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Age Effects in Education: A Double Disadvantage for Second-Generation Immigrant Children

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Abstract. A *double disadvantage* occurs when the interaction of two disadvantages generates an additional disadvantage. We show that second-generation immigrant children in the Italian primary school experience a double disadvantage that, relative to the average native, reduces scores in Italian by 17% and in Math by 20%. The double disadvantage stems from the interaction of the immigration background with age effects (namely, Absolute Age Effect and Relative Age Effect). In a policy perspective, we show that controlling for age effects in class composition criteria pursues integration because it delivers extra benefits to second-generation immigrant children. Besides, we point out the possibility of exploiting the larger impact of the relative age on second-generation children in order to support their performance and reduce the large penalization associated to the immigration background.

Keywords: second-generation immigrants · education · age effects · double disadvantage

JEL classification: I21, J01, J13, Z13.

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1 Introduction

The *double disadvantage hypothesis* suggests that the interaction of two disadvantages may generate an additional disadvantage. We investigate the impact of two disadvantages on the school performance of second-generation immigrant children in the Italian primary school.¹ The first source of disadvantage is the immigration background. The second source of disadvantage, which is common to native children, is the exposure to age effects (Absolute Age Effect and Relative Age Effect).

The risk of a double disadvantage is particularly insidious because authorities tend to focus on single disadvantages rather than on their interactions. Failing to recognize these interactions may foster the intergenerational transmission of deprivation and undermine the effort of integrating the second generations.

The immigration background is known to put a penalty on parental socioeconomic and cultural resources, which are known to be essential for school performances (Algan et al., 2012; Dustmann et al., 2012; Dustmann and Glitz, 2011; Ochinata and Van Ours, 2012). As for age effects, many studies (Black et al., 2011; Crawford et al., 2014; Elder and Lubotsky, 2009; Peña, 2017)) find that age affects school performances through two main channels: the Absolute Age Effect (henceforth AAE), and the Relative Age Effect (henceforth RAE). The former occurs because older children can benefit from greater knowledge and maturity. 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.² In our case, a double disadvantage (henceforth DD) appears if the second-generation status reinforces the AAE or the RAE. We do find that a DD in Italian scores does exist. As for Math, the DD only concerns the RAE.

The detection of a DD in the childhood raises serious concerns, since it exacerbates the vulnerability of children who are already disadvantaged, 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 push the child onto different educational tracks 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 migration background. Lüdemann and Schwerdt (2013) show that the interaction of the migration 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

¹ 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”.

² Relatively older children show higher self-esteem and leadership (Dhuey and Lipscomb, 2008; 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).

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.

We contribute to the existing literature in three ways. First, we provide novel evidence that the interaction of the age effects with the immigration 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. 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 second generations. Thus, any policy reducing the RAE is expected to reduce the achievement gap and foster integration. In other words, the benefits of policies that reduce age variability tend to be underestimated, as their integration content is not evident. Pushing this reasoning further, one may even think of *exploiting* the RAE in order to benefit second generations and contrast the large penalty associated to the immigration 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 generates a DD in Italian proficiency. 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). Hence, redshirting could be useless, and even harmful for the proficiency of 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 enrol 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.³ 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 immigration background puts a larger 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 children’s 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 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

³ 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.

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 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 for second-generation children, \mathbf{X} is a vector of controls for 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. The coefficients β_4 and β_5 identify respectively the additional effect of AAE and RAE 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, child’s maturity. The relative age RA_{ic} is the difference between the oldest classmate and child’s own age and it captures peer effects.⁴

Given this specification, we address three important issues well-known in the literature: 1) the collinearity between AAE and RAE; 2) the endogeneity of age; 3) the endogeneity of the enrollment date.

An issue of collinearity between AAE and RAE naturally arises, for a student who is older at the moment of the test is also older with respect to her classmates. 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 absolute and relative age. Specifically, the heterogeneity in birthdates provides the variation to identify the relative age of each pupil within the same class. The availability of test scores at two different points in time provides the variation to identify the absolute age effect.

As for the endogeneity of age, we know that it arises for many potential reasons. First, parents

⁴ Similar results considering 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.

may to some extent plan the birth of their children (Buckles and Hungerman, 2013). 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.

Finally, to address the endogeneity of the enrollment, 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)) and we adopt a Two-Stage Least Squares (2SLS) strategy where we instrument absolute age with “expected” absolute age (AA_{it}^e) and relative age with “expected” relative age (RA_{ic}^e).

The idea behind the construction of an “expected” age consists of assigning the child the date of birth she would have absent anticipation or redshirting. This, in turn, makes the enrollment date exogenous. We compute the expected absolute age (AA_{it}^e) and the expected relative age (RA_{ic}^e) from the re-assigned date of birth. We use two slightly different methods to reassign the age, generating two IVs.

