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GIFT OF TIME AND FAMILY GIFT: THE EFFECT OF EARLY SCHOOL ENTRY ON PUPILS PERFORMANCE

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Gift of Time and *Family Gift*: The Effect of Early School Entry on Pupils Performance

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Abstract

This paper provides a comprehensive analysis of the effect of early school entry on educational outcomes using standardized test score data on Italian pupils. The empirical procedure is designed to disentangle the effect of regular entry (*Gift of Time*) from possible unobserved confounding factors (*Family Gift*) affecting both enrollment decision and schooling outcome. We tackle the issue of selection on unobservables by using a Regression Discontinuity Design so that exogenous age thresholds are used to compare children with similar age but different educational choices. Our estimates suggest that anticipated school entry may generate severe penalties in test scores which persist during primary school. Our findings have policy implications for parents, which struggle with the question of whether they should send their children to school as soon as they are eligible, and for governments, which can change cutoff birth date for first enrollment into school.

Keywords: Age at school entry, primary school, standardized test scores.

JEL code: I20, H52.

1 Introduction

In the past, child development researchers have often argued that children's "readiness" for school is an important factor that determines school success. However, there is a considerable debate in the research community regarding how school readiness can be measured. In the absence of any consensus, researchers have traditionally used chronological age as the standard to evaluate it. There are two dominant viewpoints surrounding the entrance age debate. On the one hand, basic human capital theory suggests that children should start formal learning as soon as possible: the earlier children enroll at school, the sooner they begin accumulating skills (Bedard and Duhey, 2012). Moreover, some authors suggest that young children are more receptive for learning than older ones and believe that school provides the nurturing environment that helps to promote children's learning and development (Datar, 2006). On the other hand, child developmentalists have stressed that age and human capital could be complement so that young children might not be mature enough to learn complex material at school (Mayer and Knutson, 1999). In other words, children need the *Gift of Time* and general out-of-school experience to have a better schooling performance. As a consequence, enrolling a pupil before he/she is ready for the rigor of formal education may turn out to be less productive than waiting until he/she is more mature. The school entrance age also has an impact on lifetime earnings. Individuals who start school in advance enter the labor market earlier, and can collect the returns of their human capital investments over a longer time horizon (Friedriksson and Ockert, 2005). Conversely, children entering the labor market one year later could be more likely to have the necessary skills and maturity to succeed in school and therefore to learn more in each grade. In this perspective, postponing school entrance implies better skills, which may provide higher wages (Helder and Lubotsky, 2008).

The identification of the effect of age at school entry is not an easy task. The main reason is that parental decisions to delay or expedite their child's school entry are almost certainly related to both households' and pupils' characteristics which can simultaneously affect schooling outcomes through several channels. It follows that the evaluation of the causal effect (if any) of entry age on schooling outcomes, i.e., the presence of a *Gift of Time* is particularly problematic because of the presence of potential *Family Gift* shaping pupils' cognitive and schooling ability.

Having these caveats in mind, in this work we address the following research questions:

1) Do younger entrants achieve lower test scores compared to older entrants, i.e., does exist a *Gift of Time*?

2) Is the evaluation of the achievement gap biased by unobservable characteristics, i.e., does exist a *Family Gift*?

3) Do these differences in achievement scores persist during primary school?

The identification of these points is achieved throughout a strategy designed to disentangle the treatment effect of early entry from possible unobserved confounding factors affecting both enrollment and schooling outcomes. We deal with selection on unobservables bias by means of a Regression Discontinuity Design so that exogenous age-thresholds are used to compare pupils with almost identical age but different educational choices. Our empirical analysis is carried out on data containing the universe of students who attend primary school in Italy. Our measures concerning pupils' performance are based on Standardized National Tests

Score in Mathematics and Reading implemented by the National Institute for the Educational Evaluation of Instruction and Training (INVALSI). Our results suggest that students who enroll in advance perform worse than regular ones. We point out that a severe distortion in the evaluation of the true effect of early entry arises when neglecting unobserved characteristics driving the early school decision. Since pupils in advance tend to be selected according to their schooling ability, the real impact of early entry on schooling performance is underestimated. After we get rid of selection bias, we find that anticipating pupils perform substantially worse than regular ones. This effect proves to be particularly scarring since it lasts for the entire path of primary education.

The paper proceeds as follow. The next Section provides a review of the main recent studies. Section 3 describes how our paper adds to the existing literature and gives an intuition of our identification strategy. Section 4 highlights data source and variables used in the analysis. Section 5 presents the derivation of our empirical strategy while Section 6 discusses the main results as well as several robustness and falsification exercises. Some concluding remarks are addressed in Section 7.

2 Literature Review

Since the '80s several studies have exploited the variation in school entry age to identify its effect on educational performance showing that there is a disadvantage to early entry (Cleborne, 1983; Uphoff and Gilmore, 1985).[1]

[1] Although the interest in this subject has grown since the 80s, a first contribution dates from the early '30s, when the SUMMIT New Jersey school system was interested in determining which students to admit into first grade. To help answer

Typically, the outcome variable examined in the literature is children's achievement test scores in the primary grades. Most of studies focuses on within grade comparisons of performance of older and younger school entrants who differ in birth dates within the year (for a review see Stipek, 2003). The evidence from this literature suggests that youngest students have lower test scores compared to oldest students in the same grade (Sweetland and De Simone, 1987; Jones and Mandeville, 1990; Sharp, 1995; Strøm, 2004; Datar, 2006; Helder and Lubotsky, 2008; McEwan and Shapiro, 2008; Crawford et al., 2010) and are more likely to repeat a grade (Helder and Lubotsky, 2008; McEwan and Shapiro, 2008). Only few studies provide evidence that youngest students achieve higher test scores than oldest ones (Leuven et al., 2010; Robertson, 2011). Economists have also shown interest in the effects of age at school start on educational attainments and wages. This literature provides mixed results. Some studies find that older entrants attain slightly less education (Angrist and Krueger, 1991, 1992; Fertig and Kluve, 2005; Dobkin and Ferreira, 2010) and lower labor market outcomes (Angrist and Krueger, 1991). In contrast, Fredriksson and Ockert (2006) and Kawaguchi (2011) find evidence in support of higher educational attainment and wages for students who enter school at an older age. The positive association between these variables is also provided by Bedarh and Duhey (2012).

Instead of discussing in details this impressive wide literature, a schematic summary is provided in Tables 1 and 2. In these tables, we pose focus on the effect of age on the evaluated outcome variables. Moreover, we emphasize methods of

to this question, Bigelow (1934) studied the achievement of 127 fourth graders in the school system finding that children who were older when they began first grade were less likely to repeat one of the first three grades and also tended to score higher on the achievement test.

analysis and results. We remark that most of these studies use quarter of birth or legal entry age as instruments to deal with the endogeneity issue. This approach has been recently criticized by Barua and Lang (2009) who show that the quarter of birth and the legal entry age instrument give biased estimates of the policy-relevant local average treatment effect (LATE) because of the failure of the monotonicity assumption. These authors propose an instrument that satisfies the monotonicity assumption and gives a consistent estimates of the policy-relevant LATE showing that the effect of school entry age on educational attainment appears to be very close to zero. As things stand, evidence of the entry age effect on schooling outcomes appear to be far from being well defined.

3 Our Insights and Identification Procedure

Our paper follows the recent attempts of Crawford et al. (2010) and Dobkin and Ferreira (2010) to provide estimates which are not derived by means of instrumental variables techniques. We present an original empirical procedure designed to disentangle the treatment effect (anticipated entrance in primary school) from possible unobserved confounding factors affecting enrollment decisions as well as schooling outcomes. The Italian normative setting regulating access to primary education allows us to address this point. Italian primary schools usually start in September. In a given year (say year t) all pupils who are 6 years old and those who will be 6 years old by December 31st *must* start school in September. Then, the law also *permits* enrollment to pupils who will be aged 6 by April 30th in $t+1$. Crucially, this is only an opportunity (it is not mandatory) and it is apparent that self-selection into schools may be related to potentially unobserved characteristics.

At this stage, it is important to remark that also part of the pupils who are aged 6 in t are affected by a selection problem. This is true for those who became 6 years old between January 1st and April 30th in year t since these are pupils whose parents decided not to send them at school in advance in $t-1$. Therefore, among scholars in the same class, only those aged 6 between May 1st and December 31st in year t do not suffer from self-selection into education. In this setting, we can estimate the effect on schooling outcomes of anticipating the entry age of one year.

