WORKING PAPER NO. 567

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June 2020

This version July 2021

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ISSN. 2240-9696

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Age Effects in Primary Education: A Double Disadvantage for Second-Generation Immigrants

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Abstract
The integration of second-generation immigrant children is a major challenge for the receiving countries, especially where immigration is a recent phenomenon. Apart from family, integration begins at school. We study whether the immigrant background interacts with age effects (namely, absolute age effect and relative age effect), generating additional barriers (double disadvantage) for second-generation children in the Italian primary school. We can identify these effects because we exploit the heterogeneity in children's birthdates and because the test is given at two different points in time. We find evidence of a double disadvantage that, relative to the average native, reduces scores in Italian by 17% and in Math by 20%. In a policy perspective, we show that controlling for age effects in class composition criteria promotes integration because it delivers extra benefits to second-generation immigrant children. Besides, we point out the possibility of turning the large impact of the relative age on second-generation children to their advantage, in order to reduce the sizable penalization associated with the immigrant background.

JEL Classification: I21, J01, J13, Z13.

Keywords: second-generation immigrants, education, age effects, double disadvantage.

Acknowledgements: we thank Antonio Acconcia, Alberto Bucci, Simon Burgess, Vincenzo Carrieri, Fausto Galli, Ellen Greaves, Tullio Jappelli, Annamaria Menichini, Fabio Postiglione, Hans H. Sievertsen and participants to the 35th AIEL Conference. This paper uses confidential data provided by the Italian Institute for the Evaluation of the Educational System (INVALSI). The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the INVALSI. All remaining errors are our own. Funding: this study was funded by the Italian Ministry of Research and University (PRIN 2017) grant no. 2017KHR4MB. Declaration of interests: the authors declare no conflict of interest.

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1 Introduction

The birth of a large second generation is a sometimes overlooked consequence of the immigration into the developed countries.[1] While these children help to compensate the aging of rich societies, little is known about their future. Are they going to catch up with the natives or to be permanently marginalized?[2] In the long run, the answer depends on a successful integration in the receiving societies. Integration, however, begins *early* in life. Apart from family, school is the gate of the integration process. Early educational outcomes can have long-lasting consequences due, for instance, to grade retention or mechanisms that amplify the initial educational gaps, pushing the child onto different school tracks (Cunha and Heckman, 2007). Second-generation immigrant children[3] are more fragile than their native peers, because, other things being equal, their immigrant background is a further source of disadvantage (Algan et al., 2012; Dustmann et al., 2012; Dustmann and Glitz, 2011; Ochinata and Van Ours, 2012). In the literature, the possibility that the interaction of two disadvantages generates an additional disadvantage is known as the *double disadvantage hypothesis* or *cumulative disadvantage hypothesis* (Dicks and Lancee, 2018; Taş et al., 2014).

In this paper, we study whether the interaction of the second-generation status with age-induced disadvantages generates a double disadvantage (henceforth DD) in the primary school performance. The age-induced disadvantages we are considering are, respectively, the Absolute Age Effect (henceforth AAE) and the Relative Age Effect (henceforth RAE). The former occurs because, in principle, older children can benefit from greater knowledge and maturity (Black et al., 2011; Crawford et al., 2014; Elder and Lubotsky, 2009; Peña, 2017). The latter comes from peer effects that could, for instance, hinder self-esteem in pupils who feel weaker and less confident than their older peers in the classroom.[4]

The risk of a DD is particularly insidious, since authorities tend to focus on single disadvantages rather than on their interactions. Failing to recognize these interactions may foster the intergenerational transmission of inequality and undermine the integration of the second generations. In our case, a DD appears if the second-generation status reinforces the AAE or the RAE. We do find that a DD in Italian scores exists. As for Math, the DD only concerns the RAE.

Identifying the AAE and the RAE is subject to well-known econometric issues: age effects are collinear, and have rarely been disentangled in the literature (Black et al., 2011; Cascio and Schanzenbach, 2016; Elder and Lubotsky, 2009; Peña, 2017; Peña and Duckworth, 2018). Fol-

[1] Immigrant second generations are about 12% of total population in the US (Trevelyan et al., 2016), and 6.5% in the EU (EUROSTAT, 2014). In Italy, the figure is 2.5%, but the share of the population in the age 0-5 is 15% (ISTAT, 2018).

[2] Permanent marginalization is known as "segmented assimilation" or "downward assimilation" (Alba and Nee, 2003; Portes and Rumbaut, 2001). Borjas (1993) reports evidence of the downward assimilation of Mexican immigrants in the US. Further examples concern African Americans or Native Americans (Hughes and Thomas, 1998). See Algan et al. (2010) for worrying evidence on France, Germany and the UK.

[3] We define "second-generation immigrant children" the children born in Italy with both non-Italian parents. We define "natives" the children born in Italy with both Italian parents. Throughout the paper, "second generation" always stands for "second-generation immigrant".

