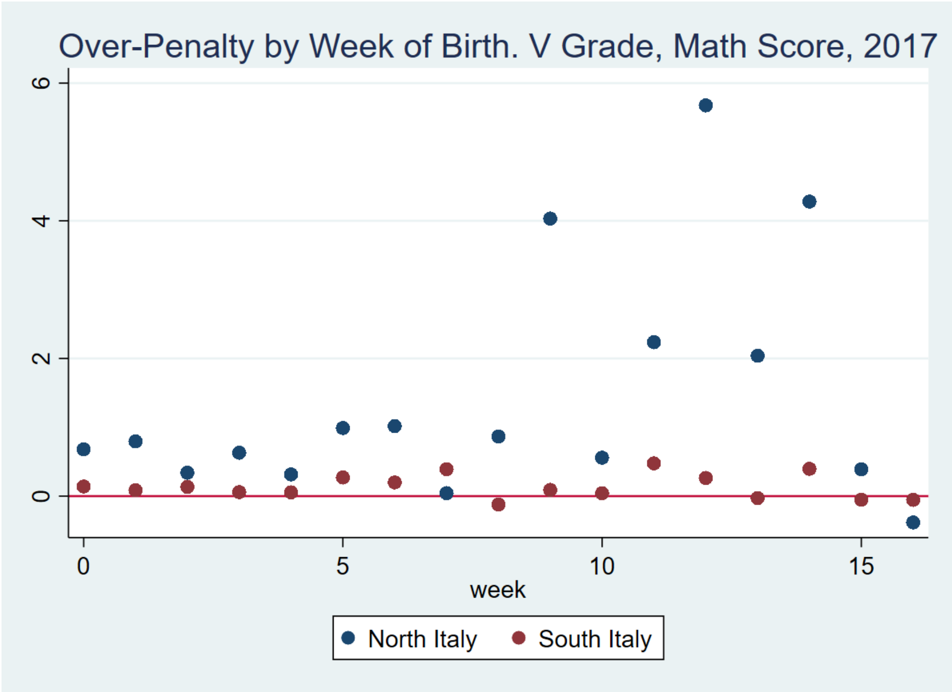


Figure 7. Std. Score, V grade





7 The Moratti Reform

As described in section 3, the Moratti reform, voted in 2003, changed the enrollment system to primary school in Italy, moving the cut-off from the 31st of December to the 30th of April.

As mentioned, the implementation of the reform was gradual: the cut-off was moved to the 28th of February for the first 2 years, then it became the 31st of March and from a.y. 2006/2007 onward it has been the 30th of April. Invalsi data allow me to study only the effect of the last part of the reform, when the cut-off was changed from the 31st of March to the 30th of April. In this way using data from the VIII grade, I will have two cohorts of students who were enrolled to primary school before the reform (VIII graders in s.ys. 2011/2012 and 2012/2013) and 4 cohorts enrolled after the reform.

7.1 Methodology for the Estimation of the Effect of the Reform

As already noticed, the main issue in quantifying the effect of school starting age in the Italian case is that it is strongly endogenous. Whereas in the previous analysis I did not have any exogenous variation in the cut-off date, the Moratti reform provides a good quasi-experimental framework to estimate more safely the effect of early enrollment, at least for a subpopulation of early entrants. In this case, I will use an instrumental variable approach, using as instrument the difference-in-difference estimator which exploits the exogenous variation in early enrollment due to the Moratti reform of 2003. This methodology has been used in several works, from Duflo (2001) who estimated the effect of a vast school construction program in Indonesia, to Angrist which dedicated many works on the econometrics valence of this approach (1996 work with Imbens is a good example). If the School Starting Age was exogenous I would estimate the following regression:

$$Score_{it} = \alpha_0 + \rho Early_{it} + \pi X_{it} + e_{it},$$

where $Score_{it}$ is the score at Invalsi test (Math or Italian) of student i in year t, and $Early_i$ is a dummy equal to 1 if student i was enrolled earlier to school. In order to overcome the omitted variable bias, which is likely to be very significant in this context, I will use a 2 stage least square estimation strategy where the first stage regression is the following:

$$Early_{it} = \beta_0 + \beta_1 G_i + \beta_2 T_t + \beta_3 G_i T_t + \epsilon_{it}.$$

This first stage is a simple difference in difference equation where the outcome variable is the dummy Early. The variable G is a dummy equal to 1 if individual i is born in April (affected by the Moratti reform), and 0 if born from May to December (not affected) and the variable T is equal to 1 if t>2013. Hence, the coefficient of interest is β_3, which will measure how much the difference between early entrants born in April and born after April, increased because of the reform. In this framework, the reduced form equation is given by:

$Score_{it} = \delta_0 + \delta_1 G_i + \delta_2 T_t + \delta_3 G_i T_t + \varepsilon_{it}$

where δ_3 is the difference in difference estimator for the effect of the reform on Invalsi Score.

As a result, our estimator of interest is $\hat{\rho}$, the so-called "Wald-Did Estimator":

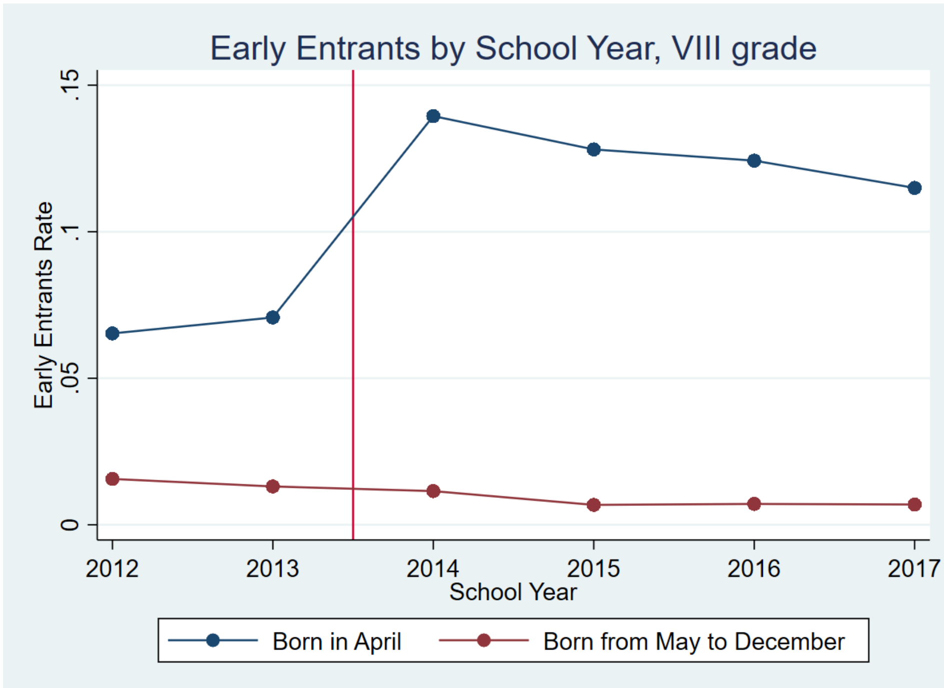
$\hat{p} = \frac{\hat{\delta}_3}{\hat{\beta}_3} = \frac{DiD_{RF}}{DiD_{FS}}$.

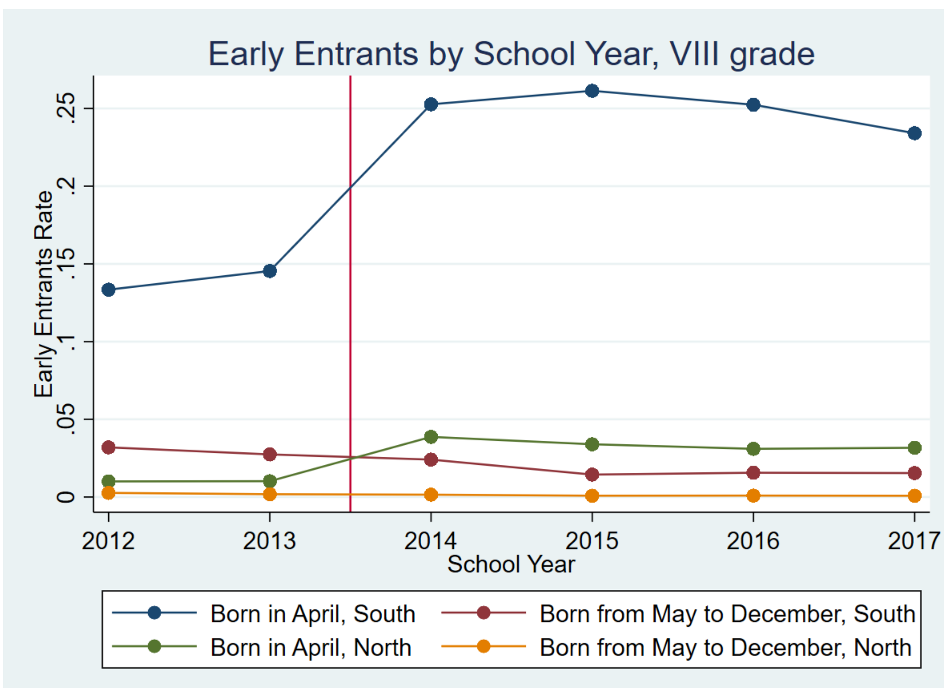
Following the work of Dechaismartin and Hoautefouille (2018), this estimator represents the Local Average Treatment Effect for the "Switchers". Switchers are those students who moved up the enrollment because of the reform and that would have not done so if the system had not changed.

Figure 8 shows how the percentage of early enrolled students born in April changed after the reform, compared to students born between May and December.

The top panel reports the variation using data from students from all italian territory, the bottom panel reports differences between North and South of Italy. I will use this exogenous variation to identify the effects of early enrollment in the VIII grade Invalsi test scores.

Figure 8. Early Entrants by School Year





7.2 Identification

In order to be consistent, this approach relies on 5 main assumptions, which are the typical assumptions required for the difference in difference and for the instrumental variable approach. First of all both the variables G and T must be exogenous. Since G represents the month of birth, and the value of T switches at the time of the reform, I can safely argue that these variables are exogenous: month of birth is casual and there are no reason to believe that the reform was expected, nor that is correlated with other relevant variables. This is also confirmed by the results presented in section 5.1. Another important assumption is that the instrument is "strong". Figure 8 shows that the instrument is strong and that the parallel trend assumption for the ratio of early entrants seems to be satisfied: we can see how there is a significant skip in the number of early enrollers born in April after the reform, whereas among not eligible, the percentage of early enrollers stays very close to zero. The difference was significant also before the reform because age is clearly a determinant in the choice for early enrollment. However, after the reform, being easier to enroll earlier pupils born in April, this difference more than double. Table 14 shows the result from the first-stage regression for Italy, North-Italy and South-Italy. Estimates for β_3 are significant in all specifications used, with a stronger effect of the reform in the South. In the North the percentage of early enrollers born in April increases from 1% to 3.6%, whereas in the South it goes from 14% before the reform to 25%. It is also worth to notice that the percentage of early enrollers for not eligible slightly decreases after the reform. One possible explanation is that before the reform, the "early enrollment" was actually a "skip" of the first grade and this possibility was available to all students, independently of their month of birth. The system indeed allowed parents to enroll the child directly to the II grade at the age of 6, conditional on passing an examination. To prepare children for this test, private schools or teachers organized specific classes. After the reform, the demand for this service decreased, given that most of it came from parents of children born in the first quarter of the year. With the Moratti reform, these special classes have not been anymore necessary for children born before May, and then the availability of this service decreased. However, the decrease in early enrollers due to the reform was very limited (less than 1%) and is not likely to bias the results.

To control for school-level covariates, I also include school fixed effects in all regressions.

Given the strong geographic heterogeneity in the effect of the reform on early enrollment, I will also present results from subsamples of Northern and Southern regions.

Table 11 presents results from the 2SLS regressions. The coefficients for the variable *Early* represent

Table 14. First Stage: Dep. Var.: Early Entrant

VARIABLES	(1) Italy	(2) North Italy	(3) South Italy
April	0.053***	0.108***	0.008***
	(0.002)	(0.003)	(0.001)
PostReform	-0.005***	-0.012***	-0.001***
	(0.000)	(0.001)	(0.000)
April*PostReform	0.066***	0.124***	0.025***
	(0.002)	(0.003)	(0.001)
Constant	0.014***	0.029***	0.002***
	(0.000)	(0.000)	(0.000)
Observations	2,142,087	845,504	901,118
R-squared	0.053	0.100	0.018
Number of Schools	8,274	3,272	3,539
School FE	Yes	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

the estimate for the Local Averager Treatment Effect, in other words, the effect of early entrance for the "*Switchers*". The estimated LATE for standardized scores in Italian is -0.3 s.d. and statistically significant. This means that on average, students born in April that were enrolled earlier, and that would have started regularly without the reform, scores 0.3 s.d. less in the Italian test, compared with their score if they had started regularly. The same estimate is not statistically significant for scores in math. Looking at columns 3-6, we can see that the coefficient is statistically significant only for students in the South and only for scores in the Italian test. However, all coefficients have the expected negative signs.

An interesting exercise is to compare these coefficients with the coefficients from a linear regression of standardized scores on the month of birth for students born between May and December, not eligible for early enrollment. This is very similar to the exercise done in previous sections. This time, I want to check whether the effect for switchers is different from the linear effect of age on scores for VIII graders. Table 16 shows the coefficients for equation (1) using standardized scores in VIII grade.

Coefficients show that the effect of age is higher for scores in Italian than for scores in Mathematics (0.017 s.d. vs 0.010 s.d.), consistently with results from 2SLS regressions. Moreover, the coefficients for both scores are lower than in II and V grade, confirming that the effect of age on scores decreases with age. Multiplying coefficients in table 11 for twelve will give the predicted linear effect of being

Table 15. 2SLS regression, Instrument: DiD - Moratti Reform

	(1)	(2)	(3)	(4)	(5)	(6)
	ITA	MATH	ITA	MATH	ITA	MATH
VARIABLES	Italy	Italy	South	South	North	North
Early	-0.296***	-0.112	-0.229***	-0.086	-0.340	-0.248
	(0.068)	(0.069)	(0.059)	(0.059)	(0.282)	(0.292)
April	0.096***	0.064***	0.092***	0.056***	0.090***	0.068***
	(0.007)	(0.007)	(0.012)	(0.012)	(0.008)	(0.008)
PostReform	-0.018***	-0.008**	-0.011*	-0.006	-0.027***	-0.012***
	(0.003)	(0.004)	(0.006)	(0.008)	(0.003)	(0.004)
Constant	0.085***	0.062***	0.072***	0.052***	0.100***	0.076***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.002)	(0.003)
Observations	2,117,866	2,122,883	830,613	829,701	896,446	900,359
Number of Schools	8,271	8,273	3,270	3,271	3,538	3,539
School FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

one year younger. These would be 0.204 s.d. for Italian and 0.12 s.d. for Mathematics. Recalling that the estimated LATE represents the effect of being one year younger at the moment of the test, we can see that the LATE is not far from the linear effect of age on score (-0.296 s.d. vs -0.204 s.d. for Italian and -0.112 s.d. vs -0.120 s.d. for Mathematics).

Table 16. Linear effect of age on scores, VIII grade

Linear effect of age on scores, VIII grade

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Italy	Italy	South	South	North	North
Month of Birth	-0.017***	-0.010***	-0.016***	-0.009***	-0.017***	-0.010***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.222***	0.137***	0.194***	0.130***	0.243***	0.151***
	(0.005)	(0.005)	(0.008)	(0.010)	(0.006)	(0.007)
Observations	1,632,357	1,635,971	639,083	638,259	691,784	694,710
R-squared	0.001	0.000	0.001	0.000	0.002	0.001
Number of Schools	8,268	8,270	3,268	3,269	3,537	3,538
School FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.3 Robustness Check: Placebo Tests

In order to see if the results are driven by something I am not controlling for, I run two different placebo tests.

The first one is made by artificially moving the Moratti Reform to two years later. In the second I keep the original reform year, but I move the cut-off date, from the 30th of April to July 31st, as if eligibles to early enrollment were children born between January and July. If the specification used above is robust, we will expect no significant coefficient for the LATE. Table 17 shows that this seems to be the case, reassuring that our identification strategy is solid. In fact, the coefficients for the LATE are in the first row of columns 2 and 4, and they are not significantly different from zero. Coefficient *Placebo DiD1* and *Placebo DiD2* are the coefficients for the first stage for the placebo instruments. They are statistically different from zero but their magnitude is negligible.

Table 17. Placebos. First Stage Dep. Var.: Early Entrant; 2SLS Dep. Var. Scores at Std Tests

	Placebos					
	(1)	(2)	(3)	(4)	(5)	(6)
	1st St.	2SLS	1st St.	2SLS	1st St.	2SLS
	Early	ITA	MAT	Early	ITA	MAT
VARIABLES	Placebo Reform	Placebo Reform	Placebo Reform	Placebo cutoff	Placebo cutoff	Placebo cutoff
Early		-0.266	0.054		-0.512	-1.006
		(-0.606)	(0.123)		(-0.605)	(-1.196)
April	0.124***	0.093*	0.044			
	(49.942)	(1.773)	(0.832)			
Placebo Reform	-0.002***	-0.012***	-0.012***			
	(-8.649)	(-3.620)	(-3.192)			
Placebo DiD1	-0.011***					
	(-6.525)					
PostReform				-0.010***	-0.020***	-0.014***
				(-19.177)	(-4.127)	(-2.583)
Placebo Cut-off				-0.017***	-0.068***	-0.051***
				(-23.298)	(-9.409)	(-7.140)
Placebo DiD2				0.006***		
				(13.151)		
Constant	0.009***	0.075***	0.059***	0.024***	0.123***	0.099***
	(36.850)	(16.671)	(12.872)	(41.357)	(8.790)	(7.050)
Observations	1,451,144	1,451,144	1,451,089	1,911,597	1,644,556	1,648,236
R-squared	0.070			0.005		
Number of Schools	8,147	8,147	8,147	8,272	8,268	8,270

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.4 Triple Difference as Instrument

A further check is to use a triple difference in difference approach. Given that the effect on the reform is very limited in the North, with the percentage of early entrants born in April which increase from 1% to the 3.5%, and much more strong in the South (from 14% to 25%), I can add North-South difference to the initial Diff-in-Diff approach. Since in theory, the reform was applied to all the schools on the Italian territory, this would not be an appropriate approach, since we do not know why in the North the number of early entrants is so limited compared to the South. However, it could give more insights on the effect of the reform on scores of students in the South. In this section, I will then use the triple-difference estimator as an instrument for the school starting age. In fact, even if the North-South difference is clearly not exogenous, it can still be a reliable approach since the number of early entrants in the North is close to zero. An example of a triple-difference approach is given by the work of Muralidharan and Prakash (2017) who used it to estimate the effect of a program that provided bicycles to girls who continued to secondary school. However, here I use the triple difference estimate also as an instrument.

The estimation strategy would be the following. In the first stage I estimate the effect of the reform on the North-South difference in the percentage of early entrants born in April:

$$Early_{it} = \beta_0 + \beta_1 G_i + \beta_2 T_t + \beta_3 S_{it} + \beta_4 G_i T_t + \beta_5 G_i S_{it} + \beta_6 T_t S_{it} + \beta_7 G_i T_t S_{it} + \epsilon_{it}$$

Where S is a dummy for South Italy and β_7 is the triple-diff. coefficient of interest. β_4 is the diff-in-diff estimate as in the previous section, but for the North Italy.