First, we follow the same definition of expected age as in Peña and Duckworth (2018). In this setting, the expected absolute age is the age at test of a hypothetical youngest classmate who enrolled as early as permitted. This hypothetical child is identified after reassigning the date of birth. 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. We proceed 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 birth date 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 a suitable expected age. This generates 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 date of birth is reassigned as if the pupil were enrolled as a regular student. We create a 8-month year (May 1 - December 31) and we “squeeze” the birth dates 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).

We show our results in the next section.

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).⁵

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

⁵ 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.⁶ Then, we implement the alternative IV strategy, using our “expected regular age” instrument (Strategy B). Tables 7 and 8 shows 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.⁷ 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-generations immigrant children in the Italian primary school. Our findings support existing evidence on the penalization originating from the immigration 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.⁸

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

⁶ 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.

⁷ This phenomenon 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. 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.

⁸ 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 sections are available.

DD, which amplifies the benefits for the second generations.

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Figures and Tables

Fig. 1. Histogram

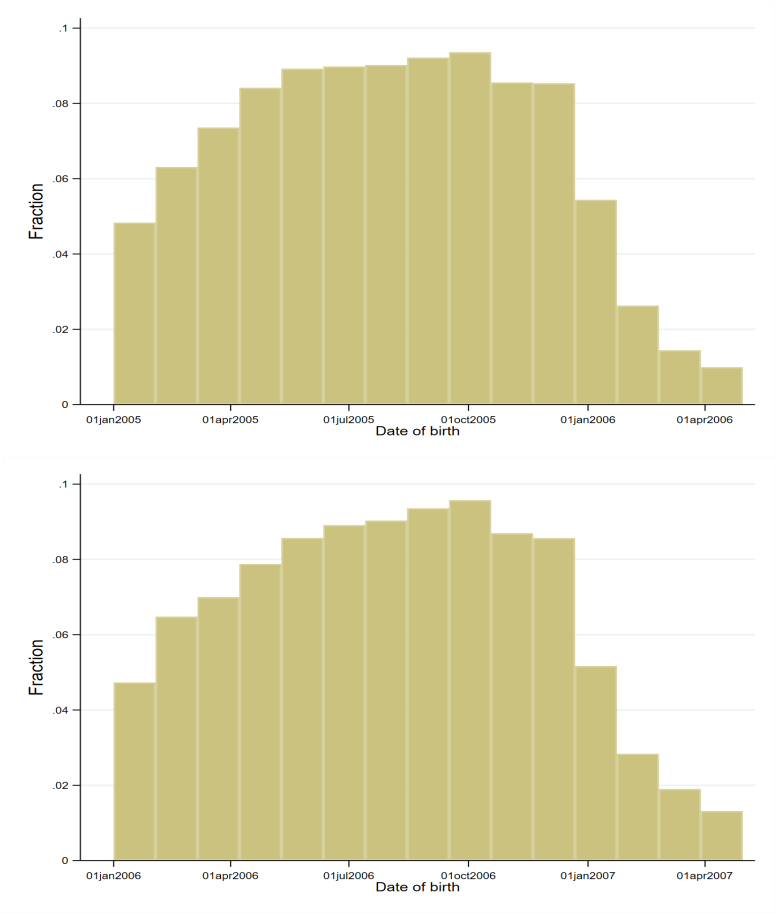


Fig. 2. Actual and assigned calendar month of birth





	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

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

Variable	Natives (1)	Second-Gen. (2)	t-stat (3)
Score in Italian 2nd	64.594 (0.023)	56.540 (0.082)	94.119***
Score in Italian 5th	63.246 (0.022)	54.502 (0.081)	103.858***
Score in Math 2nd	59.134 (0.023)	51.849 (0.082)	85.619***
Score in Math 5th	58.137 (0.023)	51.077 (0.083)	82.024***
Mother's Higher Education	0.226 (0.0006)	0.145 (0.002)	42.678***
Father's Higher Education	0.175 (0.0005)	0.120 (0.002)	31.313***
Mother Unemployed	0.358 (0.0007)	0.611 (0.003)	-96.894***
Mother Blue-collar worker	0.119 (0.0004)	0.263 (0.002)	-62.005***
Mother White-collar worker	0.427 (0.0007)	0.068 (0.001)	244.224***
Mother self-employed	0.096 (0.0004)	0.058 (0.001)	29.890***
Father Unemployed	0.046 (0.0003)	0.09998 (0.002)	-34.016***
Father Blue-collar worker	0.272 (0.0006)	0.614 (0.003)	-131.702***
Father White-collar worker	0.413 (0.0007)	0.083 (0.001)	209.078***
Father self-employed	0.263 (0.0006)	0.199 (0.002)	29.794***
ESCS Student	0.131 (0.001)	-0.486 (0.004)	162.482***
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 (0.00875)	-0.00912 (0.00924)	-0.00677 (0.00840)
March	-0.00848 (0.00853)	-0.0111 (0.00900)	-0.00227 (0.00818)
April	-0.0340*** (0.00867)	0.0171* (0.00908)	-0.0223*** (0.00830)
May	-0.0144* (0.00848)	-0.0159* (0.00895)	-0.00681 (0.00813)