[4] Relatively older children show higher self-esteem and leadership (Dhuey and Lipscomb, 2008; Fumarco and Schultze, 2020; Thompson et al., 2004); less psychological problems (Dee and Sievertsen, 2018; Matsubayashi and Ueda, 2015; Thompson et al., 1999); are less likely to be victimized (Ballatore et al., 2020; Mühlenweg, 2010)

lowing Peña and Duckworth (2018), we can identify the AAE because, in our sample, the test given at two different points in time provides the required independent variation in absolute age, keeping relative age constant. The variation given by the heterogeneity in children's birthdates is used to identify the RAE.
However, disentangling these age effects is not enough, since the children's age — that determines both AAE and RAE — is endogenous: the Italian law allows wide margins of discretion on primary school enrollment, which may vary from age 5 to 7.[5] Thus, in line with the literature (Bedard and Dhuey, 2006; Dhuey and Lipscomb, 2010; Fumarco et al., 2020; Nam, 2014; Peña and Duckworth, 2018), we adopt a Two-Stage Least Squares where we instrument the absolute age with an "expected" absolute age and the relative age with an "expected" relative age.
The idea behind the construction of an "expected" age consists of assigning the child the age she would have absent anticipation or delay in the enrollment. We construct two IVs. The first is widely used in the literature (see Peña and Duckworth (2018)), whereas the second is built *ad hoc* by exploiting the characteristics of the Italian enrollment system. Both IVs give the same results. Finally, as a robustness check, we estimate our model on a subset of children whose enrollment *cannot* be manipulated, confirming our findings.
The detection of a DD in the childhood raises serious concerns: the accumulation of disadvantages exacerbates the vulnerability of children who are already penalized, and, in perspective, increases future inequalities. In the childhood, pupils are still building the basis of human capital accumulation, and mechanisms like the dynamic complementarity and the self-productivity of skills are going to amplify early educational gaps, which may become permanent and have lifetime consequences (Cunha and Heckman, 2007). From this point of view, our work shows some analogies with an emerging literature in early childhood interventions that studies the interaction of consecutive shocks and/or investments (Duque et al., 2019; Johnson and Jackson, 2019; Rossin-Slater and Wust, 2020).
However, very few papers look at the interaction between age effects and the immigrant background. L*ü*demann and Schwerdt (2013) show that the interaction of the immigrant background with less favorable socioeconomic status puts a DD on second generations in Germany at the transition to secondary school tracks. Dicks and Lancee (2018) find that RAEs and immigrant-specific disadvantages generate a DD in grade retention rates for 15 years old immigrant students in France. Lenard and Peña (2018) point out that part of the educational gap between minority and non-minority students in North Carolina is due to the higher frequency of *redshirting* (i.e. delayed school enrollment) in the majority group.
Our contribution to the literature is threefold. First, we provide novel evidence that the interaction of the age effects with the immigrant background, which are rarely considered in combination, causes a DD for *second-generation* children. Second, we assess the differential contribution of absolute and relative age to the DD. Third, we point out that, since interaction effects (i.e., DDs) exist, policies targeted to contrast age effects work as integration policies. In other words, the benefits of policies that reduce age dispersion tend to be underestimated,

[5] The Italian enrollment regulation is discussed in detail in section 2.

as their integration content is not evident. For instance, in the absence of a DD, reducing the RAE would benefit to the same extent both natives and second generations, leaving the expected achievement gap unchanged. Instead, the presence of a DD makes such a reduction more effective for the second generations. Thus, any policy reducing the RAE is expected to reduce the achievement gap and foster integration. Pushing this reasoning further, one may even think of *exploiting* the RAE in order to contrast the large penalty associated to the immigrant background in our estimates. This could be possible by adopting class composition criteria that *increase* the relative age of second-generation children with respect to their native classmates. As for the AAE, our estimates indicate that postponing enrollment has tiny negative effects for both natives and second generations in all subjects, even though it only generates a DD in Italian. This is consistent with some evidence showing that children may learn more at school than at home (Black et al., 2011; Cahan and Cohen, 1989), in particular for what concerns the outcome in Italian. Hence, redshirting could be useless, and even harmful for the proficiency of the second generations in Italian.

The rest of the paper is organized as follows: Section 2 describes the Italian institutional framework and the data; Section 3 presents our empirical strategy; Section 4 discusses our results, and Section 5 concludes.

2 Institutional framework and data

In the Italian school system, children normally enroll in the first grade of the primary school (grades 1 to 5, corresponding to ISCED level 1) the year they turn six. However, the law allows large flexibility in the enrollment of the "youngest" children. The Italian system can be understood through an example. The current school year begins in September, 2021. The law establishes that children who turn 6 from May 1 to December 31, 2021 must be enrolled. On the other hand, children who turn 6 from January 1 to April 30, 2022 can choose to be enrolled either in the current or in the next school year.

In the first grade of the primary school, this creates three groups of pupils: 1) those born between May 1 and December 31, 2015 ("regulars"); 2) those born between January 1 and April 30, 2016 ("anticipating"); 3) those born between January 1 and April 30, 2014 ("redshirting"). This means that in the same class we can observe children born more than one year apart (January 1, 2016-April 30, 2014). Thus, age might be correlated with unobservable factors in the error term, biasing OLS estimates of the age effect on educational outcomes.