The reduced form will instead tell how much the North-South difference in the gap in scores between born in April (*G=1*) and Not-eligible (*G=0*) increases after the reform:

$$Score_{it} = \gamma_0 + \gamma_1 G_i + \gamma_2 T_t + \gamma_3 S_{it} + \gamma_4 G_i T_t + \gamma_5 G_i S_{it} + \gamma_6 T_t S_{it} + \gamma_7 G_i T_t S_{it} + \epsilon_{it}$$

I will then use the triple difference estimator on the first stage as an instrument for the effect of early enrollment. In this case, I am measuring the LATE for those students early enrolled in the South because of the reform that would have been enrolled regularly if they were in the North. Even if this interpretation may be tricky and a bit strained, remember that in the North almost no student born in April is enrolled earlier. In this framework, I am assuming that the impact of the reform and the reasons why early enrollment is widely more common in the South are exogenous. Hence, this has to be considered as additional analysis and not as the main specification for the identification of the effect of the reform.

The estimator of interest is then $\hat{\rho}$, that I call here the "Wald-Triple-diff Estimator":

$$\hat{p} = \frac{\hat{\gamma}_7}{\hat{\beta}_7} = \frac{TripleD_{RF}}{TripleD_{FS}}.$$

Table 15 shows the results. Columns 4 and 5 report the estimate for $\hat{p}$. They are consistent with estimates for the effect of the reform found using other approaches (around -0.2 s.d. for Italian and

-0.1 s.d and not statistically significant for Mathematics).

Table 18. Triple Diff-in-Diff. Dep. Var.: Score in Italian

	Triple Diff-in-Diff				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Early	RF - ITA	RF - MAT	2SLS - ITA	2SLS - MAT
Triple Diff.	0.098***	-0.015	-0.007		
	(0.003)	(0.010)	(0.010)		
Early				-0.191*	-0.099
				(0.103)	(0.107)
South	0.027***	-0.039***	0.083***	-0.089***	0.039***
	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)
aprile	0.008***	0.099***	0.074***	0.091***	0.067***
	(0.001)	(0.006)	(0.006)	(0.005)	(0.005)
PostReform	-0.001***	-0.014***	0.068***	-0.037***	0.059***
	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
April*Post	0.025***	-0.006	0.000	-0.006	-0.000
	(0.001)	(0.007)	(0.007)	(0.009)	(0.009)
South*April	0.102***	-0.022**	-0.018**	0.002	-0.004
	(0.002)	(0.008)	(0.008)	(0.018)	(0.019)
South*Post	-0.011***	0.053***	-0.138***	0.066***	-0.132***
	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.002***	-0.013***	-0.060***	0.111***	0.038***
	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,746,695	1,921,011	1,923,932	1,727,132	1,730,133
R-squared	0.103	0.001	0.001	-0.002	0.001

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

8 Conclusions

Statistics on academic results of Italian students are presented every year by the Ministry of Education. A lot of attention is given on the divide between Northern and Southern students. This work shows that a significant percentage of this gap is due to the difference in early enrollment. Even if the Invalsi reports recognize that in the South early enrollment is more common, this study is the first one to provide empirical evidence on the effects on scores of this heterogeneity in school starting age. Moreover, I provide evidence that even if more skilled pupils are selected into early enrollment, they do not recover better than the average. This could mean that a lot of potential from high skilled children is wasted by the choice of the parents of sending them too early to primary school. The determinants of this gap is not studied in this paper, however, it is hard to believe that parental background or beliefs are the only drivers. In fact, the geographic gap could not be explained simply by heterogeneity in parents' characteristics. Moreover, the difference is in the demand for early enrollment: school rules are very similar across regions. Consequently, it is likely that two different equilibria arise because of some kind of social norm, or because parents in the South are more likely to imitate the behavior of their peers. Social interaction effects are then very plausible to play an important role in this framework. However, to study them was not the purpose of this work.

The second important result of this paper lies in the analysis of the reform of the primary school enrollment system. The change in the rules made it easier for parents to enroll children earlier, as a result, the North-South gap in the average age of the same grade cohort increased. This exogenous variation generates an increase in the regional divide in scores at standardized test, creating a dramatic jump in the number of early starters, especially in the South. After the reform, even more high skilled pupils in the South have been sent to primary school earlier, potentially harming their skill formation.

Policymakers should take into account this phenomenon when studying academic achievement differentials within the country and this work suggests that the reform had a negative effect on students' performance. Not only it generated more within-class variation in age in the South, making the teachers' work harder, but also it lowered the academic performance of students.

The main conclusion of this paper is then that early enrollment is a negative practice and that parents should not have flexibility in the choice of school starting age.

References

[1] Joshua D. Angrist, Erich Battistin, and Daniela Vuri. In a small moment: Class size and moral hazard in the Italian Mezzogiorno. *Am. Econ. J. Appl. Econ.*, 9(4):216–249, 2017.

[2] Joshua D. Angrist, Guido W. Imbens, and Donald B. Rubin. Identification of Causal Effects Using Instrumental Variables. *J. Am. Stat. Assoc.*, 91(434):444–455, 1996.

[3] Pier Francesco Asso, Laura Azzolina, and Emmanuele Pavolini. *L'Istruzione Difficile, I Divari nelle Competenze fra Nord e Sud.* 2015.

[4] Kelly Bedard and Elizabeth Dhuey. The persistence of early childhood maturity: International evidence of long-run age effects. *Q. J. Econ.*, 121(4):1437–1472, 2006.

[5] Marco Bertoni, Giorgio Brunello, and Lorenzo Rocco. When the cat is near, the mice won't play: The effect of external examiners in Italian schools. *J. Public Econ.*, 104:65–77, 2013.

[6] Karen L. Bierman, Marcela M. Torres, Celene E. Domitrovich, Janet A. Welsh, and Scott D. Gest. Behavioral and cognitive readiness for school: Cross-domain associations for children attending head start. *Soc. Dev.*, 2009.

[7] Sandra E. Black, Paul J. Devereux, and Kjell G. Salvanes. Too young to leave the nest? The effects of school starting age. *Rev. Econ. Stat.*, 2011.

[8] John Bound, David A. Jaeger, and Regina M. Baker. Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *Journal of the American Statistical Association*, 1995.

[9] H. C.M. CARROLL. SEASON OF BIRTH AND SCHOOL ATTENDANCE. *British Journal of Educational Psychology*, 1992.

[10] Thomas Cornelissen and Christian Dustmann. Early school exposure, test scores, and noncognitive outcomes. *Am. Econ. J. Econ. Policy*, 11(2):35–63, 2019.

[11] Flavio Cunha and James Heckman. The technology of skill formation. *Am. Econ. Rev.*, 97(2):31–47, 2007.

[12] Flavio Cunha, James J. Heckman, Lance Lochner, and Dimitriy V. Masterov. Chapter 12 Interpreting the Evidence on Life Cycle Skill Formation. *Handb. Econ. Educ.*, 1(06):697–812, 2006.

[13] C. De Chaisemartin and X. D'Haultfoeuille. Fuzzy differences-in-differences. *Rev. Econ. Stud.*, 85(2):999–1028, 2018.

[14] Esther Duflo. Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment. *Am. Econ. Rev.*, 2001.

[15] Todd E. Elder and Darren H. Lubotsky. Kindergarten Entrance Age and Children's Achievement. *J. Hum. Resour.*, 44(3):641–683, 2009.

[16] Ainhoa Aparicio Fenoll, Nadia Campaniello, and Ignacio Monz. Parental Love Is Not Blind : Identifying Selection into Early School Start. *Work. Pap.*, 2018.

[17] Peter Fredriksson and Björn Öckert. Life-cycle effects of age at school start. *Econ. J.*, 124(579):977–1004, 2014.

[18] C. Gillberg. Do children with autism have March birthdays? *Acta Psychiatrica Scandinavica*, 1990.

[19] James J. Heckman. Schools, skills, and synapses. *Econ. Inq.*, 2008.

[20] Italian Ministry of Education. Rapporto Prove Invalsi. Technical report.

[21] By Karthik Muralidharan and Nishith Prakash. Cycling to School: Increasing Secondary School Enrollment for Girls in India and various seminar participants for helpful comments and suggestions. *Am. Econ. J. Appl. Econ.*, 9(3):321–350, 2017.

[22] Andrea Mühlenweg, Dorothea Blomeyer, Holger Stichnoth, and Manfred Laucht. Effects of age at school entry (ASE) on the development of non-cognitive skills: Evidence from psychometric data. *Econ. Educ. Rev.*, 31(3):68–76, 2012.

[23] E. O'Callaghan, T. Gibson, H. A. Colohan, D. Walshe, P. Buckley, C. Larkin, and J. L. Waddington. Season of birth in schizophrenia: Evidence for confinement of an excess of winter births to patients without a family history of mental disorder. *British Journal of Psychiatry*, 1991.

[24] Michela Ponzo and Vincenzo Scoppa. The long-lasting effects of school entry age: Evidence from Italian students. *J. Policy Model.*, 2014.

[25] P. C. Sham, E. O'Callaghan, N. Takei, G. K. Murray, E. H. Hare, and R. M. Murray. Schizophrenia following pre-natal exposure to influenza epidemics between 1939 and 1960. *British Journal of Psychiatry*, 1992.

[26] Seung Hee Son, Kangyi Lee, and Miyoung Sung. Links Between Preschoolers' Behavioral Regulation and School Readiness Skills: The Role of Child Gender. *Early Educ. Dev.*, 2013.

Appendix A

Graphs of scores on age-in-months for each year in the dataset:

Figure 9

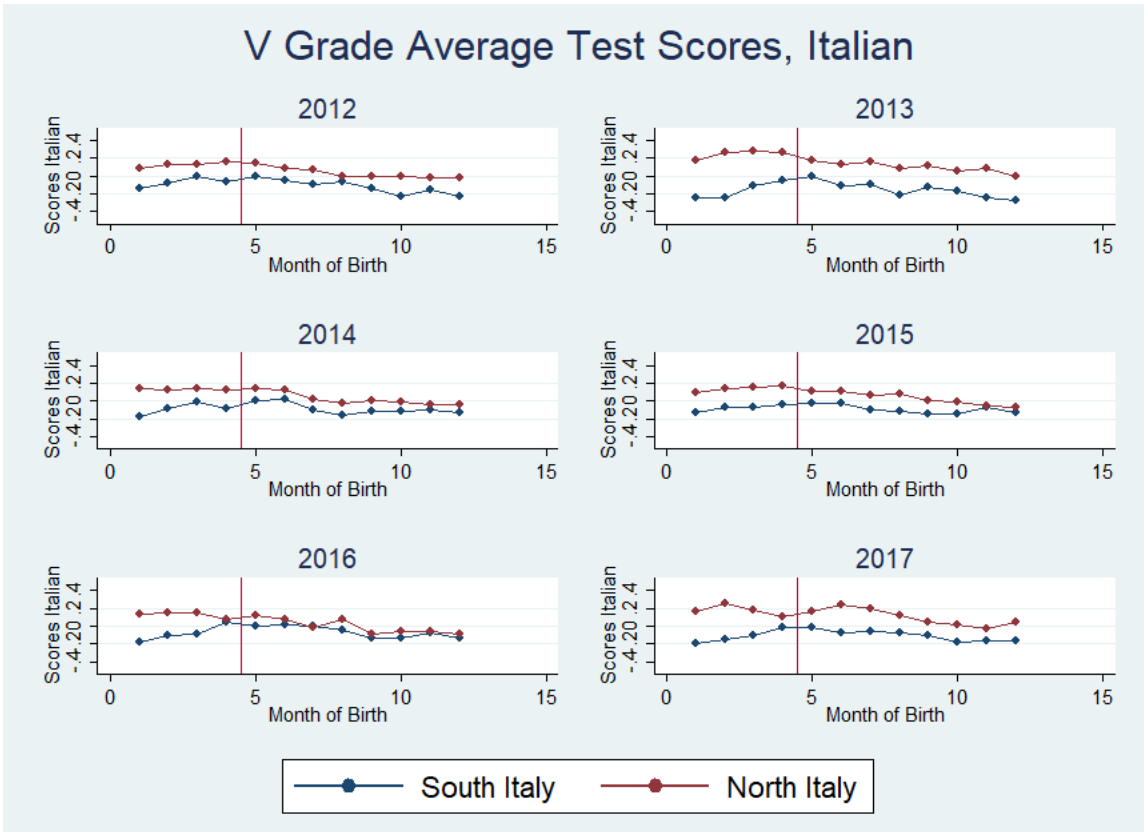
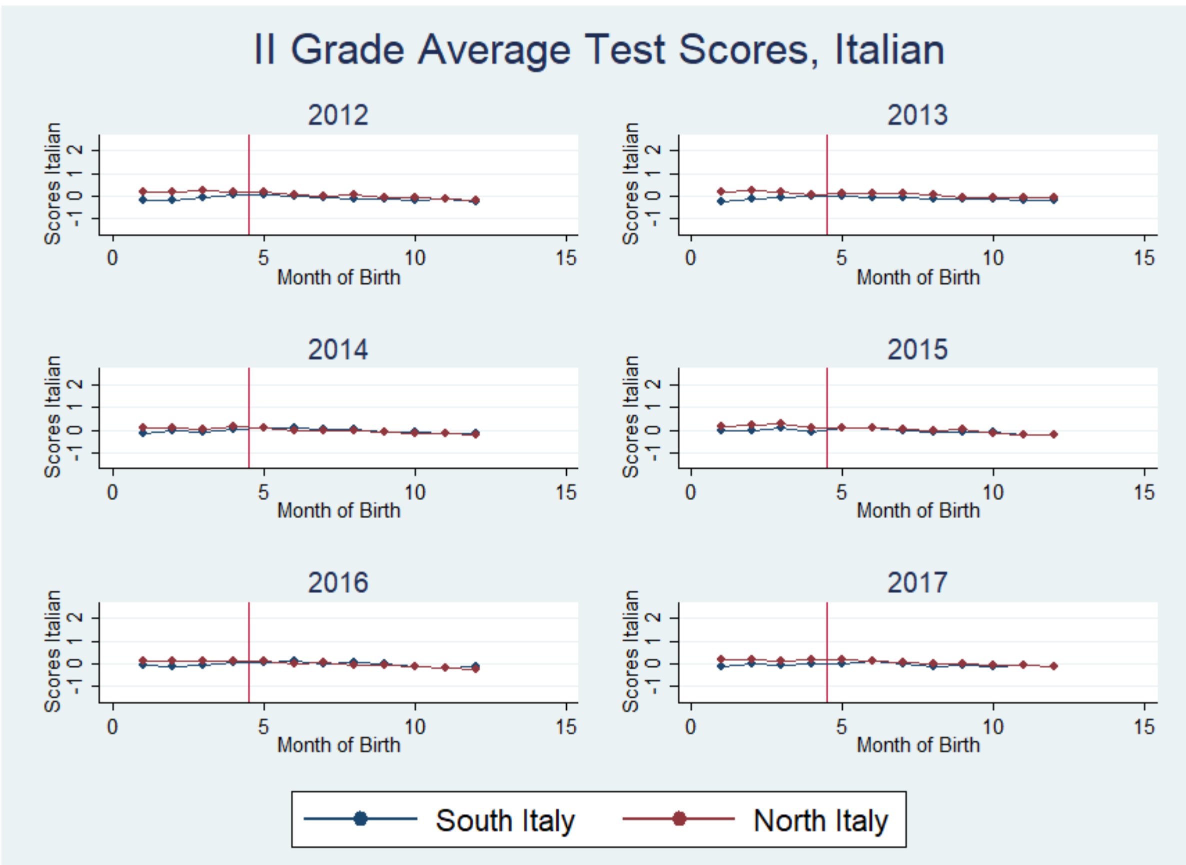


Figure 10


II Grade Average Test Scores, Italian
2012
2013
2014
2015
2016
2017
Scores Italian
-1 0 1 2
0
5
10
15
Month of Birth
South Italy
North Italy

Appendix B

Table19 and 20 presents coefficients for linear effect of age on scores of not eligible students for II and V grade respectively.

Table 19. Coefficients for linear effect of age on II Grade Scores in Italian, North vs South Italy

			Panel A South Italy			
	(1)	(2)	(3)	(4)	(5)	(6)
	2012	2013	2014	2015	2016	2017
Month of birth	-0.030***	-0.022***	-0.032***	-0.039***	-0.038***	-0.023***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)
Constant	0.149***	0.075	0.261***	0.256***	0.316***	0.140**
	(0.056)	(0.058)	(0.057)	(0.071)	(0.058)	(0.058)
Observations	6,914	6,136	6,512	4,368	6,267	6,571
R-squared	0.004	0.002	0.004	0.006	0.006	0.002
			Panel B North Italy			
Month of Birth	-0.038***	-0.042***	-0.026***	-0.048***	-0.039***	-0.031***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	0.301***	0.402***	0.152**	0.368***	0.273***	0.257***
	(0.053)	(0.062)	(0.063)	(0.061)	(0.063)	(0.061)
Observations	7,858	5,509	5,618	5,337	5,409	5,420
R-squared	0.006	0.007	0.003	0.010	0.006	0.004
			Panel C Interaction			
Month of Birth	-0.038***	-0.042***	-0.026***	-0.048***	-0.039***	-0.031***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
South	-0.152**	-0.327***	0.109	-0.112	0.043	-0.117
	(0.077)	(0.085)	(0.085)	(0.094)	(0.085)	(0.084)
Interaction	0.008	0.020**	-0.006	0.009	0.001	0.008
	(0.008)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Constant	0.301***	0.402***	0.152**	0.368***	0.273***	0.257***
	(0.053)	(0.062)	(0.063)	(0.061)	(0.063)	(0.061)
Observations	14,772	11,645	12,130	9,705	11,676	11,991
R-squared	0.006	0.010	0.004	0.008	0.006	0.003
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20. Coefficients for linear effect of age on II Grade Scores in Math, North vs South Italy

	Panel A South Italy					
	(1)	(2)	(3)	(4)	(5)	(6)
	2012	2013	2014	2015	2016	2017
Month of birth	-0.031***	-0.024***	-0.045***	-0.041***	-0.019***	-0.026***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
Constant	0.223***	0.089	0.421***	0.295***	0.153**	0.171***
	(0.060)	(0.061)	(0.064)	(0.076)	(0.064)	(0.060)
Observations	6,598	5,886	6,339	4,136	6,103	6,337
R-squared	0.003	0.002	0.007	0.006	0.001	0.003
	Panel B North Italy					
Month of Birth	-0.043***	-0.042***	-0.026***	-0.045***	-0.032***	-0.039***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Constant	0.297***	0.368***	0.123**	0.324***	0.221***	0.316***
	(0.051)	(0.060)	(0.059)	(0.060)	(0.059)	(0.060)
Observations	7,673	5,346	5,509	5,247	5,285	5,258
R-squared	0.008	0.008	0.003	0.009	0.005	0.007
	Panel C Interaction					
Month of Birth	-0.043***	-0.042***	-0.026***	-0.045***	-0.032***	-0.039***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
South	-0.074	-0.278***	0.299***	-0.029	-0.067	-0.145*
	(0.079)	(0.086)	(0.087)	(0.097)	(0.087)	(0.085)
Interaction	0.012	0.018*	-0.019**	0.004	0.013	0.013
	(0.009)	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)
Constant	0.297***	0.368***	0.123**	0.324***	0.221***	0.316***
	(0.051)	(0.060)	(0.059)	(0.060)	(0.059)	(0.060)
Observations	14,271	11,232	11,848	9,383	11,388	11,595
R-squared	0.006	0.008	0.009	0.007	0.003	0.005
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21. Coefficients for linear effect of age on V Grade Scores in Italian, North vs South Italy