Consider pupils who started school in t and will be aged 6 in April of year $t+1$. In order to compare their schooling outcome with that of their classmates who became 6 years old in May of year t an Average Treatment on the Treated (ATT) estimation procedure may be implemented. The ATT estimator gives a parameter $\hat{\beta}_{ATT}$ which provides an estimate of the effect on schooling outcomes of entering school 1 year and 1 month earlier. However, while the group of older pupils does not suffer from any enrollment selection, pupils in advance are selected according to their parents' choice. Therefore, the Conditional Independence Assumption (CIA) required to obtain unbiased ATT estimates is likely to fail and, consequently, the estimated parameter is potentially biased since:

$$\hat{\beta}_{ATT} = \underbrace{\hat{\beta}}_{unbiased\ effect\ of\ early\ entry\ on\ scores} + \underbrace{\check{\beta}}_{effect\ of\ unobserved\ confunders\ on\ scores} \tag{1}$$

Notwithstanding, from eq. (1) it appears that the unbiased parameter of early entry on pupil's performance ($\hat{\beta}$) can still be evaluated. This requires that the effect of unobserved components on test scores ($\check{\beta}$) is firstly estimated and then expunged from $\hat{\beta}_{ATT}$. We estimate $\check{\beta}$ by relying on a Regression Discontinuity Design (RDD) which evaluates difference in scores of pupils aged 6 in December of year t with respect to those aged 6 in January of year $t+1$. As far as the impact of just one month on schooling performance is negligible, differences in test scores between these two groups of pupils should only reflect unobserved heterogeneity related to selection issues. Following this strategy we can firstly estimate the mean effect of unobserved confounders on test score. Then, we can evaluate the effect of entering primary school one year earlier on test scores using $\hat{\beta}_{ATT}$ and $\check{\beta}$.

4 Data and Descriptive Statistics

Data used in this work have been collected by the INVALSI, which yearly assesses students' knowledge in Reading (Italian Language) and Mathematics through the National Service for the Evaluation of Education and Training (SNV).[2] Standardized tests are administered in the primary school (Grade 2 and 5), in the lower secondary school (Grade 6 and 8), and in the upper secondary school (Grade 10). For the purpose of the present study, we use data of primary education - both the 2nd and the 5th grade - of the school year 2011/2012.[3] In our case we use information on about 500,000 pupils.

[2] Reading test is divided into three main sections: 1) Reading comprehension of a narrative text, 2) Reading comprehension of expository text, and 3) Grammatical knowledge and skills. Mathematics test is divided into four areas: 1) Numbers, 2) Space and figures, 3) Data and forecasts, 4) Relations and functions. At the 2nd grade of primary school, the maths test is limited to the first three areas.

[3] Norms regulating early school entry discussed in Section 3 have been introduced in 2006 by the so called Fioroni reform. As a consequence, children in grades higher than the 5th cannot be used for our analysis since they started primary school before 2006. For pupils who attend the 2nd grade in 2011/2012, the law concerning their first school enrollment is the Ministerial Circular n.4/2010: School enrollment for school year 2010/2011. For pupils who attend the 5th grade in 2011/2012, the law concerning their first school enrollment is the Ministerial Circular n.74/2006: School enrollment for school year 2007/2008.

Data set of the INVALSI contains standardized tests scores in reading and mathematics. On top of that, useful data on personal, family and schooling background of students, gender, date and country of birth of pupils, country of birth, occupational status and educational level of their parents and territorial characteristics are provided. This rich data set gives us the opportunity of controlling for many relevant observable characteristics which have not been considered in recent studies on the field. Among others, Crawford et al. (2010) realize the limits imposed by information contained in their available data set. Moreover, since INVALSI identifies each year a number of schools where the test is done in the presence of an external observer, it is possible to control for the phenomenon of cheating. All variables used in the analysis are described in Table 3.

Rather than focusing on descriptive statistics of all variables, we prefer to report mean and standard deviation of the dependent variables in our analysis – test scores in Reading and Mathematics – by date of birth and by parental background. In Table 4 (Column I), at the 2nd grade there is an advantage for pupils enrolled in advance compared with regular students only in mathematics test scores. This gap does not fade away during school. Concerning language test scores, advanced pupils appear to perform as good as regular ones. Interestingly, if we split the group of regular pupils in order to untangle those who could enroll in advance but have decided to enroll regularly (i.e. those aged 6 in the first four months of year t) we detect some additional insights. In particular, in Column II of Table 4 regulars appear to have lower Mathematics test scores than both the oldest and the youngest pupils. For Reading, regulars perform worse than older pupils only. This preliminary evidence, which requires further investigations, shows that when dealing with Mathematics tests both the age and the selection effect could be present, while for Reading skills age proves to be more important than selection. Turning to family background, in Table 5 and Table 6 we observe that pupils with more educated parents have a higher score than those with low educated parents: mean test score increases with educational qualifications of both father and mother. Mean score gap reaches approximately 10 points considering students with parents who have a high level of education with respect to those who have parents with a low level of education. Some difference also arises across pupils from families that are heterogeneous in terms of income. Students in low-income families perform worse than students in medium- and high-income ones. This is possibly due to a better cultural environment for children in non-disadvantaged environments providing them ample opportunities to develop their cognitive and language skills.

5 The Empirical Framework

To examine the effect on schooling performance of one year difference in age at school entry, we start by estimating the Average Treatment effect on the Treated (ATT). In the presence of potential selection on *observables*, the ATT can be consistently estimated by running OLS on a sample of pupils who started school in year t and become 6 years old in either May of year t or April of year $t+1$ according to the following framework which includes variables that may potentially affect the outcome as well as treatment participation:

$$Y_{ics} = \alpha + \beta Age_{ics} + \gamma StudC_{ics} + \delta ClassC_{ics} + \phi SchoolC_{ics} + \eta ParentsC_{ics} + \varepsilon_{ics}. \quad (2)$$

In eq. (2) Y is performance measured by normalized test score in either Reading or Mathematics of student i in the class c in the school s; $StudC$, $ClassC$, $SchoolC$, $ParentsC$ are vectors of student, class, school characteristics and parent's socioeconomic background respectively, as defined in Table 3, which for the sake of simplicity from now on will be indicated all together as **z**; ε is the error term. Age is a variable taking the value 1 for pupils aged 6 in April of year $t+1$ and 0 otherwise. The estimated parameter β associated to this variable gives us the treatment effect i.e.:

$$\hat{\beta}_{ATT} = E[Y_{ics}|\mathbf{z}_{ics}, Age_{ics} = 1] - E[Y_{ics}|\mathbf{z}_{ics}, Age_{ics} = 0] \tag{3}$$

However, in the presence of selection on *unobservables* the ATT estimators is given by:

$$E[Y_{ics}|\mathbf{z}_{ics}, Age_{ics} = 1] - E[Y_{ics}|\mathbf{z}_{ics}, Age_{ics} = 0] = \hat{\beta} + (\textit{selection effect}) \tag{4}$$

where $\hat{\beta}$ indicates the unbiased estimator of β in eq. (2). To obtain unbiased estimates of the treatment on schooling outcomes, the selection effect should be differentiated out from $\hat{\beta}_{ATT}$, i.e.:

$$\hat{\beta} = \hat{\beta}_{ATT} - (\textit{selection effect}). \tag{5}$$

Albeit the approach contained in eq. (5) grounds on a clear-cut identification procedure, its application requires a non trivial evaluation of the selection effect.[4] In our case we can consistently estimate the selection effect using a RDD approach.

[4]See p. 845 in Cameron and Trivedi, 2005, for a complete discussion.

The idea is as follows. We start by evaluating scores along pupils' month of birth and we investigate whether any discontinuity arises at the threshold imposed by the Italian normative setting for mandatory school entrance. The cutoff point is posed between children who will be 6 years old in December of year t and those who will be aged 6 in January of year $t+1$. The main assumption is that whether a child is born in December or in January is completely random. Then, the only difference arising between these two groups is that those born in January have been selected by their family to be enrolled at school. In this way, it is possible to assess the effect of selection on schooling outcomes and then to evaluate the pure effect of early schooling through eq. (5), i.e., we can identify $\hat{\beta}$.

6 Findings

6.1 Main Results

In Table 7 we start by presenting preliminary OLS estimates of eq. (2) using all pupils in each grade. Coefficients associated to our controlling variables are significant, going in the expected direction and we avoid to present long comments on quite standard results. In this case regressor of main interest is "*Students in Advance*" which in this case is a dummy variable taking the value 1 for pupils who were 6 years old between January 1st and April 30th in year $t+1$ and 0 for all others who were 6 during year t. The former get on average, a score of 2.043 points less than regular students in Reading and 1.862 points less in Mathematics at the 2nd grade. At the 5th grade, the gap reduces to 0.842 points less in Reading and -0.901 point less in Mathematics. As amply discussed, we cannot give any causal interpretation on these results. To make one step further, we start by estimating the ATT using only a sample of pupils who were 6 years old in May of year t and those who were aged 6 in April of year $t+1$. In this case, our interest is on the effect of one year early school entry on test scores. We use a Propensity Score Matching Method which allows to control for all observed variables that are likely to affect the treatment. The ATT is evaluated using the nearest-neigbor matching estimators.[5] We repeat this procedure for Reading and Mathematics test scores and for both 2nd and 5th grade and the results are reported in Table 8. Interestingly, all coefficients confirm previous findings, that is, the presence of a significant penalty for pupils who entered primary school one year earlier. Results are robust and obtained using about 25,000 observations for each specification.