We use standardized test scores in Italian and Math administered by the Italian National Institute for the Evaluation of the Education System (INVALSI). The *whole* population of students in the 2nd and the 5th grade of the primary school is tested. The INVALSI test is designed by Italian teachers selected by INVALSI according to their experience and education. INVALSI framework is based on the National Standards set by MIUR (Ministero dell'Istruzione, Università e Ricerca, 2012).

We observe one cohort in the school years 2012-13 (2nd grade) and 2015-16 (5th grade). Another cohort is observed in the school years 2013-14 and 2016-17. The comparability of outcomes across different grades is certified by INVALSI due to vertical continuity in the design of the tests and diachronic anchoring techniques.[6] We rely on these waves because they contain the exact students' birthdate, which we need to disentangle RAEs from AAEs.

The final sample includes 644 521 natives and 49 832 second-generation children. Table 1 presents the descriptive statistics in the groups of natives and second-generation children. The test on the difference in mean (t-test) clearly suggests that the natives perform systematically better in both Italian and Math, and that the educational gap seems to persist over time. More specifically, the educational gaps in Italian and Math are almost similar in magnitude. Even though one may expect that the immigrant background puts a penalization on Italian, language proficiency is also a prerequisite for understanding Math classes. Thus, it is quite reasonable that low proficiency in Italian comes along with low Math scores (Isphording et al., 2016).

The data include detailed information on family characteristics (like father's and mother's education and employment) and home possessions (e.g., the availability of computers, internet connections, quiet rooms, books, and so on) which also matter for school performance. Table 1 confirms that second-generation children face worse socioeconomic conditions. Their parents are generally less educated, more unemployed, or employed in low-wage jobs. As such, the empirical strategy is crucial to separate the impact of the family background from the age effects (RAE and AAE) on pupils' performances.

The characteristics of the family are summarized in the ESCS index, a synthetic index of economic, social and cultural status that we include in our empirical investigation. By construction, its mean is set equal to zero, and its standard deviation to one. Again, the negative sign in Table 1 points out the disadvantage of the second generations. Not surprisingly, the difference with respect to the average student is also statistically highly significant.

Given the longitudinal structure of the data, we can follow the answers of the same cohort of students from the 2nd grade to the 5th grade (2012-13/2015-16 and 2013-14/2016-17). As suggested by Peña and Duckworth (2018), the combination of information on children's birthdates and the longitudinal dimension of our dataset provides a way to decompose absolute and relative age. This because the heterogeneity in birthdates provides a variation useful to identify the relative age of pupils within the same class, while the availability of test scores at two different points in time gives a variation suitable to identify the absolute age effect for each pupil. Figure 1 shows the students distribution by date of birth in the two waves. As expected, only "regular" students born between May 1 and December 31 are (approximately) uniformly distributed.

3 Empirical Strategy

To empirically investigate the existence of a DD, we first disentangle the AAE and the RAE; then, we analyze their interaction with a second-generation dummy. We estimate the following

[6] Diachronic anchoring assures that the results are measured on the same scale. Vertical continuity assures that the test assesses the persistence of the skills acquired in the previous grades. This aim is achieved through specific questions, and by multiple field-trials in sample schools. INVALSI publishes every year a reference framework (*Quadro di Riferimento*) that discusses the methodological issues of each test.

model for student test scores:

$$Score_{ict\tau} = \beta_0 + \beta_1 AA_{it\tau} + \beta_2 RA_{ic} + \beta_3 Second_i + \beta_4 AA_{it\tau} * Second_i + \beta_5 RA_{ic} * Second_i + \\ + \mathbf{X}_{ict\tau}\rho + \lambda_c * \mu_\tau + \epsilon_{ict\tau} \quad (1)$$

where $Score_{ict\tau}$ is the test score (respectively, in Italian and Math) for student i, in class c, in year t, in cohort τ, *Second* is a dummy indicating the second generation, $\mathbf{X}$ is a vector of controls for the socioeconomic status, $\lambda_c * \mu_\tau$ are class-by-cohort fixed effects, and $\epsilon_{ict\tau}$ is an error term capturing time varying idiosyncratic shocks or unobserved class characteristics. Controlling for class-by-cohort fixed effects allows us to isolate potential time-invariant differences across waves. This is equivalent to a within transformation, where we subtract the mean of the class-cohort from each variable in the model (this means that the identification comes from the variation with respect to the variance and higher moments) and allows us to capture possible dynamic selection into classes or unobservable group shocks (Ballatore et al., 2020; Elsner and Isphording, 2017). β_4 and β_5 are the coefficients of interest. They identify, respectively, the additional effect of AA and RA on children's performance due to the second-generation status. The absolute age $AA_{it\tau}$ is defined as the age on the test day, measured in days and divided by 365.25. It captures the knowledge the child has accumulated and, in general, her maturity. The relative age RA_{ic} is computed as the difference between the oldest classmate and child's own age; it captures peer effects.[7] Given this specification, we address two well-known issues in the literature: 1) the endogeneity of the student's age within a class; 2) the collinearity between AAE and RAE.

