Lost in Translation. Reading Performance and Math Performance of Second-Generation Immigrant Children in Italy
(PRELIMINARY! please do not make public)

Mariagrazia Cavallo[1] and Giuseppe Russo[2]

[1] University of Bristol
[2] University of Salerno, CSEF, GLO

Abstract. This paper studies the effect of language proficiency on Math achievement for ten-year-old second-generation immigrant children in the Italian primary school. Through an IV strategy that exploits the heterogeneity in birthdates and the variation in linguistic distances, we find that these children face a trade-off between learning Italian and learning Math. We show that this outcome is led by children with a non-Romance linguistic background, which does not allow to benefit from similarities to Italian. As suggested by the linguistics literature, we provide supportive evidence that this result arises from the existence of proficiency thresholds that have to be crossed in order to understand the classes. We confirm that the trade-off arises when proficiency is below the threshold that is commonly adopted to indicate a sufficient command of the language. Finally, we introduce an intuitive model of the learning process that provides theoretical foundations to our results and a unified framework to interpret the mixed findings in the literature.

JEL classification: I21, I24, Z13.

Keywords: Second-Generation Immigrants · Language Proficiency · Math Performance · Linguistic Distance · Threshold Effects.

1 Introduction

The adaptation of the immigrants to the receiving society is an intergenerational process that involves many socioeconomic dimensions (Constant et al., 2009; Constant and Zimmermann, 2008). In this progression, however, the main prerequisite for integration in *all* dimensions is language acquisition, which can therefore be considered as the most important form of human capital (Chiswick and Miller, 2015).[3] Likewise, in education, language acquisition is not only an outcome but also a prerequisite for the acquisition of further skills (Isphording et al., 2016). The importance of language proficiency for the achievement in Math is possibly the best example of its crucial function of prerequisite. Indeed, one may think that language proficiency is weakly or not at all related to Math. Instead, it is now widely accepted that Math depends to a large extent on oral communication, and cannot be viewed as a non-verbal subject (Wilkinson,

[3] An extensive literature has found that language proficiency affects a variety of outcomes, from labor market earnings (Bleakley and Chin, 2004; Brell et al., 2020; Chiswick and Miller, 2010; Dustmann and Fabbri, 2003), to occupational sorting and the choice of college major (Bacolod and Rangel, 2017), to health and health insurance coverage (Clarke and Isphording, 2017; Dillender, 2017), to fertility decisions (Aoki and Santiago, 2018), and many other socio-economic outcomes (Guven and Islam, 2015).

2019).
The objective of this paper is to identify the causal effect of language acquisition on Math achievement for second-generation immigrant children at the age of 10.[4]
Since the immigrant background penalizes the school performance of these children (see table 1 and Abatemarco et al. (2021)), language skills are even more important for them than for their native peers. Actually, language is the vehicle through which students learn and apply Math, and is used in testing Math skills.[5] Besides, the ability to participate in classroom interactions, ask questions, express doubts, is crucial in order to benefit from the Math classes just as from other classes. This is supported by recent findings showing that verbal skills affect the acquisition of Math skills (Aucejo and James, forthcoming). Identifying this effect is therefore essential to understand the formation of second generations' human capital at the very beginning of their integration process, when early educational gaps that are likely to persist in the adulthood can still be prevented (Almond et al., 2018).

However, estimating to what extent language proficiency determines Math achievement is subject to fundamental identification challenges. Both Math and language scores are driven by the same unobservable variables, such as ability and motivation. Besides, in the case of second generations, other unobservable mechanisms -like family self-selection along dimensions that are relevant for school performance- may be at work, making causal estimation even harder. By the simple fact that second generations usually suffer from a socioeconomic disadvantage, it might be difficult to disentangle the effects on educational performance due to language barriers from the effects due to other dimensions of the immigrant background. In order to overcome these difficulties we use an IV strategy that exploits the heterogeneity in birthdates and the variation in the linguistic origins of second-generation children. We construct an instrument that combines both these sources of variation; namely, the interaction between the linguistic distance from Italian and the child's age. The age captures the length of exposure to the Italian language and society. The linguistic distance captures the difficulty of adaptation with respect to the language spoken at home.[6] The interaction of these variables can be interpreted as the difference in the exposure to the destination language across the different linguistic distances, or the effect of the linguistic distance as the exposure to Italian changes.[7] It is crucial to remark that endogeneity along the single dimensions, which can easily appear, does *not* invalidate our identification. For instance, parental help may depend on linguistic distance and/or age. Since we control for both these variables, we capture this kind of endogeneity. In addition, controlling for the single dimensions assures the validity of our identification even in case of endogeneity in *both* dimensions, as long as the unobserved pattern that creates endogeneity is additive and

[4] In order to simplify the notation, throughout the paper the term 'second-generation' stands for 'second-generation(s) immigrant.'

[5] Notice that special Math textbooks exist for children who do not speak the mother tongue. For Italy, see Arici and Maniotti (2010).

[6] Our data report this information.

[7] Our strategy shows some analogies with the approach by Bleakley and Chin (2004). These authors exploit the interaction between age at arrival and non-English origins to measure the causal effect of *first-generation* immigrants' language skills on earnings. Notice that this instrument cannot be used for second generations, who were born in the host country.

separable. Put differently, our identification does not hold only if age and linguistic distance are linked along a third dimension — which affects school performance — in a non-linear way. Thus, the conditions to jeopardize our identification look quite restrictive. We find it hard to conceive a mechanism of this kind, but we perform several checks that may bring it to light and find no evidence.
Summarizing, our key identifying assumption is that —conditional on a set of control variables, *including age and linguistic distance*— the interaction between age and linguistic distance only affects the performance in Math through Italian. We run additional robustness checks on various indicators that may reveal a violation of the exclusion restriction, but we do not find suggestive evidence against our strategy.

Few authors have attempted at measuring the effect of language proficiency on Math achievement, with mixed results. While Isphording et al. (2016) find that language proficiency positively affects Math performances, Aparicio-Fenoll (2018) finds no evidence of such an effect.[8] We find that proficiency in Italian has a *negative* effect on the performance in Math. According to our estimates, a one standard deviation increase in the Italian score decreases, on average, the score in Math by 0.335 standard deviations.[9]

To the best of our knowledge, this is the first time that such a trade-off comes to light. However, we do not read this result as a proof that higher language proficiency reduces mathematical skills; rather, we deduce that, in Italy, linguistic integration is not yet achieved at the end of the primary school. Since poor language proficiency undermines not only the acquisition of Math, but also of other skills, this could further amplify the educational disadvantage of the second generations, fostering social exclusion and inequality.
We try to go deeper into the causes behind this worrisome result, and show that the estimated effect of language proficiency on Math performance hides a heterogeneous effect. **Actually, if we split our sample between children with a Romance background and with a non-Romance background, only the latter are subject to the trade-off. Why does the Romance background give an advantage? It is quite plausible that children with this background can learn Italian faster than their non-Romance peers, thus they become able to fully understand the classes sooner.** This mechanism is consistent with the existence of proficiency thresholds that have to be crossed before the gains from language acquisition are effective.
Sufficiency thresholds are widely discussed in the linguistics literature, where it is often presumed that a sufficient language proficiency is required *to gain access to the curriculum*.[10] This corresponds to the universal practice of setting minimum language requirements for foreign students. Beyond the sufficiency threshold, further language progress is less relevant for understanding Math classes. Thus, any trade-off between Italian and Math should appear below sufficiency. We check for this effect by considering a threshold corresponding to the score for attaining Proficiency Level 3, which is commonly used to indicate a sufficient command of the

[8] As we explain in Section 3, both Isphording et al. (2016) and Aparicio-Fenoll (2018) rely on IV strategies.
[9] Notice that our results are not directly comparable to the above-mentioned authors, since they focus, respectively, on first-generation students aged 15 and a mix of first and second-generation children aged 6-12.
[10] See Cummins (2000) for a survey of the issues related to the so-called "threshold hypothesis", or, equivalently, "Cummins hypothesis".

language.[11] Our estimates suggest that the negative effect is indeed led by children below the threshold. For the other children, our instrument is weak: in all likelihood, once a sufficient command of Italian is achieved, further exposure to the language does not significantly increase the Math score.

Finally, we present a simple theoretical framework able to unify our empirical findings. Our model is based on two building blocks: 1) language proficiency is a prerequisite to learn Math; 2) however, before the benefits of language proficiency can be effective, a threshold has to be crossed. The first building block uses language as an *intermediate input* for producing Math knowledge. The second building block embodies the threshold through a Stone-Geary-like production function. We solve the problem of a child who gets utility from school grades and has to allocate her study time between Language and Math. This simple problem has to be solved in two cases: the first concerns the children who are below or on the threshold, the second those who are above it. In the first case, we show that, at the equilibrium, an increase in the Italian grade implies a decrease in the Math grade. This reproduces the kind of trade-off that emerges from our estimates. On the other hand, children above the threshold can benefit from their command of the language and improve their grade in both subjects.

Our research contributes to the literature in many respects. First, we propose an IV strategy that can be used to analyse the effect of linguistic proficiency on the Math performance of the *second* generations. Second, we show that an insufficient command of the language may lead the most fragile children to underperform in other fundamental subjects (like Math). Third, we help to shed further light on the mechanisms that govern the relationship between language proficiency and Math acquisition.

Our conclusion that second-generation children with poor linguistic performance are still struggling to catch-up with language at the age of 10, and they are able to do so only at the cost of reducing their performance in other subjects, sounds particularly worrying. Actually, the structure of the curricula in terms of subjects taught and exams rests on the assumption that children master the language at the end of the primary school. Thus, in the absence of appropriate interventions, the future integration of second-generation children looks jeopardized at the age of 10. In this sense, we register a poor performance of the Italian primary school.[12] More generally, our findings suggest that destination countries should make every effort in order to make linguistic integration effective in the very first years of education, where "effective" means that *all* children should cross the sufficiency threshold. Notice that the existence of a threshold makes marginal actions inappropriate, because marginal improvements in proficiency would hardly be enough for most children who are lagging behind.

Our results also convey the message that investing in the linguistic integration of the first generations should be a priority, since its benefits spillover to the second generations. Actually,

[11] This refers to the widely adopted scale that evaluates proficiency on a range from Level 1 (lowest) to 5 (highest). Level 3 is defined by scores in the range of $(95\%; 110\%]$ of the natives' average. The Italian National Institute for the Evaluation of the Education System complies with this definition. (*Indicazioni Nazionali e Linee Guida* (National Educational Criteria) stated in the *D.M. n. 254 del 16/11/2012*) and the INVALSI framework, (INVALSI (2018)).

[12] These children account for 65.70% of the second generations in the school year 2014-15, 51.23% in the school year 2015-16, 66.13% in the school year 2016-17, and 54.27% in the school year 2017-18.

it could be that part of the difficulties second-generation children have to face comes from a poor practice of the destination language at home.

The rest of the paper is organized as follows. Section 2 describes our data. Section 3 introduces our empirical strategy and discusses the validity of our instrument. Section 4 presents our findings. Section 5 provides a theoretical framework to interpret our results and the underline skills production mechanisms. Section 6 concludes.

2 Data

This paper uses data on the performance in Italian and Math on the standardized test administered by the Italian National Institute for the Evaluation of the Education System (INVALSI). We consider the entire population of second-generation immigrant students at the end of the primary school, namely in the 5th grade.[13] We exploit a repeated cross-section for the school years 2014-15, 2015-16, 2016-17, 2017-18, and 2018-19, where we observe 136,613 second-generation immigrant students.[14]

The INVALSI tests are standardized, anonymous, and marked outside the schools. Scores are adjusted for the possibility of cheating, which has been sometimes detected (Angrist et al., 2017; Bertoni et al., 2013; Quintano et al., 2009).[15] The mathematical section of the test includes questions about geometry, mappings, and data analysis. The test of Italian focuses on text comprehension and on the grammatical and lexical structure of the sentence. This test of language proficiency is much more reliable than self-reported assessments, which avoids issues of non-classical measurement error.