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A South Italy			
	2012	2013	2014	2015	2016	2017
Month of birth	-0.0311***	-0.0307***	-0.0192***	-0.0151**	-0.0228***	-0.0230***
	(-6.13)	(-5.33)	(-3.73)	(-2.58)	(-4.27)	(-4.19)
_cons	0.145**	0.109*	0.0758	0.0323	0.127**	0.0892
	(3.27)	(2.18)	(1.67)	(0.63)	(2.70)	(1.86)
N	7413	7109	7501	5181	7347	7454
			Panel B North Italy			
Month of Birth	-0.0225***	-0.0221***	-0.0271***	-0.0290***	-0.0289***	-0.0341***
	(-5.04)	(-3.72)	(-5.31)	(-6.11)	(-5.57)	(-6.01)
_cons	0.224***	0.287***	0.252***	0.275***	0.238***	0.384***
	(5.75)	(5.47)	(5.63)	(6.57)	(5.15)	(7.76)
N	8212	6038	6182	6376	6200	6081
			Panel C Interaction			
Month of Birth	-0.0225***	-0.0221***	-0.0271***	-0.0290***	-0.0289***	-0.0341***
	(-5.04)	(-3.72)	(-5.31)	(-6.11)	(-5.57)	(-6.01)
South	-0.0794	-0.177*	-0.176**	-0.243***	-0.111	-0.294***
	(-1.35)	(-2.44)	(-2.76)	(-3.67)	(-1.68)	(-4.28)
Month_South	-0.00856	-0.00864	0.00791	0.0140	0.00611	0.0111
	(-1.27)	(-1.05)	(1.09)	(1.86)	(0.82)	(1.41)
_cons	0.224***	0.287***	0.252***	0.275***	0.238***	0.384***
	(5.75)	(5.47)	(5.63)	(6.57)	(5.15)	(7.76)
N	15625	13147	13683	11557	13547	13535

t statistics in parentheses

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

Appendix C

Figure 3 for each year:

Figure 11

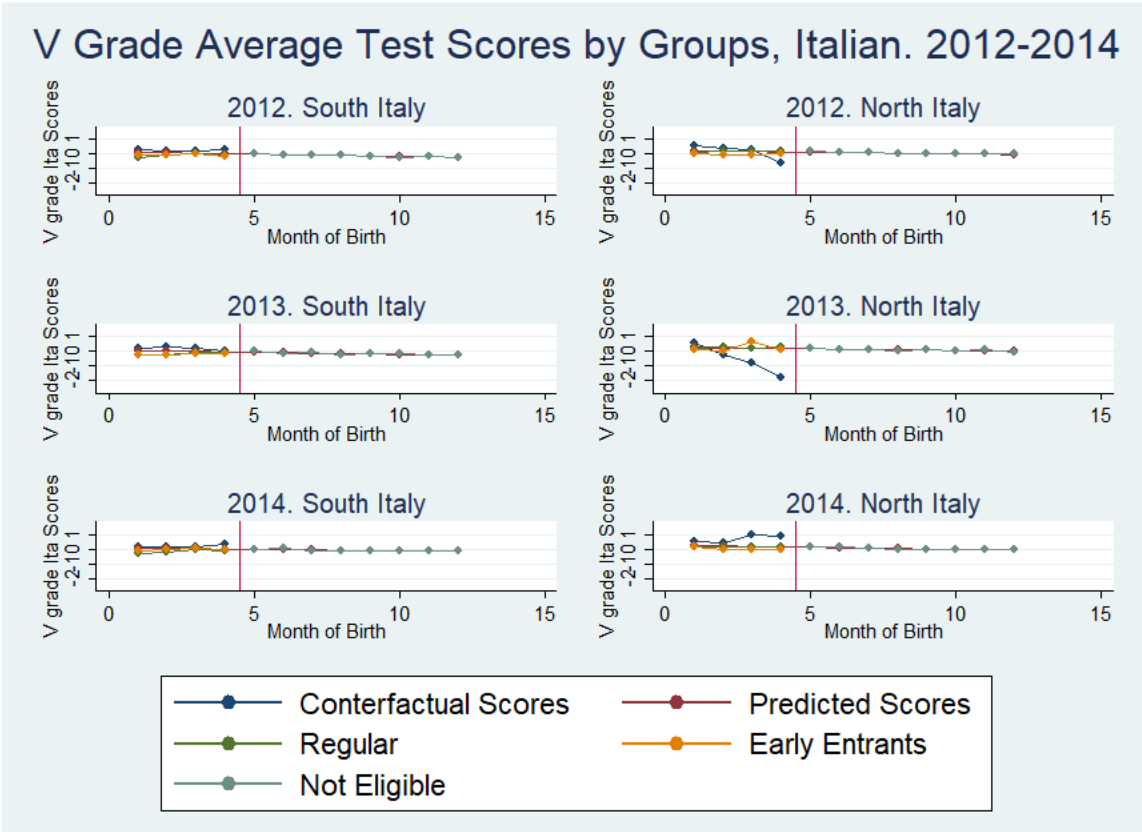
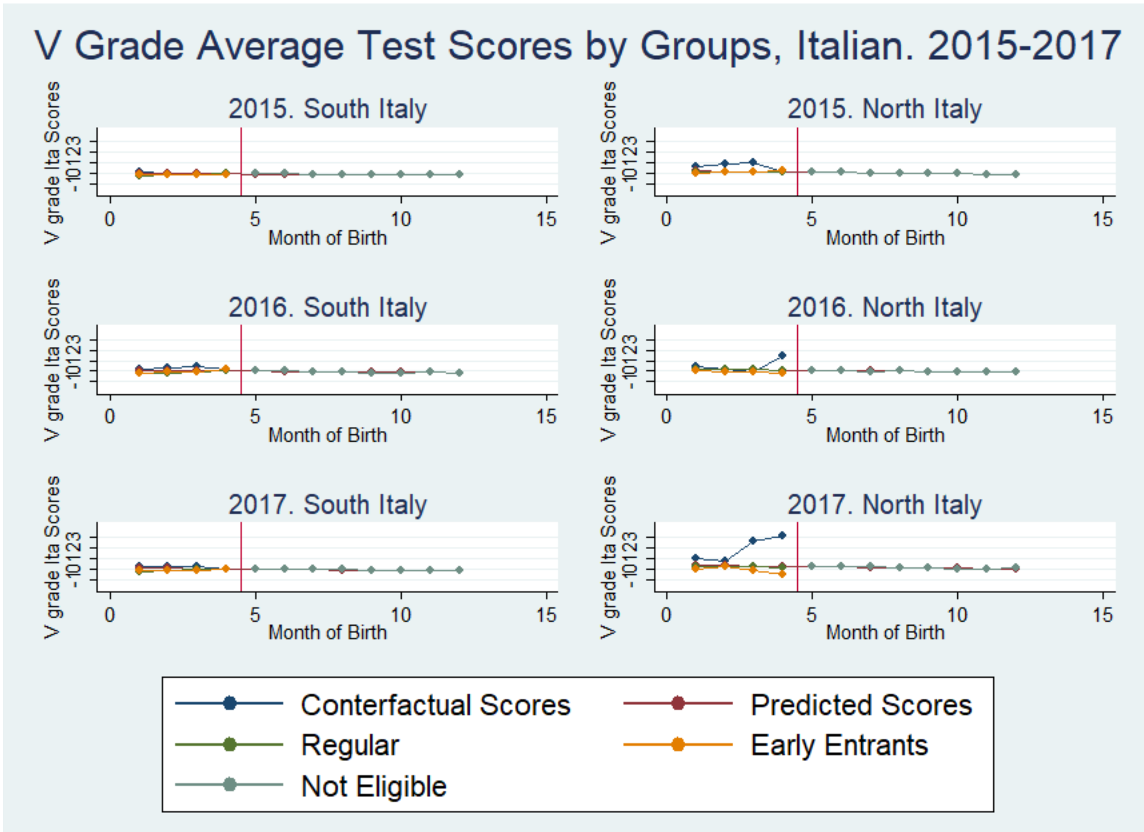

V Grade Average Test Scores by Groups, Italian. 2012-2014
2012. South Italy
2012. North Italy
2013. South Italy
2013. North Italy
2014. South Italy
2014. North Italy
V grade Ita Scores
Month of Birth
Conterfactual Scores
Predicted Scores
Regular
Early Entrants
Not Eligible

Figure 12



V Grade Average Test Scores by Groups, Italian. 2015-2017
2015. South Italy
2015. North Italy
2016. South Italy
2016. North Italy
2017. South Italy
2017. North Italy
V grade Ita Scores
-10123
0
5
10
15
Month of Birth
Conterfactual Scores
Predicted Scores
Regular
Early Entrants
Not Eligible

Chapter 2:

Understanding the Early Enrollment in South Italy: Evidence from a Survey in Primary and Pre-Primary Schools

Giorgio Monti

University of Bologna

Abstract

Parental investments in early education play a huge role in the technology of skill formation. In this work, I will study the phenomenon, common in the Italian Southern regions, of early enrollment. It consists of the practice of enrolling children born between January and April to primary school when they are 5, one year before than regular students. Since 2003 the Italian enrollment system allows this practice, and in Chapter 1 of this thesis I gave evidence that it has negative effects on standardized scores, also increasing the gap between North and South Italy. To study the determinants of this practice, I designed a survey for parents of children enrolled in pre-primary school and in grade I of primary school in the school year 2018-2019. I administered the questionnaires in 5 schools located in Palermo, the capital city of Sicily, where the percentage of early entrants is slightly over 50%. With answers from the survey, I create an original dataset with 812 observations from 67 classes. Data confirms that there is selection in the choice: parents of early starters are on average more educated and live in richer neighborhoods. Moreover, using also a larger administrative dataset from the same schools in the questionnaire sample, I analyzed how social interactions affect the choice. Using the approach proposed by Graham (2008) I estimated a social multiplier of 2.7. However the subsample of pupils born between January and April is still limited, and a wider sample would be necessary to make a deeper analysis.

1 Introduction

Children's human capital formation strongly depends on parenting styles and family investment in education (Cunha 2015). Economics traditionally tries to explain differences in investments by cost-benefit analysis. In the case of investment in early education, parents cannot know exactly the amount of the benefits, which will realize only several years later, and then they are subject to high uncertainty. Cunha and coauthors (2013) show that disadvantaged parents may underestimate the returns to investment in early education, and there are also researches that show how intervention aimed to improve parental beliefs on returns have a positive impact in child developmental outcomes (Fitzsimons et al., 2016; Leffel and Suskind 2013).

In this chapter, I will try to give some insights about the phenomenon of early enrollment to primary school in South Italy. As explained in the previous chapter of this thesis, in Italy parents have the possibility to enroll their child to primary school one year earlier if she was born between the 1st of January and the 30th of April. Even if the system is the same for the whole territory, in the South the percentage of parents who choose to do so is around 5 times the percentage of northern parents who do this choice (50% vs 10%). This heterogeneity translates in a gap between the average age of cohorts: for a given grade, an average student in the South is 1.5 months younger than the average student in the North. This also generates an additional gap in outcomes: as shown in Chapter 1, around 60% in the gap in standardized test scores in Italian of II graders comes from the difference in age, and this percentage is still the 20% for V graders.

In this work, I will present the result of a survey of parents of children enrolled to primary and pre-primary public schools in Palermo, the capital city of Sicily (South Italy), where the percentage of students born between January and April who are early enrolled to primary school is 52%, very close to the South-Italy mean. Fenoll and coauthors (2018) show that there is a strong selection in the early enrollment: children who enter earlier would have performed in the top percentiles if they were enrolled regularly. However, as results from the previous chapter of this thesis pointed out, they do not seem to recover better than the average from being one year younger. Moreover, this result does not explain why the difference in the number of early enrollers is so huge between the South and the North. From interviews of school administrators, it is very likely that this is not due to different enrollment rules: the difference is then in the demand for this practice.

Responses from the surveys show that parents who enroll earlier the child to primary school are on average more educated and live in richer neighborhoods. Given that the North of Italy is on average richer and more educated than the South, this result may seem counterintuitive: family income and education cannot be the main reasons for early enrollment. From the data of the survey, it is not possible to say why in the two territories the equilibrium in early enrollment is so different, especially because the primary schools in Italy are administrated by the central government, and local administrations have little power on the issue. On the other hand, from the answers of the parents, I was able to have some preliminary results on social interaction effects. It is very likely that in this framework, parents are highly influenced by the choice of other parents. Early enrollment in the South can be seen as a social norm, and to not enroll earlier a child born in the first months of the year can be seen as a bad signal on the pupil's ability.

The article will proceed as follows: Section 2 describes the questionnaire structure, location and target; in Section 3 I will show summary statistics from the survey and from municipality administrative data; Section 4 presents preliminary results on determinants of early enrollment; Section 5 studies Social Interaction Effects and Section 6 concludes.

2 The Questionnaire[1]

The questionnaire was designed to be filled either by one parent or by both parents together and it was composed of 5 typologies of questions:

1. Family Background and Composition
2. Parents activities at home with the child and parents beliefs about child ability
3. Parents Expectations on the academic achievement of the child
4. Social interaction with other parents in the same class
5. Question about the choice of early enrollment (only for parents of children born between 1st of January and 30th of April)

In the first part, parents are asked questions about their age, the number of people living in the house, the marital status, their education and their employment. The answers were useful firstly to understand the family background of students in different parts of the city. Secondly, and most importantly for the purpose of this work, they allow understanding how parents' characteristics are associated with different choices.

[1] The template of the questionnaire is attached at the end of this chapter

In the second section, there are more articulated questions on the activities that parents do with their children. Some examples are: “How many days in a week do you read to your child” or “How many days in a week do you play with your child with alphabet learning toys?”. Other questions in this section are on the frequency they call for a baby-sitter and on the other relatives who take care of the child (Grandparents or siblings). The activities parents do with the child are very important for the formation and development of the pupil’s skill as well, and the answers to these questions allow to analyse this aspect of parenting. In this part of the questionnaire, I also asked questions about the parents’ perception of the child’s ability in reading, writing and simple arithmetic. The answers are given on a 1 to 5 scale, where 1 means very bad and 5 very good. Parental beliefs on the child’s ability can be also seen as their beliefs about the child’s readiness to start primary school and then it is likely to be crucial in the choice of early enrollment.

The third set of questions investigates expectations about the future academic achievement of the child. Parents are asked which level of education they expect their child will achieve (mandatory school, high school diploma or graduation) and whether they expect the child will fail at least one year during his academic path (No, more no than yes, 50-50 probability, more yes than no and Yes). The options available to parents may seem too vague, but it is important to keep in mind that half of the respondents have low education, and may have problems in understanding the concept of probability, as shown by a pilot questionnaire. Expectations about the educational achievement of the child are important to understand the subjective beliefs of parents and their effects on investment in education and hence on the choice of early enrollment.

How much parents interact with parents of their child’s classmates may be crucial in many important aspects of parenting. Parents could imitate the behavior of their peers and are likely to make the decision taking into account the choices of other parents or social norms. In section 4 of the questionnaire, I asked how frequently the child meets her classmates outside school, meets friends other than her classmates, and how frequently parents talk with parents of the child’s classmates. The frequency is asked in days in a week.

The last section of the survey was targeted only to parents of children eligible for early enrollment (born between 1st of January and 30th of April). In this part, I asked whether they follow the opinion of the pre-primary teacher about early enrollment, and to select the main reasons why they asked for early enrollment (or why they did not). In this way, I can control if the choice of early enrollment simply follows the tindications of the teachers. However, this does not seem to be the case.

In the end, the questionnaire had 48 questions, and was designed such that parents would spend 15 to 20 minutes to complete it.

3 Descriptive Statistics

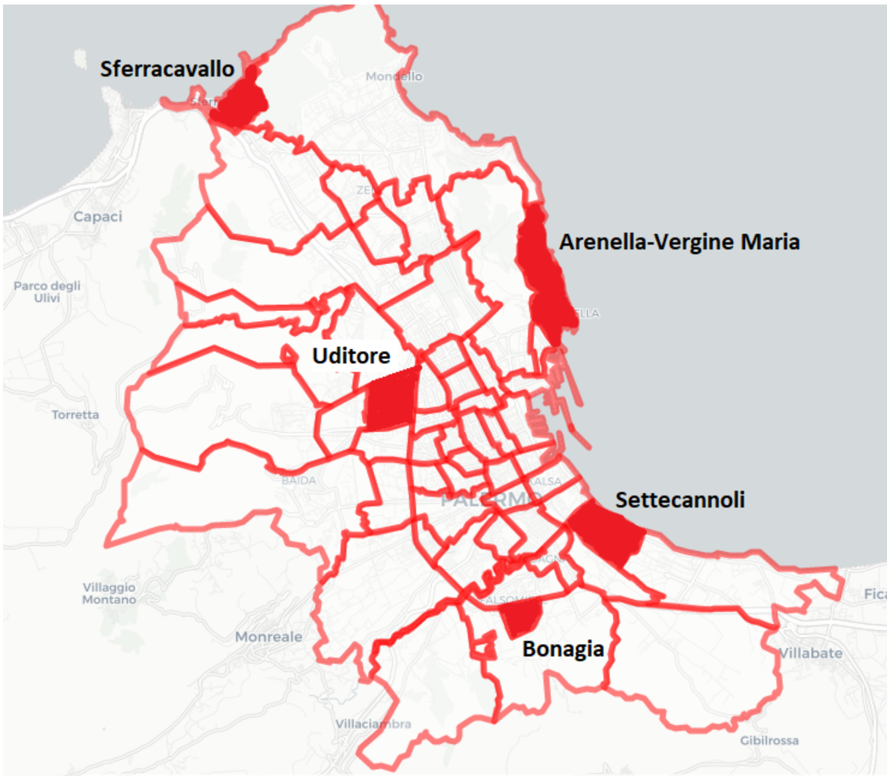
The survey was administered between March and April 2019 in 5 public schools in 5 different neighborhoods in Palermo. The 69 public schools of the municipality were invited to participate by the Regional Scholastic Office of Palermo, the local branch of the Italian Ministry of Education, and the schools were selected by a chronological criterion: the first 5 schools who answered were selected. In total only 7 schools answer positively: one was not included in the survey because it has a 40% of immigrant students, and then it will not be useful for the purpose of the research, and a second was excluded because it was too small: it as only two grade I class and no pre-primary class.

Figure 1 shows the location of the selected schools in the municipality territory. The selected schools are located quite far from each other and all across the territory: “Sferracavallo” is a peripheric neighborhood in the North-West mainly inhabited by fishermen and tourism sector workers. It is quite separated from the city, and also difficult to reach by public transportation. It is often considered more like a small town rather than a part of Palermo. “Arenella-Vergine Maria” is an ancient neighborhood on the shore as well, but with different characteristics: it includes the second biggest cemetery of the town and people mainly work in four sectors: services connected to funerals, fishing, shipyards and as dockworkers, since the big harbor of Palermo is very close to the neighborhood. “Uditore” is the richest neighborhood among those included in the research. It is a recent residential area, inhabited by people working in a wide range of sectors. On the other hand, “Settecanoli” in the South of the city, is the poorest area in the sample, and also one of the poorest areas in the city. Together with “Brancaccio” which is just next to it, they have been sadly famous for the strong presence of mafia families. After the bombing of the city during World War II, this area hosted a significant percentage of displaced people who lived in the city center. In the end “Bonagia”, is a residential area similar to Uditore, but it is poorer: most of the people who live there, have arrived from the countryside during the last decades.

Figure 1 shows the geographic location of the neighborhood and table 1 present summary statistics.

From table 1 it is evident how the neighborhoods are very different from each other. Data comes from the Municipality, and are referred to 2011. Is it possible to see how Settecannoli is the most populated neighborhood in the sample and has the highest percentage of minor at risk with almost

Figure 1



17 minors every thousand who are signaled to the social services (USSM). Moreover, for 2108 children between 0 and 3 it has only 28 spots in one public nursery school. All the other areas have USSM which is less than half of that in Settecannoli, with a minimum of 5.2‰ in Uditore, who also has the highest number of Public Nursery Schools with 243 spots for 1156 children who are between 0 and 3.