As we have discussed, the interpretation of the $\hat{\beta}_{ATT}$ parameter must be very cautious since, albeit the use of propensity score implies that selection on observables is not present in our data, potential unobserved factors may drive pupils into the treatment. These unobserved components can affect test scores so that we do not have an identification of the *Gift of Time* effect. Indeed, *Family Gift* may affect cognitive schooling ability as well as early enrollment decisions leading to a biased estimation of the early school entry effect. Parental decisions to delay or expedite their child's school entry are related to specific characteristics of children and parents. Children who begin school early are likely to be particularly skilled or gifted but we can ignore that they may come from disadvantaged families which can't afford an extra year of pre-schooling in kindergarten. In this case, postponing

[5]Estimates of the propensity score are available from the authors. We remark that different matching procedures (Kernel - different types - and Stratification) yield almost identical point esimates for the ATT.

school entrance would impose potentially large costs on families, such as child care costs and lost wages from reduced labor force participation of mothers in order to care for their children. To tackle the issue of selection on unobservables we adopt the RDD strategy.

Figure 1, 2, 3 and 4 contain a graphical illustration of the RDD estimates for Reading and Mathematics test scores at the 2nd and at the 5th grade respectively. Estimates of the selection effect ($\hat{\beta}_{RDD}$) are provided in Table 9. As it appears in all figures, a significant effect arises around the threshold highlighting a *positive* selection effect. The results are confirmed for all grades and for both mathematics and reading test scores. In addition, albeit we report results arising from a single bandwidth, we remark that the dimension of our sample size is such that different bandwidths are likely to generate almost identical outcomes. This finding - which is robust at 1% significance level as reported in Table 9 - highlights that in Italy those children who anticipate schooling enrollment are actually different with respect to the average of their regular peers and, in particular, they appear to be selected on the basis of characteristics which positively affect schooling outcomes. In other words anticipating pupils benefit from a positive *Family Gift*.

We can now turn our attention to the presence of the *Gift of Time* effect. Table 10 contains differences between $\hat{\beta}_{ATT}$ and $\hat{\beta}_{RDD}$ coefficients providing unbiased estimates of schooling performance of pupils anticipating of one year school entry. We detect severe penalty for anticipating pupils which would be underestimated if the selection bias were not considered. Penalties are present in both Reading and Mathematics and persist during the entire primary education path.

6.2 Can the Gift of Time Redeem the Family Gift?

In this Paragraph we present an empirical exercises to further inspect the presence of a *Gift of Time*. Consider an RDD design where pupils aged 6 in January of year $t+1$ are compared with those born in November-December of year t. In this case, we are constructing a comparison group which includes pupils older than those used in our previous RDD since in this case only those born in December were considered. This approach - based on the assumption that the month of bird is random - yields the possibility of inspecting whether pupils that are on average two month older than the "selected ones" are able to close the score gap. This procedure can be repeated by keeping fixed the treated group (pupils in advance born in January $t + 1$) and comparing them with pupils aged 6 in the period October-December of year t; in the period September-December, and so on. In this way we can check if a *Gift of Time* actually exists since, in this case, we should observe that the RDD parameters is decreasing in the average age of the control group.

Estimates are reported in Table 11 and a graphical illustration is also provided in Figures 5-8. The results go in the expected direction. When pupils get older, they perform better in test scores compared with pupils in advance since the gap between selected and unselected is decreasing in age. Interestingly, if we consider Reading test scores for pupils at the second grade (Figure 5) age proves to be particularly important since the selection effect disappears after 6 months and a "pivotal-point" arises: the selection effect becomes negative, highlighting that at the 2nd grade reading skills are particularly sensitive to the *Gift of Time*. The same decreasing path arises for mathematics at the second grade (Figure 6).

However, albeit decreasing, in this case the selection effect remains positive and statistically significant highlighting that when mathematical reasoning and logical-skills are required differences between selected pupils and the average population cannot be completely redeemed by the *Gift of Time*. The same is true for both Reading and Mathematics scores at the 5th grade (Figure 7 and 8 respectively). Overall, the results show that a *Gift of Time* actually exists since selection becomes less important when age increases. In addition, the *Family Gift* appears to be important and long-lasting during primary school.

6.3 Robustness Check and Falsification Exercises

In this Paragraph we present a robustness and a falsification exercise to check the reliability of our RDD estimation of the selection effect. The idea is to present an alternative identification strategy which is based on entry-age provincial variation arising for pupils at the 5nd grade. In this case, we can provide an estimation of the selection effect which relies on a very different construction of treated and control groups as well as an alternative estimation procedure. Finally, a falsification test is also discussed.

An alternative identification procedure can be constructed in our case since the Italian legislation allows for autonomous setting of school entry-age in the provinces of Trento and Bolzano who are recognized by the Italian Constitutional Law as two Special and Autonomous Provinces. The provincial legislation in Trento and Bolzano can depart from the National Law by setting different threshold for mandatory schooling. In 2006, the province of Trento has fixed mandatory schooling for those children who become 6 years old before the 30th of September

2006 allowing for *optional* enrollment of pupils who reach the age of 6 in the period October 1st - December 31st (L.P. 270/2006). It is then possible to use this provincial variation to build up an alternative identification strategy of the selection effect. In particular we can compare selected pupils resident in the province of Trento with all other pupils in Italy who must start school if born between October and December 2006. More precisely, we are interested in a sort of difference-in-differences estimator whose intuition is graphically provided in Figure 9. In this figure we draw a negative relation between test scores and month of birth and a negative gap between pupils from Trento and those from the rest of Italy. From this graph it is easy to gather that in order to estimate the selection effect on test scores some steps are required. In particular, we need to evaluate: *i*) the difference in test scores between pupils born in the period December 1st - September 30th resident in Trento and those born in the same period who are resident in the rest of Italy; *ii*) the difference in test scores between pupils born in the period October 1st - December 31st resident in Trento and those born in the same period who are resident in the rest of Italy; *iii*) the difference between these two differences. Whether a selection effect is present we should detect an improvement in test score performance for pupils resident in Trento born after October 2006 with respect to the performance of the Trento pupils born before October 2006 when compared with their peers from the rest of Italy. In this way we have an alternative estimate of the *Family Effect*.

In addition, this identification strategy can be supported by a placebo test implemented by using the Autonomous Province of Bolzano. Indeed, in 2006 the provincial law fixing entry-age did not depart from the national legislation (L.P. 40/2006) hence there is scope for a falsification exercise.

Table 12 contains the results. The OLS estimators applied to 5nd grade pupils resident in the Province of Trento for both Reading and Mathematics confirm the presence of a positive selection effect. In this case, pupils in advance perform better in terms of test scores with respect to children in the same province. Interestingly, if we replicate the empirical exercise using pupils born between October 1st and December 31st in the province of Bolzano, we do not detect any significant parameter.

7 Concluding Remarks

In this paper we examine the effect of age at school entry on Italian standardized test scores exploiting the peculiar Italian normative setting. Unlike other studies, we deal with selection on unobservable by estimating the potential selection bias comparing pupils who *should* start school in year t and pupils who have the *opportunity* to start school in that year. Through this strategy we are able to estimate unbiased effect of starting primary school one year earlier on test scores. We provide results which are consistent with most of the existing literature, i.e., the youngest children in a classroom have scores lower than their older classmates. The unbiased effect of early schooling on test scores is negative both in Reading and in Mathematics and, more interestingly, it tends to persist during primary school. This evidence is not based on instrumental variables techniques whose robustness has been heavily questioned in the literature. We point out that a severe distortion in the evaluation of early entry arises when neglecting the effect of unobserved characteristics driving school entry decisions. In particular, in the presence of a positive *Family Gift,* leading best pupils to enter school in advance, the penalty imposed by early school entrance is substantially underestimated.

The question concerning at which age a child should start school is a controversial topic in education policy. Governments could change cutoff birth date for first enrollment into school, weighting penalties of being younger at school entry against the costs for parents in terms of child care and delayed entrance in the labor market. Our work contributes to this debate posing a word of warning on the magnitude of the skill gap and on its persistence during the entire primary education track. Further researches should be devoted to understand if this gap is actually bridged in the long run.