Additional information comes from the "Student's Questionnaire", a questionnaire that is administered to 5th-grade students on the same date of the Math test. Information on parent's education, occupational status and home possessions is summarized in a synthetic index of economic, social, and cultural status (ESCS index). Other useful information comes from questions about the student herself, her family, and her attitude towards the classes and the test. In particular, pupils are asked whether they speak Italian or other languages at home.[16]

The linguistic distance from Italian (henceforth only "linguistic distance") is a continuous variable computed through the Automated Similarity Judgment Program (ASJP) database, which is commonly used in linguistic analyses.[17] [18]

[13] We define second generations as children born in Italy with *both* non-Italian parents. Equivalently, we define natives as children born in Italy with both Italian parents.

[14] The question that identifies the linguistic origin of pupils has been introduced in 2014.

[15] Cheating is a broad concept that denotes any attempt to alter the results both by students and teachers (Jacob and Levitt (2003)).

[16] Namely, Albanian, Arabic, Chinese, Croatian, French, Greek, Hindi, English, Ladin, Portuguese, Romanian, Slovenian, Spanish, German, or a language not included in the previous list.

[17] See Wichmann, Holman, and Brown (eds.), 2018. The ASJP Database (version 18). This measure of linguistic distance is built by comparing the inner structure of 40 words in all the world's languages and gives a continuous measure that ranges from a minimum distance of 58.77 (Romanian-Italian) to a maximum distance of 101.14 (Chinese-Italian). It compares the phonetic similarity between pairs of words in two languages that have the same meaning. This should capture the existence of common ancestries that can affect the ease of learning Italian (Isphording and Otten (2013)).

[18] We also used another measure of linguistic distance computed by `elinguistics.net` (eLinguistics, 2020). This measure focuses on the genetic proximity between languages, comparing their sound correspondence. A recent literature in linguistics suggests that there can exist a link between the sound system of a language, the climate and the geographic

As Isphording et al. (2016) and Clarke and Isphording (2017), we use a continuous measure of the linguistic distance rather than a dummy variable to better control for the heterogeneity in the linguistic origins.

A major advantage of our analysis is that the linguistic distance refers to the language *actually* spoken at home. Though most authors try to infer this language from information on the country of origin, associating a country to a single language is not always possible, since different languages may be spoken in the same country. This is the case of many North-African countries that are a major source of emigration to Italy.[19] Notice that, even when such association is possible, this does not imply that the parents speak their mother tongue with their children in the destination country.

To discuss the validity of our instrumental variable strategy we also consider additional questions that are only asked in the Student's Questionnaire (2014-15), such as whether the child has been victimized by peers, teacher's attitude, parents' incentives, preferences for Math and Italian, and socio-emotional skills.

Some descriptive statistics for the main variables are summarized in Table 1.

Table 1: Descriptive Statistics. Natives vs. Second Generations

Variable	**Natives**	**Second Generations**	**Diff.**
Math	58.2736	51.2491	7.0245***
	(0.0500)	(0.1807)	(0.1875)
Italian	63.3606	54.5137	8.8469***
	(0.0443)	(0.1600)	(0.1660)
Female	0.4949	0.4962	-0.0012
	(0.0004)	(0.0014)	(0.0015)
Age in months	129.3916	130.3539	-0.9623***
	(0.0075)	(0.0271)	(0.0281)
ESCS student	0.1421	-0.5009	0.6430***
	(0.0032)	(0.0114)	(0.0119)
Obs	1,704,750	136,613	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Standard Errors in parenthesis clustered at the school-cohort level.

Natives perform better than second-generation immigrants both in Math and in Italian. On average, the gap between second generations and natives is 8.8 points in Italian and 7.0 in Math. However, second generations also face worse socioeconomic conditions, so this result is expected.

conditions of the place where it is spoken (Everett et al., 2015, 2016). As a consequence, this measure possibly controls for spatial and geographic factors. The results are indistinguishable with respect to the other measure, and are not reported for brevity. They are available upon request.

[19] For instance, immigrants from Morocco can speak Arabic, French, or Spanish; immigrants from Egypt speak Arabic, French or English; immigrants from Tunisia speak Arabic or French, and immigrants from India speak Hindi or English. Immigrant stocks from these countries are sizable in Italy: on December 31, 2018, we observe 422,980 immigrants from Morocco, 126,733 from Egypt, 95,071 from Tunisia, and 157,965 from India. Source: ISTAT (2018).

3 Empirical Strategy

As a first approach to evaluate the relationship between the performance in Math and the performance in Italian, we estimate a standard regression:

$$Math_{isct} = \beta_0 + \beta_1 Italian_{isct} + \beta_2 Dist_{isct} + \beta_3 Age_{isct} + \mathbf{X}\lambda + \vartheta_{sct} + \epsilon_{isct}, \tag{1}$$

where the dependent variable is the score in Math of student i, in school s, class c, cohort t; *Italian* is the score in Italian; *Dist* is the linguistic distance between the language spoken at home and Italian; *Age* is the student's age (measured in months); $\mathbf{X}$ is a vector of socioeconomic controls; ϑ_{sct} are school-by-class-by-cohort fixed effects, that allow us to control for unobserved differences within a school-class and across cohorts, and for dynamic selection;[20] ϵ_{isct} is the error term, clustered at the school-class-cohort level to allow for a possible correlation within each school-class-cohort.[21]

This specification suffers from an omitted variable bias, because many crucial factors behind the educational results in both Italian and Math (like abilities and motivation) are not observable. To estimate a consistent effect of linguistic proficiency on Math, we use an instrumental variable approach. The IV method is common to Isphording et al. (2016) and Aparicio-Fenoll (2018), who also tried to estimate the effect of immigrants' language skills on Math results. In the line of Bleakley and Chin (2004, 2008, 2010), these authors rely on a quasi-experimental framework, by comparing immigrants with different ages at arrival and different linguistic origins.[22] However, the features intrinsic to this construction make it impossible to use their IVs for the *second* generations: the age at arrival effect cannot be exploited for children born in the destination country. As a consequence, we have to develop an alternative IV, for which, as we argue later on, we propose the interaction between age and linguistic distance from Italian.

Thus, we estimate a two-stage least squares model, where the first stage is given by

$$Italian_{isct} = \alpha_0 + \alpha_1 Age_{isct} * Dist_{isct} + \alpha_2 Dist_{isct} + \alpha_3 Age_{isct} + \mathbf{X}\rho + \varphi_{sct} + \eta_{isct}, \tag{2}$$

and the second stage is given by

$$Math_{isct} = \gamma_0 + \gamma_1 \hat{Italian}_{isct} + \gamma_2 Dist_{isct} + \gamma_3 Age_{isct} + \mathbf{X}\delta + \theta_{sct} + \xi_{isct}. \tag{3}$$

where $\hat{Italian}_{isct}$ is the predicted score in Italian from the first-stage.

Our instrument exploits the heterogeneity in children's birthdates and the variation in linguistic distances. Notice first that neither age nor linguistic distance alone can be an instrument. For instance, proficiency in Italian improves with a longer exposure to language, thus with age. However, an "older" age gives the child more time to learn Math as well, generating a violation of

[20] This is equivalent to a within transformation, where we subtract the mean of the school-class-cohort from each variable in the model. We also estimate variations of this model with separate class or school and cohort fixed effects; namely, a two-way fixed effects where we assume that cohort effects are not nested within school-classes, schools, or classes.

[21] We also estimate variations of this model with different levels of clusterization.

[22] Their instruments are given by the interaction between the immigrants' age at arrival and the linguistic distance or a dummy for non-English speaking countries.

the exclusion restriction. In addition, age could also capture grade retention and/or enrollment manipulation by parents. While grade retention is very rare in Italy, enrollment manipulation is particularly relevant (Abatemarco et al., 2021).[23] Finally, there exists evidence of seasonality-in-fertility effects (Buckles and Hungerman, 2013), for which we check by adding month fixed effects in some specifications. All these issues make age not suitable as an instrumental variable. As for the linguistic distance, it is not suitable as well. Different linguistic origins may induce a different selection in the migration decision (for instance, because a greater distance increases the cost of language acquisition or because of cultural differences). This kind of selection depends on unobservable characteristics that could be conveyed to the second generation. To the extent that these characteristics affect the acquisition of cognitive and non cognitive skills, they induce endogeneity.

For all these reasons, we control for any *direct* effect related to age and linguistic distance. On the other hand, we use their *interaction* as our instrument. The interaction between age and linguistic distance captures the exposition to Italian *across different languages*, or, alternatively, the effect of the linguistic distance at different levels of exposure to Italian.

The key identifying assumption is that, conditional on our controls, the interaction between age and linguistic distance directly affects only the score in Italian. Formally, the exclusion restriction is

$$E(\epsilon_{isct}|Age_{isct} * Dist_{isct}, Dist_{isct}, Age_{isct}, \mathbf{X}, \vartheta_{sct}) = 0. \tag{4}$$

In other words, the interaction term $Age * Dist_{isct}$ has no *direct* effect on the score in Math. The relevance of the instrument is examined in Section 4.1. In the following section, we review different mechanisms that may undermine our identification. We discuss why they do not apply to our case, and show a set of regressions that support our claim.

3.1 Identification issues

Threats to our identification arise if there exist unobservable characteristics that make the *interaction* between age and linguistic distance endogenous. In this respect, it is crucial to remark that endogeneity along a *single* dimension (i.e., age or linguistic distance) or even — under mild conditions— along *both* dimensions does *not* invalidate our instrument. In the case of a single dimension, it is easy to figure out a mechanism that creates endogeneity. For instance, parents whose linguistic background is far from Italian could put more effort in helping their children, but this does not undermine our identification, since the linguistic distance is in the controls. The same holds for age: parental help could depend on the child's age, for which we control.

Explaining why even endogeneity along two dimensions is also not enough to invalidate our instrument is less straightforward. For our identification to hold, we need that, as we fix one dimension and move along the other, the effect is the same at *any level of the fixed dimension.*

[23] In Italy the school year begins in September. Though enrollment is compulsory for all children who are 6 in September, parents can enroll younger children provided that they turn 6 by April 30 of the following year. As a consequence, children born between January 1 and April 30 can be enrolled when they are still 5, or wait one more year.

For instance, if we fix age and move along linguistic distance, the effect of the latter must be the same at any age. In other words, there must not exist an unobserved mechanism that changes the effect of the linguistic distance at different ages. Alternatively, there must not exist an unobserved mechanism that changes the effect of age at different linguistic distances. This occurs as far as any endogenous relationship between linguistic distance and age is additive and separable. Thus, the conditions required to jeopardize our identification look quite restrictive, and we find it hard to figure out a mechanism that could make our IV endogenous. In what follows, however, we try to empirically verify its existence by checking some correlations we should observe were our instrument endogenous.
The circumstances that may invalidate our instrument can be traced back to the natives' or parents' behavior. In the following, we discuss some major examples. The data used in this section come from the Student's Questionnaire, which is administered in the 5th grade and asks questions about family conditions and preferences. Many questions change over time, thus they are dropped in some waves. We report the reference wave for each question.

Discrimination.

Native peers could discriminate second-generation children in social interactions, leading to a failure of exposure to Italian. In this section, we use reported victimization as a proxy of discrimination.
Discrimination against peers who speak different languages is plausible, but, as we argued above, this is not enough to invalidate our identification. In order to understand our reasoning in practice, consider first that, as is well-known, younger children are more likely to be victimized. This creates endogeneity in one dimension. Besides, it is also true that children with a distant linguistic background (say, showing a foreign accent) are more likely to be discriminated. This creates endogeneity in the other dimension. For our instrument to be endogenous, a pattern that links age-related discrimination to linguistic discrimination is required. Thus, discrimination should be correlated to the *interaction* between age and linguistic distance.
In order to perform this check, we use the following questions on victimization (Student's Questionnaire 2014-15):

- *During this school year, how often have you been teased by other students at school?*
- *During this school year, how often have you been insulted by other students at school?*
- *During this school year, how often have you been isolated or excluded from other students at school?*
- *During this school year, how often have you been beaten by other students at school?*

and we estimate the following LPM:[24]

$$y_{isct,\,t=2015} = \beta_0 + \beta_1 Dist_{isct,\,t=2015} + \beta_2 Age_{isct,\,t=2015} + \beta_3 Age_{isct,\,t=2015} * Dist_{isct,\,t=2015} + \\ + \mathbf{X}\lambda + \vartheta_{sc} + \epsilon_{isct,\,t=2015} \quad (5)$$

[24] In alternative specifications, we have also estimated a probit and an ordered probit.

where for $y_{isct,\, t=2015}$ we consider in turn the dummy for whether the child is teased, insulted, isolated or beaten by other children at school. Though a higher linguistic distance increases the probability of experiencing discrimination, (Table 26), this does not happen for the interaction (*Age*Distance*) whose coefficient is not significant (Table 27).