Age can be manipulated through anticipation or redshirting. In order to address this issue, we follow an established approach in the literature (see for instance Bedard and Dhuey (2006); Dhuey and Lipscomb (2010); Nam (2014); Schneeweis and Zweimüller (2014); Peña and Duckworth (2018); Fumarco et al. (2020)), and we adopt a Two-Stage Least Squares (2SLS) strategy where we instrument absolute age with "expected" absolute age (${AA^e}_{it}$) and relative age with "expected" relative age (${RA^e}_{ic}$). The idea behind the construction of an "expected" age consists of assigning the child the age she would have absent anticipation or redshirting, making the enrollment date exogenous.

We construct the expected absolute age (${AA^e}_{it}$) following Peña and Duckworth (2018): first of all, we reassign the date of birth in order to undo redshirting or anticipation; then, we single out the youngest child in each class. The age of this (hypothetical) child is the expected absolute age, and is used for all classmates. Notice that plainly using the reassigned age would retain the collinearity between absolute and relative age (in other words, there would still be within class variation of both absolute and relative age). In order to avoid this issue, everybody in the class must be assigned the same age. Figure 3 intuitively features the correlation between

[7] We find similar results using as reference the youngest, the average and the median age classmate. The rank of the child within the class may also be useful if children compare themselves to all classmates rather than only the oldest/youngest/median. To take into account this possibility, as robustness, we replicate our specification replacing the regressors of interest with student's ordinal age rank in the school cohort. Results are robust to this test and available upon request.

the expected absolute age so constructed and the reassigned age within class. Clearly, as the youngest child in a class grows older, her classmates do so as well.

Then, on the basis of the reassigned birthdates, we compute the expected relative age ($RA^e{}_{ic}$) as the difference between the child's own age and the oldest child's age in the class.

We use two slightly different methods to reassign age, generating two IVs. In order to understand the reassigning process, it is useful to remind that in Italy anticipation is a standard practice. Thus, we have to reassign both redshirting and anticipating children. In this framework, the reassignment works as follows: consider first the anticipating group. The parents of these children were allowed to wait one more year before enrolling their children. However, they have chosen not to do so, because — for any reason — they *wanted* their children be the youngest in class. On the other hand, parents of redshirting children made the opposite choice, and they *wanted* their children be the oldest in class. We can undo this choice by re-assigning the birthdate as follows: we move one year *backwards* the birth year of *anticipating* children, and one year *forward* the birth year of *redshirting* children (see Figure 2). Therefore, we reproduce the distribution of the enrollments one would observe if anticipation or redshirting were not allowed, and we obtain our favorite IV (hereafter, Strategy A).

Next, we construct another instrument we call "expected *regular* age" (hereafter, Strategy B). In the case of Strategy B, the expected age is computed as before, but the date of birth is reassigned as if the pupil were enrolled among regular students. We create a 8-month year (May 1 - December 31) and we "squeeze" the birthdates into this fictional year. For *redshirting* students, we shift *forward* the month of birth: those born in January are assigned to May, those born in February to June, and so on. For *anticipating* students, we shift *backwards* the month of birth: those born in April are assigned to December of the previous year, those born in March to November of the previous year, and so on (see again Figure 2 for the method used to assign the expected birthdate).

As for the collinearity between AAE and RAE, we know that it arises for a student who is older at the moment of the test is also older with respect to her classmates. Overcoming the collinearity requires independent variation between absolute and relative age. As a consequence, AAE and RAE have rarely been disentangled in the literature (Black et al., 2011; Cascio and Schanzenbach, 2016; Elder and Lubotsky, 2009; Peña, 2017; Peña and Duckworth, 2018). Following Peña and Duckworth (2018), we take advantage of the information on children's birthdates and of the longitudinal dimension of our data to disentangle AAE and RAE. We are able to identify these effects because the test given at two different points in time provides the required independent variation in absolute age, keeping relative age constant.

Finally, according to Buckles and Hungerman (2013), we take into account the possibility of seasonality in births. Table 2 shows indeed that we cannot rule out seasonality-in-fertility effects. For this reason, we control for the socio-economic status by including the ESCS index in all specifications. We also add month fixed effects in our preferred specification, without altering our results.

4 Results

In Tables 3 and 4, we report the OLS and IV estimates of Equation 1 for Italian and Math respectively. In the OLS regression (Column 1), we regress the test score in Italian and Math on AA, RA, the dummy *Second*, their interactions and the ESCS index, which captures a set of socio-economic characteristics X. As we noticed before, these coefficients can be biased by family planning, redshirting, anticipation, or (though very rare in the Italian Primary School) grade retention. Therefore, in Columns (2) to (5) we report the 2SLS regressions following our Strategy A. We include in the main specification class-by-wave fixed effects and month of birth fixed effects with standard errors clustered at the student level (Column 5).[8]

First of all, let us remark the substantial disadvantage captured by the second-generation dummy, which is negative and significant at the 1% level. Being second generation reduces the normalized score by 2.9 points in Italian (4.5% relative to the sample average), and by 4 points in Math (6.8% relative to the average).