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Table 1 – Literature Review by Author, Outcome Variables, Method and Results

Author	Age variable	Outcome variable	Method	Results
Angrist and Krueger (1991)	Season of birth	Schooling and earnings	OLS 2SLS: Quarter of birth as an instrument for education	Children born in the first quarter of the year have a slightly lower average level of education than children born later in the year; students who are compelled to attend school longer by compulsory schooling laws (the youngest) earn higher wages as a result of their extra schooling.
Angrist and Krueger (1992)	Age at school entry	Educational attainment	2SLS: Quarter of birth as an instrument for entry age	Older entrants tend to attain slightly less education.
Strøm (2004)	Enrollment age	Achievement tests in reading	OLS	Students born late in the calendar year achieve significantly lower test scores in reading compared to their oldest classmates. The disadvantage from being the youngest is highest for children with relatively large home and parental resources.
Fertig and Kluve (2005)	a) Age at school entry b) Being deferred, i.e. enrolling at age 7 versus enrolling at age 6	Schooling degree and probability of repeating a grade	a) linear probability b) matching models c) 2SLS: Age at school entry according to the regulation as an instrument for actual age at school entry	a) e b) an older age at school entry is associated with a higher probability to repeat a class, a lower probability to receive a high schooling degree in West Germany, and a) a higher probability to attain a low schooling degree or less in the Eastern part of the country; b) No difference for East Germany; c) no effect of age at school entry on educational performance.
Datar (2006)	Age at school entry	Math and reading test scores	2SLS, two instruments for entrance age: (i) Number of days between a child's 5th birthday and the school's cutoff date, and (ii) State's kindergarten entrance cutoff date	1-year delay in kindergarten entrance is associated with a significant increase in math and reading test scores at kindergarten entry. This initial advantage increases by half a point in math and by 1 point in reading during the first 2 years in school.
Fredriksson and Öckert (2006)	Age at school entry	Education and labour market outcomes	2SLS: Expected age at school entry as an instrument for actual school starting age	Children who start school at an older age do better in school and go on to have more education than their younger peers. The long-run earnings effects are positive but small. However, since starting school later entails the opportunity cost of entering the labour market later, the net earnings effect over the entire life-cycle is negative.
Helder and Lubotsky (2008)	Age at school entry	Test scores; probability of repeating kindergarten, 1st or 2nd grade	OLS 2SLS: Predicted entrance age as an instrument for actual entrance age	Being a year older at the beginning of kindergarten reduces the probability of repeating kindergarten, first, or second grade in primary school. They also find differences in reading and math test scores, but as children progress through school, achievement gaps between older and younger children tend to fade away. The entrance age effect is larger and more persistent among children from higher socioeconomic status families. Having older classmates tends to raise reading and math achievement but also increases the probabilities of repeating a grade.
McEwan and Shapiro (2008)	Delayed school enrollment	Test scores, probability of repeating first grade	OLS 2SLS: Birth dates as instruments for first grade enrollment age	One-year delay decreases the probability of repeating first grade, and increases fourth and eighth grade test scores.
Barua and Lang (2009)	Age at school entry	Educational attainment	2SLS: Effect of requiring a child to enter school in the year she turns six when she would otherwise have entered a year earlier as an instrument for age at school entry	The effect of school entry age on educational attainment is very close to zero.
Crawford et al. (2010)	Month of birth	Achievement test scores	Regression discontinuity approach	Younger children perform, on average, significantly worse in national achievement tests than the older peers.
Dobkin and Ferreira (2010)	Age at school entry	Educational attainment and labour market outcomes	Regression discontinuity approach	School entry laws increase educational attainment of students who enter school early, but also lower their academic performance while in school. No evidence that the age at which children enter school effects job market outcomes.
Leuven et al. (2010)	Age at school entry	Language and math scores	OLS	One additional month of time in school increases language and math scores of disadvantaged pupils while for non-disadvantaged pupils there are no effects.

Table 1 – continued.

Author	Age variable	Outcome variable	Method	Results
Kawaguchi (2011)	Age at school entry	Test scores, educational attainment, and labour market outcomes	OLS	Older children in a school cohort obtain higher test scores and more education years than their younger peers. This difference in academic outcomes seem to turn into higher annual earnings among males.
Robertson (2011)	Age at school entry	Reading and math test scores, grade retention	OLS 2SLS: Quarter of birth as an instrument for age at school entry	Older students appear to do worse on standardized tests scores than their younger peers for the 3rd and 8th grades, whereas there are no age effects in the 5th grade (OLS). The oldest students achieve higher results on math and reading tests, as well as have lower grade retention (2SLS).
Bedard and Duhey (2012)	Age at school entry	Adult wages	OLS	One-month increase in the minimum school entry age increases wages.

Table 2 – Literature Review by Author, Outcome Variable, Method and Results in Term of Best Performers

Author	Outcome variable				Method			Best performers	
	Test scores	Educational attainment	Labor market outcomes	Other	OLS	2SLS	Other	Youngest	Oldest
Angrist and Krueger (1991)		■	■		■	■		■	
Angrist and Krueger (1992)		■				■		■	
Strøm (2004)	■				■				■
Fertig and Kluve (2005)		■ (Schooling degree)		■ (Probability of repeating a grade)		■	■ (Linear probability; Matching models)	■	
Datar (2006)	■					■			■
Fredriksson and Öckert (2006)	■	■	■			■			■
Helder and Lubotsky (2008)	■			■ (Probability of repeating a grade)	■	■			■ (Gap fade away through school)
McEwan and Shapiro (2008)	■			■ (Probability of repeating a grade)	■	■			■
Barua and Lang (2009)		■				■			
Crawford et al. (2010)	■						■ (Regression discontinuity approach)		■
Dobkin and Ferreira (2010)		■	■				■ (Regression discontinuity approach)	■ (Educational attainment)	
Leuven et al. (2010)	■				■			■ (For disadvantaged pupils)	
Kawaguchi (2011)	■	■	■		■				■
Robertson (2011)	■			■ (Grade retention)	■	■		■ (OLS)	■ (2SLS)
Bedard and Duhey (2012)			■		■				■

Table 3 – Description of Variables

DEPENDENT VARIABLES:		*Description*	
Standardized test scores in Reading and Mathematics		Continuous variable (scale from 0 to 100)	
REGRESSORS: *Group*	*Dimensions*	*Description*	*Dummy variables*
Student characteristics	Date of birth (Year)	Dummy variable	$Year_{t-n}$ (n-year Delayed students, n>0) $Year_t$ (Regular students) $Year_{t+1}$ (Students "In advance")
	Date of birth (Four months)	Dummy variable	1st Four months $(January\text{-}April)_t$ (Students not enrolled "In advance") 2nd Four months $(May\text{-}August)_t$ (Regular students) 3rd Four months $(September\text{-}December)_t$ (Regular students) 1st Four months $(January\text{-}April)_{t+1}$ (Students "In advance")
	Gender	Dummy variable	Male Female
	Country of birth	Dummy variable	Italy Foreign Country
	Pre-school attendance	Dummy variable	Daycare (yes/no) Kindergarten (yes/no)
School characteristics	School size	Continuous variable	-
	Class size	Continuous variable	-
	Indet of Sample school	Dummy variable	Sample school School no sample
	School weekly hours	Dummy variable	Up to 30 hours From 31 to 39 hours 40 hours
Parents' background	Father's/Mother's country of birth	Dummy variable	Italy Foreign Country
	Father's/Mother's educational qualification	Dummy variable	Low if educational qualifications are: primary school certificate, lower secondary school certificate, vocational secondary school diploma (3 years of study) Medium if educational qualifications are: upper secondary school diploma, another qualification higher than diploma (Fine Arts Academy, Conservatory, etc.) High if educational qualifications are: university degree or postgraduate qualification
	Father's/Mother's employment status	Dummy variable	Unemployed Homemaker Low if employment statuses are: Laborer, services personnel, member of cooperatives Medium if employment statuses are: Self-employed worker (trader, farmer, craftsman, mechanic, etc.); Teacher, employee, military in career; Retired worker High if employment statuses are: Entrepreneur, landowner; Manager, university lecturer, officer; Professional employee or freelancer (doctor, lawyer, psychologist, researcher, etc.)
Territorial characteristics	Macro-geographical area	Dummy variable	North Centre South and Islands
	Regions	Dummy variable	Abruzzo, Basilicata, Calabria, Campania, Emilia-Romagna, Friuli-Venezia Giulia, Lazio, Liguria, Lombardia, Marche, Molise, Piemonte, Puglia, Sardegna, Sicilia, Toscana, Umbria, Valle d'Aosta, Veneto, Autonomous Province of Bolzano, Autonomous Province of Trento
Interactions	Interaction "Trento*September-$December_t$"	Dummy variable	Autonomous Province of Trento*Students born between September and December of the $year_t$
	Interaction "Bolzano*September-$December_t$"	Dummy variable	Autonomous Province of Bolzano* Students born between September and December of the $year_t$