Table 2 reports instead summary statistics on the schools, and on parents who replied to the survey. The biggest school analysed is the one located in Bonagia, who has 382 students, whereas the smallest is located in Arenella and has 150 students. The overall response rate was quite high, being around 70%, with no-school with a percentage of respondents lower than 57%. The final dataset has 812 observations. The administration of the surveys was indeed made to parents by teachers, who strongly supported the research. The answers are consistent with data from the neighborhood: Uditore presents the lowest percentage of unemployed parents, the highest percentage of parents with at least a high school diploma and who are graduated. Overall the data reflects the low human capital of Palermo inhabitants: Mothers without a diploma is close to 50% in most of the areas, and around 70% is either unemployed or a housekeeper.

Table 1

	Data on Neighborhoods				
	Arenella	Bonagia	Settecannoli	Sferracavallo	Uditore
pop 0/3	358	1677	2108	904	1156
pop 0/5	542	2548	3253	1394	1730
Public Nursery	0	3	1	0	5
Nursery Spots	0	197	28	0	243
USSM (‰)	8.40	9.20	16.65	7.20	5.20

Table 2

	Arenella	Bonagia	Settecannoli	Sferracavallo	Uditore
Size	150	382	346	158	182
Response Rate	0.83	0.61	0.57	0.74	0.79
Early Entrants	0.55	0.31	0.35	0.50	0.61
Mother at Home	0.72	0.70	0.68	0.72	0.59
Father unemployed	0.18	0.27	0.21	0.32	0.17
Mother High School	0.48	0.53	0.49	0.53	0.69
Father High School	0.43	0.40	0.46	0.42	0.57
Mother Graduated	0.07	0.11	0.15	0.05	0.17
Father Graduated	0.04	0.06	0.09	0.02	0.09

The percentage of early entrants reflects what already noticed in the introduction: the highest rate is in Uditore with the 61% of children born between January and April, who either are attending the I grade of primary as early starters in the school year 2018/2019 or are 5 years old in 2019 and will attend the I grade in the school year 2019/2020. On the other hand, the lowest rates of early entrants are in the two schools in the South of the city, Bonagia and Settecannoli, where they are 31% and 35% respectively.

3.1 Descriptive statistics for Early Entrants

To give a sense of the selection in early enrollment, Table 3 shows the descriptive statistics for early entrants and for regular students.

Numbers in bold represent significant differences between early entrants and regulars. As expected, parents who enroll the child earlier are on average more educated. Moreover, they have better expectations about the future educational achievement of the child (the variable *Expected Education* is a discrete variable that can have values from 1 to 3, where 1 is mandatory schooling, 2 means high school diploma and 3 college graduation). Parents who choose the early enrollment also respond to spend

Table 3

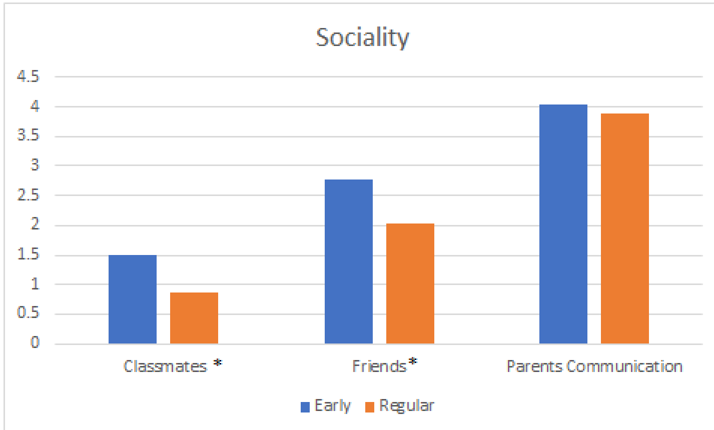
	Early	Regular	Diff.	t-stud Diff.
Female	0.56	0.42	**0.14**	**2.26**
Mother High School	0.63	0.48	**0.15**	**2.29**
Father High School	0.56	0.41	**0.15**	**2.38**
Mother Graduated	0.15	0.10	0.05	1.17
Father Graduated	0.05	0.08	-0.03	0.80
Mother at home	0.61	0.70	-0.09	1.49
Father Unemployed	0.25	0.23	0.02	0.25
Home Education	3.92	3.76	0.16	0.75
Expected Education	2.47	2.30	**0.17**	**2.06**
Perceived Ability Math	2.94	2.91	0.03	0.19
Perceived Ability Read.	3.28	3.30	-0.02	0.14

slightly more time in home education than parents who choose regular enrollment. These differences between regulars and early enrolled students are consistent with those presented in table 5 of Chapter 1. Surprisingly, there is no significant difference in the perceived ability, neither in mathematics, nor in reading, between parents of early enrolled and regular students. We would expect that parents decide for early enrollment also because they have a better perception of their children's ability when compared with parents who decide to enroll their children to primary school one year later.[2]

Another interesting aspect to analyze is the difference in the intensity of social interaction between the two groups. Figure 2 shows the frequency by which the child meet classmates and other friends outside school and how much the parents communicate with parents of their child's classmates. The figure shows that children who are early enrolled meet their friends and classmates more frequently on average than regulars, and the difference is statistically significant at the 5% confidence level. Also parents of early enrollers communicate slighlty more with other parents, compared with regulars' parents. However, this difference is not significant at the 10% confidence level.

[2]Perceived ability is a variable constructed by taking the mean of answers on a Likert scale from 1 (very bad) to 5 (very good) to questions 24-28 for literacy and 29-31 for mathematics of the questionnaire attached to this chapter.

Figure 2



4 Empirical Analysis of the Early Enrollment

In this section, I present the results on the estimation on the size of the effect of parental background on early enrollment.

In the final sample I have 812 observations, but for the analysis I can only use parents from children born between January and April, eligible for the Early Enrollment. I end up with a sample of 237 parents of children eligibles. Table 4 presents results of OLS regressions where the dependent variable is a dummy equal to 1 if parents have chosen to enroll the child earlier to primary school.

From table 4 it is possible to see that almost none of the coefficients has statistical significance. This can be due to the fact that the sample is limited, and to the fact that the choice has more to do with social interactions or with some kind of social norm than strictly to parents' characteristics. However, the signs of the coefficient are always consistent with the story that more educated and more wealthy parents enroll their child earlier: mothers who do not work are less likely to enroll the child earlier, the coefficient for the dummy on having completed high school is also positive and close to significance. Moreover, results from regressions give two other important insights: females are more likely to be enrolled earlier and if the child has no elder siblings (the variable *Eldest* is a dummy equal to 1 if the child is the eldest sibling) she is about 10% less likely to be early enrolled *ceteris paribus*. The first result is consistent with the fact that girls are often considered mature earlier than boys (Bierman et al., 2009; Son et al., 2013), the second instead may be explained by the fact that if a child has an older sibling already enrolled to primary school, parents may find convenient to have two

Table 4. Determinants of Early Enrollment: OLS regressions

VARIABLES	(1) Early	(2) Early	(3) Early	(4) Early	(5) Early	(6) Early
Feb	-0.220**	-0.218**	-0.231**	-0.171*	-0.174*	-0.186*
	(-2.523)	(-2.549)	(-2.501)	(-1.877)	(-1.945)	(-1.898)
March	-0.213**	-0.242***	-0.205**	-0.147	-0.184**	-0.159
	(-2.486)	(-2.852)	(-2.173)	(-1.636)	(-2.063)	(-1.556)
April	-0.268***	-0.274***	-0.311***	-0.226**	-0.247***	-0.328***
	(-3.209)	(-3.376)	(-3.450)	(-2.562)	(-2.842)	(-3.453)
female	0.154**	0.137**	0.069	0.219***	0.199***	0.138*
	(2.495)	(2.269)	(1.021)	(3.432)	(3.162)	(1.899)
Mother HS	0.079	0.063	-0.030	0.044	0.017	-0.082
	(1.012)	(0.828)	(-0.371)	(0.526)	(0.211)	(-0.945)
Father HS	0.129*	0.100	0.095	0.096	0.064	0.080
	(1.814)	(1.410)	(1.191)	(1.250)	(0.840)	(0.981)
Mother Unemp.	-0.072	-0.059	-0.168**	-0.119	-0.110	-0.247***
	(-0.980)	(-0.783)	(-2.051)	(-1.596)	(-1.483)	(-3.120)
Eldest	-0.109*	-0.113*	-0.136**	-0.105	-0.110	-0.090
	(-1.761)	(-1.791)	(-2.006)	(-1.612)	(-1.638)	(-1.242)
Read Ability Perc.				0.019	0.030	0.057
				(0.583)	(0.895)	(1.398)
Math Ability Perc.				-0.016	-0.013	-0.031
				(-0.409)	(-0.328)	(-0.647)
Exp. Grad.				0.105	0.124*	0.070
				(1.405)	(1.695)	(0.911)
Constant	0.505***	0.537***	0.713***	0.436***	0.439***	0.627***
	(4.337)	(4.682)	(5.743)	(2.843)	(2.997)	(3.477)
Observations	235	235	235	216	216	216
R-squared	0.145	0.190	0.529	0.181	0.221	0.568
Fixed Effects	No	School	Class	No	School	Class

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

children in the same school as soon as possible.

It is also important to notice that some estimates change quite significantly when adding school and class fixed effects. It is indeed very likely that school selection is not exogenous. First of all, school selection is mainly based on location, and where parents live depends obviously to many variables. Moreover, to include class fixed effect is likely to remove a lot of the variability in the data, already limited. Since only students eligible for enrollment are included in this analysis, I have an average of just 4.2 observations per class.

However, all the coefficients have the same signs as in the regressions using the INVALSI data whose results were presented in table 6 of Chapter 1: more educated parents are more likely to early enroll their child to school, whereas unemployed parents in the South are less likely to do that.

The main limitation here seems to be the small size of the sample. A follow up was supposed to take place in March 2020, after a new cohort of parents would have decided about early enrollment. However, because of Covid-19 crisis, schools were forced to close and faced several problems in managing on-line learning. For these reasons, it wasn't possible to gather additional data and to make the analysis more powerful. To compensate for this problem, I gathered additional administrative data. However, this data do not contains information about parents' background, and was used only to do the preliminary analysis on social interaction effects exposed in the next section.

5 Peer Effects Analysis

As noticed, social interactions are likely to be very important in the choice of enrollment. In fact, parental background and beliefs cannot fully explain why so many parents in the South enroll earlier their child to school, compared to those in the North of Italy. Identification of Peer Effects has been investigated for years in economic literature. In his pioneering study, Manski (1993) distinguishes three kinds of peer effects: *exogenous effects*, the influence of exogenous peer characteristics, *endogenous effects*, the influence of peer outcomes, and *correlated effects*, the effects of facing the same environment and more generally of being subject to a common influence.

Firstly, I am interested in establishing whether the parents' choice for early enrollment is affected by the prevalence of that choice among parents of children in the same pre-primary class. I choose the class as relevant group for interaction because I assume that children mainly interact with their classmates and consequently, parents interact more with parents of classmates. Since the choice for early enrollment is only available to parents of children born between the 1st of January and 30th of April, the relevant group for social interaction is constituted by parents of children in the same class born in that period of the year. Parents have time to decide whether to early enroll their children to primary school in the following year usually until the end of February of the year when their child turns 5. I will also assume that the choice of parents of child i is public to parents of i' s classmates.

In this section, I use two different methods to study the magnitude of social interactions effects.

The first one follows the empirical specification of Case and Katz (1991) and Gaviria and Raphael (2001), the second one relies on the excess variance approach proposed by Graham (2008).

In the first analysis, I model individual behavior (parents choice for early enrollment) with the simple linear equation:

$$Y = \alpha + X\beta + \theta\bar{Y}_c + \epsilon$$

where Y is the binary outcome for the choice of early enrollment, X is a vector of child and parents characteristics, $\bar{Y}_c$ is the average incidence of the early enrollment in class c, and ϵ is a random component independent across individuals. In this framework, average characteristics of students in class c $\bar{X}_c$ do not affect directly Y, (no exogenous effects) but only indirectly through the behavior of the group.

I will then estimate the model:

$$Y_{ics} = \alpha_s + X_{ics}\beta + Q_{cs}\phi + \theta\bar{Y}_{-ics} + \epsilon_{ics} \tag{1}$$

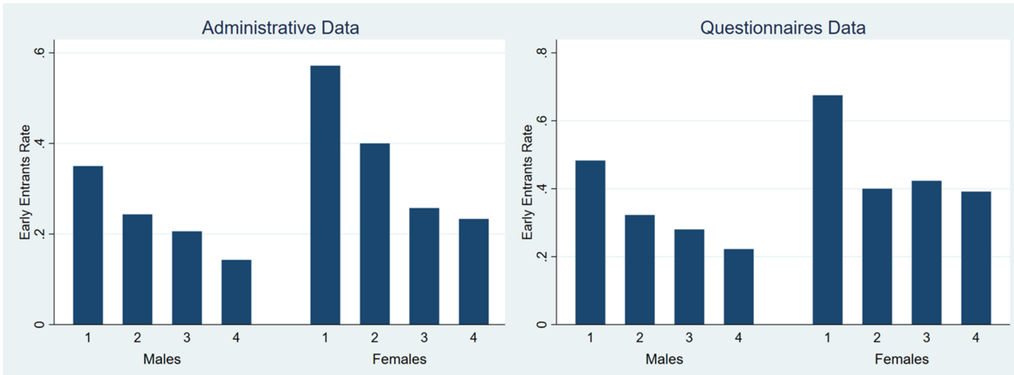
where Y_{ics} is the probability that parents of student i, in class c, of school s, will choose early enrollment, X_{ics} is a vector of students and parents characteristics;$\bar{Y}_{-ics}$ is the proportion of parents of children in the same class of i that choose early enrollment, after excluding parents of i. Q_{cs} is a vector of class characteristics and ϵ_{ics} is random disturbance.

In the estimation of this equation there are many potential sources of endogeneity bias. First of all, it assumes that the average behavior of the group affects individual behavior, but straightforwardly, also the opposite is true. Hence, individual error term will be correlated with $\bar{Y}_{-ics}$, and OLS estimates will be biased. Secondly, error terms of students in the same class will be correlated if relevant class-specific variables are omitted. And finally, if there is sorting in classrooms according to some unobservables, OLS will be biased upward.

To correct for the endogeneity bias coming from simultaneous effect, I assume that $\bar{X}_{-ics}$, average background characteristics of children in the same class of i and of their parents, do not affect directly the choice of i, but only indirectly through $\bar{Y}_{-ics}$. As a result, under this assumption, $\bar{X}_{-ics}$ will provide a natural set of instruments for $\bar{Y}_{-ics}$ (Gaviria and Raphael 2001).

As previously said, along with data from the questionnaires, I also gathered administrative data from the schools that participated to the survey. These data include all students in pre-primary classes of selected schools. For these students I only know the class, the date of birth, the gender and the choice for early enrollment. The administrative data have the advantage of not having missing observation nor missing classes, but on the other hand, give no information about parents. However, some of the

Figure 3. Early Entrants rate by Month of Birth and Gender



information could be enough to have some preliminary evidence of social interaction effects.

The administrative dataset contains 262 observations of pre-primary students eligible for early enrollment (Questionnaires dataset contains information about 148 students of pre-primary school eligible for early enrollment). Data come from the same 5 schools where the questionnaires were handed out. However, since not every class agreed to participate in the questionnaire, administrative data contain observation from 57 classrooms (questionnaires were collected in 37 pre-primary classes).

Using both samples I will first estimate coefficient from equation (1) and then I will show results from 2sls regression using average background variables of classmates $\bar{X}_{-ics}$ as instruments.

To decide which instruments best fit in this framework I will start by analyzing the effect of month of birth on the decision of early enrollment. In previous sections, I showed how parents and children characteristics affect the choice of early enrollment when not taking into account social interactions. However, I did not show how the month of birth affects the choice (in Chapter 1 I show these results for the entire sample of INVALSI test takers). In both samples I used here (questionnaires and administrative data), the pattern is the same: students born in January are more likely to be enrolled early than those born in April. This result has a straightforward interpretation: older students are more likely to be enrolled earlier because parents may perceive them as ready for primary school, and will perceive the cost of early enrollment as lower. Both Administrative and Questionnaires data also show that females are more likely to be early enrolled. Figure 3 shows the percentage of early entrants by Birth of Month and gender.

Gender and months of birth of other students in the same class who are eligible for early enrollment are then two candidates for instrumental variables. To run 2 stages least square regression using these variables as instruments for the average choice among parents of classmates of child i, I need to rely on some assumptions. First of all, months of birth and gender of classmates of the children i will not affect directly the choice of parents of i, but only through affecting the average choice for early enrollment among parents of eligible classmates. Moreover, I need to assume that classes in pre-primary are not formed accordingly to the month of birth nor to gender. In the end, as in any IV regressions, the instrument must not be "weak": average month of birth and gender across classmates have to affect significantly the average choice of their parents.

Table 5 reports OLS estimates of equation (2) and the two-stage least squares using gender and month of birth of peers as instruments. In all specifications I include school fixed effect to control for school characteristics and thenfor a potential source of correlated effects. For example, I will control for school policy of class formation, school quality in terms of services for students, and so on. Hence I will allow for sorting across schools, and I will only assume random assignment in classes with respect to month of birth and gender.

To check that this assumption is satisfied in the schools in the sample, I followed the method used by Ammermueller and Pischke (2009) to test whether class assignment follows some rules based on gender, age or parental background. In fact, parental background and gender are also important determinants of early enrollment. I run Pearson χ^2 tests of independence between students' characteristics and classroom assignment within each school. Table 6 reports the results.

All the p-values are well above the 5% level, giving evidence of random assignment with respect for gender, parents' education and eligibility for early enrollment.

Results reported in table 5 seems to confirm the presence of social interaction effects. However, using both questionnaires and administrative data, the estimates for the effects of average choice in the group dramatically increase when moving from OLS to 2SLS. OLS estimates say that to move from a class with no parents of eligible students opting for early enrollment to a class where 50% of eligibles decides for early enrollment, increase the probability of enrolling own child to primary school earlier by 28% and 15% using questionnaires and administrative data respectively. The coefficient for the TSLS is instead higher and very similar for both samples, being around 0.76. These estimates reflect the effect of moving to a class where the average of early enrollment among eligibles is higher because of exogenous change in class distribution of month of birth and gender. Although this heterogeneity makes it more difficult to fully rely on these results, there is preliminary evidence that peers' choices

Table 5. OLS vs TSLS regressions with inclusion of peer influence

	Quest.	Quest.	Admin.	Admin.
	(1)	(2)	(3)	(4)
VARIABLES	Early	Early	Early	Early
	OLS	TSLS	OLS	TSLS
$\bar{Early}_{-ics}$	0.565***	0.762***	0.303**	0.771*
	(4.620)	(3.388)	(2.333)	(1.648)
Feb	-0.316***	-0.324***	-0.117	-0.127*
	(-2.770)	(-3.145)	(-1.475)	(-1.700)
March	-0.277***	-0.269***	-0.227***	-0.238***
	(-2.668)	(-2.596)	(-2.931)	(-3.200)
April	-0.304***	-0.317***	-0.280***	-0.296***
	(-2.864)	(-2.887)	(-3.996)	(-3.810)
female	0.080	0.047	0.102*	0.094*
	(0.901)	(0.565)	(1.908)	(1.742)
Father HS	0.006	0.002		
	(0.068)	(0.031)		
Mother Unemp.	0.034	0.010		
	(0.363)	(0.107)		
eldest	-0.068	-0.078		
	(-0.787)	(-0.968)		
Constant	0.380***	0.340**	0.330***	0.235
	(2.708)	(1.965)	(4.669)	(0.916)
Observations	121	121	262	262
R-squared	0.340	0.325	0.187	0.144
F 1st-Stage		10.30		22.94
Fixed Effects	School	School	School	School

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Tests for Independence of Peer Variables and Class Assignment

	Arenella	Bonagia	Settecannoli	Sferracavallo	Uditore
Parents' Education:					
Pearson χ^2	0.218	0.872	0.762	0.267	0.166
Female					
Pearson χ^2	0.856	0.098	0.536	0.539	0.520
Eligibles					
Pearson χ^2	0.459	0.807	0.260	0.746	0.539

have a significant effect in this framework. I showed in chapter 1 that early enrollment is much more common in the South than in the North of Italy and that it has been true for decades. This probably means that parents in the South follow some kind of social norm or share a common belief about benefits from early enrollment. However, results just shown suggest that so many parents choose the early enrollment not only because they shared some kind of norm (correlated effects), but also because they have the propensity to behave like their peers (endogenous effects).