Tables 3 and 4 show that for natives the RAE is quite similar in Italian and Math (4 points). A one standard deviation (0.30) difference in relative age across classmates translates into an increase of 1.9% in the Italian score and 2% in the Math score. As for the AAE, we find a tiny negative effect whose interpretation is discussed later on. A one standard deviation (1.53) difference in absolute age translates into a decrease of 1% in the Italian score and 0.9% in the Math score.

The DD emerges when the interaction with the second-generation dummy reinforces the AAE or the RAE (AA*Second and RA*Second respectively). Thus, we estimate four interactions: two in Italian and two in Math. Both interactions are 1% significant in Italian, whereas a 1% significant DD shows up only for the relative age in Math.

For a second-generation child, the coefficient of RA is about 7 percentage points in Italian (3 points more than the natives), and 7.6 percentage points in Math (twice as much as the natives). This indicates that a one-standard deviation difference in relative age across classmates translates into an increase of 3.3% in the Italian score and 3.9% in the Math score for second generation children.

The negative effect of AA is 0.194 percentage points higher for the second generations in Italian (Table 3, Column 5), but 0.125 percentage points lower in Math (Table 4, Column 5). Provided that the RAE dominates the AAE in all subjects, the overall age effect (i.e., the sum of AAE and RAE) is positive (17% in Italian and 20% in Math, relative to the average native). Thus, we confirm the usual finding that older children perform better.

In this framework, since older children have spent more time at home before being enrolled, the negative coefficient estimated for AA simply suggests that children learn more at school than at home. Indeed, several contributions find that what really matters for test scores is school exposure (Black et al., 2011; Cahan and Cohen, 1989; Elder and Lubotsky, 2009). This interpretation is additionally supported by the presence of a DD on the absolute age in Italian

[8] Given the longitudinal structure of the data, we cluster by student to account for the dependency across observations at the individual level.

but not in Math: if second-generation children practice a poor Italian at home, they should enter school as soon as possible. On the other hand, it is unlikely that any child (native or second-generation) receives formal education in Math at home, and this is the reason why staying home does not generate any further disadvantage in Math.
Finally, notice that redshirting or anticipation could generate a violation of the monotonicity assumption, invalidating the instrumental variable strategy (Barua and Lang, 2016). To address this issue, for robustness, we first estimate the model on the subsample of "regulars", confirming our findings (Tables 5 and 6) — recall from Section 2 that the enrollment of "regular"children cannot be manipulated.[9] Then, we implement the alternative IV strategy, using our "expected regular age" instrument (Strategy B). Tables 7 and 8 show that baseline results are statistically and economically confirmed.

5 Conclusions

Multiple disadvantages jeopardize the integration of the immigrants everywhere in the world. Failed integration generates poverty and exclusion, and may lead to the incorporation of the immigrant communities as permanently disadvantaged minorities. When interactions among different disadvantages generate further penalization, interventions focusing on only one source of disadvantage can unexpectedly fall short of their objectives and hinder overall progress, because the sources of persistence stay masked (Taş et al., 2014).
We studied second-generation children in the Italian primary school. Our findings support existing evidence on the penalization originating from the immigrant background and from age effects. Besides, and most importantly, we bring to light the existence of a DD in Italian and Math, showing that these disadvantages interact and reinforce each other.
Policy implications are straightforward: 1) reducing age differences among classmates helps to reduce the achievement gap among natives and second generations; 2) postponing school enrollment does not benefit children, and, in particular, harms second generations with respect to their performance in Italian; 3) the large effect of the relative age on second-generation children could be turned to their advantage by increasing their relative age. This policy might be implemented by forming sections for each class such that second-generation children are (on average) never younger than their native classmates.[10]
According to our findings, these cost-free policies should not only improve school performances, but also promote integration. The contribution to the integration stems from cutting down the DD, which amplifies the benefits for the second generations.

[9] We have further restricted this subsample by excluding all children born in May. We chose to do so because, in special cases and subject to the school's authorization, the law extends the cutoff date to May 31. In this sense, there is some endogeneity in the decision not to use this option.

[10] We provide an example in the framework of the Italian regulation described in Section 3. Creating sections where second-generation children are (on average) never younger than natives is possible as follows: put in the first section the anticipating natives, together with anticipating and regular second generations. Then, put in the second section regular and redshirting natives, together with redshirting second generations. This method can be refined when more than two sections are available.