Table 4 – Mean and Std. Dev. of Test Scores by Date of Birth Variable

	Column I		Column II		
	Year$_t$ (REGULAR STUDENTS)	Year$_{t+1}$ (STUDENTS IN ADVANCE)	1st Four months$_t$ (STUDENTS NOT ENROLLED IN ADVANCE)	2nd and 3rd Four months$_t$ (REGULAR STUDENTS)	1st Four months$_{t+1}$ (STUDENTS IN ADVANCE)
Reading – 2nd Grade	72.65	72.74	74.25	72.15	72.74
	(17.36)	(18.10)	(16.63)	(17.46)	(18.10)
Reading – 5th Grade	79.49	79.79	80.10	79.78	79.79
	(13.24)	(13.28)	(13.05)	(13.22)	(13.27)
Maths – 2th Grade	64.64	66.63	66.23	64.13	66.63
	(20.87)	(22.14)	(20.10)	(20.99)	(22.14)
Maths – 5th Grade	58.32	60.12	58.93	58.10	60.12
	(21.10)	(21.80)	(20.80)	(21.19)	(21.80)

Table 5 – Mean and Std. Dev. of Test Scores by Father's Background

	Educational Qualification			Employment Status				
	Low	Medium	High	Unemployed	Homemaker	Low	Medium	High
Reading – 2nd Grade	70.01	75.02	77.94	68.17	68.02	69.84	74.28	75.81
	(17.93)	(16.16)	(15.26)	(19.85)	(17.90)	(17.86)	(16.60)	(16.00)
Reading – 5th Grade	77.15	81.64	84.17	74.20	76.65	77.11	80.65	82.36
	(14.01)	(11.83)	(10.77)	(15.95)	(14.09)	(14.00)	(12.53)	(11.65)
Maths – 2th Grade	62.17	67.02	69.88	62.07	58.37	61.86	66.30	67.63
	(21.37)	(20.00)	(19.19)	(23.37)	(20.21)	(21.23)	(20.34)	(19.89)
Maths – 5th Grade	55.44	61.01	64.64	53.65	54.11	55.14	59.94	61.87
	(21.41)	(20.40)	(19.64)	(22.86)	(20.77)	(21.36)	(20.78)	(20.23)

Notes: Low, Medium and High Educational Qualification and Low, Medium and High Employment State defined in Table 3.

Table 6 – Mean and Std. Dev. of Test Scores by Mother's Background

	Educational Qualification			Employment Status				
	Low	Medium	High	Unemployed	Homemaker	Low	Medium	High
Reading – 2nd Grade	69.04	74.58	78.00	70.25	70.78	69.51	75.45	75.92
	(18.30)	(16.13)	(15.15)	(18.37)	(18.41)	(17.26)	(15.84)	(15.82)
Reading – 5th Grade	76.44	81.46	84.17	76.68	77.57	77.08	82.02	82.32
	(14.32)	(11.78)	(10.68)	(14.95)	(14.45)	(13.50)	(11.52)	(11.36)
Maths – 2th Grade	61.38	66.51	69.74	62.69	63.91	60.47	67.07	67.16
	(21.69)	(19.99)	(19.14)	(21.73)	(22.03)	(20.45)	(19.67)	(19.58)
Maths – 5th Grade	54.63	60.66	64.62	54.92	56.92	53.94	61.40	61.25
	(21.55)	(20.36)	(19.59)	(21.82)	(22.09)	(20.51)	(20.09)	(19.96)

Note: Low, Medium and High Educational Qualification and Low, Medium and High Employment State defined in Table 3.

Table 7 – OLS Estimates of the Effect of Year of Birth on Normalized Test Scores

	Reading		Mathematics	
	2nd Grade	5th Grade	2nd Grade	5th Grade
STUDENT CHARACTERISTICS				
Date of birth (Year)				
$Year_{t+1}$ *(Students "In Advance")*	-2.043***	-0.842***	-1.862***	-0.901***
$Year_{t-n}$ *(Delayed Students)*	-3.887***	-5.587***	-2.832***	-4.879***
(Omitted Variable: $Year_t$ – Regular students)				
Gender				
Male	-1.204***	-2.323***	1.017***	2.285***
(Omitted Variable: Female)				
Country of birth				
Italy	2.674***	2.036***	1.912***	1.690***
(Omitted Variable: Foreign country)				
Pre-school attendance				
Daycare	-0.319***	-0.452***	-0.294***	-0.680***
(Omitted Variable: No)				
Kindergarten	2.821***	2.667***	2.842***	2.795***
(Omitted Variable: No)				
SCHOOL CHARACTERISTICS				
School size	-0.002***	0.005***	-0.0002	0.008***
Class size	-0.021***	0.036***	-0.107***	-0.024***
Index of sample school				
Sample school	-4.404***	-2.070***	-6.728***	-5.588***
(Omitted Variable: School no sample)				
School weekly hours				
From 31 to 39 hours	-1.131***	0.084	-0.982***	-0.150
40 hours	-1.108***	-0.757***	-1.079***	-0.691***
(Omitted Variable: Up to 30 hours)				
FAMILY BACKGROUND				
Father's country of birth				
Italy	3.317***	2.089***	2.661***	2.202***
(Omitted Variable: Foreign country)				
Mother's country of birth				
Italy	2.558***	1.566***	2.104***	1.783***
(Omitted Variable: Foreign country)				
Father's educational qualification				
Medium	2.590***	2.294***	2.722***	3.030***
High	3.876***	3.289***	4.332***	4.802***
(Omitted Variable: Low)				
Mother's educational qualification				
Medium	3.327***	3.061***	3.322***	3.887***
High	5.407***	4.452***	5.340***	6.198***
(Omitted Variable: Low)				
Father's employment status				
Unemployed	-1.646***	-2.326***	-1.495***	-1.977***
Homemaker	-0.283	-1.087**	-0.794	0.310
Medium employment status	1.006***	0.779***	0.976***	1.171***
High employment status	0.821***	0.853***	0.772***	1.080***
(Omitted Variable: Low employment status)				
Mother's employment status				
Unemployed	-0.297*	-0.529***	0.030	-0.393*
Homemaker	-0.333***	-0.427***	0.190	0.498***
Medium employment status	1.193***	0.833***	1.694***	2.220***
High employment status	0.691***	0.285***	0.938***	0.856***
(Omitted Variable: Low employment status)				
TERRITORIAL CHARACTERISTICS				
Macro- geographical area				
North	-2.867***	-0.308***	-8.000***	-4.761***
Centre	-2.023***	-0.210***	-5.627***	-3.949***
(Omitted Variable: South and Islands)				
Number of Obs.	282.468	276.307	282.742	275.851

Notes: i) * p<0.1, ** p<0.05, *** p<0.01; ii) Coefficients are estimated with robust standard errors. Variables defined in Table 3.

Table 8 – Treatment Effect of Early Schooling on Pupil's Performance. ATT Nearest Neighbor Estimates

	Reading		Mathematics	
	2nd Grade	**5th Grade**	**2nd Grade**	**5th Grade**
Treatment Effect (β_{ATT})	-4.344***	-2.313***	-2.962***	-1.751***

Notes: i) * p<0.1, ** p<0.05, *** p<0.01; ii) ATT Nearest Neighbor uses the nearest-neighbor matching method; iii) Coefficients are estimated with bootstrap standard error; iv) Propensity scores include covariates as in Table 7.

Table 9 – RDD Estimates of Early Schooling on Pupil's Performance

	Reading		Mathematics	
	2nd Grade	**5th Grade**	**2nd Grade**	**5th Grade**
Treatment Effect (β_{RDD})	2.286***	1.693***	4.470***	3.157***

Notes: i) * p<0.1, ** p<0.05, *** p<0.01; ii) Kernel used: triangle; iii) Cutoff date: January_{t+1}.

Table 10 – Consistent and Unbiased Estimates of Early Schooling on Pupil's Performance

	Reading		Mathematics	
	2nd Grade	**5th Grade**	**2nd Grade**	**5th Grade**
Treatment Effect (β_{ATT})	-4.344***	-2.313***	-2.962***	-1.751***
Treatment Effect (β_{RDD})	2.286***	1.693***	4.470***	3.157***
Unbiased Effect (β)	**-6.630*** **	**-4.006*** **	**-7.432*** **	**-4.908*** **

Note: Unbiased effect is calculated according to eq. (5).