Discrimination by teachers is another potential source of endogeneity. We try to investigate this issue, and estimate Equation 5 by considering various measures of teachers' attitude as dependent variables. In particular, we consider the following questions (Student's Questionnaire 2014-15):

– *In my class, when we have an issue, we are listened to*;
– *In my class, we are listened to attentively when we interact during the lesson*;
– *In my class, we are encouraged to ask questions during the lesson.*

Though there is some evidence of a negative correlation between linguistic distance and teachers' attention (Table 37), this does not happen for the interaction *Age*Distance*, whose coefficient is not significant (Table 38).

Self-segregation.

Immigrant households could try to reduce the exposure to the Italian culture in order to preserve their traditional norms and customs. We can roughly check for this issue by considering the correlation between the interaction *Age*Distance* and the probability that second-generation children isolate their peers. In particular, we use the following question (Student's Questionnaire 2014-15):

– *During this school year, how often have you isolated or excluded other students at school?*

to estimate Equation 5. Table 28 shows no significant correlation between the probability of isolating or excluding peers and the interaction *Age*Distance*. This is in line with the literature about endogenous segregation, which shows rather that the (choice of) separation from the receiving society may occur at *any* level of linguistic distance (Battu et al., 2007; Bisin et al., 2011, 2016; Constant et al., 2009; De Martì Beltran and Zenou, 2017). Self-segregation may even occur in minorities speaking *the same* language as the majority. For instance, it is well-known that African American students in the US may be ambivalent about performing well at school because this may be blamed as "acting white"(Austen-Smith and Fryer, 2005; Fryer Jr. and Torelli, 2010).

Enrichment activities.

Households can support their children with homework, tutoring, reading or other activities. As usual, while one can figure out a rationale for parents' behavior in response to age and linguistic distance alone, it is unlikely that families adjust the intensity of these activities as a result of a further (unobserved) non-separable effect that links age and linguistic distance. The existing evidence shows that parental support depends on education and income (for which we control),

rather than -for instance- linguistic distance (Aguiar and Hurst, 2007; Doepke and Zilibotti, 2019; Duncan and Murnane, 2011).
However, as a further check, we examine the correlation between *Age*Distance* and several variables that should predict parental support; namely, the number of books at home, the availability of a quiet place to study, computers, encyclopedias, internet connections, own rooms (Student's Questionnaire 2014-15; 2015-16; 2016-17; 2017-18; 2018-19). We estimate the following LPM:

$$y_{isct} = \beta_0 + \beta_1 Dist_{isct} + \beta_2 Age_{isct} + \beta_3 Age_{isct} * Dist_{isct} + \mathbf{X}\lambda + \vartheta_{sct} + \epsilon_{isct} \quad (6)$$

where y_{isct} are dummies for any of these outcomes. These variables are unrelated to the interaction *Age*Distance* in most cases (Tables 29 and 30).[25] On the other hand, father's and mother's job and education are quite more likely to be related to *Age*Distance* (Tables 31, 32, 33, 34, 35, 36). This seems to confirm that parental help can be captured by observable variables.

Preferences.

Other concerns could arise if, due to the lack of language proficiency, children with an immigrant background would rather prefer Math, or put more effort on this subject.
To investigate this issue, we consider the following questions (Student's Questionnaire 2014-15):

- *How much do you agree with the following statement? I like studying Math*
- *How much do you agree with the following statement? I like studying Italian*

and we estimate the following LPM:

$$\begin{aligned} Math\ Preferences_{isct,\, t=2015} &= \beta_0 + \beta_1 Italian_{isct,\, t=2015} + \beta_2 Math_{isct,\, t=2015} + \\ &+ \beta_3 Dist_{isct,\, t=2015} + \beta_4 Age_{isct,\, t=2015} + \beta_5 Age_{isct,\, t=2015} * Dist_{isct,\, t=2015} + \mathbf{X}\lambda + \vartheta_{sc} + \epsilon_{isct,\, t=2015} \end{aligned} \quad (7)$$

where $Math\ Preferences_{isct,\, t=2015}$ is a dummy for whether the student likes studying Math, while $Italian_{isct,\, t=2015}$ and $Math_{isct,\, t=2015}$ are the score in Italian and the score in Math respectively. We find that preferences for Math are unrelated to the interaction Age*Linguist Distance (Table 40, column (1)).
In the same vein, we investigate the correlation between the taste for Math and the taste for Italian. If a lack of proficiency induced children to put more effort in Math and to dislike Italian, then we should observe a negative correlation between tastes for Math and tastes for Italian. However, by estimating the following LPM

$$Math Preferences_{isct,\, t=2015} = \beta_0 + \beta_1 Italian Preferences_{isct,\, t=2015} + \mathbf{X}\lambda + \vartheta_{sc} + \epsilon_{isct,\, t=2015} \quad (8)$$

[25] For these tables, questions come from the Student's Questionnaire 2014-15; 2015-16; 2016-17; 2018-19.

we find that this correlation is indeed *positive* (Table 40, column (2)). These results plausibly exclude that our results are driven by preferences.

Socio-emotional skills

Another possible confounding factor could be related to a specific impact of socio-emotional skills on test scores for second-generation children. Since more mature children should feel more confident, we may conjecture a negative relation between anxiety and age. Besides, it could happen that more linguistically distant children feel more anxious when facing a test written in Italian. To investigate this issue, we consider the following questions (Student's Questionnaire 2014-15; 2015-16; 2016-17):

- *Even beforehand, I was worried for the test*
- *I was so nervous that I was not able to find the answers*
- *While I was answering, I had the feeling of going wrong*
- *While I was answering, I felt calm*

and we estimate Equation 5 by considering these outcomes.
In Table 41, we observe that being worried for the test, being nervous, or thinking to be wrong are all positively correlated to the linguistic distance. Feeling calm is negatively correlated to the linguistic distance. Thus, we detect some correlation between text anxiety and linguistic distance.
On the other hand, correlation with age is less clear. While feeling worried for the test and thinking to be wrong are negatively related to age - which confirms that more mature children seem to be more confident- being nervous is positively related to age, and feeling calm looks not related. However, in Table 42 the interaction *Age*Distance*, is almost always unrelated to text anxiety.[26]

Enrollment manipulation.

In many cases, parents can manipulate school enrollment.[27] The parents with a linguistic background far from Italian could delay the enrollment of their children, in order to give them more time to learn the language. However, the opposite also holds: the parents could be willing to expose their children to Italian schools as soon as possible, thus anticipating their enrollment. These possibilities determine a potential relationship between age and linguistic distance. To investigate this issue, we estimate the following LPM:

$$y_{isct} = \beta_0 + \beta_1 Dist_{isct} + \mathbf{X}\lambda + \vartheta_{sct} + \epsilon_{isct} \tag{9}$$

where y_{isct} is a dummy equal to one if the child is late enrolled. The correlation between linguistic distance and the probability of postponing the enrollment is significant but almost

[26] Even though feeling nervous is statistically significant at the 10% level, the magnitude of the coefficient is almost zero.
[27] See footnote 22 for information on the enrollment procedure in Italy. Notice also that enrollment manipulation is not possible for children who turn 6 between May 1 and December 31.

negligible (0.000357) (Table 43). Thus, it seems that the linguistic distance *per se* only plays a minor role in the enrollment. Controlling for age should be sufficient to clean this effect.

4 Results

In Table 3, we report the OLS estimation of Equation 1 on the whole sample of second-generation children. We report four specifications. The first is a two-way fixed effect model, where we control for separate cohort and class fixed effects. The second is a class-by-cohort fixed effect model. The third is a school-by-class-by-cohort fixed effect model, which is our preferred specification. The fourth is a school-by-class-by-cohort fixed effect model where we also add month fixed effects to account for possible seasonality in birth effects.

We find a sizable positive relationship between the score in Italian and the score in Math. Increasing the score in Italian by one point increases the score in Math by 0.618 points (equivalently, a 1 standard deviation increase in the Italian score implies, on average, 0.602 standard deviations increase in the Math score). However, this relationship can hardly capture a causal effect, since it also includes the effect of the unobservables.

We report the first and the second stage of the 2SLS estimation (Equation 2 and Equation 3) in Tables 6 and 8. Now, we find a *negative* relationship between the score in Italian and the score in Math. In our preferred specification, increasing the score in Italian by one point decreases the score in Math by 0.344 points (equivalently, a 1 standard deviation increase in the Italian score, on average, decreases the score in Math by 0.335 standard deviations). This negative coefficient points to a trade-off between learning Italian and learning Math. Apparently, children have to sacrifice their performances in other subjects if they want to improve their proficiency in Italian. In this sense, this finding does *not* contradict the idea that language proficiency is a prerequisite for understanding Math classes. Rather, it suggests that the trade-off is fueled by an insufficient knowledge of Italian.

It is also interesting to remark the difference between the OLS and IV estimates. The OLS estimator looks heavily *upward* biased. This is not surprising, since the naïve partial correlation between the score in Italian and the score in Mathematics is driven by the omitted variables. Isphording et al., 2016 and Aparicio-Fenoll, 2018 identify as well an upward bias, though less considerable. In our case, the ability bias seems to be higher in absolute value than the negative value of the instrumented coefficient, which is the reason why the OLS coefficient is positive. This outcome is in line with the recent literature that confirms the crucial importance of unobserved cognitive and non-cognitive abilities —and of their interaction— for educational performances (Cunha et al., 2006; Almlund et al., 2011).

4.1 First stage

Table 6 reports the first stage of our IV estimation strategy (Equation 2). Our instrument is the interaction between age (measured in months) and the linguistic distance from Italian, which are both continuous variables. As a consequence, the coefficient on their interaction measures how many units the slope of Italian on Age is predicted to change with a one-unit increase in the linguistic distance. A higher linguistic distance makes exposure less effective; thus the negative correlation we find is as expected.[28]

The coefficient of Age is positive and significant at the 1% level (except for the fourth specification). Notice that, since in the first-stage regression we have the interaction *Age*Distance*, this coefficient captures the effect of age *only when the linguistic distance is zero,* namely, in the case of second-generation children who speak Italian at home. For non-Italian speakers, the effect of age is given by $\alpha_1 * (Distance) + \alpha_3$.[29] For instance, in the case of the Chinese, who are the most linguistically distant, it is -0.130 score points. As expected, the effect of age (namely, exposure) decreases as the linguistic distance increases.

The coefficient of the linguistic distance is also positive and significant at the 1% level. Again, since we have the interaction *Age*Distance*, by itself, it only gives the effect of the linguistic distance *when age is zero*. When we consider this effect conditioned on a more plausible age, it becomes negative as expected. For instance, at the age of 123 months (10.25 years), it is -0.029. At the age of 132 months (11 years), it is -0.057 score points. Thus, *the effect* of the linguistic distance decreases as the exposure increases.

Finally, the weak identification test confirms that the instrument is relevant. The Kleibergen-Paap Wald rk F statistic is 89.87 and the critical values vary between 5.53 and 16.38, in our preferred specification (Table 6, Column 3).

4.2 Second stage

Turning to the second stage (Equation 3), we note that the coefficient of the instrumented score in Italian is negative and significant at the 1% level. Increasing the score in Italian by one point *decreases* by 0.344 points the score in Math. As argued above, the negative coefficient suggests that the children in our sample still have to sacrifice their performances in other subjects if they want to improve their proficiency in Italian.

We try to shed further light on this trade-off. First, we show that the estimated effect of language proficiency on Math performance masks a heterogeneous effect. In particular, the IV estimates could be interpreted as a LATE, and would be informative of the sub-sample of individuals for whom the treatment status is affected by a change from z to z' (the *compliers*), for any pair (z, z') of values of $Age * Distance_{isct}$. More generally, in our data, while children with a Non-Romance linguistic background face the trade-off, this is not the case for children with a Romance background, who plausibly benefit from similarities with the language spoken at home. In addition, we further argue that the causal relationship between proficiency in Italian and scores in Math may be nonlinear. In other words, the proficiency necessary to understand a Math class is well below the proficiency necessary to understand Dante's Divine Comedy.