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Figures and Tables

Fig. 1. Histogram

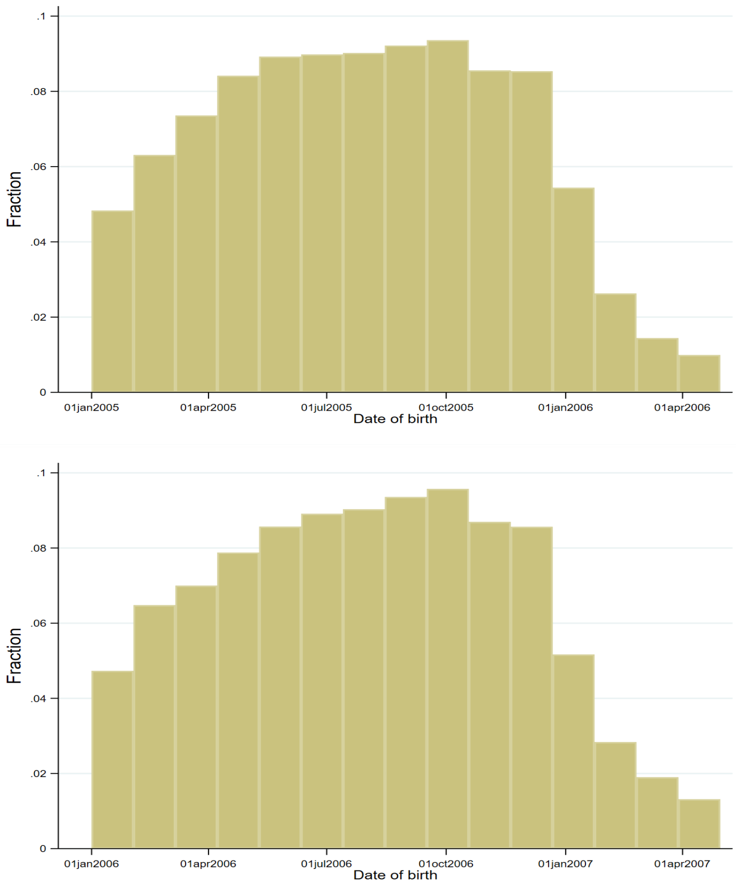

Fig. 1 shows the children's distribution with respect to the month of birth. Notably, the distribution is *grosso modo* uniform for months from May to December, indicating the endogeneity of early and late enrollments. The distributions are remarkably similar across the waves we use.

Fig. 2. Actual and assigned calendar month of birth

	Strategy A IV: expected age															
	Redshirting				Regular								**Anticipation**			
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr
Birth month	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12
Assigned birth month	**9**	**10**	**11**	**12**	1	2	3	4	5	6	7	8	**-3**	**-2**	**-1**	**0**
	Strategy B IV: expected *regular* age															
	Redshirting				Regular								**Anticipation**			
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr
Birth month	-3	-2	-1	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	9	10	11	12
Assigned birth month	**1**	**2**	**3**	**4**	1	2	3	4	5	6	7	8	**5**	**6**	**7**	**8**

Fig. 2 explains the birth date reassignment. Regular children are born in the 8 months that go from May (labeled 1) to December (labeled 8). Redshirting children are labeled with numbers from 0 to -3. Anticipating children are labeled with numbers from 9 to 12. In strategy A, we switch the anticipating children (9, 10, 11, 12) to the redshirting positions (0, -1, -2, -3), and viceversa. In strategy B, we "squeeze" all the children into the "regular" months in such a way that the oldest *redshirting* child (labeled -3) is equivalent to the oldest "regular" child (labeled 1), and so on. Analogously, the youngest *anticipating* child (labeled 12) is equivalent to the youngest *regular* child (labeled 8), and so on.

Fig. 3. Graphical intuition

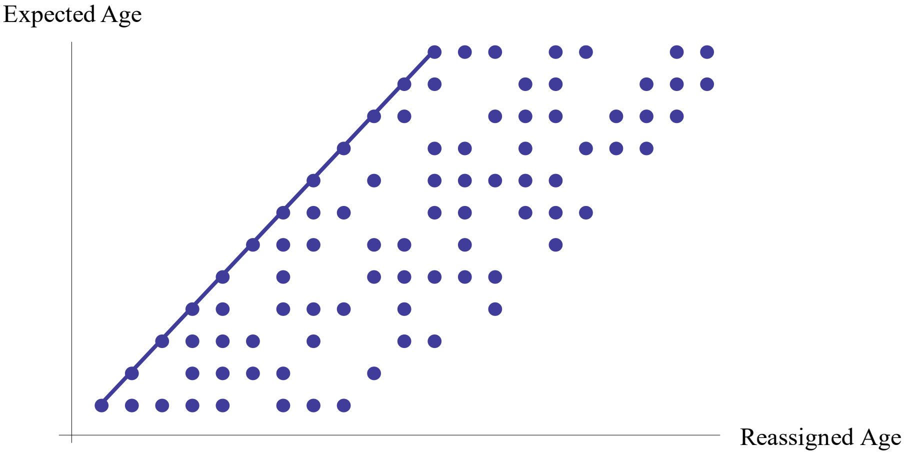

Fig. 3 aims to intuitively show the correlation between the reassigned age and the reassigned age of the youngest child — namely, expected age — used as instrumental variable. On the y-axis, we put the youngest hypothetical student for each class (for simplicity, there is just one class for each youngest age). The x-axis indicates the reassigned age. Each horizontal dotted line represents a class, and each dot represents a child. For simplicity, there is just a child for each age. The dot on the 45^o line is the youngest child in class, and the dots to her right are the older classmates. From the figure it is visible that, as the age of the youngest child increases, so does the reassigned age of the other children.