Table 11 – Treatment Effect (RDD) of Pupils Grouped by Months of Birth

Cutoff date	Reading		Mathematics	
	2^{nd} Grade	5^{th} Grade	2^{nd} Grade	5^{th} Grade
Cutoff between Dec_t and Jan_{t+1}	2.286***	1.693***	4.470***	3.157***
Cutoff between Nov-Dec_t and Jan_{t+1}	2.477***	1.278***	4.371***	2.899***
Cutoff between Oct-Dec_t and Jan_{t+1}	1.375***	0.968***	3.129***	2.395***
Cutoff between Sept-Dec_t and Jan_{t+1}	1.126***	1.293***	4.155***	2.810***
Cutoff between Aug-Dec_t and Jan_{t+1}	0.876***	0.737***	2.533***	2.037***
Cutoff between Jul-Dec_t and Jan_{t+1}	0.619***	0.597***	2.228***	1.833***
Cutoff between Jun-Dec_t and Jan_{t+1}	0.368***	0.441***	1.927***	1.623***
Cutoff between May-Dec_t and Jan_{t+1}	0.114	0.272***	1.635***	1.391***
Cutoff between Apr-Dec_t and Jan_{t+1}	-	0.183*	-	1.288***
Cutoff between Mar-Dec_t and Jan_{t+1}	-	0.116	1.250***	1.211***
Cutoff between Feb-Dec_t and Jan_{t+1}	-0.343**	0.223	1.164***	1.179***
Cutoff between Jan-Dec_t and Jan_{t+1}	-0.451***	0.069	1.111***	1.190***

Note: * p<0.1, ** p<0.05, *** p<0.01.

Table 12 – OLS Estimates for Autonomous Province of Trento and Bolzano

	Reading		Mathematics	
	5^{th} Grade Trento (Treatment)	**5^{th} Grade Bolzano (Placebo)**	**5^{th} Grade Trento (Treatment)**	**5^{th} Grade Bolzano (Placebo)**
Autonomous Province of either Trento or Bolzano	-2.050***	-3.421***	-8.101***	-5.905***
Students born between September-December of the $year_t$	-1.487***	-1.493***	-2.147***	-2.156***
Interaction: Students born between September-December of $year_t$ times Province of either Trento or Bolzano	-1.693**	-0.211	-2.893**	-0.941
Number of Obs.	276.304	276.304	275.850	275.850

Notes: i) * p<0.1, ** p<0.05, *** p<0.01; ii) Coefficients are estimated with robust standard errors; iii) Estimates include covariates as in Table 7, geographic controls include provinces instead of macro-areas.

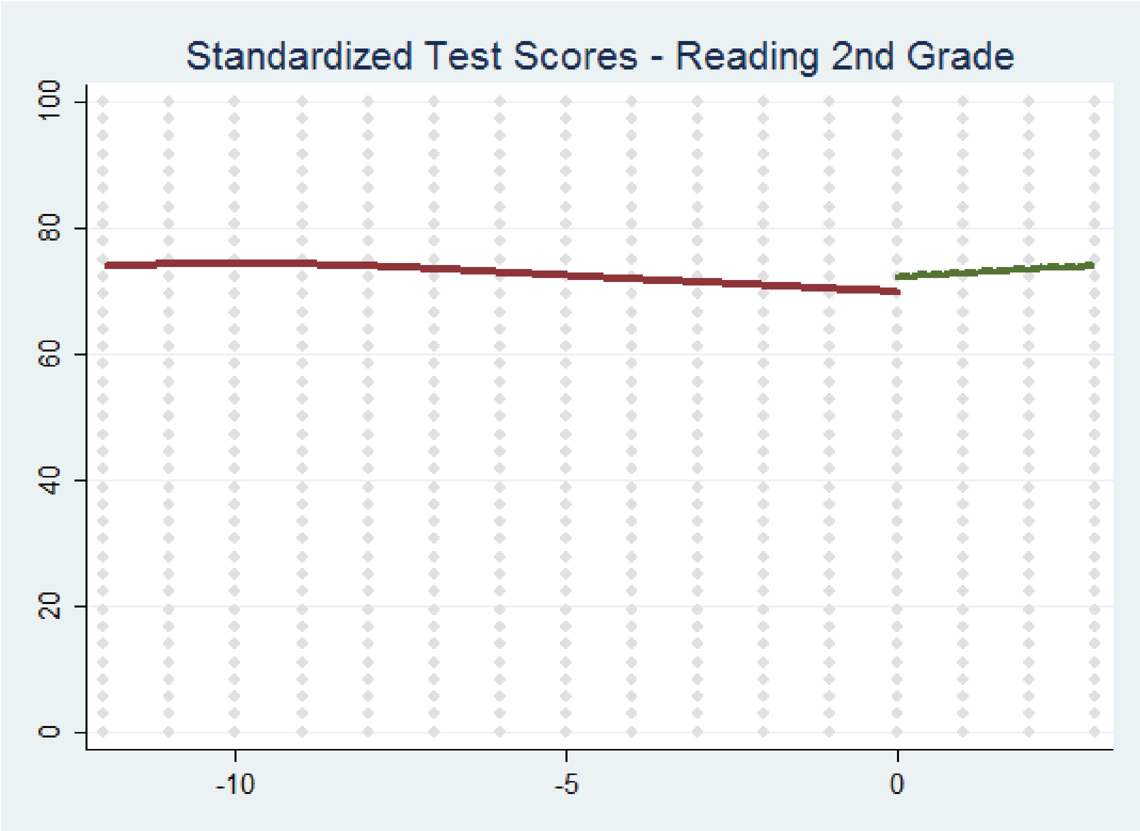

Figure 1 – RDD estimates. The horizontal axis reports months of birth, it ranges from January of the year *t* to April of the year *t+1;* the cutoff is set at January *t+1*. Difference across the margin is statistically significant at 1% level. The vertical axis reports test scores in Reading for all pupils at the 2nd Grade in Italian Schools (282.468 obs.).

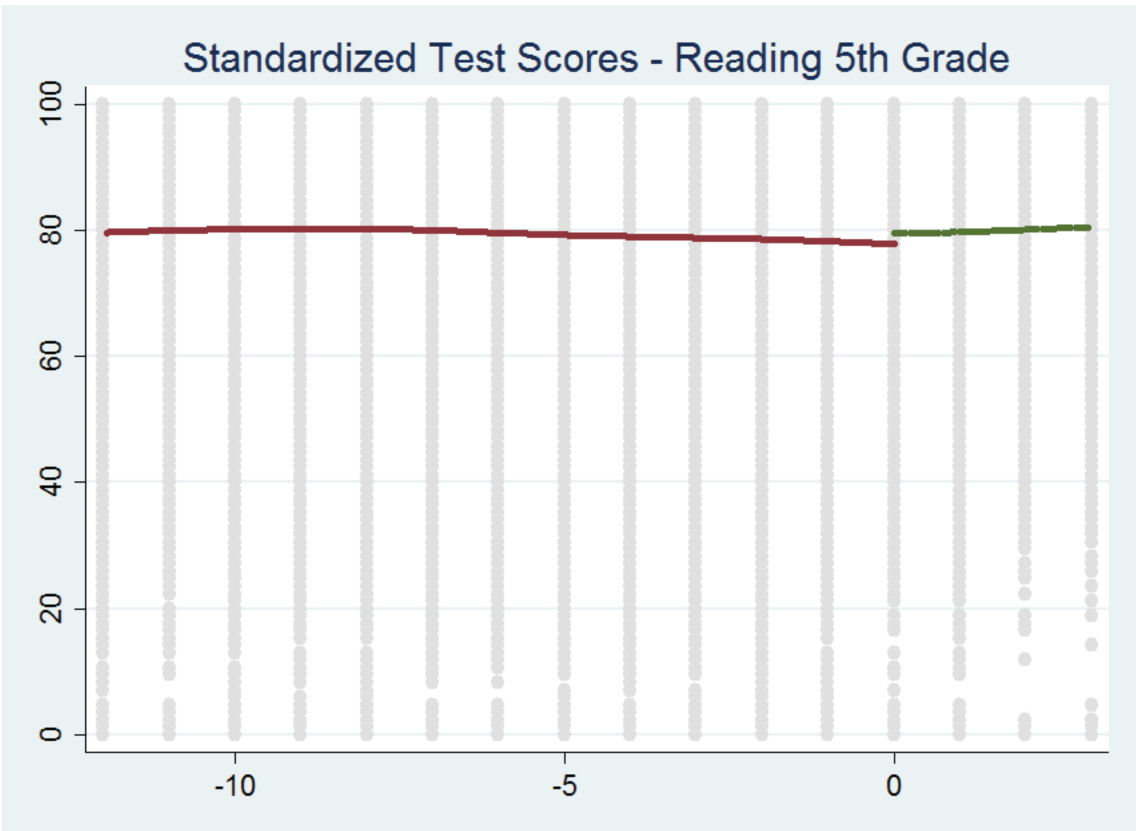

Figure 2 – RDD estimates. The horizontal axis reports months of birth, it ranges from January of the year *t* to April of the year *t+1;* the cutoff is set at January *t+1*. Difference across the margin is statistically significant at 1% level. The vertical axis reports test scores in Reading for all pupils at the 5th Grade in Italian Schools (276.307 obs.).