With this data I only observe the choice at one point in time for specific classes and schools. Hence, it would not be possible to directly observe a fully reliable source of exogenous variation in peer composition.

To give further evidence of the significance of peers' choice for the decision of early enrollment, in the next section I will follow the approach proposed by Graham (2008) who identifies peer effects based on contrasts in excess variance across social groups of exogenously different sizes.

5.1 The Excess Variance Approach

In his work of 2008, Graham proposed a new approach to identify social interaction using conditional variance restriction. Assuming that social interactions are in the linear-in-means form (Manski 1993), he estimated consistently the social multiplier by looking at the contrasts in excess variance across groups of different sizes. In this framework I can use the same method, assuming that the number of pupils eligibles for early enrollment in a class of pre-primary school is random. Compared to other work that studied the covariance implications of social interactions (Glaeser, Sacerdote and Scheinkman, 1996, 2003), Graham provided the basis and transparent conditions for point identification.

The main idea proposed by Graham is that the unconditional between-group variance is a sum of three terms: the variance of group-level heterogeneity (in this framework it can be considered as teacher characteristics), the between-group variance of individual-level heterogeneity (e.g. the variance of average parents characteristics that affect the choice of early enrollment), and finally the strength of social interaction. If there are social interactions, between-group variation in the choice of early enrollment should reflect between-group variation in peer characteristics. The problem for identification comes from the fact that excess variance can come from either group-level heterogeneity or from variation in peer characteristics across classes. Consequently, to use unconditional within- and between- group sample variance cannot be enough to test social interactions. To construct a test for social interaction, it is necessary to compare within- and between-group variances across two or more subpopulations with the same distribution of group-level heterogeneity, but a different distribution of peer characteristics.

The choice for Early Enrollment of child i in the pre-primary class c is given by:

$$Early_{ci} = \alpha_c + (\gamma_0 - 1)\bar{\varepsilon}_c + \varepsilon_{ci} \tag{2}$$

where α_c represents class-level heterogeneity, that can be interpreted for example by teacher propensity to suggest early enrollment, ε_{ci} represents student-level heterogeneity that may come from variation in income, family background, parental beliefs about the readiness of the child, and $\bar{\varepsilon}_c$ is the class mean of ε_{ci}. Following Graham, I also have another variable W_c which is a dummy indicating a small number of student eligibles for early enrollment ($W_c = 1$) or a large number of eligibles ($W_c = 0$). In the sample I have, I divided the class in two groups basing on the value of the median number of eligibles in a class. As a result, $W_c = 1$ when there are less than 7 eligibles and 0 otherwise. The variable W_c is then necessary to separate the sample in two subpopulations. We assume that students are randomly assigned to one of the two subpopulations. The intuition proposed by Graham is that in class with a large number of eligibles, clusters of students with parents more inclined to early enrollment are often offset by clusters of parents with low propensity to early enrollment. In classes with few eligibles, it is more probable to see parents with similar propensity to early enrollment (above or below the average). Consequently, the variance of parents' propensity to early enrollment is greater across the set of classes with few eligible ($W_c = 1$) than it is across the set of classes with a number of eligibles above the median ($W_c = 0$).

The model also requires some additional restrictions on the conditional distribution of the individual choice $\underline{Early}_c$ given W_c, which allow the identification of γ_0. More specifically the model allows class-level heterogeneity (e.g. teacher propensity to suggest early enrollment), to vary with class type in a heterogeneous way. Similarly, it allows parents characteristics that affect the choice of early enrollment to vary across W_c.

I then define within- and between-group squares of the data by:

$G_c^w = \frac{1}{M_c}\frac{1}{M_c - 1}\sum_{i=1}^{M_c}(Early_{ci} - Ear\bar{l}y_c)^2$, the within-group squares and

$G_c^b = (Ea\bar{r}ly_c - \mu_{Early}(W_c))^2$, the between-group squares.

where $\mu_{Early}(w)$ is the average of early entrants in classes of type $W_c = w$, and M_c is the number of eligible in class c.

Assuming that M_c, and then the assignment to W_c, is random, and assuming also that W_c generates exogoneous variation in in the variance of parents' propensity to early enroll the child, (formally that $E[G_c^w|W_c = 1] \neq E[G_c^w|W_c = 0]$), the social multiplier γ_0 is identified by the Wald-estimator:

$$\gamma_0 = \frac{E[G_c^b|W_c = 1] - E[G_c^b|W_c = 0]}{E[G_c^w|W_c = 1] - E[G_c^w|W_c = 0]} \tag{3}$$

In other words, W_c, the assignment to a class with a small or a large number of eligibles, can be used as an instrument for the within-class squares.

The excess variance measured with this approach can be then interpreted as the social multiplier.

Table 7 presents the estimate for the social multiplier γ_0. Estimates are based on the administrative data sample used also in the previous section. It reports GMM estimates for γ_0^2 for early enrollment based on Graham (2008) routine which requires the parametric assumption that $\mu_{Early}(W_c) = W_{1c}'\pi_1 + W_{2c}'\pi_2$ and base estimation on the unconditonal moment restriction:

$$\mathbb{E}[W_c(G_c^b - W_{1c}'\beta_0 - G_c^w\gamma_0^2)] = 0 \tag{4}$$

where the included instrument W_{1c} equals a full vector school dummies and W_{2c} is the excluded instrument, the dummy variable for whether a classroom has a low number of eligibles for early enrollment. G_c^b is constructed by substituting $\mu_{Early}(W_c)$ with the fitted value of associated with the OLS fit of $Early_{ic}$ onto W_{1c} and W_{2c}.

We can see that the hypothesis of weak instrument is rejected, since the F-statistics for the first-stage is 31.03. The estimate for γ is 7.67 suggesting a social multiplier of around 2.77. To have a sense of the magnitude, consider that 1 standard deviation change in the mean of unobserved propensity to early enrollment in a class, ε_c, is given by $\sigma_\varepsilon/\sqrt{M_c}$ assuming random assignment. Hence, the effect on parents decision about early enrollment of a 1 standard deviation change in the mean propensity of parents of students in the same class of pre-primary, relative to a 1 standard deviation change in their own propensity is given by $(\gamma_0 - 1)/\sqrt{M_c}$. In a class with 7 eligibles students this translates into a relative change in probability of early enrollment of around 0.67.

Moreover, the p-value for the test that the multiplier is higher than 1 (no social interaction effect) is 0.05, reinforcing the claim that social interactions have indeed a primary role in the choice.

Administrative data do not include many variables on schools, classes and students. As a result, it would be unfeasible to perform additional tests to confirm the robustness of these results. However, the results from the analysis of excess variance, together with the estimates from OLS and 2SLS presented in the previous section give preliminary evidence on the importance of peers' choice about early enrollment. As already noticed, early enrollment in the South is widely spread, whereas in the

Table 7. GMM Estimate for the Social Multiplier

VARIABLES	(1) Early
γ^2	7,67**
	(3.389)
Observations	268
N Class	51
p-value $H_0 : \gamma^2 = 1$	0.05
F 1st-Stage	31.03
School F.E.	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

North very few parents decide for this option. To study the reason behind this difference is not the aim of this work. However, this preliminary investigation on peer effects shows that in the South, parents seem to be widely influenced by others. A possible explanation is that in a class with many children eligibles to early enrollment, parents are more exposed to this social norm and are more likely to decide for early enrollment after comparing their child with other eligible children of parents in their network. In this framework, I considered as network only parents of eligible children in the same class. This is a clear limitation due to data availability, but it is reasonable to believe that parents will mainly look at this group. Given that early enrollment may have detrimental effects on educational outcomes, as already reported in the first chapter, this could be a case where social interactions lead parents to make an inconvenient choice for the development of their child.

6 Conclusions and Further Development

Understanding why parents in the South are more likely to enroll their child earlier to primary school is relevant because it can give important insights on the heterogeneity of parents' preferences in investments in early education. In this chapter, I used data from a survey conducted in the spring of 2019 in pre-primary and in 1st grade of 5 schools in the southern city of Palermo. The dataset, even if limited, offers some useful insight about the early enrollment. Firstly, it confirms that also in Palermo early enrollment is more common in schools located in richer neighborhoods, and among more educated parents. Moreover, girls are more likely to be early enrolled, mainly because parents consider them mature for formal schooling earlier than boys. However, parental background and beliefs cannot explain alone all the heterogeneity in the intensity of this phenomenon. Social interactions seem indeed to be crucial in this kind of framework. It could be that parents simply imitate their peers and that there is also some kind of social norm, developed mainly in the South, that encourages parents to enroll their children younger to primary school. In the last sections of the work, I present preliminary results on social interaction effects on the choice. They suggest that indeed the composition of the pre-primary class of the child has a significant impact on the choice.

Unfortunately, the covid-19 crisis did not allow me to gather additional data because of the closing of all schools in Italian territory from the end of February, just after parents made the decision for early enrollment. However, using additional administrative data the results for the importance of social interactions in this framework seem to be confirmed.

This chapter, together with chapter 1, has the aim of investigating a phenomenon that drives a significant part of the gap in standardized scores between South and North Italian students. Given that Invalsi Standardized test scores are taken into account by the Ministry of Education and the government to design optimal education policy, I strongly believe that additional research on the topic is requested. The absence of fully available and centralized data on pre-primary education makes this kind of analysis hard for researchers. For example, to administer the same survey in schools in North Italy would have required the inclusion of too many schools to administer questionnaires, since some of them reported to have no early enrolled students in their classes. However, school digitalization may help dramatically the research also in this field.

References

[1] Andreas Ammermueller and Jörn Steffen Pischke. Peer effects in european primary schools: Evidence from the progress in international reading literacy study. *Journal of Labor Economics*, 27(3):315–348, 2009.

[2] Karen L. Bierman, Marcela M. Torres, Celene E. Domitrovich, Janet A. Welsh, and Scott D. Gest. Behavioral and cognitive readiness for school: Cross-domain associations for children attending head start. *Social Development*, 2009.

[3] Anne C Case and Lawrence F Katz. The Company You Keep: The Effects Of Family And Neighborhood On Disadvantaged Youths. *Working Paper Series*, 1991.

[4] Flávio Cunha. Subjective Rationality, Parenting Styles, and Investments in Children. In *Families in an Era of Increasing Inequality*, pages 83–94. 2015.

[5] Flavio Cunha, Irma Elo, and Jennifer Culhane. Eliciting Maternal Expectations about teh Technology of Cognitive Skill Formation. *NBER Working Paper Series*, wp 19144, 2013.

[6] Ainhoa Aparicio Fenoll, Nadia Campaniello, and Ignacio Monz. Parental Love Is Not Blind : Identifying Selection into Early School Start. *Working Paper*, 2018.

[7] Emla Fitzsimons, Bansi Malde, Alice Mesnard, and Marcos Vera-Hernández. Nutrition, information and household behavior: Experimental evidence from Malawi. *Journal of Development Economics*, 122:113–126, 2016.

[8] Alejandro Gaviria and Steven Raphael. School-based peer effects and juvenile behavior. *Review of Economics and Statistics*, 83(2):257–268, 2001.

[9] E. L. Glaeser, B. Sacerdote, and J. A. Scheinkman. Crime and Social Interactions. *The Quarterly Journal of Economics*, 1996.

[10] Edward L. Glaeser, Bruce I. Sacerdote, and Jose A. Scheinkman. The social multiplier. *Journal of the European Economic Association*, 1(2-3):345–353, 2003.

[11] Bryan S. Graham. Identifying Social Interactions through Excess Variance Contrasts. *Econometrica*, 2008.

[12] Kristin Leffel and Dana Suskind. Parent-directed approaches to enrich the early language environments of children living in poverty. *Seminars in Speech and Language*, 2013.

[13] Charles F. Manski. Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies*, 60(3):531, 1993.

[14] Seung Hee Son, Kangyi Lee, and Miyoung Sung. Links Between Preschoolers' Behavioral Regulation and School Readiness Skills: The Role of Child Gender. *Early Education and Development*, 2013.

Caratteristiche, Aspettative e Investimenti in Educazione dei genitori dei bambini della scuola dell'infanzia.

Questionario per la comprensione e l'analisi delle scelte dei genitori riguardo l'educazione pre-primaria nel Comune di Palermo.

Progetto di ricerca del dott. Giorgio Monti, dottorando del Dipartimento di Scienze Economiche dell'Università di Bologna in collaborazione con l'Ufficio Regionale Scolastico della Regione Sicilia.

Il progetto e la somministrazione dei questionari sono stati approvati dal comitato etico dell'Università di Bologna.

Istituto Comprensivo Statale Mattarella-Bonagia

Questionario per la Scuola dell'Infanzia

Questionario Scuola dell’Infanzia

Sezione 1: Istruzioni per la compilazione

Il seguente questionario ha come obiettivo quello di raccogliere dati sugli investimenti in educazione e sulle aspettative dei genitori riguardo al futuro dei loro figli. Inoltre, verranno chieste informazioni generali sui genitori e verranno anche fatte ulteriori domande riguardanti l'anticipo scolastico.
Per anticipo scolastico si intende la scelta di iscrivere i propri figli alla prima elementare con un anno di anticipo.
Dopo la riforma Moratti del 2003, tale scelta è riservata soltanto ai genitori di bambini nati tra l' 1 Gennaio e il 30 Aprile. Questi genitori possono scegliere far iniziare la prima elementare al figlio/a a 5 anni (e qua si parla di anticipo) o farlo restare un altro anno alla scuola dell'infanzia per iscriverlo regolarmente a 6 anni.
Le sezioni 2-4 del questionario sono rivolte a tutti i genitori, indipendentemente dal giorno di nascita del figlio/a.
LA SEZIONE 5 è dedicata SOLTANTO ai genitori dei bambini NATI TRA L'1 GENNAIO E IL 30 APRILE.
Il questionario può essere compilato soltanto una volta per ogni bambino (da un solo genitore o da entrambi assieme).
Per tutto il questionario quando si fa riferimento a suo figlio/a, si intende il figlio che frequenta la classe da cui le è arrivata l'invito a rispondere.
Si prega di rispondere nel modo più sincero possibile. I questionari sono completamente anonimi e non verranno trasmessi a nessuna parte terza.

Sezione 2: Informazioni sui genitori e sulla composizione familiare

1. **Il questionario è compilato da:**

Padre/Padre Adottivo/Tutore legale uomo…………☐

Madre/Madre Adottiva/Tutrice legale donna…….. ☐

Entrambi i genitori/tutori legali insieme……..……☐

2. **Qual è il suo stato civile?**

Sposato/a……………☐

Celibe/Nubile……….☐

Vedovo/a…………….☐

3. **Con chi vive suo figlio/a?**

Con entrambi i genitori biologici/adottivi……….☐

Con la madre………………………………………………☐

Con il padre…………………………………………………☐

Altro:_______________..................................☐

4. **Dov'è nato suo figlio/a?**

In Italia………………………………..☐

In un altro paese UE……………☐

In un paese extra-UE……………☐

5. **Qual è il sesso di suo figlio/a?**

Maschio……….☐

Femmina……….☐

6. **Qual è la data di nascita di suo figlio/a? (gg/mm/aaaa)**

____

La preghiamo adesso di elencare gli eventuali fratelli e sorelle di suo figlio/a indicando per ognuno l'anno di nascita e la classe frequentata quest'anno (es. 2010 – 3° elementare):

Nel caso in cui suo figlio/a abbia più di 5 fratelli, inserisca gli altri sotto nella risposta riguardante il fratello nr 5

Fratello/Sorella nr 1

____

Fratello/Sorella nr 2

____

Fratello/Sorella nr 3

____

Fratello/Sorella nr 4

____

Fratello/Sorella nr 5

____

____

____

____

7. **In che anno è nata la madre/tutrice legale?**

____

8. **Dov'è nata la madre/tutrice legale?**

In Italia……………………………….☐

In un altro paese UE……………☐

In un paese extra-UE……………☐

9. **In che anno è nata il padre/tutore legale?**

____

10. **Dov’è nata il padre/tutore legale?**

In Italia……………………………..☐

In un altro paese UE……………☐

In un paese extra-UE……………☐

11. **Qual è il più alto titolo di studio raggiunto dalla madre/tutrice legale?**

Licenza Elementare………………………….. ☐

Licenza Media………………………………….. ☐

Diploma di scuola superiore…………….. ☐

Laurea……………………………………………. ☐

Altro titolo post-lauream…………………..☐

12. **Qual è il più alto titolo di studio raggiunto dal padre/tutrice legale?**

Licenza Elementare………………………….. ☐

Licenza Media………………………………….. ☐

Diploma di scuola superiore…………….. ☐

Laurea……………………………………………. ☐

Altro titolo post-lauream…………………..☐

13. **Qual è la situazione lavorativa della madre?**

Occupata Full-time (35 ore settimanali o più)…………. ☐

Occupata Part-time (meno di 35 ore settimanali)…... ☐

Disoccupata (in cerca di lavoro)……………………………. ☐

Casalinga……………………………………………………………. ☐

Pensionata………………………………………………………….. ☐

Altro (Specificare)………………………………………………. ☐

14. **Qual è la situazione lavorativa del padre?**

Occupato Full-time (35 ore settimanali o più)………….. ☐

Occupato Part-time (meno di 35 ore settimanali)……. ☐

Disoccupato (in cerca di lavoro)……………………..……… ☐

Casalingo………………………………………………………………… ☐

Pensionato…………………………………………………………….... ☐

Altro (Specificare)…………….……………………….…………… ☐

15. **In quale fascia rientra lo stipendio netto guadagnato dalla madre nello scorso anno (in €)?**

0-10000………………………….. ☐

10001-20000………………….. ☐

20001-30000………………….. ☐

30001-40000………………….. ☐

40001-50000………………….. ☐

50001-60000………………….. ☐

60001-70000………………….. ☐

70001-80000………………….. ☐

Maggiore di 80000………... ☐

16. **In quale fascia rientra lo stipendio netto guadagnato dal padre nello scorso anno (in €)?**

0-10000………………………….. ☐

10001-20000………………….. ☐

20001-30000………………….. ☐

30001-40000………………….. ☐

40001-50000………………….. ☐

50001-60000………………….. ☐

60001-70000………………….. ☐

70001-80000………………….. ☐

Maggiore di 80000………... ☐

Sezione 3: Educazione e cura del figlio/a

17. **Dalla nascita fino ai 3 anni per quanti anni suo figlio/a è stato iscritto all'asilo nido?**

0……☐

1……☐

2….. ☐

3….. ☐

18. **Prima di essere iscritto nell'attuale istituto, suo figlio/a era iscritto in un'altra scuola dell'infanzia? (Non asilo nido)**

Sì……☐

No….☐

19. **Nell'ultimo anno con quale frequenza ha usufruito dell'aiuto di una baby-sitter per la cura di suo figlio/a?**

Contrassegna solo un ovale

Meno di 1 volta al mese	**1 volta al mese**	**2 volte al mese**	**3 volte al mese**	**più di 3 volte al mese**
◯	◯	◯	◯	◯

Quanti giorni a settimana almeno uno dei due genitori svolge le seguenti attività con suo figlio/a?