June	-0.000365 (0.00858)	-0.0263*** (0.00908)	0.00884 (0.00823)
July	0.0136 (0.00843)	-0.0362*** (0.00895)	0.0209*** (0.00809)
August	0.0182** (0.00847)	-0.0359*** (0.00900)	0.0243*** (0.00813)
September	-0.0174** (0.00843)	-0.00768 (0.00888)	-0.00471 (0.00807)
October	-0.0201** (0.00844)	0.00320 (0.00887)	0.00412 (0.00808)
November	-0.0320*** (0.00868)	0.00486 (0.00911)	-0.0115 (0.00831)
December	-0.0223*** (0.00864)	0.0148 (0.00906)	-0.0135 (0.00827)
Constant	-0.564*** (0.00609)	-0.776*** (0.00642)	-0.304*** (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*** (0.00783)	-0.486*** (0.00797)	-0.486*** (0.00797)	-0.456*** (0.00796)	-0.456*** (0.00796)
RA	4.994*** (0.0613)	4.358*** (0.176)	4.317*** (0.175)	3.465*** (0.135)	4.005*** (0.0855)
AA*Second	-0.249*** (0.0285)	-0.171*** (0.0292)	-0.172*** (0.0291)	-0.193*** (0.0295)	-0.194*** (0.0295)
RA*Second	1.127*** (0.242)	2.739*** (0.747)	2.757*** (0.746)	3.016*** (0.684)	2.948*** (0.687)
Second	-2.604*** (0.310)	-2.577*** (0.432)	-2.556*** (0.432)	-2.889*** (0.420)	-2.899*** (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*** (0.00764)	-0.350*** (0.00776)	-0.349*** (0.00776)	-0.341*** (0.00776)	-0.341*** (0.00776)
RA	5.009*** (0.0646)	4.507*** (0.186)	4.566*** (0.186)	3.758*** (0.138)	3.965*** (0.0860)
AA*Second	0.0710*** (0.0268)	0.130*** (0.0275)	0.131*** (0.0275)	0.126*** (0.0277)	0.125*** (0.0277)
RA*Second	1.165*** (0.249)	3.297*** (0.772)	3.272*** (0.769)	3.699*** (0.685)	3.495*** (0.688)
Second	-4.668*** (0.295)	-4.210*** (0.430)	-4.241*** (0.429)	-3.876*** (0.409)	-3.953*** (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*** (0.0103)	-0.341*** (0.0103)	-0.386*** (0.0106)
RA	2.927*** (0.120)	2.908*** (0.120)	6.626*** (0.135)
AA*Second	-0.213*** (0.0369)	-0.213*** (0.0369)	-0.197*** (0.0381)
RA*Second	2.298*** (0.486)	2.327*** (0.485)	1.445*** (0.481)
Second	-2.201*** (0.471)	-2.176*** (0.471)	-3.312*** (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*** (0.00997)	-0.159*** (0.00996)	-0.190*** (0.0103)
RA	3.938*** (0.126)	3.964*** (0.126)	6.358*** (0.137)
AA*Second	0.0592* (0.0345)	0.0595* (0.0345)	0.0684* (0.0356)
RA*Second	1.590*** (0.498)	1.548*** (0.496)	1.207** (0.482)
Second	-4.204*** (0.456)	-4.239*** (0.455)	-4.257*** (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*** (0.00784)	-0.440*** (0.00781)	-0.440*** (0.00781)	-0.455*** (0.00796)	-0.455*** (0.00796)
RA	4.997*** (0.0615)	5.879*** (0.0753)	5.856*** (0.0753)	5.697*** (0.0693)	4.237*** (0.0758)
AA*Second	-0.250*** (0.0285)	-0.223*** (0.0285)	-0.223*** (0.0285)	-0.218*** (0.0290)	-0.218*** (0.0290)
RA*Second	1.111*** (0.243)	0.546* (0.292)	0.582** (0.291)	1.011*** (0.279)	0.987*** (0.279)
Second	-2.605*** (0.311)	-3.108*** (0.320)	-3.084*** (0.321)	-3.547*** (0.321)	-3.590*** (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*** (0.00765)	-0.329*** (0.00761)	-0.328*** (0.00761)	-0.339*** (0.00775)	-0.339*** (0.00775)
RA	5.016*** (0.0647)	5.747*** (0.0793)	5.780*** (0.0791)	5.749*** (0.0704)	4.235*** (0.0761)
AA*Second	0.0681** (0.0268)	0.0853*** (0.0267)	0.0853*** (0.0267)	0.0897*** (0.0272)	0.0897*** (0.0272)
RA*Second	1.156*** (0.250)	0.637** (0.300)	0.584* (0.299)	0.751*** (0.280)	0.700** (0.280)
Second	-4.643*** (0.295)	-5.036*** (0.305)	-5.070*** (0.305)	-4.883*** (0.306)	-4.938*** (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