[28] Alternatively, this coefficient can also be interpreted as how many units the slope of Italian on the linguistic distance is predicted to change with a one-unit increase in the exposure to Italian. Similarly, the effect of linguistic distance decreases as the exposure to Italian increases.

[29] See Jaccard and Turrisi (2003) for a useful review.

Once the threshold for understanding a Math class is attained, further progress in Italian could be little relevant for the Math performance. Therefore, we expect that the trade off could be particularly relevant for children who under-perform in Italian.

4.3 Romance vs Non Romance

We report our IV analysis for Romance and Non Romance language speakers in Tables 10, 12, 14, 16. The idea behind this distinction is that learning Italian may take longer for Non-Romance speaking children, since Romance speakers are used to a language close to Italian. Actually, Romance speakers perform better than Non Romance speakers, both in Math and in Italian. On average, the gap between Non Romance and Romance is 6.29 points in Italian and 3.24 in Math (Table 2).

Table 2: Descriptive Statistics. Romance vs. Non Romance

Variable	**Romance**	**Non Romance**	**Diff.**
Math	52.4977	49.2568	3.2409***
	(0.1048)	(0.1335)	(0.1697)
Italian	56.9943	50.7063	6.2880***
	(0.0962)	(0.1223)	(0.1556)
Female	0.4995	0.4910	0.0084***
	(0.0018)	(0.0022)	(0.0029)
Age in months	130.1655	130.4236	-0.2582***
	(0.0173)	(0.0219)	(0.0279)
ESCS student	-0.4120	-0.6392	0.2272***
	(0.0044)	(0.0056)	(0.0072)
Obs	83,351	52,730	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Standard Errors in parenthesis clustered at the school-cohort level.

After instrumenting, we observe different trajectories within the two subsamples. In Table 14, we report the first stage for Non-Romance speakers. The instrument is relevant. The Kleibergen-Paap Wald rk F statistic is 43.19 and the critical values vary between 5.53 and 16.38 in our preferred specification (Table 14, Column 3). In Table 16, we report the second stage for Non-Romance speakers. The effect of the score in Italian is negative and statistically significant at the 1% level. Increasing the score in Italian by one point decreases the score in Math by 0.549 points, in our preferred specification (equivalently, a 1 standard deviation increase in the Italian score implies, on average, 0.535 standard deviations decrease in the Math score).
As for Romance speakers, we report the first stage in Table 10. The instrument is weak. The Kleibergen-Paap Wald rk F statistic is 2.93 and the critical values vary between 5.53 and 16.38, in our preferred specification (Table 10, Column 3). In the second stage, (Table 12) the estimated coefficient of the score in Italian is now positive but, as expected, statistically insignificant.

Overall, these findings suggest that the trade-off between acquiring mathematical skills at the cost of reducing proficiency in Italian especially concerns Non-Romance children. Romance languages speakers plausibly take advantage of complementarities in languages, find it easier to learn Italian and, at the age of 10, are not anymore subject to the trade-off. This should be the reason why the instrumental variable loses relevance in this subset.

4.4 Threshold effects

In order to test the existence of a language proficiency threshold for understanding Math classes, we first have to identify a proper threshold. Since INVALSI approves Proficiency Level 3 as a "sufficient" knowledge of Italian, we compute the threshold accordingly.[30]

In Table 18, we report the first-stage estimation for second-generation children whose performance in Italian is under Proficiency Level 3. Again, we may note that the effect of exposure to Italian decreases as the linguistic distance increases, and the effect of the linguistic distance decreases as the exposure increases.

The weak identification test shows that the instrument is relevant. The Kleibergen-Paap Wald rk F statistic is 32.01 and the critical values vary between 5.53 and 16.38, in our preferred specification (Table 18, Column 3). Second-stage estimates are in Table 20. The effect of the Italian score on the Math score is negative and statistically significant at the 1% level. Increasing the score in Italian by one point decreases the score in Math by 1.298 points, depending on the specification (equivalently, a 1 standard deviation increase in the Italian score implies, on average, 1.265 standard deviations decrease in the Math score). This suggests that the trade-off we bring to light is driven by the subsample of children below the sufficiency threshold (namely, Proficiency Level 3).

The same estimation strategy for second-generation children who perform beyond the threshold does not work as well. In Tables 22 and 24, we report the first and the second stage for children above the sufficiency proficiency level. The instrument is weak, suggesting that exposure to Italian *per se* does not explain the performance in Italian *beyond sufficiency*. The Kleibergen-Paap Wald rk F statistic is 2.06 and the critical values vary between 5.53 and 16.38, in our preferred specification (Table 22, Column 3). As a consequence, we cannot use our instrument to estimate the causal effect of the Italian score on the Math score for students on or above Proficiency Level 3.

5 A theoretical tour of our results

In this section, we build on the existing literature and sketch a basic model of the learning process that is compatible with our findings. Our main argument is that the mechanism behind language acquisition requires a peculiar production function.

[30] Proficiency Level 3 is defined as a score belonging to a range that goes from 95% to 110% of the natives' average score. Thus, we take the lower bound, namely 95%, as our threshold.

5.1 The production of knowledge

In its very essence, learning is a technology. As such, it can be described by a production function, which, borrowing from the R&D literature, we call "knowledge production function"(henceforth KPF). What do we know about the features of this technology? In the literature, few papers try to model how children learn. Our natural starting point is the seminal contribution by Cunha and Heckman (2007), who point out two essential mechanisms at work in the childhood; namely, the *self-productivity of skills* and the *dynamic complementarity of skills.* The former indicates that, in the educational process, the output of a stage is the input of the following stage. The latter points out that skills produced at one stage raise the productivity at subsequent stages.

In our framework, we use both these ideas, but, in line with the linguistics literature and our findings, we also consider the existence of *thresholds* in language acquisition. As we have stressed, these thresholds are taken for granted in a number of everyday circumstances. The standard practice of requiring language certifications to foreign students is a major example.[31] In other words, universities put a *lower bound* on the language proficiency of foreign students before enrolling *any* course. The implicit assumption here is that this lower bound discriminates the students able to understand the classes from those who aren't.

In this framework, the dynamic complementarity arises just because language proficiency is a prerequisite for learning Math: we can think of the knowledge of Italian (measured by the test score) as an *intermediate input* for producing Math knowledge. Thus, we need two KPFs: one for Italian, and one for Math. In order to preserve the intuition, in what follows the KPF of Italian is as simple as possible, and we assume that its output (the score in Italian, I) is a strictly increasing, strictly concave, and twice continuously differentiable function of the time spent studying Italian in the current period (L_{it}) **plus the stock of knowledge of Italian inherited from the past (I_0), which catches the self-productivity of skills. This additive term disappears in the maximization, but is relevant because it summarizes the child's past achievements.**

Finally, to complete the description of the KPF, it is important to notice that, when we measure knowledge, any assessment is inevitably noisy. Scores can be affected by various unobservable circumstances, like the ability to perform, the health conditions on the day of the exam, or even good luck. In order to account for this noise in our KPF, we introduce** an additive, normally distributed random term $\rho \in [-a, a]$ with zero mean and finite variance $[\rho \sim \mathcal{N}(0, \sigma_\rho^2)]$. Thus, the KPF of Italian is

$$I = f(L_{it} + I_0) + \rho. \tag{10}$$

The knowledge of Math (i. e., the score in Math) depends on the time spent in studying Math (L_{mat}) **plus the previous knowledge of Math (M_0),** and on the intermediate input of Italian, for which we introduce a threshold level. A notable example of a technology with

[31] For instance, Erasmus students are usually required a B2 English level certificate on the Common European Framework of Reference (CEFR). In the case of graduate admissions, C1 level is even more common.

threshold is the Stone-Geary production function.[32] In the Stone-Geary function, a positive output only appears after the input has crossed the threshold. For our purposes, however, we assume that some output (i. e. learning) exists even *inside* the threshold. This happens because, though the child finds it hard to understand the teacher, she can learn, for instance, by reading the textbooks. In other words, we have two cases: inside the threshold the child learns without benefiting from language proficiency, and beyond she does. The noise in the measure of knowledge is added, for simplicity, through the same random term ρ we use for the Italian KPF. This can be summarized as follows.
Let M be the score in Math. The Math KPF is given by

$$M = \begin{cases} g(L_{mat} + M_0, I_{it}; \bar{I}) + \rho & \text{if } I_{it} > \bar{I} \qquad \text{(A)} \\ \\ h(L_{mat} + M_0) + \rho & \text{if } I_{it} \leq \bar{I} \qquad \text{(B)} \end{cases} \tag{11}$$

where $g(.)$ and $h(.)$ are two strictly increasing, strictly concave, and twice continuously differentiable functions.[33] We also assume $\frac{\partial g(.)}{\partial L_{mat}} > \frac{\partial h(.)}{\partial L_{mat}}$. In line with the dynamic complementarity, this assures that the marginal productivity of time spent studying Math is higher in case (A).

5.2 Utility maximization

For our illustrative purposes, we assume that the child has a strictly increasing, strictly concave, twice continuously differentiable utility defined on her score in Math and Italian:

$$u = u(M, I; \delta) \tag{12}$$

where $\delta \in (0, 1)$ is a weight that measures the preference for Math relative to Italian. We assume that the scores in Italian and Math are complements. In other words, even though a child may have different tastes for Italian and Math, she likes the scores in *both* subjects. This interpretation perfectly mirrors our estimates in section 4.1.4, **which show a positive association between the taste for Math and the taste for Italian.**
We normalize the time endowment to unity, thus the time constraint is

$$L_{it} + L_{mat} = 1, \tag{13}$$

where L_{it} and L_{mat} are, respectively, the time devoted to studying Italian and Math.
The child maximizes the utility (12) subject to the time constraint (13).
Naturally, being in case (A) or (B) on the Math KPF makes a crucial difference, and we have to take into account how the threshold affects the child's behavior. **To this aim, notice that

[32] Notably, Beattie and Aradhyula (2015) stress that "it is hard to think of many production processes where one may reasonably expect positive output with input levels close to zero". In many processes, threshold levels of the requisite inputs are the norm rather than the exception.

[33] For any $\ell_{mat} \in (0, 1)$, the function M(.,.) is left-continuous in $(\ell_{mat}, \bar{I})$: $\lim_{(L_{mat}, I_{it}) \longrightarrow (\ell_{mat}, \bar{I})^-} M(L_{mat}, I_{it}) = h(\ell_{mat})$.

we can partition the children between those who start the school year beyond the threshold (case A) and those who start inside the threshold (case B). The different initial conditions are due to the different stocks of inherited knowledge, which are known to the children, who are are aware of their previous grades and of their proficiency.[34] Therefore, those in case (B) realize the benefits of moving to case (A). We discuss the optimization problem in what follows.**

Case A:

Consider case (A) of the Math KPF (11). The child maximizes the (expected) utility (12), namely

$$E[(f(.) + \rho), (g(.) + \rho), \delta] \tag{14}$$

subject to the time constraint (13). **Through the Bolzano-Weierstrass theorem, we know that this problem has a solution. Since the utility is strictly concave and the constraint is linear, the solution is unique.**[35] Thus, there exists a pair (L^*_{mat}, L^*_{it}) that gives, respectively, the optimal time devoted to study Math and the optimal time devoted to study Italian.
By substituting the equilibrium values L^*_{mat} and L^*_{it} into the KPFs, the equilibrium score in Math is

$$M^* = g(L^*_{mat}, I^*; \bar{I}). \tag{15}$$

At the equilibrium, the effect of the score in Italian on the score in Math is given by the derivative

$$\frac{\partial M^*}{\partial I^*} = \frac{\partial g(L^*_{mat}, I^*; \bar{I})}{\partial I^*} + \frac{\partial g(L^*_{mat}, I^*; \bar{I})}{\partial L^*_{mat}} \frac{dL^*_{mat}}{dI^*}. \tag{16}$$

**In equation (16), the first term on the right-hand side is the effect of increasing the language proficiency. This effect is positive, because proficiency helps to understand the classes. Since, however, increasing the Italian score requires sacrificing some time spent on Math, the second term on the right-hand side measures the ensuing marginal loss in the Math score.[36] **
Derivative (16) is positive if

$$\frac{\partial g(L^*_{mat}, I^*; \bar{I})}{\partial I^*} > -\frac{\partial g(L^*_{mat}, I^*; \bar{I})}{\partial L^*_{mat}} \frac{dL^*_{mat}}{dI^*}. \tag{18}$$

[34] Formally, children in case A have I_0 such that $f(0 + I_0) > \bar{I} + a$. In other words, even though they choose the corner solution $L^*_{it} = 0$ and receive the worst negative shock $(-a)$, they are still beyond the threshold. All children with a lower I_0 are in case B.