Table 1. Sample description: natives vs. second-generations

Variable	**Natives (1)**	**Second-Gen. (2)**	**t-stat (3)**
Score in Italian 2nd	64.594	56.540	94.119***
	(0.023)	(0.082)	
Score in Italian 5th	63.246	54.502	103.858***
	(0.022)	(0.081)	
Score in Math 2nd	59.134	51.849	85.619***
	(0.023)	(0.082)	
Score in Math 5th	58.137	51.077	82.024***
	(0.023)	(0.083)	
Mother's Higher Education	0.226	0.145	42.678***
	(0.0006)	(0.002)	
Father's Higher Education	0.175	0.120	31.313***
	(0.0005)	(0.002)	
Mother Unemployed	0.358	0.611	-96.894***
	(0.0007)	(0.003)	
Mother Blue-collar worker	0.119	0.263	-62.005***
	(0.0004)	(0.002)	
Mother White-collar worker	0.427	0.068	244.224***
	(0.0007)	(0.001)	
Mother self-employed	0.096	0.058	29.890***
	(0.0004)	(0.001)	
Father Unemployed	0.046	0.09998	-34.016***
	(0.0003)	(0.002)	
Father Blue-collar worker	0.272	0.614	-131.702***
	(0.0006)	(0.003)	
Father White-collar worker	0.413	0.083	209.078***
	(0.0007)	(0.001)	
Father self-employed	0.263	0.199	29.794***
	(0.0006)	(0.002)	
ESCS Student	0.131	-0.486	162.482***
	(0.001)	(0.004)	
Obs.	644 521	49 832	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard Errors in parenthesis.

Table 2. Mothers' characteristics

	Low Education	**High Education**	**Unemployed**
February	0.00277	-0.00912	-0.00677
	(0.00875)	(0.00924)	(0.00840)
March	-0.00848	-0.0111	-0.00227
	(0.00853)	(0.00900)	(0.00818)
April	-0.0340***	0.0171*	-0.0223***
	(0.00867)	(0.00908)	(0.00830)
May	-0.0144*	-0.0159*	-0.00681
	(0.00848)	(0.00895)	(0.00813)
June	-0.000365	-0.0263***	0.00884
	(0.00858)	(0.00908)	(0.00823)
July	0.0136	-0.0362***	0.0209***
	(0.00843)	(0.00895)	(0.00809)
August	0.0182**	-0.0359***	0.0243***
	(0.00847)	(0.00900)	(0.00813)
September	-0.0174**	-0.00768	-0.00471
	(0.00843)	(0.00888)	(0.00807)
October	-0.0201**	0.00320	0.00412
	(0.00844)	(0.00887)	(0.00808)
November	-0.0320***	0.00486	-0.0115
	(0.00868)	(0.00911)	(0.00831)
December	-0.0223***	0.0148	-0.0135
	(0.00864)	(0.00906)	(0.00827)
Constant	-0.564***	-0.776***	-0.304***
	(0.00609)	(0.00642)	(0.00584)
Obs	1,178,650	1,178,650	1,178,650

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Standard Errors in Parenthesis Clustered by Student

Table 3. Italian (Strategy A)

	OLS (1)	**IV (2)**	**IV (3)**	**IV (4)**	**IV (5)**
AA	-0.398***	-0.486***	-0.486***	-0.456***	-0.456***
	(0.00783)	(0.00797)	(0.00797)	(0.00796)	(0.00796)
RA	4.994***	4.358***	4.317***	3.465***	4.005***
	(0.0613)	(0.176)	(0.175)	(0.135)	(0.0855)
AA*Second	-0.249***	-0.171***	-0.172***	-0.193***	-0.194***
	(0.0285)	(0.0292)	(0.0291)	(0.0295)	(0.0295)
RA*Second	1.127***	2.739***	2.757***	3.016***	2.948***
	(0.242)	(0.747)	(0.746)	(0.684)	(0.687)
Second	-2.604***	-2.577***	-2.556***	-2.889***	-2.899***
	(0.310)	(0.432)	(0.432)	(0.420)	(0.420)
Obs	1,385,460	1,385,460	1,385,460	1,385,460	1,385,460
Controls	✓	✓	✓	✓	✓
Wave FE	✗	✗	✓	✗	✗
Class-by-wave FE	✗	✗	✗	✓	✓
Month FE	✗	✗	✗	✗	✓

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Standard Errors in Parenthesis Clustered by Student

Table 4. Math (Strategy A)