20. **Leggere Libri**

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**
◯	◯	◯	◯	◯	◯	◯	◯

21. **Raccontare Storie**

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**
◯	◯	◯	◯	◯	◯	◯	◯

22. **Giocare con giochi didattici per imparare i numeri**

0 1 2 3 4 5 6 7

23. **Giocare con giochi didattici per imparare l'alfabeto**

0 1 2 3 4 5 6 7

In una scala da 1 a 5 dove 1 è molto male e 5 molto bene, quanto bene suo figlio/a riesce a fare le seguenti attività?

24. **Riconoscere le lettere dell'alfabeto**

Molto Male 1 2 3 4 5 Molto bene

25. **Leggere parole**

Molto Male 1 2 3 4 5 Molto bene

26. **Leggere frasi**

Molto Male 1 2 3 4 5 Molto bene

27. **Scrivere lettere dell'alfabeto**

Molto Male 1 2 3 4 5 Molto bene

28. **Scrivere alcune parole**

Molto Male 1 2 3 4 5 Molto bene

29. **Contare i numeri**

Molto Male 1 2 3 4 5 Molto bene

30. Scrivere i numeri

	1	2	3	4	5	
Molto Male	◯	◯	◯	◯	◯	Molto bene

31. Fare semplici operazioni (addizioni e sottrazioni)

	1	2	3	4	5	
Molto Male	◯	◯	◯	◯	◯	Molto bene

32. Indichi quali altri parenti si occupano della cura di suo figlio/a durante la settimana (aiuta a fare i compiti, gioca con lui/lei, va a prenderlo/a a scuola etc.).
Seleziona tutte le voci applicabili.

Nonno/Nonna............ ☐

Zio/Zia......................... ☐

Fratello/Sorella........... ☐

Altro:___________..... ☐

33. In una settimana, quante volte suo figlio/a incontra uno o più compagni di scuola al di fuori dell'orario scolastico?

0	1	2	3	4	5	6	7
◯	◯	◯	◯	◯	◯	◯	◯

34. In una settimana, quante volte suo figlio/a incontra uno o più amici diversi dai compagni di scuola?

0	1	2	3	4	5	6	7
◯	◯	◯	◯	◯	◯	◯	◯

Indichi su una scala da 1 a 5 dove 1 indica "Molto in disaccordo" e 5 indica "Molto d'accordo" quanto è d'accordo con le seguenti affermazioni riguardanti la scuola dell'infanzia frequentata da suo figlio.

35. **La maggior parte degli insegnanti di mio figlio/a mi sembrano competenti e motivati**

1 ◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯

36. **I progressi di mio figlio/a sono seguiti con attenzione dalla scuola**

1 ◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯

37. **La scuola di mio figlio offre agli studenti una buona formazione**

1 ◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯

38. **La scuola di mio figlio/a offre una comunicazione efficace tra scuola e famiglie**

1 ◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯

<u>Sezione 4: Aspettative sul futuro di suo figlio/a</u>

39. **Con quale probabilità pensa che suo figlio/a verrà bocciato almeno una volta durante il suo percorso scolastico?**

Sicuramente Sì…………………… ☐

Più Si che No……………………… ☐

Al 50% Sì al 50% No……………. ☐

Più No che Sì……………………… ☐

Sicuramente No…………………. ☐

40. **Secondo lei, quale sarà il livello di istruzione che raggiungerà suo figlio/a?**

Scuola dell'Obbligo (16 anni di età o 2° anno scuola superiore)………… ☐

Diploma di scuola superiore……………………………………………………………… ☐

Laurea o altro titolo post-lauream…………………………………………………… ☐

Se suo figlio/a è nato tra l'1 Maggio e il 31 Dicembre, il questionario per lei finisce qui.
Se suo figlio/a è nato tra l'1 Gennaio e il 30 Aprile la preghiamo di rispondere alle ultime domande nella sezione 5.

Sezione 5: Informazioni sull'anticipo scolastico

Compilare solo se suo figlio/a è nato tra l'1 Gennaio e il 30 Aprile, indipendentemente dall'anno di nascita.

41. **Quale pensa che sia la percentuale di genitori di bambini nati tra l'1 Gennaio e il 30 Aprile che decide di anticipare l'iscrizione del proprio figlio alla scuola elementare?**
    Scriva un numero da 0 (Nessuno) a 100 (Tutti)

    ___________%

42. **Quante volte in una settimana parla coi genitori dei compagni di classe di suo figlio/a?**

	1	2	3	4	5	
Mai	◯	◯	◯	◯	◯	Tutti i giorni

43. **Dalle informazioni in suo possesso, per quanti alunni nella stessa classe di suo figlio/a (nati tra l'1 Gennaio e il 30 Aprile), è stata richiesta l'iscrizione anticipata alla scuola primaria? (inserisca un numero)**

    ____

44. **Ha lei stesso richiesto l'iscrizione anticipata alla scuola primaria per suo figlio/a?**

Si………………… ☐

No……………… ☐

45. **Prima di decidere se iscrivere o meno suo figlio in anticipo, ha seguito il parere delle maestre/maestri di suo figlio?**

Non ho chiesto il parere delle maestre/maestri…………………………… ☐

Ho chiesto ma NON ho seguito il parere delle maestre/maestri……. ☐

Sì, ho chiesto e ho seguito il parere delle maestre/maestri…………….☐

46. **Prima di decidere se iscrivere o meno suo figlio in anticipo, ha seguito il parere di un esperto diverso dalle maestre/maestri di suo figlio? (Pediatra, Pedagogista, Psicologo Infantile)**

Non ho chiesto il parere di un esperto………………………………………… ☐

Ho chiesto ma NON ho seguito il parere di un esperto…………………. ☐

Sì, Ho chiesto e ho seguito il parere di un esperto……………….………. ☐

47. **Prima di decidere se iscrivere o meno suo figlio in anticipo, con quanti amici (al di fuori dei genitori dei compagni di asilo di suo figlio/a) ne ha parlato? (indichi un numero)**

    ____

48. **Qualora abbia deciso di iscrivere suo figlio/a in anticipo alla scuola primaria, indichi fino a 2 motivi, tra i seguenti, che l'hanno portata a questa scelta:**
    Metti la crocetta su massimo 2 opzioni

Penso che mio figlio/a sia pronto per la scuola elementare……….…………… ☐

Non voglio separarlo dai suoi amici che sono stati iscritti in anticipo……… ☐

Vedo che mio figlio/a si annoia all'asilo…………………………………………………☐

Le maestre o un esperto mi ha consigliato di farlo…………………………………..☐

Le ricordiamo di firmare il modulo sul consenso informato che le è stato consegnato insieme al questionario.

Chapter 3:

School Goes Online: The Effects of the Electronic Gradebook on Students' Achievement

Giorgio Monti

Abstract

This chapter studies the effect of the introduction of the electronic gradebook (register) in Italian schools promoted by the Italian government on students' achievement. I will use data from the INVALSI School Administrators Survey and Standardized Test Scores, focusing on students attending the tenth grade. I will show that the introduction of the electronic register increased scores at standardized test by 0.10 to 0.15 s.d. in Mathematics and Italian respectively. Since the timing of the introduction of the electronic register was not the same in all italian schools and likely to depend on school characteristics, I will focus on within-school variation in the gradebook format, controlling for other school time-variant characteristics and time trends.The positive effect on standardized scores is likely to be driven by higher parents' control and reduced parents-students and parents-teachers information frictions. Moreover, I found that the effect of the electronic register is higher for girls for scores in Italian and for boys when looking at scores in mathematics, possibly because of gender stereotypes. In addition, the effect is stronger for children with more educated parents. Consequently, although the electronic register seems to have improved scores overall, it may increase the gender gap in STEMs and the heterogeneity in scores coming from parental background. Finally, I also found that the effect of the electronic register for scores in both mathematics and italian is significantly different from zero only for ten graders and not for fifth and eighth graders.

1 Introduction

Family background and parenting style are among the most important determinant of school achievement. Most models of human capital development rely on the assumption that parents have total control over investments in their children's education. This assumption is less reliable as the students get older and more independent (Cunha and Heckman, 2007). As the children grow up it is more likely that their preferences diverge from those of their parents and this increases the agency problem, making it more difficult for parents to affect their skills. The information frictions in the parent-child relationship represent a crucial aspect of this agency problem (Bergman, 2015). In the last decade, many education systems have started to incentivize the use of new technologies in education to limit this issue. Indeed, new technologies may improve data management and school-to-parent communication at a relatively low cost. Many researchers have studied the impact of technology on educational attainment (see Escuenta et al, 2017 for an extensive survey). Some studies have analyzed the effects on education of information technology such as access to the Internet (Goolsbee and Guryan, 2006) , computers (Fairlie 2012, Bulman and Fairlie 2016) , teacher dashboards (Tyler, 2013), mobile devices (Fryer, 2016) and computer-aided learning (Barrow et al, 2009). In line with this literature, the present paper studies the adoption and the effects of school-to-parent communication technology. In the last decade, this type of technology has become very common and nowadays is adopted in almost every school in western countries (Bergman 2016). This technology is considered particularly useful since it reduces dramatically the cost of informing parents about students behavior and academic progress. Moreover, it comes at almost no cost for parents and it is also relatively cheap for schools. Bergman (2015) estimates that to provide additional information to parents as in his study, would cost $156 per child per year and lead to a 0.10 standard deviation increase. To make a comparison, providing financial incentives for high school students would cost $538 to get the same increase (Fryer, 2011). In another experimental study, Bergman and Chan (2017) spent only $63 to send more than 32000 text messages and additional $7 per students for the gradebook and the personnel training. Many studies have shown how information asymmetries between parents and children can impede human capital investments (Bursztyn and Coffman, 2012; Hao et al., 2008; Weinberg, 2001). Hence, mitigating these asimmetries can improve student achievement and often at negligible costs for school administrations (Kraft and Rogers, 2015; Bergman; 2016). There are two main channels through which reducing parents-child information asymmetries can affect positively academic achievement and behavior at school. The first channel is parental monitoring. Informing parents about their kids' grades, absences and misbehaviors, allow them to promptly intervene in case of necessity, thus facilitating education investments at home. Rogers and Feller (2018) show that parents have biased beliefs about students absences and implement an experiment where treated parents received personalized information about their kids' behavior. The treatment reduced absenteeism by 10%, and corrected the misbeliefs. Another channel is through the improvement of the teacher-parents communication. Parents know the schedule of the classes, can directly ask questions to the teacher and be advised personally. How these two channels work, depends heavily on parents' and teachers' characteristics. Each family has his own parenting style that affects academic results and behavior of children differently and depends on several background characteristics such as parents' education and socio-economic status (Doepke and Zilibotti, 2017). Another important element of the functioning of teacher-parents communication is nudging. How information is given to parents is indeed critical in implementing these new technologies. Kraft and Rogers (2015) experimentally show "need to improve" messages are more effective than "encouragement" messages, even if both treatments are effective compared to the control group where parents received no information. However, to simply provide technological tools to parents and teachers may not be enough to improve communication and to reduce Parents-Child information frictions. In fact, the availability of this instrument does not guarantee that families effectively use them. Bergman (2016) argues that parent-portal technology requires a pull. The experimental evidence such as those described by Kraft and Rogers (2014) and Bergman (2014) is instead based on treatments that push information out to families. Bergman (2016) analyzes schools where an electronic portal where available to all parents. In a random sample of these schools, he randomly selected a group of parents who received additional remainders informing them on the existence of the online portal and giving further instructions on how to obtain credentials. Parents in the treated groups increased the usage of the web-portal and a positive (but small) effect on children's results were found. Among the schools that participated the experiment, the share of parents who ever logged in the portal in the previous year was just 24% and only the 4%

of parents logged in at least once a week. The author also shows that the share of parents who ever log in is strongly correlated with measures of family income, school-level test scores and teacher usage. This suggests that the communication technology may actually increase existing gaps between income and performance groups.

Researchers in educational sciences have also investigated the importance of parental involvement in education. Wilder (2014) provides an extensive meta-analysis on the studies of the effects of parental involvement in education. The author considers different definitions of parental involvement, including parent-child communication about school (Jeynes, 2005), home supervision (Hill and Tyson, 2009), homework assistance (Pattal et al. 2008), participation in school activities (Jeynes 2005; Hill and Tyson, 2009) or communication with school (Jeynes 2012). Whatever is the definition considered, parental involvement have a significant role in children's academic achievement. On the other hand, some studies have found a negative correlation between parental involvement and children's results, a fact that can be explained by the "*Reactive Hypothesis*" (Catsambis 2001; McNeal 2012), whereby parents tend to increase their involvement in education when their child under-performs.

In this paper I will focus on the Italian case. In 2012, the Italian government asked schools to introduce the electronic Logbook (or Gradebook), a type of Learning Management System (LMS) that improves dramatically parental access to information about students' performance. With this technology parents are updated every day on students' grades, absence and misbehavior reports. There are several companies that provide the service. Although LMS company can supply some additional tools, such as notifications or platforms for homework and e-learning, all of them provide daily updated information about grades in written and oral tests and absences. The percentage of schools that use the Electronic Logbook in the school year 2019/2020 sharply increased over time, passing from 60% in the school year 2013/2014 to almost 100% in 2019/2020.

2 Institutional Background and Data

In 2012 the Italian Parliament passed a law on the digitalization and dematerialization of the public sector[1]. One article in the law prescribed that: "From the school year 2012-2013, schools and teachers adopt online logbooks and send communication to students and families in electronic format". In the same article, it was also written: "The Ministry of Education prepares within 60 days from the date of entrance into force of this law, a plan for the dematerialization of administrative procedures relative to Education, University and Research, and of the relation with the teacher community." The main problem of the law was that the "Plan for dematerialization" mentioned, was never implemented. As a result, the government did not distribute any additional financial resources to schools. Hence, the adoption of the Electronic Logbook was not considered mandatory. The result was that the timing of the introduction of this new technology was not the same for each school. On the other hand, it was relatively cheap and many schools found it convenient to adopt it at their own cost; as mentioned above, nowadays almost every school in the country uses it. The Italian educational system seems to be underdeveloped in terms of innovation and technology, compared to other western countries. Italy has the highest percentage of teachers with more than 50 years (62% vs 35% OECD average) and it is 25th in Europe for internet usage (59%) and 23rd for basic technological skills (47%). Given these premises, since 2012, the Italian government has been put effort in promoting innovation in schools. In particular, the "Buona Scuola" (Italian for "Good School") reform of 2015 included the "Piano Nazionale per la Scuola Digitale" (PNSD; National Plan for the digital school). The first intervention aimed to bring new technologies in the schools is the 2008 "IWB (Interactive White Board) plan" of 2008, which consisted of an investment of more than 90 million euros to bring the IWB in more than 35000 classes and trained more than 70000 teachers to its use. In 2013 the government allocated 15 million euros to install Wi-Fi connection in about 1500 schools and the Italian educational system also receives European funds: more than 60 million euros in the period 2007-2013. The PNSD provided additional funds to extend the intervention to all Italian schools (more than 100 million euros for the period 2016-2020), and invested other 140 million to realize interventions that incentivize digital learning. Moreover, it allocated

[1] Legge 7 agosto 2012, n. 135

48 million euros for the introduction of the electronic gradebook in all primary school classes. Given the several governmental interventions to improve the technological assets in schools, it is challenging to isolate the effect of the introduction of one specific tool. The INVALSI (the Italian national agency for the evaluation of the educational system) collects every year data on students' educational attainment in 5 different stages (2nd, 5th, 8th, 10th and 13th grade) and information from a subsample of teachers and school administrators. Data on the introduction of the electronic logbook comes from the survey for school administrators, where it is asked whether teachers in the schools use it or not. This survey was firstly implemented in the school year 2013/2014 and contains also information about other technological assets of the school, such as a functioning Wi-Fi connection, the presence of a IT lab and the presence in each class of a personal computer at the use of the teachers. I will perform some balance checks to ensure that the choice of the sample is random. To increase the sample size, I will also assume that the introduction is irreversible: once a school introduce the Electronic Logbook, it will never go back to the paper book. This is a reasonable assumption, also confirmed in the available data. In this way I will assume that if a school did not have the Electronic Gradebook in 2014 it didn't have it either before, and I can match the test scores from that schools for additional years. As already noticed, the introduction of the Electronic Logbook is likely to be endogenous and to depend on schools and students characteristics, such as socio-economic background and funds available to the schools. To limit this issue I will focus on within-school variation and I will control for possible time-variant confounders and for school-specific time trend. Unfortunately, the Italian ministry of education does not provide additional data. Hence I do not know which kind of electronic logbook the school adopted, neither the specific tools parents in each school may use to monitor their child and to communicate with teachers. In addition, I cannot see how much parents use this technology. I do not have data on log-ins, and I cannot investigate which factors affect parents' utilization. However, the simple introduction of this new technology seems to have an impact, and the result shown in this work will measure an Intention to Treat Effect (ITT). Data on students' standardized tests in Italian and Mathematics contains also information on the students background. I can check the heterogeneity of the effect across several characteristics such as gender, age, parents education and occupational status, country of origin, school typology and geographic location.

3 Summary Statistics

3.1 The survey for school administrators and the adoption of the electronic register

As already mentioned, I know whether a school has adopted the electronic register only for a subsample of schools. This subsample is selected randomly by the INVALSI each year. I was able to expand the subsample assuming that the adoption is irreversible: once a school introduces the electronic register, it will never come back. As a result, if I observe that a school has not adopted the new technology in year T, I assume that in every school year t<T the same school did not have the electronic register. Using the same logic, if I observe that a school has the electronic logbook in year T, it also has it in year t>T. In this way, I was able to use additional data and to expand the sample for the analysis.

In the analysis I will focus on the second year of high school (grade 10). Table 1 shows summary statistics about Italian schools, divided by the presence in the sample used in the analysis (NP meaning not present, P present). It is possible to see that there are not significant difference in family background variables: average parents education and immigrant status is very similar across the two groups. However, there are some differences between the groups. Schools in the sample have on average slightly lower average test scores and Socio-Economic Status index (SES). Another possible issue in the sample is that in 2015 there was a teacher strike in the south where about 50% of teachers refuses to take the INVALSI test in their classes. As a result, that year only 17% of the schools are located in southern regions, whereas this percentage is about 35% other years. Since the strike was at the teacher level and not at the school level, this may affect data on scores and individual characteristics of students, but not data about schools. In fact, we can see that the number of schools in the sample does not drop. Whereas these problems may harm the external validity of the analysis, the estimates of the effect of the introduction of electronic logbook should not be biased, since I will look in within-school variations.