[35] **This optimization problem is usual except for the presence of the random term ρ in the KPFs. However, since ρ is continuously distributed on the closed interval $[-a, a]$ and its variance is finite, the objective function (12) is still continuous. Given that the time constraint (13) is compact, we can apply the Bolzano-Weierstrass theorem.

[36] To prove that this term is negative note that, by the time constraint, $L^*_{mat} = (1 - L^*_{it}) = (1 - f^{-1}(I^*))$. Thus,

$$\frac{dL^*_{mat}}{dI^*} = -\frac{df^{-1}(I^*)}{d(I^*)} < 0. \tag{17}$$

This condition shows when increasing the score in Italian goes along with an increase in the Math score. When condition (18) holds, the child collects large gains from language acquisition and dynamic complementarity. Now we move to the children inside the threshold.

Case B:

The children inside the threshold are aware of the benefits of language acquisition, but, since their achievement is *uncertain*, they cannot be sure of moving across $\bar{I}$. Nonetheless, they realize that their chances increase with the time spent studying Italian. Let us denote the probability of crossing the threshold with $p(L_{it}) \in (0,1)$.[37] Thus, they end up in case (A) with probability $p(L_{it})$, and in case (B) with probability $(1 - p(L_{it}))$.
Finally, they maximize

$$E[u] = p(L_{it})[u(f(.), g(.); \delta)] + (1 - p(L_{it}))[u(f(.), h(.); \delta)] \tag{19}$$

subject to the time constraint (13).
In this problem, the conditions to apply the Bolzano-Weierstrass theorem still hold. Again, since the utility (19) is strictly concave and the constraint is linear, the problem has a unique solution (L^*_{mat}, L^*_{it}). Ex post, either the child succeeds in crossing the threshold or she does not. If she succeeds, she moves to case (A) of the Math KPF. If she does not succeed, she stays in case (B), thus $M^* = h(L^*_{mat})$.

At the equilibrium, the effect of the score in Italian on the score in Math is given by the derivative

$$\frac{\partial M^*}{\partial I^*} = \frac{\partial h(.)}{\partial L^*_{mat}} \frac{\partial L^*_{mat}}{\partial I^*}, \tag{20}$$

**which is is unambiguously negative.[38]
Derivative (20) shows that, when the child is below the sufficiency threshold in Italian, she *always* faces a trade-off between Italian and Math. More generally, derivatives (16) and (20) show the possibility of a trade-off between Italian and Math even though language proficiency is a prerequisite to understand Math. Thus, they provide a theoretical foundation to the mixed results in the literature.**

6 Conclusions

In this study, we tried to estimate the effect of language acquisition on the performance in Math of second-generation children at the end of the Italian primary school. This age deserves

[37] We assume $\frac{dp}{dL_{it}} > 0$ and finite.
[38] Notice that $L^*_{it} = f^{-1}(I^*)$; then, by the time constraint (13), $M^* = h(1 - f^{-1}(I^*))$. Thus we have

$$\frac{\partial M^*}{\partial I^*} = -h'(1 - f^{-1}(I^*))f^{-1\prime}(I^*) < 0 \tag{21}$$

because the marginal productivity $h^{'}(.)$ is positive, as well as the inverse function of the marginal productivity $f^{'}(.)$.

special attention, since, as a vast literature suggests, 1) early educational gaps may have lifetime effects and, in any case, are hard to recover in later years; 2) language proficiency is required to acquire other forms of human capital; 3) language proficiency is crucial for the social and economic integration of the second generations.

The literature is still in the making, and the results are so far ambiguous. While Isphording et al. (2016) find a positive effect of linguistic performances on Math outcomes for 15 years-old first-generation immigrants, Aparicio-Fenoll (2018) finds no evidence of such an effect on a mixed sample of first and second-generation children aged 6-12. In turn, we find that higher scores in Italian *reduce* the score in Math for *second-generation* immigrant children in Italy.

As we have shown in our model, this finding does not contradict the idea that language proficiency is a prerequisite for understanding Math classes taught in Italian. Rather, it points out that second generations are still struggling to learn Italian at the age of 10, and they can do so only at the cost of reducing their performance in other subjects. In line with the linguistics literature, our model is based on the hypothesis that the benefits of language acquisition show up only once the child crosses a threshold of sufficiency, which we identify according to widely adopted criteria. In practice, we confirm that the trade-off between Italian and Math is driven by children below the threshold. These children account for 59% of our sample. Thus, it seems that the the Italian school is failing the objective of reducing the intergenerational transmission of inequality: the large majority of the second-generations is already being left behind. These children cannot benefit from the complementarity between language proficiency and other forms of human capital as their native peers. They look doomed to poor educational performances and, consequently, poor labor market outcomes.[39] In the long run, this penalization may easily transform immigrant dynasties into permanently disadvantaged minorities, fostering a dangerous social stratification.

Overall, our findings have profound policy implications. They suggest that primary education should consider linguistic integration as a priority, and strive to lead children with poor linguistic backgrounds to the sufficiency threshold. This means that *marginal* interventions would hardly be effective for those who are lagging behind, and that only large-scale investments in education would be able to foster intergenerational integration.[40]

In general, we confirm that policies aimed to linguistic integration should be of the greatest importance because they yield high social returns not only in the short run (by improving the economic opportunities of the newcomers) but also in the very long run (by intergenerational spillovers). Unlike policies that take place later in life, achieving linguistic integration in the primary school can be simpler and produce permanent effects.

[39] Notice also that disadvantages tend to grow over time, due to mechanisms like the dynamic complementarity and the self-productivity of skills outlined by Cunha and Heckman (2007).

[40] The awareness of this issue is increasing in Italy: since 2012, the Ministry of Education has introduced the possibility of adopting customized study plans *(piani di studio personalizzati)* for children with limited proficiency in Italian. These plans may be adopted by the schools after a linguistic assessment of the child. They replace the most linguistically demanding subjects with easier ones, or simply reduce the educational objectives the student has to meet to pass her grade. There also exist some Math textbooks for children with limited command of Italian. However, these measures are not yet a systematic approach to the linguistic integration of the minorities.

Acknowledgements

This paper uses confidential data kindly provided by the statistical archives of 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.
We are grateful to Antonio Abatemarco, Gaetano Bloise, Alberto Bucci, Simon Burgess, Vincenzo Carrieri, Fausto Galli, Tullio Jappelli, Immacolata Marino, Jeremy McCauley, Annamaria Menichini, Tommaso Oliviero, Annalisa Scognamiglio, Hans H. Sievertsen, Francesca Toscano, Christine Valente and seminar participants at the University of Bristol and the University of Trieste. We also thank Patrizia Giannantoni for her support in providing us with the data. The usual disclaimers apply.

References

Abatemarco, Antonio, Mariagrazia Cavallo, Immacolata Marino, and Giuseppe Russo (2021). "Age Effects in Education: A Double Disadvantage for Second-Generation Immigrant Children". *GLO Discussion Paper* 761.

Aguiar, M. and E. Hurst (2007). "Measuring Trends in Leisure: The Allocation of Time Over Five Decades". *Quarterly Journal of Economics* 122, pp. 969–1006.

Almlund, Mathilde, Angela Lee Duckworth, James Heckman, and Tim Kautz (2011). "Personality psychology and economics". *Handbook of the Economics of Education. In E. Hanushek, S. Machin, and L. Woessmann (eds.)* 4, pp. 1–181.

Almond, Douglas, Janet Currie, and Valentina Duque (2018). "Childhood Circumstances and Adult Outcomes: Act II". *Journal of Economic Literature* 56.4, pp. 1360–1446.

Angrist, Joshua D., Erich Battistin, and Daniela Vuri (2017). "In a Small Moment: Class Size and Moral Hazard in the Italian Mezzogiorno". *American Economic Journal: Applied Economics* 9.4, pp. 216–49.

Aoki, Yu and Lualhati Santiago (2018). "Speak better, do better? Education and health of migrants in the UK". *Labour Economics* 52, pp. 1 –17.

Aparicio-Fenoll, Ainhoa (2018). "English proficiency and mathematics test scores of immigrant children in the US". *Economics of Education Review* 64, pp. 102–113.

Arici, Maria and Paola Maniotti (2010). "Studiare matematica e scienze in italiano L2. Unità di apprendimento per alunni stranieri della scuola primaria". *Erickson.*

Aucejo, Esteban M. and Jonathan James (forthcoming). "The Path to College Education: The Role of Math and Verbal Skills". *Journal of Political Economy.*

Austen-Smith, David and Roland G. Fryer (2005). "An Economic Analysis of Acting White". *The Quarterly Journal of Economics* 120.2, pp. 551–583.

Bacolod, Marigee and Marcos A. Rangel (2017). "Economic Assimilation and Skill Acquisition: Evidence From the Occupational Sorting of Childhood Immigrants". *Demography* 54.2, pp. 571–602.

Battu, H., McDonald M., and Zenou Y. (2007). “Oppositional Identities and the Labor Market”. *Journal of Population Economics* 20.3, pp. 643–667.

Beattie, Bruce R. and Satheesh Aradhyula (2015). “A Note on Threshold Factor Level(s) and Stone-Geary Technology”. *Journal of Agricultural and Applied Economics* 47.4, pp. 482–493.

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

Bisin, A., E. Patacchini, T. Verdier, and Y. Zenou (2011). “Formation and Persistence of Oppositional Identities”. *European Economic Review* 55.8, pp. 1046–1071.

— (2016). “Bend It Like Beckham: Ethnic Identity and Integration”. *European Economic Review* 90.C, pp. 146–164.

Bleakley, Hoyt and Aimee Chin (2004). “Language Skills and Earnings: Evidence from Childhood Immigrants”. *The Review of Economics and Statistics* 86.2, pp. 481–496.

— (2008). “What Holds Back the Second Generation?: The Intergenerational Transmission of Language Human Capital Among Immigrants”. *Journal of Human Resources* 43.2, pp. 267–298.

— (2010). “Age at Arrival, English Proficiency, and Social Assimilation Among U.S. Immigrants”. *American Economic Journal: Applied Economics* 2.1, pp. 165–192.

Brell, Courtney, Christian Dustmann, and Ian Preston (2020). “The Labor Market Integration of Refugee Migrants in High-Income Countries”. *Journal of Economic Perspectives* 34.1, pp. 94–121.

Buckles, Kasey S. and Daniel M. Hungerman (2013). “Season of Birth and Later Outcomes: Old Questions, New Answers”. *Review of Economics and Statistics* 95.3, pp. 711–724.

Chiswick, Barry R. and Paul W. Miller (2010). “Occupational language requirements and the value of English in the US labor market”. *Journal of Population Economics* 23.1, pp. 353–372.

— (2015). “International Migration and the Economics of Language”. *Handbook of the Economics of International Migration* 1.5, pp. 211–269.

Clarke, Andrew and Ingo Isphording (2017). “Language Barriers and Immigrant Health”. *Health Economics* 26.6, pp. 765–778.

Constant, Amelie, Liliya Gataullina, and Klaus Zimmermann (2009). “Ethnosizing Immigrants”. *Journal of Economic Behavior & Organization* 69.3, pp. 274–287.

Constant, Amelie F. and Klaus F. Zimmermann (2008). “Measuring Ethnic Identity and Its Impact on Economic Behavior”. *Journal of the European Economic Association* 6.2-3, pp. 424–433.

Cummins, Jim (2000). “Language, power, and pedagogy: Bilingual children in the crossfire”. Multilingual Matters LTD.