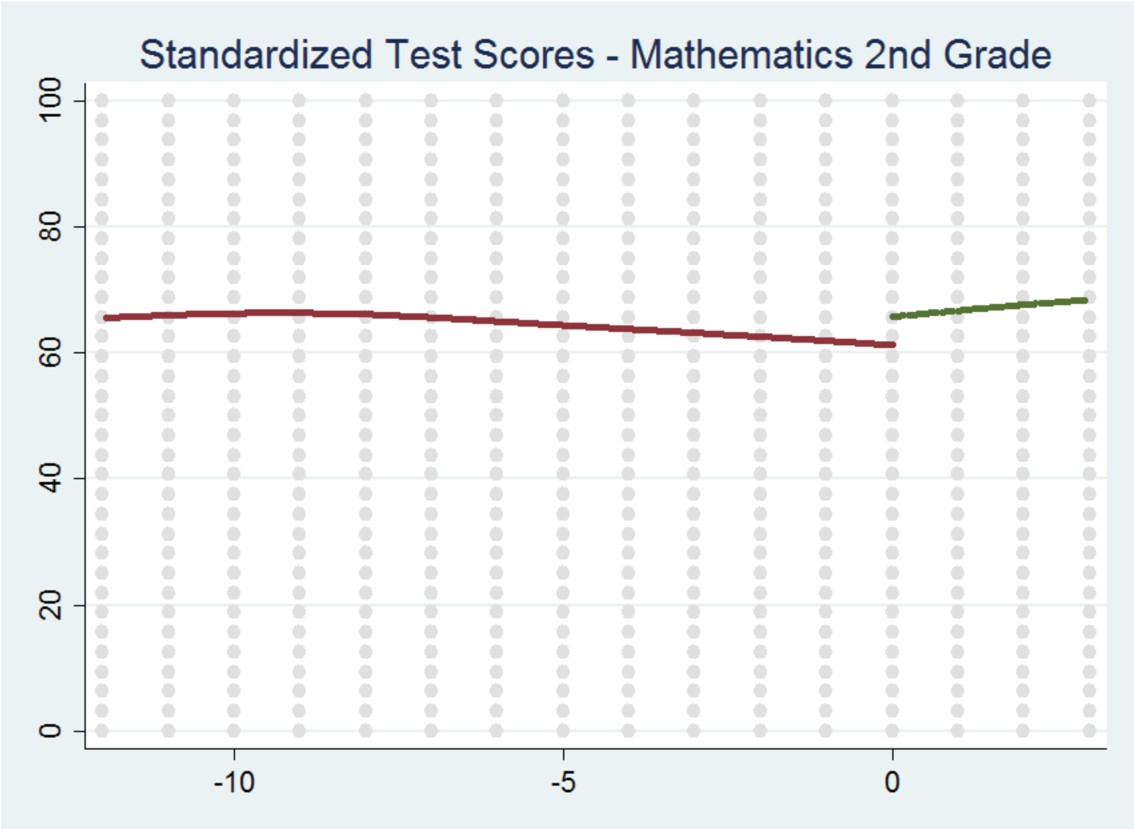

Figure 3 – RDD estimates. The horizontal axis reports months of birth, it ranges from January of the year *t* to April of the year *t+1;* the cutoff is set at January *t+1*. Difference across the margin is statistically significant at 1% level. The vertical axis reports test scores in Mathematics for all pupils at the 2nd Grade in Italian Schools (282.742 obs.).

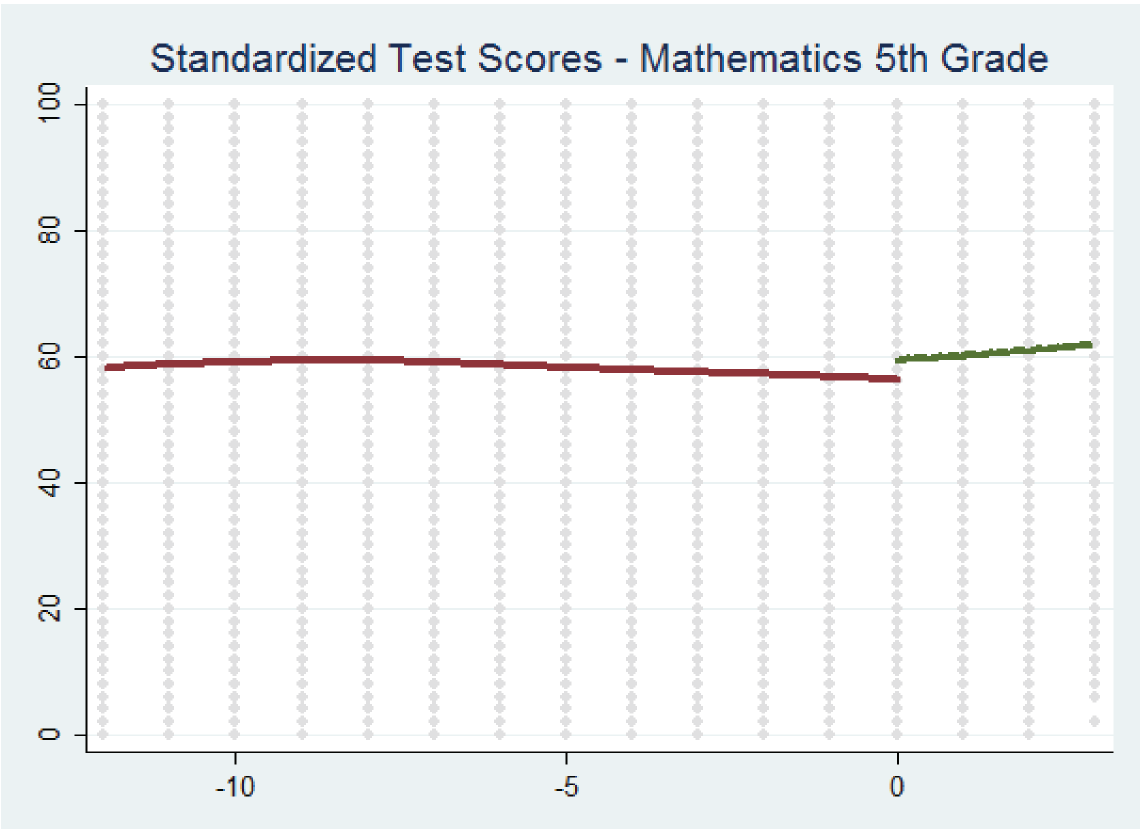

Figure 4 – RDD estimates. The horizontal axis reports months of birth, it ranges from January of the year *t* to April of the year *t+1;* the cutoff is set at January *t+1*. Difference across the margin is statistically significant at 1% level. The vertical axis reports test scores in Mathematics for all pupils at the 5th Grade in Italian Schools (275.851 obs.).

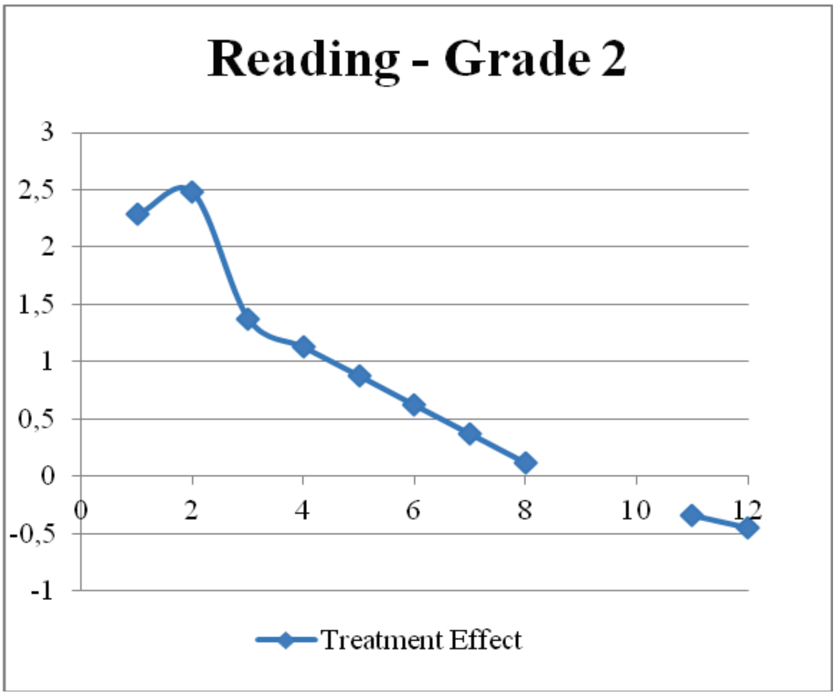

Figure 5 – Trend in the treatment effect of students grouped by months of birth.
The horizontal axis reports date of birth of students by cutoff order as in Table 11.
The vertical axis reports treatment effect of students grouped by months of birth
in Reading at the 2nd Grade in Italian Schools (282.468 obs.).