Figure 1 shows the evolution of the adoption of the electronic register in Italian schools. The top-left panel shows the overall evolution, the bottom-left panel shows the heterogeneity across the Italian territory, the top-right graph shows the heterogeneity across different school

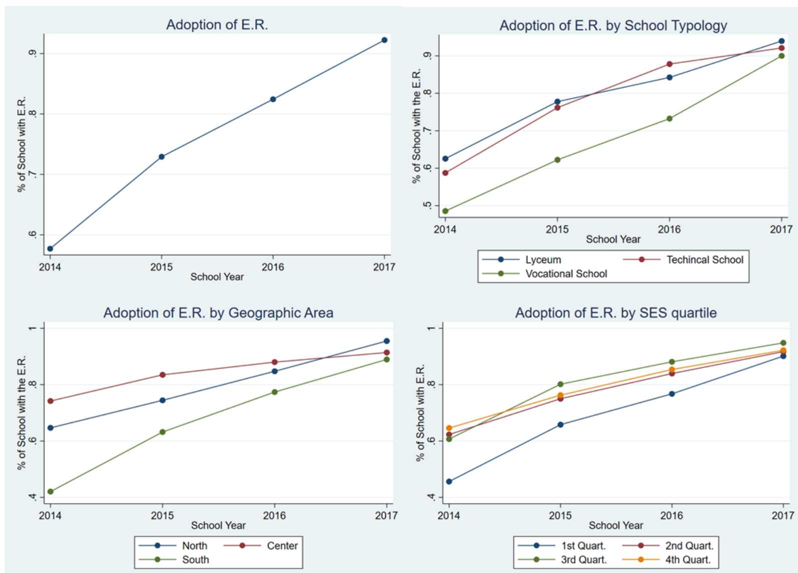
Table 1: Summary Statistics by Presence in the School Survey Sample

	2014		2015		2016		2017	
	NP	P	NP	P	NP	P	NP	P
Score Ita	0.023	-0.073	0.015	-0.024	0.010	-0.010	-0.007	0.006
Score Mat	-0.008	0.043	0.025	-0.061	0.025	-0.062	0.009	-0.026
SES index	0.024	-0.033	0.045	0.004	0.044	-0.013	0.042	-0.008
Foreign	0.106	0.102	0.138	0.140	0.117	0.121	0.100	0.109
Mother HS	0.366	0.358	0.361	0.367	0.377	0.380	0.380	0.388
Father HS	0.326	0.321	0.315	0.326	0.328	0.336	0.328	0.334
Mother Grad.	0.249	0.233	0.289	0.272	0.288	0.266	0.287	0.264
Father Grad.	0.227	0.209	0.257	0.237	0.248	0.222	0.236	0.211
North	0.464	0.400	0.651	0.611	0.495	0.503	0.423	0.488
South	0.368	0.442	0.159	0.172	0.324	0.300	0.384	0.317
Nr. of Schools	4382	1047	3266	1299	3345	1833	3162	2073

typology and the bottom-right panel shows heterogeneity across quartile of school average SES index.

The graphs show that in 2014 almost 60% of Italian High schools have already adopted the electronic register, and this percentage steadily increases every year reaching more than 90% in 2017. In 2020, virtually 100% of schools have adopted it. However, as shown by the other graphs, the adoption was not homogeneous across schools. In 2014 the percentage of high school in the South (historically the poorest area of the country) with the new technology was just above the 40% whereas it was already above 60% and 70% in the Northern and in Center regions respectively. There are also big differences across school typologies. In 2014 more than 60% of Lyceums, schools that prepare for university and that are typically attended by students from richer families, already had the electronic register. Technical schools, typically more technologically oriented, present a similar pattern compared to lyceums. On the other hand, vocational schools, attended on average by students from families with a lower socio-economic status, and aimed to prepare students for specific jobs, started with a lower adoption rate (below 50% in 2014). Dividing schools by quartile of average SES index, it is also possible to notice that only the schools in the lowest quartile present a systematic lower adoption rate, whereas all other schools have similar rates. In spite of this heterogeneity in the adoption of the electronic register, all sub-groups of schools clearly tend to converge to similar adoption rates. Hence, what significantly change across these schools is the timing of the adoption. Unfortunately, there is no information about previous years, and it is not possible to use in the analysis data from schools that have already adopted the technology in 2014.

Figure 1: Adoption of Electronic Register by School Year



As already said, even if data from school administrator surveys are available only for 4 school years, from 2014 to 2017, assuming that the adoption is irreversible, I was able to add data from Invalsi test score in 2012 and 2013 for those school that in 2014 had not introduced the electronic register yet.

Table 2 shows the number of schools I observed in the sample, divided by the number of observations and by register format. Among schools that are present only for one year in the sample, 1204 had the electronic register and 363 had not. Clearly, I cannot observe a change in the format for these schools and then I cannot use them in the analysis. There are 674 schools that appeared twice in the sample. Among them, 137 change the electronic format between 2014 and 2017, 455 are always observed when they have already adopted the electronic logbook and 82 never had it. 245 schools are present 3 years out of 4 in the sample and for 71 of them I observed a change in the format, and among the 99 schools that are present every year in the final sample, 33 switched to the electronic register in the period 2014-2017.

Table 2:

	Register Format		
Nr. of Years in the sample	Never Electronic	Always Electronic	Change
1	363	1204	0
2	82	455	137
3	23	151	71
4	8	58	33

3.2 Variables on students achievements

Students achievement in 10th grade is measured by scores in INVALSI tests. INVALSI provides both raw and standardized scores. One issue with these scores is cheating. Invalsi tests are indeed also used to evaluate school and teacher performance. In such test-based accountability system, there are incentives for teachers, students and even school administrators to inflate scores. Bertoni et al. (2013) have measured the size of the cheating in Italian schools by looking at difference in scores between classes where Invalsi randomly sent external examiners and those where the test where directly monitored by teachers. They found a negative effect of score on having the external monitor and argued that it is due to reduced cheating than to anxiety of having an external examiner. To reduce this issue and make data more reliable, INVALSI creates a measure to correct scores for cheating by looking at inconsistencies in correct answers. There are no reasons to believe that cheating is related to the introduction of the electronic register, however, I will use corrected scores.

The Invalsi test for 10th graders is divided in 3 parts: Italian, Mathematics and English comprehension. In this analysis I will use data from Italian and Mathematics tests. The Italian test is mainly focused on reading comprehension and vocabulary, whereas the Mathematics test is based on logical questions and exercises on concepts that students are supposed to learn during the first two years of high school.

3.3 Variables on students background

Along with the test sheets, students are requested to fill a short questionnaire on their families. These questionnaires contain questions about parents education level, job and country of origin. Moreover, students are asked what language they speak at home, how many books they have, whether they have their own bedroom, a place where to study, a computer for their personal use, a mobile phone and a functioning internet connection at home. There are also questions on their relationship with classmates, on their study method, and on their opionion on school environment. Parental background is universally recognized to be a crucial factor in children development and academic achievement. Italy is only ranked 34th in the Global Social Mobility Index (World Economic Forum Report, 2019) and the probability to go to college is double if parents have a college degree compared to students with parents with a diploma and nine times the probability a student with parents without a diploma enrolls to university (OECD, 2014). Moreover, parents characteristics determine critically the parenting style (Doepke and Zilibotti, 2017) , and affect significantly the adoption of new technologies. The more educated are the parents, the more likely is that they can use technologies and that they care more about students achievement. This is a particularly important aspect in this study: parental background may indeed affect dramatically the use of the electronic logbook. As a result, the effect of the introduction of this new technology on students' achievement is expected to depend heavily on parents' characteristics.

3.4 Variables on teachers and school characteristics

For a subsample of school, Invalsi gathers also data about schools and teachers of Mathematics and Italian. The school administrators fill the survey about their school, answering questions about school-parents relationship (e.g. frequency of meeting with parents, functioning of parents assembly), on the presence of technological tools in the school (functioning internet connection, IT lab) and on personal characteristics of the administrators (for how many years she has been administering that specific school, level of education and field of specialization). These variables are potential confounder for the effect of the introduction of the electronic register. In fact, if the introduction of the electronic logbook is associated with a change in the administrators or with investments in other technological tools for the schools it would be hard to isolate the effect of the introduction of one specific technology. Observing this data allows me to control for other change in the school. Also teacher answer questions about the technological tools available in the class, about their level of education and about their relationship with parents. All of this variables can be potentially related with the effect of the electronic logbook on students results.

4 Empirical Strategy

The Italian law that introduced the electronic register in schools can be viewed as exogenous. However, as already noticed, the timing of the introduction is not random. Even if nowadays virtually every school in Italy uses the electronic logbook, it is reasonable to assume, and summary statistics confirm this hypothesis, that richer schools introduced the new technology earlier. Data on the adoption of the electronic register starts in 2014, where already almost 60% of the Italian schools had adopted it. As a result, to isolate the effect of the electronic register is not possible to simply compare schools that have it and schools that don't. A first step to isolate the effect of this new technology consists of looking at within-school variation. In the empirical strategy I will then introduce school fixed effect as a first step. However, this can be not enough to identify the effect. Other school characteristics may change along with the adoption of the electronic register. To mitigate this issue I will control for other school time-variant characteristics such as the presence of a IT lab, of a functioning internet connection and the presence of a personal computer in each class. The adoption of the electronic logbook can happen as well after a change in the school administration: data allows me to control also for this.

Hence I will firstly estimate the effect of the introduction of the electronic register as follows:

$$Y_{ist} = \alpha_s + \gamma_t + \beta_1 ER_{st} + X'_{ist}\mathit{\Gamma} + C'_{st}\mathit{\Pi} + \varepsilon_{is} \tag{1}$$

Outcomes Y_{is} are standardized test scores for both mathematics and Italian. ER_{st} is a dummy equal to 1 if school s in year t has the electronic register. X_{ist} is a vector of students i individual characteristics (parental background) and C is a vector of school s characteristics at year t (internet connection, availability of personal computer for teachers, presence of a IT lab). Consequently, the main coefficient of interest will be β_1. Since I do not know how much parents use the electronic logbook after the introduction, β_1 will measure the Intention to Treat Effect. (ITT)

Another possible issue may be the so-called "*Galton Fallacy*": if schools introduced the electronic logbook as a reaction of a particularly bad performance the previous year, the positive effect found in the regression can be just due simply to regression towards the mean. To control for this I will add a specification including school specific time trend.

In separate subsections, I will also show the heterogeneity of the effect across gender, family background and geographic location. In the end, I will compare results from the 10th grade with those from lower grades.

5 Results

5.1 Main results

A simple comparison between schools with and without the electronic register will not identify the effect of the new technology. As already noticed, the timing of the introduction is very likely to depend on school characteristics, in terms of students background, teacher and school director experience. Schools attended by richer students and located in more developed areas are more likely to introduce the Electronic Register earlier, and any results coming from a simple OLS regression of standardized test scores on a dummy indicating the adoption of the new logbook would hence suffer of selection bias. To test this hypothesis I run three different regressions: the first is a simple OLS regression without control, in the second I will add students SES index as control variable, and in the third, I will add province fixed effect. Table 3 shows the results. The first two columns come from the simple OLS regressions where the dependent variable is the standardized test scores in Italian and Mathematics. The difference in means between school with and without the Electronic Logbook is 0.47 and 0.46 s.d. for Math and Italian scores respectively. However, just adding the SES index as control reduces the coefficients to 0.37 and 0.33 respectively, and including also province fixed effects makes the coefficients drop to 0.26 and 0.22 s.d.. This is a first evidence that there is indeed a selection bias in the standard OLS specification.

Table 3: OLS Regressions

VARIABLES	(1) Math	(2) Ita	(3) Math	(4) Ita	(5) Math	(6) Ita
ER	0.471***	0.455***	0.369***	0.330***	0.262***	0.216***
	(82.987)	(72.615)	(68.715)	(58.425)	(44.557)	(37.328)
SES index			0.230***	0.243***	0.182***	0.192***
			(117.185)	(126.011)	(90.264)	(96.939)
Constant	-0.185***	-0.138***	-0.162***	-0.079***	-0.105***	-0.079***
	(-26.449)	(-19.114)	(-24.043)	(-12.154)	(-16.745)	(-12.925)
Observations	240,033	239,779	227,625	225,770	207,373	205,763
R-squared	0.034	0.030	0.086	0.091	0.182	0.170
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Prov. F.E.	No	No	No	No	Yes	Yes

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

To limit this issue I will then focus on within-school variation. Table 4 reports results from different specifications all including school fixed effects. Columns 1 and 2 show results from the baseline specification, without the inclusion of any time-variant characteristics of neither students nor schools. The estimated effect of the introduction of the Electronic Register is higher for Italian than for Mathematics test scores, 0.15 vs 0.09 s.d. Column 3 and 4 report the estimates resulting from running the same regressions on a smaller sample of schools. More specifically, in these regressions I used a dataset where the additional observations are not included as specified in section 3.1. The results do not change significantly and this reassures that the inclusion of additional year, assuming the irreversibility of the adoption of the electronic register, does not affect the results. In all the other regression I will hence use the expanded dataset. In column 5 and 6 are reported coefficients estimated by running the same regression in column 1 and 2 but with the addition of control variable (SES index, presence of an IT lab in the school, availability of personal computer for teaching) and by dropping from the sample those schools that changed the administrators in the previous 2 years. This reduces the sample from 555 to 398 observations for schools and from around 240000 to around 175000 students. However, results do not change much. The coefficient for the effect of the electronic register on scores in mathematics stays 0.09 s.d. and for italian it slightly increases to 0.17 s.d.. Finally, the last two columns show the coefficients from the regressions that include school-specific time trends. The estimated effects slighlty increase for both Mathematics and Italian test scores, 0.15 and 0.23 s.d. respectively, but both are now significant only at the 10% confidence level. This is however reassuring that the "*Galton Fallacy*" is not driving results in this framework. I do not have an explaination for why the effect of the introduction of the electronic logbook seems to be stronger for the results in the Italian test scores than for Mathematics, nor the literature has investigated this kind of heterogeneity. A deeper knowledge of the use of the electronic register by both teachers and parents would be required to study this evidence, but this dataset does not allow us to do so.

Table 4: School F.E. Regressions

VARIABLES	(1) Math	(2) Ita	(3) Math - Only obs.	(4) Ita - only obs.	(5) Math	(6) Ita	(7) Math	(8) Ita
ER	0.093**	0.149***	0.096**	0.163***	0.092**	0.172***	0.151*	0.226*
	(2.468)	(3.083)	(1.891)	(2.616)	(1.968)	(2.822)	(1.651)	(1.933)
Constant	-0.043*	-0.036	-0.037	-0.072*	-0.004	-0.002	-0.090	-0.099
	(-1.927)	(-1.631)	(-1.245)	(-1.873)	(-0.155)	(-0.056)	(-1.509)	(-1.298)
Observations	240,033	239,779	140,154	140,097	174,900	173,549	174,900	173,549
R-squared	0.006	0.005	0.007	0.007	0.007	0.007	0.032	0.042
Number of Schools	555	555	551	551	398	398	398	398
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Controls	No	No	No	No	Yes	Yes	Yes	Yes
School Spec. Time Trends	No	No	No	No	No	No	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2 Heterogeneity across gender

Boys and girls perform very differently depending on the subject, with boys doing better in science and technology and girls outperforming boys in humanities. Math performance is strongly correlated with readiness for STEM universities and with future labor market outcomes (Card and Payne, 2018). As a result, this gender gap has been widely studied, since it has potential consequences for the underrepresentation of women in high paid fields (OECD, 2015). This gap is mainly driven by culture and social conditioning: the stereotype that girls do not perform well in STEM (Science, Technology, Engineering and Mathematics) and are more suited for subjects such as languages, psychology, and humanities in general (Nollenberger, Rodriguez-Planas, and

Sevilla 2016). Even if the literature nowadays agrees that there is no biological evidence for such a theory, both parents and educators stereotypes have been contributing to keeping this gap wide (Carlana, 2019), and parenting style is still very different depending on the gender of the child (Doepke, Zilibotti 2019). As a result, the introduction of the electronic register may have very different effects depending on the gender of the students. Table 5 reports estimates for the effect of the electronic register for boys and girls. Column 1 and 2 show the estimates for the effect on standardized scores in mathematics for boys and girls respectively, obtained by dividing the sample. Columns 3 and 4 do the same but for standardized scores in Italian. As expected, the effect on scores in mathematics is slightly lower for females and the opposite is true for scores in Italian. Columns 5 and 6 shows the estimates when using the entire sample and adding the interaction term between electronic register and gender. Females perform better than males in Italian and the opposite is true for mathematics, a result consistent with the literature. Moreover, the coefficient for the interaction term confirm the results of the columns 1-4: the effect of the electronic logbook on mathematics score is lower for female and that on score in italian is lower for male. This result suggests that the introduction of the new technology may increase the gender gap, potentially because parents control more boys study of mathematics and girls study of Italian.

Table 5: Heterogenity by Gender

VARIABLES	(1) Math - Males	(2) Math - Females	(3) Ita - Males	(4) Ita - Females	(5) Math	(6) Ita
ER	0.101*	0.088*	0.166**	0.172***	0.115**	0.146**
	(1.789)	(1.935)	(2.438)	(2.590)	(2.325)	(2.356)
Female					-0.178***	0.086***
					(-9.109)	(5.402)
ER*Female					-0.047*	0.051**
					(-1.963)	(2.548)
Constant	0.103***	-0.120***	-0.086**	0.154***	0.081***	-0.010
	(3.333)	(-3.526)	(-2.400)	(5.728)	(2.627)	(-0.335)
Observations	90,922	83,215	89,533	82,271	174,137	171,804
R-squared	0.006	0.010	0.008	0.010	0.020	0.012
Number of School	397	386	397	386	398	398
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
School F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5.3 Heterogeneity by School Typology

Italian secondary schools are divided in three main categories: Lyceums, Technical Schools and Vocational Schools. Each category has some subcategories, but I cannot see that in the data. Lyceums are attended on average by students from richer neighborhoods, with more educated parents and are supposed to prepare for college. Technical Schools are instead generally attended by males and are supposed to prepare for technical jobs in mechanics, electronics, chemical industry or IT. Students in technical schools come from poorer family on average and generally look for a job after the diploma. Vocational schools are instead intended to prepare for jobs in the service sector (e.g. Hotels and Restaurants) and their average student has a poorer family and social background than those of the other two types of school.

Given these differences, I separate the dataset by typology and look at the effect of the electronic register for each of them. Table 6 reports results for each kind of school. The coefficient for the electronic register is significant only for lyceums, where the average student has a richer and more educated family compared with other schools. The effect is still higher for Italian than for Mathematics, and it seems to decrease monotonically when passing from Lyceums to Technical schools and then to vocational schools.

Table 6: Heterogeneity by By School Typology

VARIABLES	(1) Math - Lyceum	(2) Ita - Lyceum	(3) Math - Tech.	(4) Ita - Tech.	(5) Math - Voc.	(6) Ita - Voc.
ER	0.160**	0.247**	0.093	0.176	0.019	0.078
	(2.115)	(2.293)	(0.935)	(1.519)	(0.417)	(1.396)
Constant	0.288***	0.396***	0.132***	-0.010	-0.817***	-0.821***
	(5.800)	(9.898)	(3.720)	(-0.191)	(-19.021)	(-13.325)
Observations	82,859	82,705	54,957	54,914	37,847	38,024
R-squared	0.012	0.015	0.007	0.008	0.003	0.002
Number of cod_tipo	145	145	136	136	117	117
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
School F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 reports the differential effect across gender for each type of school. It is consistent with results in table 5, even if the coefficient for the interaction between the female dummy and the electronic register is significant only when looking at scores in Italian in lyceums. However, all the coefficients have the expected sign, and the most of them are close to being statistically significant.

Table 7: Heterogeneity by By School Typology and Gender

VARIABLES	(1) Math - Lyceum	(2) Ita - Lyceum	(3) Math - Tech. Sc.	(4) Ita - Tech. Sc.	(5) Math - Voc. Sc.	(6) Ita - Voc. Sc.
ER	0.191**	0.199*	0.101	0.153	0.033	0.078
	(2.171)	(1.772)	(0.973)	(1.265)	(0.745)	(1.332)
Female	-0.266***	0.008	-0.142***	0.120***	-0.048**	0.201***
	(-8.354)	(0.344)	(-4.043)	(3.924)	(-2.590)	(10.387)
ER*Female	-0.043	0.083***	-0.021	0.045	-0.040	0.006
	(-1.168)	(2.970)	(-0.533)	(1.344)	(-1.549)	(0.191)
Constant	0.453***	0.425***	0.172***	-0.014	-0.798***	-0.885***
	(7.813)	(10.468)	(5.208)	(-0.296)	(-17.711)	(-14.464)
Observations	82,627	81,485	54,831	54,104	37,442	36,950
R-squared	0.038	0.018	0.014	0.015	0.005	0.015
Number of schools	145	145	136	136	117	117
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
School F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.4 Heterogeneity across Parents Education

One problem with the dataset used in the analysis is that I do not know how much parents use the electronic logbook once it is adopted by the school of their child. As a result, the effect I found can only be interpreted as an intention-to-treat effect. The use of the electronic logbook by parents is likely to depend on several variables (Bergman, 2016). First of all, more educated parents are more likely to be used to technology. As a result, the use of the electronic logbook is less costly to them. Moreover, richer parents tend to have more electronic devices at home. If parents do not have any electronic device or if they hardly ever use it, they may not be affected much by the introduction of the electronic logbook.