Cunha, Flavio and James J. Heckman (2007). “The Technology of Skill Formation”. *American Economic Review* 97.2, pp. 31–47.

Cunha, Flavio, James J. Heckman, and Lance Lochner (2006). “Interpreting the Evidence on Life Cycle Skill Formation”. *Handbook of the Economics of Education. In E. Hanushek, S. Machin, and L. Woessmann (eds.)* 1.12, pp. 697–812.

De Martì Beltran, J. and Y. Zenou (2017). “Segregation in Friendship Networks”. *Scandinavian Journal of Economics* 119.8, pp. 656–708.

Dillender, Marcus (2017). “English Skills and the Health Insurance Coverage of Immigrants”. *American Journal of Health Economics* 3.3, pp. 312–345.

Doepke, M. and F. Zilibotti (2019). “Love, Money, and Parenting: How Economics Explains the Way We Raise Our Kids”.

Duncan, G. and R. Murnane (2011). “Restoring Opportunity: The Crisis of Inequality and the Challenge for American Education”. *Russell Sage, NY*.

Dustmann, Christian and Francesca Fabbri (2003). “Language proficiency and labour market performance of immigrants in the UK”. *The Economic Journal* 113.July, pp. 695–717.

eLinguistics (2020). *www.elinguistics.net*.

Everett, Caleb, Damián E. Blasí, and Seán G. Roberts (2015). “Climate, vocal folds, and tonal languages: Connecting the physiological and geographic dots”. *Proceedings of the National Academy of Sciences* 112.5, pp. 1322–1327.

— (2016). “Language evolution and climate: the case of desiccation and tone”. *Journal of Language Evolution* 1.1, pp. 33–46.

Fryer Jr., R. G. and P. Torelli (2010). “An Empirical Analysis of ”Acting White””. *Journal of Public Economics* 94.5-6, pp. 380–396.

Guven, Cahit and Asadul Islam (2015). “Age at Migration, Language Proficiency, and Socioeconomic Outcomes: Evidence From Australia”. *Demography* 52, pp. 513–542.

INVALSI (2018). “Quadro di Riferimento delle Prove INVALSI di Italiano del 30.08.2018”. *INVALSI documentation*.

Isphording, Ingo and Sebastian Otten (2013). “The Costs of Babylon—Linguistic Distance in Applied Economics”. *Review of International Economics* 21.2, pp. 354–369.

Isphording, Ingo E., Marc Piopiunik, and Nuria Rodriguez-Planas (2016). “Speaking in Numbers: The Effect of Reading Performance on Math Performance among Immigrants”. *Economics Letters* 139, pp. 52–56.

ISTAT (2018). “Bilancio Demografico Nazionale”. *Statistiche. Report* July 3rd, 2019.

Jaccard, James and Robert Turrisi (2003). “Interaction Effects in Multiple Regression, (2ˆnd ed)”. *Sage University Papers Series on Quantitative Applications in the Social Sciences* Second Edition.07-072.

Jacob, Brian A and Steven D. Levitt (2003). “Rotten apples: an investigation of the prevalence and predictors of teacher cheating”. *Quarterly Journal of Economics* 118.3, pp. 843–877.

Quintano, Claudio, Rosalia Castellano, and Sergio Longobardi (2009). “A fuzzy clustering approach to improve the accuracy of Italian student data : an experimental procedure to correct the impact of outliers on assessment test scores”. *Statistica & Applicazioni. Milano : Vita e Pensiero* VII.2, pp. 149–171.

Wilkinson, Louise C (2019). “Learning language and mathematics:A perspective from Linguistics and Education”. *Linguistics and Education* 49, pp. 86–95.

Table 3: OLS

Variable	(1)	(2)	(3)	(4)
Italian	0.620***	0.618***	0.618***	0.618***
	(0.00332)	(0.00433)	(0.00419)	(0.00420)
Age	0.187***	0.197***	0.197***	0.189***
	(0.0124)	(0.0168)	(0.0166)	(0.0204)
Distance	0.00903***	0.00876***	0.00876***	0.00879***
	(0.00123)	(0.00167)	(0.00164)	(0.00163)
ESCS student	1.100***	1.068***	1.068***	1.067***
	(0.0652)	(0.0910)	(0.0907)	(0.0907)
Female	-5.363***	-5.485***	-5.485***	-5.489***
	(0.105)	(0.140)	(0.138)	(0.138)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	136,019	136,019	136,019	136,019

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 4: OLS (standardized coefficients)

Variable	(1)	(2)	(3)	(4)
Italian	0.604***	0.602***	0.602***	0.601***
	(0.00323)	(0.00421)	(0.00408)	(0.00409)
Age	0.0421***	0.0442***	0.0442***	0.0426***
	(0.00279)	(0.00378)	(0.00373)	(0.00459)
Distance	0.0207***	0.0201***	0.0201***	0.0201***
	(0.00283)	(0.00381)	(0.00375)	(0.00374)
ESCS student	0.0464***	0.0450***	0.0450***	0.0450***
	(0.00275)	(0.00384)	(0.00382)	(0.00382)
Female	-0.137***	-0.140***	-0.140***	-0.140***
	(0.00268)	(0.00358)	(0.00352)	(0.00352)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	136,019	136,019	136,019	136,019

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 5: Reduced Form

Variable	(1)	(2)	(3)	(4)
Italian	0.622***	0.620***	0.620***	0.619***
	(0.00285)	(0.00432)	(0.00432)	(0.00433)
Age	0.0319**	0.0346	0.0346	0.0143
	(0.0159)	(0.0241)	(0.0241)	(0.0274)
Distance	-0.371***	-0.385***	-0.385***	-0.392***
	(0.0310)	(0.0470)	(0.0470)	(0.0470)
Age*Distance	0.00291***	0.00302***	0.00302***	0.00308***
	(0.000239)	(0.000361)	(0.000361)	(0.000362)
ESCS student	1.098***	1.069***	1.069***	1.067***
	(0.0593)	(0.0908)	(0.0908)	(0.0908)
Female	-5.367***	-5.489***	-5.489***	-5.494***
	(0.0938)	(0.140)	(0.140)	(0.140)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	136,019	136,019	136,019	136,019

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-cohort level

Table 6: IV (First Stage)

Variable	(1)	(2)	(3)	(4)
Age*Distance	-0.00348***	-0.00314***	-0.00314***	-0.00246***
	(0.000295)	(0.000336)	(0.000331)	(0.000330)
Age	0.200***	0.188***	0.188***	-0.0506*
	(0.0198)	(0.0230)	(0.0230)	(0.0261)
Distance	0.403***	0.357***	0.357***	0.269***
	(0.0383)	(0.0437)	(0.0431)	(0.0430)
Female	3.272***	3.254***	3.254***	3.201***
	(0.106)	(0.127)	(0.127)	(0.127)
ESCS student	3.373***	3.510***	3.510***	3.476***
	(0.0755)	(0.0857)	(0.0846)	(0.0844)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Cragg-Donald Wald F statistic	196.86	142.00	142.00	86.81
Kleibergen-Paap Wald rk F statistic	139.54	87.22	89.87	55.68
Obs	129,910	106,729	106,729	106,729

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 7: IV First Stage (standardized coefficients)

Variable	(1)	(2)	(3)	(4)
Age*Distance	-1.070***	-0.962***	-0.962***	-0.755***
	(0.091)	(0.103)	(0.102)	(0.101)
Age	0.046***	0.0430***	0.0430***	-0.0116*
	(0.00456)	(0.00527)	(0.00528)	(0.00599)
Distance	0.949***	0.837***	0.837***	0.632***
	(0.090)	(0.103)	(0.101)	(0.101)
Female	0.0859***	0.0851***	0.0851***	0.0837***
	(0.00277)	(0.00332)	(0.00333)	(0.00332)
ESCS student	0.146***	0.150***	0.150***	0.149***
	(0.00326)	(0.00366)	(0.00362)	(0.00361)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Cragg-Donald Wald F statistic	196.86	142.00	142.00	86.81
Kleibergen-Paap Wald rk F statistic	139.54	87.22	89.87	55.68
Obs	129,910	106,729	106,729	106,729

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 8: IV (Second Stage)

Variable	(1)	(2)	(3)	(4)
Italian	-0.216**	-0.344***	-0.344***	-0.631***
	(0.0944)	(0.130)	(0.129)	(0.194)
Age	0.200***	0.215***	0.215***	-0.0490
	(0.0157)	(0.0191)	(0.0190)	(0.0454)
Distance	-0.0330***	-0.0417***	-0.0417***	-0.0553***
	(0.00487)	(0.00696)	(0.00693)	(0.0102)
Female	-2.625***	-2.354***	-2.354***	-1.494**
	(0.338)	(0.453)	(0.449)	(0.651)
ESCS student	3.925***	4.450***	4.450***	5.411***
	(0.329)	(0.468)	(0.463)	(0.687)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	129,910	106,729	106,729	106,729

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 9: IV Second Stage (standardized coefficients)

Variable	(1)	(2)	(3)	(4)
Italian	-0.210**	-0.335***	-0.335***	-0.614***
	(0.0918)	(0.126)	(0.125)	(0.189)
Age	0.0447***	0.0481***	0.0481***	-0.0109
	(0.00352)	(0.00427)	(0.00424)	(0.0102)
Distance	-0.0756***	-0.0954***	-0.0954***	-0.127***
	(0.0112)	(0.0159)	(0.0158)	(0.0232)
Female	-0.0670***	-0.0600***	-0.0600***	-0.0381**
	(0.00862)	(0.0115)	(0.0114)	(0.0166)
ESCS student	0.165***	0.185***	0.185***	0.225***
	(0.0138)	(0.0195)	(0.0193)	(0.0286)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	129,910	106,729	106,729	106,729

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 10: IV (First Stage) Romance

Variable	(1)	(2)	(3)	(4)
Age*Distance	-0.000534	-0.00143*	-0.00143*	-0.00148*
	(0.000653)	(0.000847)	(0.000835)	(0.000828)
Age	0.161***	0.179***	0.179***	-0.0299
	(0.0212)	(0.0267)	(0.0266)	(0.0323)
Distance	0.056	0.167	0.167	0.175
	(0.0850)	(0.110)	(0.109)	(0.108)
Female	3.329***	3.284***	3.284***	3.224***
	(0.139)	(0.180)	(0.181)	(0.181)
ESCS student	3.608***	3.705***	3.705***	3.684***
	(0.0981)	(0.124)	(0.122)	(0.122)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Cragg-Donald Wald F statistic	0.94	5.05	5.05	5.42
Kleibergen-Paap Wald rk F statistic	0.67	2.85	2.93	3.19
Obs	76,304	54,390	54,390	54,390

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 11: IV (First Stage) Romance (standardized coefficients)

Variable	(1)	(2)	(3)	(4)
Age*Distance	-0.164	-0.439*	-0.439*	-0.454*
	(0.201)	(0.260)	(0.256)	(0.254)
Age	0.0372***	0.0411***	0.0411***	-0.00687
	(0.00489)	(0.00613)	(0.00610)	(0.00742)
Distance	0.133	0.392	0.392	0.411
	(0.200)	(0.259)	(0.255)	(0.253)
Female	0.0874***	0.0859***	0.0859***	0.0843***
	(0.00366)	(0.00471)	(0.00474)	(0.00473)
ESCS student	0.156***	0.158***	0.158***	0.157***
	(0.00424)	(0.00530)	(0.00526)	(0.00522)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Cragg-Donald Wald F statistic	0.94	5.05	5.05	5.42
Kleibergen-Paap Wald rk F statistic	0.67	2.85	2.93	3.19
Obs	76,304	54,390	54,390	54,390

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 12: IV (Second Stage) Romance

Variable	(1)	(2)	(3)	(4)
Italian	-1.031	-0.263	-0.263	-0.229
	(2.257)	(0.700)	(0.691)	(0.647)
Age	0.319	0.211*	0.211*	-0.0580
	(0.346)	(0.113)	(0.111)	(0.0476)
Distance	-0.0295	-0.0243*	-0.0243*	-0.0215*
	(0.0301)	(0.0139)	(0.0137)	(0.0119)
Female	0.00887	-2.736	-2.736	-2.928
	(7.524)	(2.311)	(2.281)	(2.100)
ESCS student	7.262	4.578*	4.578*	4.426*
	(8.146)	(2.597)	(2.565)	(2.390)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	76,304	54,390	54,390	54,390