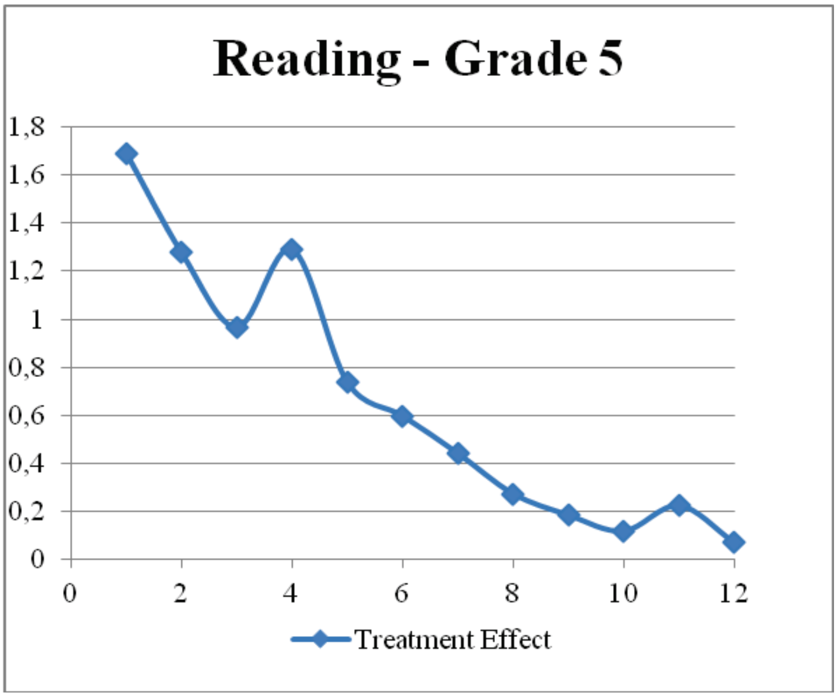

Figure 6 – Trend in the treatment effect of students grouped by months of birth.
The horizontal axis reports date of birth of students by cutoff order as in Table 11.
The vertical axis reports treatment effect of students grouped by months of birth
in Reading at the 5th Grade in Italian Schools (276.307 obs.).

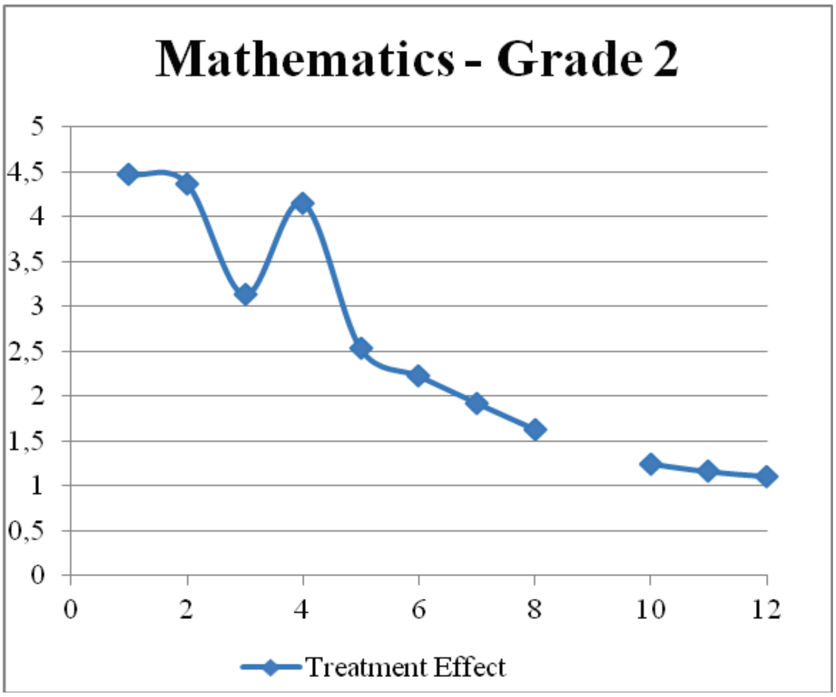

Figure 7 – Trend in the treatment effect of students grouped by months of birth.
The horizontal axis reports date of birth of students by cutoff order as in Table 11.
The vertical axis reports treatment effect of students grouped by months of birth
in Mathematics at the 2nd Grade in Italian Schools (282.742 obs.).

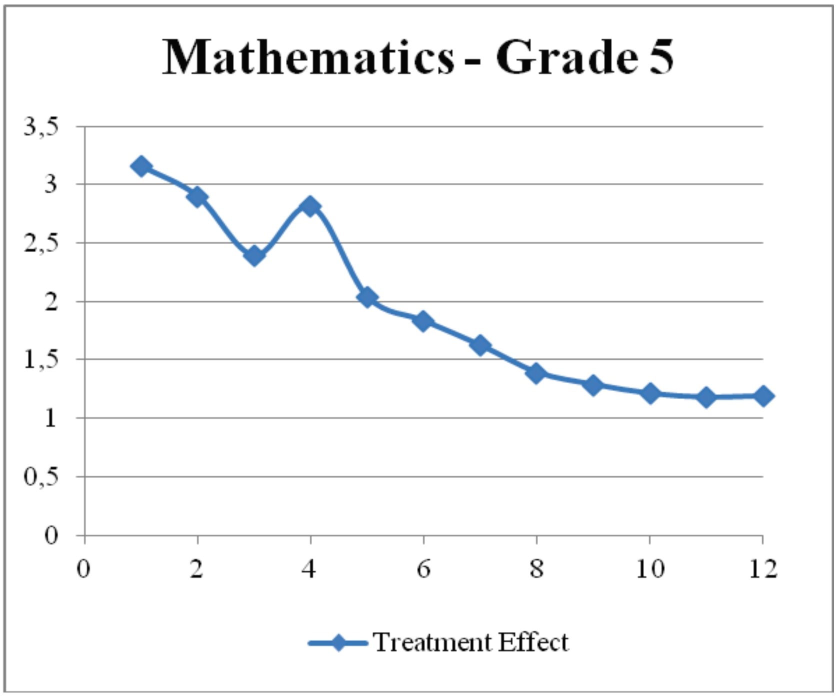

Figure 8 – Trend in the treatment effect of students grouped by months of birth.
The horizontal axis reports date of birth of students by cutoff order as in Table 11.
The vertical axis reports treatment effect of students grouped by months of birth
in Mathematics at the 5th Grade in Italian Schools (275.851 obs.).

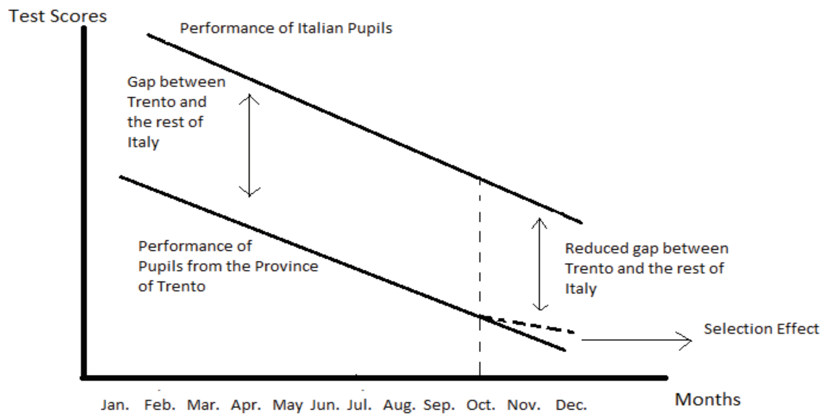

Figure 9 – Robustness Checks: Identification of the Selection Effect