Table 8 reports the results from regressions where variables for parents education are included. Mother HS and Father HS are two dummies indicating respectively whether mother's and father's higher education achievement is the high school diploma. Father Grad. and Mother Grad. are instead dummies equal to 1 if they finished college. The estimates come from the equation:

$$Y_{ist} = \alpha_s + \gamma_t + \beta_1 ER_{st} + \gamma_1 FatherHS + \gamma_2 MotherHS + \gamma_3 FatherGrad + \gamma_4 MotherGrad +$$
$$+\gamma_5 ER * FatherHS + \gamma_6 ER * FatherGrad + \gamma_7 ER * MotherHS + \gamma_8 ER * MotherGrad + X'_{ist}\mathit{\Gamma} + C'_{st}\mathit{\Pi} + \varepsilon_{is}$$

The table shows that the effect of the introduction of the electronic register is not statistically significant for students with both parents without a high school diploma. As expected the coefficient for the dummies *Mother HS*, *Father HS*, *Mother Grad* and *Father Grad.* are all positive for scores in both Mathematics and Italian with only the coefficient for *Father Grad.* on scores in mathematics not significant at the 10% level. Moreover, mother education seems to influence scores in standardized scores more than father's, especially in Italian. The main coefficients of interest in this table are however those for the interactions between parents education and the introduction of the electronic logbook. Having a mother with a high school diploma increases the effect of the introduction of the new technology by 0.07 and 0.04 s.d. for scores in Italian and Mathematics respectively. The same coefficient for having the father with a high school diploma is not statistically significant from zero with respect to scores in Italian, and 0.02 s.d. with respect to scores in Mathematics. The effect of the electronic register increases instead by 0.05 and 0.06 s.d. for Italian and Mathematics scores respectively when the mother has finished college. The coefficients for the dummy indicating a father with a college degree are very similar, but presents more heterogeneity across subject: 0.03 s.d. for scores in Italian and 0.07 s.d. for scores in Mathematics.

These results may be particularly important for teachers and policymakers in education. Introducing new technologies in school may have a positive effect only for those students that can take advantage of them thanks to more educated parents or to the familiarity they have with technology at home. If disadvantaged students and families are not given the tools to use these new technologies, the inequality in educational attainment between poor and rich risks to increase. This issue has been particularly evident during the Covid-19 crisis, with disadvantaged students unable to stay updated with school programs and lessons because of the lack of electronic devices or internet connection in their homes.

Table 8: Heterogeneity by Parents' Education

VARIABLES	(1) Ita	(2) Math
ER	0.082	0.029
	(1.613)	(0.639)
Father HS	0.054***	0.043***
	(6.016)	(4.951)
ER*Father HS	0.004	0.020*
	(0.379)	(1.833)
Mother HS	0.070***	0.044***
	(6.266)	(4.623)
ER*Mother HS	0.067***	0.061***
	(10.057)	(9.422)
Father Grad.	0.023	0.034**
	(1.489)	(2.364)
ER*Father Grad.	0.030***	0.069***
	(3.251)	(6.456)
Mother Grad.	0.038***	0.053***
	(2.680)	(4.275)
ER*Mother Grad.	0.045***	0.059***
	(4.904)	(6.016)
Constant	-0.026	-0.059*
	(-0.651)	(-1.781)
Observations	149,255	149,347
R-squared	0.040	0.031
Number of Schools	398	398
Year F.E.	Yes	Yes
School F.E.	Yes	Yes

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.5 Geographic Heterogeneity

As shown in section 3, the introduction of the electronic logbook was not homogeneous across the Italian territory. Even if nowadays this technology is in approximately every school, in 2014, the first school year the INVALSI gathers data about the register, only just above 40% of schools in the south have adopted the electronic logbook, whereas more than 60% have in Northern and Center Regions. Consequently, I will see more changes in the register format across schools in the South. Italian students have been performing very differently depending on the region of residence. Moreover, students from the South perform systematically worse than their peers in the North and in the Center, and the gap increases as the age of pupils increases (INVALSI 2018) .

Table 9 shows how the introduction of the electronic register affects students depending on the geographic location. I divided the sample in 3 subsamples, North, Center and South, and run the same regression as in previous sections.

Table 9 reports that the effect of the introduction of the electronic logbook is positive and significant only for students in the South, whereas it is very close to zero for those in the North and positive but not significant for pupils in central regions. This may be due to the fact that the South starts from very low scores (average standardized scores for Mathematics and Italian in school without the electronic register is -0.436 and -0.480 respectively versus 0.155 and 0.210 in the North) and to the fact that in the South we observe a stronger within-school variation in the electronic register.

Unfortunately, the smallest geographic level indicated in the dataset is the province. More information about the location of the schools could be very useful in order to control for the level of internet access of the area. Italy presents significant differences across its territory in terms of Internet access and it is among the European countries with the lowest use and availability of internet services (European Commission, 2019).

Table 9: Geographic Heterogeneity

VARIABLES	(1) Math - North	(2) Ita - North	(3) Math - Center	(4) Ita - Center	(5) Math - South	(6) Ita - South
ER	-0.004	0.005	0.279	0.547	0.368*	0.473*
	(-0.100)	(0.129)	(0.651)	(0.738)	(1.709)	(1.763)
Constant	0.155***	0.210***	-0.024	-0.437	-0.436***	-0.480***
	(4.887)	(6.313)	(-0.036)	(-0.444)	(-5.544)	(-4.673)
Observations	83,326	83,013	31,316	31,390	61,021	61,240
R-squared	0.017	0.017	0.020	0.024	0.067	0.086
Number of Schools	182	182	74	74	142	142
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
School F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.6 Quantile Regression

The introduction of the electronic register is likely to affect not only the average score in standardized tests, but also the entire distribution. More specifically, students who already performed well before the introduction of the new technology are not likely to be affected as much as low performers. *Ceteris paribus* parents of low performers are more likely to increase their monitoring with the availability of the electronic logbook, and they can now control absences and low grades. To study the effect of the electronic register on the distribution of scores I use the approach proposed by Machado and Silva (2019) to estimate regression quantiles by estimating conditional means. The problem of estimating quantile regressions model with fixed effects have been widely studied since they suffer from the incidental parameters problem (Lancaster, 2000). There is a wide literature that has tried to deal with this problem (e.g. Koenker, 2004; Lamarche, 2010; Canay, 2011). The main issue with these methods is that either they rely on very restrictive assumptions or they are very complex to compute. Silva and Machado claim that their method relies on testable assumptions and that it is easy to implement. They also show some empirical application in a context similar to the one of this work.

The basic assumption the authors made is that the outcome variable Y has distribution conditional on covariates that belongs to the location-scale family. They argued that the information provided by the conditional mean and the conditional scale function is equivalent to the information provided by regression quantiles, in the sense that this function fully characterizes how the regressors affect the conditional distribution.

Table 10 reports the estimates obtained by replicating the procedure proposed by Machado and Silva (Method of Moments-Quantile Regression, MM-QR) for the first, the second and the third quartile of the distribution of standardized scores in mathematics and Italian.

Results seem to confirm the prediction that the effect of the electronic register is stronger for low performers than for high achievers. The effect on the first quartile is around two times the effect on the third quartile in both Italian (0.22 s.d vs 0.12 s.d.) and Mathematics (0.13 s.d. vs 0.06 s.d.). This is consistent with the "*Reactive Hypothesis*" discussed in the introduction. Parents of low performers have a new tool to monitor children's results and behavior at school and can remediate more promptly.

Table 10: Quantile Regression, MM-QR

VARIABLES	(1) Ita - $\tau = 0.25$	(2) Math - $\tau = 0.25$	(3) Ita - $\tau = 0.5$	(4) Math - $\tau = 0.5$	(5) Ita - $\tau = 0.75$	(6) Math - $\tau = 0.75$
ER	0.221***	0.130***	0.169***	0.096***	0.121***	0.061***
	(18.018)	(12.139)	(19.175)	(11.649)	(11.492)	(5.787)
Observations	175,643	175,663	175,643	175,663	175,643	175,663
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
School F.E.	Yes	Yes	Yes	Yes	Yes	Yes

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.7 Comparison with Primary and Lower-Secondary School

The process of digitalization of Italian schools in the last decade happened in all grades. In previous sections I focused on the second year of high school (when students take the Invalsi standardized test). The second year of high school (10th grade) is the highest grade for which I observe scores in standardized test in all the school years of interest. Invalsi tests for the 13th grade were introduced only in the school year 2017-2018. First years of high school are a period of huge changes in students life: they enter at 14 years old and start to study specific subjects in a more complex way, and their preferences begin to diverge from those of their parents. Until middle school (age 11-13) students are not likely to miss school without parents permission nor to lie about their performance at school. During primary and middle school, parents have frequent contacts with teachers even without the electronic logbook, and are more acknowledged about their child's behavior. On the other hand, parental monitoring tends to decrease with the age of the child, at least when measured as parents-teacher conference attendance (Noel et al. 2013). Bergman (2016) also shows that the usage of technology such as the parent portal (very similar to the electronic logbook analyzed here) is lower in high schools when compared with middle and primary schools. Consequently, how the impact of the electronic register changes with age is not straightforward to predict ex-ante. In high schools this technology appears to be less used by parents, but in lower grades, parents were already more conscious of their child performance and behavior even before the introduction of this new technology.

Table 11 reports the estimate for the effect of the adoption of the electronic register in different grades for both mathematics and italian standardized test scores. Even if for Mathematics the coefficient is positive (+0.06 s.d.) also in 5th grade, it seems that a significant positive impact in both subjects appears only in 10th grades (column 5 and 6 report the same estimates as columns 5 and 6 in table 4). This result seems to support the hypothesis that the introduction of the electronic register has a stronger impact on high school students. However, I can not say much more about the reason why this happens. One possible explanation is that the impact of the new technology affects more the parental monitoring of older students, since in lower grades parents are more in control of their children school life. On the other hand, more data on parents' log-ins as in Bergman (2016) would be very helpful in understanding more clearly the channel through which this new technology affects the scores.

Table 11: Grades comparison

VARIABLES	(1) Math - 5th G.	(2) Ita - 5th G.	(3) Math - 8th G.	(4) Ita - 8th G.	(5) Math - 10th G.	(6) Ita - 10th G.
ER	0.062*	0.019	-0.018	-0.002	0.092**	0.172***
	(1.882)	(0.715)	(-0.973)	(-0.142)	(1.968)	(2.822)
Constant	-0.208***	-0.011	0.024*	0.018*	-0.004	-0.002
	(-5.169)	(-0.685)	(1.829)	(1.807)	(-0.155)	(-0.056)
Observations	213,645	213,905	271,082	271,099	174,900	173,549
R-squared	0.004	0.001	0.000	0.000	0.007	0.007
Number of Schools	514	514	520	520	398	398
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
School F.E.	Yes	Yes	Yes	Yes	Yes	Yes
School Controls	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6 Discussion and Conclusion

In recent years many education systems have recognized the importance of bringing technology in schools. There are many ways through which technology can be used for educational purposes. Several works have shown the impact of computer-assisted learning, internet access, availability of an electronic device and of use of educational software on academic achievement of students.

These new technological tools have a huge potential also for research in economics. They allow gathering data on students' performance, on parental involvement and on teaching methods at a relatively low cost. In this work I used administrative data to analyse the introduction of one of these technology, the electronic register (or electronic gradebook), on standardized test scores of Italian students. Evidence suggests that the introduction of this tool has indeed improved scores in standardized tests in both Italian and Mathematics, with a stronger impact on the former. Moreover, results are consistent with the hypothesis that parents care more about mathematics learning for boys and about reading for girls. This pattern has the potential consequence of increasing the gender gap. If the main channel through which the electronic register affects academic achievement is represented by a reduction in frictions in parents-teacher communication and a consequent improvement in parental monitoring, the gender difference in the effect could be due to the fact that parental monitoring is different depending on the gender and on the subject. Many researchers have shown how the gender gap in STEMs is mainly driven by cultural barriers and sterotypes that see girls less fit for scientific studies and more interested in humanities and reading. Additional research is required also in gender studies to analyze how technology in education can alleviate this issue.

Results shown in this work represent only a starting point for the research on this topic, especially in Italy. Administrative data do not tell much about the adoption of this technology by parents, neither say if teachers use it for other purposes than simply register grades, absences and misbehavior reports. Potentially the electronic logbook could work as an online portal for parents and students, where teachers can upload additional material, personalize homework for students, and send specific messages to families.

Learning Management Systems companies that provide these services to schools are increasing in number and they are radically changing learning and teaching. The COVID-19 crisis forced many schools and teachers to use such platforms and this shock has potentially increased familiarity and expertise in technology applied to education for both teachers and learners. In the last decade the Italian government has invested a significant amount of money in modernizing schools and teaching with technology. On the other hand, little has been done to reduce the technological gap among students. If students and parents do not have the instruments to use effectively the online portal, additional teaching material and other services offered by learning management systems, the investment in schools can be only partially beneficial. Furthermore, it could potentially leave even more behind children from disadvantaged families. If these families will not have the possibility to use these services, either because they do not have the electronic devices needed or because they do not have the training to use them effectively, the gap with richer families will increase.

In the end, I would like to remark the potential of technology for research in education. In the United States, the "Education Technology and Opportunity Initiative" promoted by J-Pal has exactly the purpose of promote researches that test the effectiveness of technology in schools. New technologies allow the implementation of randomized-control trials in a very cheap and easy to implement way. As a result, not only they may be beneficial for students education, but also they give researchers a useful and precise tool to measure the effects of the interventions.

Monitoring students educational path, experimenting with new teaching methods, improving teacher-parents communication: these are only some of the ways through which technology can change education systems and research in the field. This work wants to present an example of the potential effects of these technologies, trying to put a light on all the makings that they have in moving forward the research in education.

References

[1] Peter Bargman and Eric Chan. Leveraging Technology to Engage Parents at Scale: Evidence from a Randomized Controlled Trial. (May):1–50, 2017.

[2] Lisa Barrow, Lisa Markman, and Cecilia Elena Rouse. Technology's Edge: The Educational Benefits of Computer-Aided Instruction. *American Economic Journal: Economic Policy*, 2009.

[3] Peter Leopold S. Bergman. Parent-Child Information Frictions and Human Capital Investment: Evidence from a Field Experiment. *Center for Economic Studies and Ifo Institute (CESifo)*, CESifo Wor:1–66, 2015.

[4] Peter Leopold S. Bergman. Technology Adoption in Education: Usage, Spillovers and Student Achievement. *CESifo Working Papers*, 6101(6101), 2016.

[5] Marco Bertoni, Giorgio Brunello, and Lorenzo Rocco. When the cat is near, the mice won't play: The effect of external examiners in Italian schools. *Journal of Public Economics*, 104:65–77, 2013.

[6] G. Bulman and R. W. Fairlie. Technology and Education: Computers, Software, and the Internet. In *Handbook of the Economics of Education*. 2016.

[7] Leonardo Bursztyn and Lucas C. Coffman. The Schooling Decision: Family Preferences, Intergenerational Conflict, and Moral Hazard in the Brazilian Favelas. *Journal of Political Economy*, 2012.

[8] Ivan A. Canay. A simple approach to quantile regression for panel data. *Econometrics Journal*, 2011.

[9] David E. Card and A. Abigail Payne. High School Choices and the Gender Gap in STEM. *SSRN Electronic Journal*, 2018.

[10] Michela Carlana. Implicit Stereotypes: Evidence from Teachers' Gender Bias*. *The Quarterly Journal of Economics*, 2019.

[11] Sophia Catsambis. Expanding knowledge of parental involvement in children's secondary education: Connections with high school seniors' academic success. *Social Psychology of Education*, 2001.

[12] Flavio Cunha and James Heckman. The technology of skill formation. *American Economic Review*, 97(2):31–47, 2007.

[13] Matthias Doepke and Fabrizio Zilibotti. Parenting With Style: Altruism and Paternalism in Intergenerational Preference Transmission. *Econometrica*, 85(5):1331–1371, 2017.

[14] Matthias Doepke and Fabrizio Zilibotti. The Economics of Parenting Style. In *Love, Money, and Parenting*. 2019.

[15] Maya Escuenta, Vincent Quan, Andre Joshua Nickow, and Philip Oreopoulos. Education Technology: An Evidence-Based Review. NBER Working Paper No. 23744. pages 1–102, 2017.

[16] European Commission. The Digital Economy and Society Index (DESI) | Digital Single Market, 2019.

[17] Robert W. Fairlie. Academic achievement, technology and race: Experimental evidence. *Economics of Education Review*, 2012.

[18] Roland G. Fryer. Financial incentives and student achievement: Evidence from randomized trials. *Quarterly Journal of Economics*, 2011.

[19] Roland G. Fryer. Information, non-financial incentives, and student achievement: Evidence from a text messaging experiment. *Journal of Public Economics*, 2016.

[20] Austan Goolsbee and Jonathan Guryan. The impact of internet subsidies in public schools. *Review of Economics and Statistics*, 2006.

[21] Lingxin Hao, Joseph V. Hotz, and Ginger Z. Jin. Games parents and adolescents play: Risky behaviour, parental reputation and strategic transfers. *Economic Journal*, 2008.

[22] Nancy E. Hill and Diana F. Tyson. Parental Involvement in Middle School: A Meta-Analytic Assessment of the Strategies That Promote Achievement. *Developmental Psychology*, 2009.

[23] William Jeynes. A Meta-Analysis of the Efficacy of Different Types of Parental Involvement Programs for Urban Students. *Urban Education*, 2012.

[24] William H. Jeynes. Effects of parental involvement and family structure on the academic achievement of adolescents. *Marriage and Family Review*, 2005.

[25] Roger Koenker. Quantile regression for longitudinal data. *Journal of Multivariate Analysis*, 2004.

[26] Matthew A. Kraft and Todd Rogers. The underutilized potential of teacher-to-parent communication: Evidence from a field experiment. *Economics of Education Review*, 47:49–63, 2015.

[27] Carlos Lamarche. Robust penalized quantile regression estimation for panel data. *Journal of Econometrics*, 2010.

[28] Tony Lancaster. The incidental parameter problem since 1948. *Journal of Econometrics*, 2000.

[29] José A.F. Machado and J. M.C. Santos Silva. Quantiles via moments. *Journal of Econometrics*, 213(1):145–173, 2019.

[30] Ralph B. McNeal. Checking in or checking out? investigating the parent involvement reactive hypothesis. *Journal of Educational Research*, 105(2):79–89, 2012.

[31] Natalia Nollenberger, Núria Rodríguez-Planas, and Almudena Sevilla. The math gender gap: The role of culture. In *American Economic Review*, 2016.

[32] Organization for Economic Cooperation and Development. Education at a Glance 2015. Technical report, 2015.

[33] Caterina. Ricci, Roberto; Amici, Monica; Biggera, Andrea; Cuzzucoli, Emanuela, Fazio, Alessandra; Figura, Elisabetta; Fiorino, Teresa; Lasorsa, Cristina; Ponzo. RILEVAZIONI NAZIONALI DEGLI APPRENDIMENTI 2017-18. Technical report, 2018.

[34] Todd Rogers and Avi Feller. Reducing student absences at scale by targeting parents' misbeliefs. *Nature Human Behaviour*, 2018.

[35] John H. Tyler. If you build it will they come? Teachers' online use of student performance data. *Education Finance and Policy*, 2013.

[36] B. A. Weinberg. An incentive model of the effect of parental income on children. *Journal of Political Economy*, 2001.

[37] S. Wilder. Effects of parental involvement on academic achievement: A meta-synthesis. *Educational Review*, 2014.