	OLS (1)	**IV (2)**	**IV (3)**	**IV (4)**	**IV (5)**
AA	-0.303***	-0.350***	-0.349***	-0.341***	-0.341***
	(0.00764)	(0.00776)	(0.00776)	(0.00776)	(0.00776)
RA	5.009***	4.507***	4.566***	3.758***	3.965***
	(0.0646)	(0.186)	(0.186)	(0.138)	(0.0860)
AA*Second	0.0710***	0.130***	0.131***	0.126***	0.125***
	(0.0268)	(0.0275)	(0.0275)	(0.0277)	(0.0277)
RA*Second	1.165***	3.297***	3.272***	3.699***	3.495***
	(0.249)	(0.772)	(0.769)	(0.685)	(0.688)
Second	-4.668***	-4.210***	-4.241***	-3.876***	-3.953***
	(0.295)	(0.430)	(0.429)	(0.409)	(0.410)
Obs	1,385,460	1,385,460	1,385,460	1,385,460	1,385,460
Controls	✓	✓	✓	✓	✓
Wave FE	✗	✗	✓	✗	✗
Class-by-wave FE	✗	✗	✗	✓	✓
Month FE	✗	✗	✗	✗	✓

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Standard Errors in Parenthesis Clustered by Student

Table 5. Regular Italian (without May)

	(1)	**(2)**	**(3)**
AA	-0.341***	-0.341***	-0.386***
	(0.0103)	(0.0103)	(0.0106)
RA	2.927***	2.908***	6.626***
	(0.120)	(0.120)	(0.135)
AA*Second	-0.213***	-0.213***	-0.197***
	(0.0369)	(0.0369)	(0.0381)
RA*Second	2.298***	2.327***	1.445***
	(0.486)	(0.485)	(0.481)
Second	-2.201***	-2.176***	-3.312***
	(0.471)	(0.471)	(0.477)
Obs	820,072	820,072	820,072
Controls	✓	✓	✓
Wave FE	✗	✓	✗
Class-by-wave FE	✗	✗	✓

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Standard Errors in Parenthesis Clustered by Student

Table 6. Regular Math (without May)

	(1)	**(2)**	**(3)**
AA	-0.160***	-0.159***	-0.190***
	(0.00997)	(0.00996)	(0.0103)
RA	3.938***	3.964***	6.358***
	(0.126)	(0.126)	(0.137)
AA*Second	0.0592*	0.0595*	0.0684*
	(0.0345)	(0.0345)	(0.0356)
RA*Second	1.590***	1.548***	1.207**
	(0.498)	(0.496)	(0.482)
Second	-4.204***	-4.239***	-4.257***
	(0.456)	(0.455)	(0.458)
Obs	820,072	820,072	820,072
Controls	✓	✓	✓
Wave FE	✗	✓	✗
Class-by-wave FE	✗	✗	✓

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Standard Errors in Parenthesis Clustered by Student

Table 7. Italian (Strategy B)

	OLS (1)	**IV (2)**	**IV (3)**	**IV (4)**	**IV (5)**
AA	-0.399***	-0.440***	-0.440***	-0.455***	-0.455***
	(0.00784)	(0.00781)	(0.00781)	(0.00796)	(0.00796)
RA	4.997***	5.879***	5.856***	5.697***	4.237***
	(0.0615)	(0.0753)	(0.0753)	(0.0693)	(0.0758)
AA*Second	-0.250***	-0.223***	-0.223***	-0.218***	-0.218***
	(0.0285)	(0.0285)	(0.0285)	(0.0290)	(0.0290)
RA*Second	1.111***	0.546*	0.582**	1.011***	0.987***
	(0.243)	(0.292)	(0.291)	(0.279)	(0.279)
Second	-2.605***	-3.108***	-3.084***	-3.547***	-3.590***
	(0.311)	(0.320)	(0.321)	(0.321)	(0.322)
Obs	1,383,030	1,383,030	1,383,030	1,383,030	1,383,030
Controls	✓	✓	✓	✓	✓
Wave FE	✗	✗	✓	✗	✗
Class-by-wave FE	✗	✗	✗	✓	✓
Month FE	✗	✗	✗	✗	✓

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Standard Errors in Parenthesis Clustered by Student

Table 8. Math (Strategy B)

	OLS (1)	**IV (2)**	**IV (3)**	**IV (4)**	**IV (5)**
AA	-0.303***	-0.329***	-0.328***	-0.339***	-0.339***
	(0.00765)	(0.00761)	(0.00761)	(0.00775)	(0.00775)
RA	5.016***	5.747***	5.780***	5.749***	4.235***
	(0.0647)	(0.0793)	(0.0791)	(0.0704)	(0.0761)
AA*Second	0.0681**	0.0853***	0.0853***	0.0897***	0.0897***
	(0.0268)	(0.0267)	(0.0267)	(0.0272)	(0.0272)
RA*Second	1.156***	0.637**	0.584*	0.751***	0.700**
	(0.250)	(0.300)	(0.299)	(0.280)	(0.280)
Second	-4.643***	-5.036***	-5.070***	-4.883***	-4.938***
	(0.295)	(0.305)	(0.305)	(0.306)	(0.306)
Obs	1,383,030	1,383,030	1,383,030	1,383,030	1,383,030
Controls	✓	✓	✓	✓	✓
Wave FE	✗	✗	✓	✗	✗
Class-by-wave FE	✗	✗	✗	✓	✓
Month FE	✗	✗	✗	✗	✓

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Standard Errors in Parenthesis Clustered by Student