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 13: IV (Second Stage) Romance (standardized coefficients)

Variable	(1)	(2)	(3)	(4)
Italian	-1.00263	-0.256	-0.256	-0.223
	(2.195)	(0.682)	(0.673)	(0.631)
Age	0.0715	0.0471*	0.0471*	-0.0130
	(0.0776)	(0.0252)	(0.0249)	(0.0106)
Distance	-0.0675	-0.0555*	-0.0555*	-0.0492*
	(0.0689)	(0.0319)	(0.0314)	(0.0273)
Female	0.000226	-0.0697	-0.0697	-0.0746
	(0.192)	(0.0589)	(0.0581)	(0.0535)
ESCS student	0.305	0.191*	0.191*	0.184*
	(0.342)	(0.108)	(0.107)	(0.0995)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	76,304	54,390	54,390	54,390

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 14: IV (First Stage) Non Romance

Variable	(1)	(2)	(3)	(4)
Age*Distance	-0.0562***	-0.0556***	-0.0556***	-0.040***
	(0.00688)	(0.00861)	(0.00847)	(0.00842)
Age	5.385***	5.311***	5.311***	3.632***
	(0.671)	(0.842)	(0.829)	(0.828)
Distance	6.883***	6.816***	6.816***	4.834***
	(0.894)	(1.123)	(1.103)	(1.0989)
Female	3.0657***	3.118***	3.118***	3.0719***
	(0.191)	(0.264)	(0.260)	(0.259)
ESCS student	2.669***	2.750***	2.750***	2.693***
	(0.127)	(0.169)	(0.170)	(0.169)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Cragg-Donald Wald F statistic	111.81	79.43	79.43	40.99
Kleibergen-Paap Wald rk F statistic	66.74	41.75	43.19	22.96
Obs	46,022	29,984	29,984	29,984

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 15: IV (First Stage) Non Romance (standardized coefficients)

Variable	(1)	(2)	(3)	(4)
Age*Distance	-17.275***	-17.0605***	-17.0605***	-12.379***
	(2.115)	(2.640)	(2.596)	(2.584)
Age	1.241***	1.219***	1.219***	0.834***
	(0.155)	(0.193)	(0.190)	(0.190)
Distance	16.200***	15.995***	15.995***	11.345***
	(2.105)	(2.635)	(2.590)	(2.579)
Female	0.0805***	0.0816***	0.0816***	0.0804***
	(0.005008)	(0.00691)	(0.00679)	(0.00679)
ESCS student	0.115***	0.118***	0.118***	0.115***
	(0.00549)	(0.00724)	(0.00727)	(0.00724)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Cragg-Donald Wald F statistic	111.81	79.43	79.43	40.99
Kleibergen-Paap Wald rk F statistic	66.74	41.75	43.19	22.96
Obs	46,022	29,984	29,984	29,984

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 16: IV (Second Stage) Non Romance

Variable	(1)	(2)	(3)	(4)
Italian	-0.457***	-0.549***	-0.549***	-0.947***
	(0.159)	(0.210)	(0.207)	(0.358)
Age	0.166***	0.130***	0.130***	-0.190
	(0.0322)	(0.0477)	(0.0475)	(0.131)
Distance	0.240***	0.244**	0.244**	0.0810
	(0.0863)	(0.113)	(0.111)	(0.173)
Female	-1.964***	-1.658**	-1.658**	-0.481
	(0.552)	(0.749)	(0.734)	(1.181)
ESCS student	4.001***	4.218***	4.218***	5.233***
	(0.462)	(0.633)	(0.620)	(1.013)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	46,022	29,984	29,984	29,984

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 17: IV (Second Stage) Non Romance (standardized coefficients)

Variable	(1)	(2)	(3)	(4)
Italian	-0.444***	-0.535***	-0.535***	-0.923***
	(0.155)	(0.205)	(0.201)	(0.349)
Age	0.0373***	0.0292***	0.0292***	-0.0425
	(0.00721)	(0.0107)	(0.0106)	(0.0292)
Distance	0.549***	0.559**	0.559**	0.185
	(0.198)	(0.257)	(0.253)	(0.396)
Female	-0.0502***	-0.0422**	-0.0422**	-0.0122
	(0.0141)	(0.0191)	(0.0187)	(0.03010)
ESCS student	0.168***	0.176***	0.176***	0.218***
	(0.0194)	(0.0263)	(0.0258)	(0.0422)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	46,022	29,984	29,984	29,984

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 18: IV (First Stage) Below Proficiency Level 3

Variable	(1)	(2)	(3)	(4)
Age*Distance	-0.00193***	-0.00184***	-.00184***	-0.00145***
	(0.000269)	(0.000327)	(0.000324)	(0.000324)
Age	-0.00617	-0.0138	-0.0138	-0.139***
	(0.0183)	(0.0234)	(0.0234)	(0.0258)
Distance	0.225***	0.211***	0.211***	0.161***
	(0.0350)	(0.0426)	(0.0422)	(0.0421)
Female	1.455***	1.446***	1.446***	1.416***
	(0.0988)	(0.131)	(0.130)	(0.130)
ESCS student	1.389***	1.480***	1.480***	1.465***
	(0.0688)	(0.0891)	(0.0888)	(0.0888)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Cragg-Donald Wald F statistic	78.67	54.35	54.35	33.65
Kleibergen-Paap Wald rk F statistic	51.49	31.50	32.01	20.07
Obs	73,157	53,285	53,285	53,285

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 19: IV (First Stage) Below Proficiency Level 3 (standardized coefficients)

Variable	(1)	(2)	(3)	(4)
Age*Distance	-0.594***	-0.563***	-0.563***	-0.444***
	(0.0827)	(0.100)	(0.0995)	(0.0992)
Age	-0.00142	-0.00317	-0.00317	-0.0317***
	(0.00421)	(0.00537)	(0.00536)	(0.00592)
Distance	0.530***	0.495***	0.495***	0.378***
	(0.0823)	(0.0999)	(0.0991)	(0.0989)
Female	0.0382***	0.0378***	0.0378***	0.0371***
	(0.00260)	(0.00344)	(0.00340)	(0.00340)
ESCS student	0.0600***	0.0632***	0.0632***	0.0626***
	(0.00297)	(0.00381)	(0.00380)	(0.00379)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Cragg-Donald Wald F statistic	78.67	54.35	54.35	33.65
Kleibergen-Paap Wald rk F statistic	51.49	31.50	32.01	20.07
Obs	73,157	53,285	53,285	53,285

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 20: IV (Second Stage) Below Proficiency Level 3

Variable	(1)	(2)	(3)	(4)
Italian	-1.239***	-1.298***	-1.298***	-1.820***
	(0.291)	(0.377)	(0.377)	(0.579)
Age	-0.0151	-0.0134	-0.0134	-0.330**
	(0.0415)	(0.0544)	(0.0543)	(0.137)
Distance	-0.0359***	-0.0394***	-0.0394***	-0.0527***
	(0.00798)	(0.0112)	(0.0111)	(0.0165)
Female	-2.097***	-2.166***	-2.166***	-1.491*
	(0.480)	(0.618)	(0.614)	(0.888)
ESCS student	3.481***	3.759***	3.759***	4.496***
	(0.434)	(0.592)	(0.593)	(0.884)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	73,157	53,285	53,285	53,285

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 21: IV (Second Stage) Below Proficiency Level 3 (standardized coefficients)

Variable	(1)	(2)	(3)	(4)
Italian	-1.205***	-1.265***	-1.265***	-1.773***
	(0.283)	(0.367)	(0.367)	(0.564)
Age	-0.00339	-0.00299	-0.00299	-0.0738**
	(0.00931)	(0.0122)	(0.0121)	(0.0307)
Distance	-0.0822***	-0.0901***	-0.0901***	-0.120***
	(0.0183)	(0.0256)	(0.0255)	(0.0377)
Female	-0.0536***	-0.0552***	-0.0552***	-0.0380*
	(0.0123)	(0.0157)	(0.0157)	(0.0226)
ESCS student	0.146***	0.156***	0.156***	0.187***
	(0.0182)	(0.0247)	(0.0247)	(0.03680)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	73,157	53,285	53,285	53,285

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 22: IV (First Stage) Above Proficiency Level 3

Variable	(1)	(2)	(3)	(4)
Age*Distance	-.000481**	-0.000460	-0.000460	-0.000329
	(0.000232)	(0.000321)	(0.000321)	(0.000321)
Age	0.109***	0.114***	0.114***	0.0442*
	(0.0154)	(0.0211)	(0.0210)	(0.0250)
Distance	0.0524*	0.0485	0.0485	0.0317
	(0.0302)	(0.0418)	(0.0418)	(0.0419)
Female	0.753***	0.772***	0.772***	0.763***
	(0.0871)	(0.118)	(0.119)	(0.119)
ESCS student	1.0591***	1.259***	1.259***	1.254***
	(0.0552)	(0.0774)	(0.0779)	(0.0779)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Cragg-Donald Wald F statistic	5.58	3.36	3.36	1.71
Kleibergen-Paap Wald rk F statistic	4.31	2.06	2.06	1.05
Obs	48,799	30,731	30,731	30,731

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 23: IV (First Stage) Above Proficiency Level 3 (standardized coefficients)

Variable	(1)	(2)	(3)	(4)
Age*Distance	-0.148**	-0.141	-0.141	-0.101
	(0.0712)	(0.0983)	(0.0984)	(0.0985)
Age	0.0252***	0.0262***	0.0262***	0.0101*
	(0.00355)	(0.00484)	(0.00483)	(0.00573)
Distance	0.123*	0.114	0.114	0.0743
	(0.0710)	(0.0981)	(0.0982)	(0.0983)
Female	0.0198***	0.0202***	0.0202***	0.0200***
	(0.00229)	(0.00310)	(0.00311)	(0.00311)
ESCS student	0.0457***	0.0538***	0.0538***	0.0536***
	(0.00238)	(0.00331)	(0.00333)	(0.00333)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Cragg-Donald Wald F statistic	5.58	3.36	3.36	1.71
Kleibergen-Paap Wald rk F statistic	4.31	2.06	2.06	1.05
Obs	48,799	30,731	30,731	30,731

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 24: IV (Second Stage) Above Proficiency Level 3

Variable	(1)	(2)	(3)	(4)
Italian	-2.688	-3.156	-3.156	-4.836
	(1.838)	(2.895)	(2.909)	(5.617)
Age	0.443***	0.504*	0.504*	0.270
	(0.165)	(0.275)	(0.277)	(0.191)
Distance	-0.0302	-0.0421	-0.0421	-0.0598
	(0.0192)	(0.0338)	(0.0338)	(0.0633)
Female	-3.812***	-2.962	-2.962	-1.717
	(1.429)	(2.289)	(2.294)	(4.331)
ESCS student	4.748**	5.865	5.865	7.951
	(1.953)	(3.657)	(3.669)	(7.050)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	48,799	30,731	30,731	30,731

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 25: IV (Second Stage) Above Proficiency Level 3 (standardized coefficients)

Variable	(1)	(2)	(3)	(4)
Italian	-2.614	-3.0744	-3.0744	-4.711
	(1.788)	(2.821)	(2.834)	(5.472)
Age	0.0994***	0.113*	0.113*	0.0605
	(0.0370)	(0.0614)	(0.0620)	(0.0427)
Distance	-0.0692	-0.0963	-0.0963	-0.137
	(0.0439)	(0.0772)	(0.0774)	(0.145)
Female	-0.0974***	-0.0755	-0.0755	-0.0438
	(0.0365)	(0.0583)	(0.0585)	(0.110)
ESCS student	0.199**	0.244	0.244	0.331
	(0.0820)	(0.152)	(0.153)	(0.293)
Cohort FE	✓	✗	✗	✗
Class FE	✓	✗	✗	✗
Class-by-Cohort FE	✗	✓	✗	✗
School-by-Class-by-Cohort FE	✗	✗	✓	✓
Month FE	✗	✗	✗	✓
Obs	48,799	30,731	30,731	30,731

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school level (1)
Clustered Standard Errors at the school-cohort level (2)
Clustered Standard Errors at the school-class-cohort level (3) and (4)

Table 26: Discrimination

Variable	(1) **teased**	(2) **insulted**	(3) **isolated**	(4) **beaten**
Age	-0.00155	-0.00126	-0.00113	-0.000153
	(0.00127)	(0.00113)	(0.00103)	(0.000758)
Distance	0.000528***	0.000318***	0.000291***	0.000184**
	(0.000128)	(0.000113)	(0.000104)	(7.20e-05)
Female	-0.0819***	-0.0833***	-0.0375***	-0.0506***
	(0.0111)	(0.00994)	(0.00925)	(0.00621)
ESCS student	-0.00695	-0.00734	-0.00777	-0.0108***
	(0.00759)	(0.00673)	(0.00618)	(0.00412)
School-by-Class FE	✓	✓	✓	✓
Obs	20,276	20,240	20,261	20,303

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class level

Table 27: Discrimination

Variable	(1) **teased**	(2) **insulted**	(3) **isolated**	(4) **beaten**
Age	-0.000868	-0.00155	-0.00133	-0.000866
	(0.00189)	(0.00165)	(0.00146)	(0.00104)
Distance	0.00223	-0.000402	-0.000190	-0.00158
	(0.00365)	(0.00326)	(0.00293)	(0.00219)
Age*Distance	-1.30e-05	5.53e-06	3.70e-06	1.36e-05
	(2.80e-05)	(2.50e-05)	(2.25e-05)	(1.68e-05)
Female	-0.0818***	-0.0833***	-0.0375***	-0.0507***
	(0.0111)	(0.00994)	(0.00925)	(0.00621)
ESCS student	-0.00697	-0.00733	-0.00777	-0.0108***
	(0.00759)	(0.00673)	(0.00618)	(0.00412)
School-by-Class FE	✓	✓	✓	✓
Obs	20,276	20,240	20,261	20,303

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class level

Table 28: Self-segregation

Variable	**(1)**	**(2)**
Age	0.000904	0.000535
	(0.000740)	(0.00100)
Distance	0.000105	-0.000815
	(7.02e-05)	(0.00222)
Age*Distance		7.07e-06
		(1.71e-05)
Female	-0.0371***	-0.0371***
	(0.00609)	(0.00609)
ESCS student	-0.00705*	-0.00704*
	(0.00406)	(0.00406)
School-by-class FE	✓	✓
Obs	20,278	20,278

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Clustered Standard Errors at the school-class level

Table 29: Home possessions

Variable	(1) quiet place	(2) computer	(3) desk	(4) encyclopedias	(5) internet	(6) room
Age	0.00188**	0.00263***	0.000545	0.000817	0.00106	0.00252**
	(0.000777)	(0.000965)	(0.000716)	(0.00101)	(0.000692)	(0.00102)
Distance	0.00194	0.00137	0.00155	0.000988	0.00400***	-0.000417
	(0.00147)	(0.00180)	(0.00137)	(0.00188)	(0.00140)	(0.00187)
Age*Distance	-1.72e-05	-1.35e-05	-1.39e-05	-1.22e-05	-3.52e-05***	1.84e-07
	(1.13e-05)	(1.38e-05)	(1.05e-05)	(1.44e-05)	(1.07e-05)	(1.44e-05)
Female	✓	✓	✓	✓	✓	✓
School-by-class-by-cohort FE	✓	✓	✓	✓	✓	✓
Obs	105,810	105,688	106,010	105,290	105,654	105,686

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Clustered Standard Errors at the school-class-cohort level

Table 30: Home possessions (continued)

Variable	(7) books (0-10)	(8) books (11-25)	(9) books (26-100)	(10) books (101-200)	(11) books (> 200)
Age	0.000893	0.000493	-0.00113	-0.000313	5.69e-05
	(0.000813)	(0.000981)	(0.000927)	(0.000587)	(0.000409)
Distance	-0.00194	0.000493	-0.000401	0.000923	0.000922
	(0.00160)	(0.00183)	(0.00167)	(0.00103)	(0.000702)
Age*Distance	2.08e-05*	-3.23e-06	-1.31e-06	-8.63e-06	-7.67e-06
	(1.23e-05)	(1.40e-05)	(1.28e-05)	(7.91e-06)	(5.38e-06)
Female	✓	✓	✓	✓	✓
School-by-class-by-cohort FE	✓	✓	✓	✓	✓
Obs	105,767	105,767	105,767	105,767	105,767

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class-cohort level

Table 31: Father Education

Variable	(1) ISCED-1	(2) ISCED-2	(3) ISCED-3	(4) ISCED-4	(5) ISCED-5	(6) ISCED-6
Age	0.000228	0.00123	0.000283	-0.000362	0.000122	-0.00150***
	(0.000532)	(0.00101)	(0.000695)	(0.000992)	(0.000410)	(0.000568)
Distance	-0.00149	-0.00327*	-0.000361	0.00326*	0.000749	0.00112
	(0.00110)	(0.00192)	(0.00121)	(0.00175)	(0.000730)	(0.00102)
Age*Distance	1.43e-05*	3.16e-05**	3.95e-07	-3.08e-05**	-6.00e-06	-9.45e-06
	(8.43e-06)	(1.47e-05)	(9.27e-06)	(1.34e-05)	(5.60e-06)	(7.82e-06)
Female	✓	✓	✓	✓	✓	✓
School-by-class-by-cohort FE	✓	✓	✓	✓	✓	✓
Obs	110,318	110,318	110,318	110,318	110,318	110,318

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class-cohort level

Table 32: Father Occupation

Variable	(1) HISEI-1	(2) HISEI-2	(3) HISEI-3	(4) HISEI-4	(5) HISEI-5
Age	0.000737	5.86e-05	4.95e-05	-0.000272	-0.000183
	(0.000543)	(0.000182)	(0.000126)	(0.000258)	(0.000357)
Distance	0.00144	-5.15e-05	0.000132	-0.000528	-0.000140
	(0.000988)	(0.000328)	(0.000225)	(0.000482)	(0.000630)
Age*Distance	-1.02e-05	4.03e-07	-9.97e-07	4.16e-06	4.05e-07
	(7.58e-06)	(2.52e-06)	(1.73e-06)	(3.69e-06)	(4.83e-06)
Female	✓	✓	✓	✓	✓
School-by-class-by-cohort FE	✓	✓	✓	✓	✓
Obs	125,897	125,897	125,897	125,897	125,897

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class-cohort level

Table 33: Father Occupation (continued)

Variable	(1) HISEI-6	(2) HISEI-7	(3) HISEI-8	(4) HISEI-9	(5) HISEI-10
Age	8.75e-05	-0.000832**	-0.000759	1.42e-05	0.00110**
	(0.000672)	(0.000324)	(0.000897)	(0.000145)	(0.000462)
Distance	-0.00289**	-0.000886	0.00360**	3.10e-05	-0.000706
	(0.00131)	(0.000575)	(0.00166)	(0.000258)	(0.000840)
Age*Distance	2.50e-05**	5.95e-06	-3.03e-05**	-2.41e-07	5.81e-06
	(1.01e-05)	(4.39e-06)	(1.28e-05)	(1.98e-06)	(6.46e-06)
Female	✓	✓	✓	✓	✓
School-by-class-by-cohort FE	✓	✓	✓	✓	✓
Obs	125,897	125,897	125,897	125,897	125,897

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class-cohort level

Table 34: Mother Education

Variable	(1) ISCED-1	(2) ISCED-2	(3) ISCED-3	(4) ISCED-4	(5) ISCED-5	(6) ISCED-6
Age	0.000741	0.00177*	-0.000218	-0.00189*	-6.87e-05	-0.000338
	(0.000538)	(0.000995)	(0.000606)	(0.000967)	(0.000411)	(0.000630)
Distance	-0.00128	-0.00262	-0.000745	0.000840	0.000904	0.00290***
	(0.00112)	(0.00190)	(0.00105)	(0.00173)	(0.000735)	(0.00111)
Age*Distance	1.32e-05	2.64e-05*	3.96e-06	-1.27e-05	-7.31e-06	-2.36e-05***
	(8.63e-06)	(1.46e-05)	(8.08e-06)	(1.32e-05)	(5.63e-06)	(8.47e-06)
Female	✓	✓	✓	✓	✓	✓
School-by-class-by-cohort FE	✓	✓	✓	✓	✓	✓
Obs	111,413	111,413	111,413	111,413	111,413	111,413

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class-cohort level

Table 35: Mother Occupation

Variable	(1) HISEI-1	(2) HISEI-2	(3) HISEI-3	(4) HISEI-4	(5) HISEI-5
Age	0.000386	-3.96e-05	-4.39e-06	3.28e-06	0.000227
	(0.000495)	(0.000885)	(7.10e-05)	(0.000146)	(0.000293)
Distance	0.000763	0.00757***	2.98e-05	-0.000309	0.000282
	(0.000875)	(0.00161)	(0.000139)	(0.000307)	(0.000500)
Age*Distance	-6.53e-06	-5.25e-05***	-2.36e-07	2.47e-06	-2.87e-06
	(6.71e-06)	(1.24e-05)	(1.07e-06)	(2.36e-06)	(3.84e-06)
Female	✓	✓	✓	✓	✓
School-by-class-by-cohort FE	✓	✓	✓	✓	✓
Obs	126,953	126,953	126,953	126,953	126,953

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class-cohort level

Table 36: Mother Occupation (continued)

Variable	(1) HISEI-6	(2) HISEI-7	(3) HISEI-8	(4) HISEI-9	(5) HISEI-10
Age	-0.000365	-0.000491	-0.000144	-2.72e-05	0.000455
	(0.000383)	(0.000344)	(0.000791)	(7.65e-05)	(0.000403)
Distance	-0.00507***	-0.000723	-0.00134	-0.000158	-0.00104
	(0.000871)	(0.000563)	(0.00143)	(0.000141)	(0.000747)
Age*Distance	4.13e-05***	4.13e-06	4.62e-06	1.21e-06	8.39e-06
	(6.71e-06)	(4.32e-06)	(1.10e-05)	(1.08e-06)	(5.74e-06)
Female	✓	✓	✓	✓	✓
School-by-class-by-cohort FE	✓	✓	✓	✓	✓
Obs	126,953	126,953	126,953	126,953	126,953

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class-cohort level

Table 37: Teachers' attitude

Variable	**(1)**	**(2)**	**(3)**
Age	0.00123	-6.74e-05	0.000499
	(0.00128)	(0.00149)	(0.00158)
Distance	-0.000276**	-0.000265*	-8.59e-05
	(0.000130)	(0.000146)	(0.000156)
Female	0.0341***	0.0113	0.0225*
	(0.0110)	(0.0126)	(0.0135)
ESCS student	0.00865	0.0138*	0.0145
	(0.00743)	(0.00837)	(0.00882)
Constant	0.669***	0.754***	0.603***
	(0.167)	(0.195)	(0.206)
School-by-class FE	✓	✓	✓
Obs	20,152	20,122	20,146

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class level

Table 38: Teachers' attitude

Variable	**(1)**	**(2)**	**(3)**
Age	0.00258	0.00237	0.00280
	(0.00184)	(0.00220)	(0.00236)
Distance	0.00308	0.00581	0.00565
	(0.00373)	(0.00420)	(0.00449)
Age*Distance	-2.58e-05	-4.67e-05	-4.41e-05
	(2.86e-05)	(3.23e-05)	(3.45e-05)
Female	0.0341***	0.0114	0.0226*
	(0.0110)	(0.0126)	(0.0135)
ESCS student	0.00862	0.0137	0.0144
	(0.00743)	(0.00837)	(0.00882)
Constant	0.494**	0.436	0.303
	(0.240)	(0.287)	(0.308)
School-by-class FE	✓	✓	✓
Obs	20,152	20,122	20,146

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class level

Table 39: Preferences for Math

Variable	**(1)**
Italian	-0.00186***
	(0.000478)
Math	0.00548***
	(0.000418)
Age	-0.00302
	(0.00214)
Distance	-0.00453
	(0.00389)
Age*Distance	3.68e-05
	(2.99e-05)
Female	-0.0386***
	(0.0117)
ESCS student	0.00124
	(0.00796)
Obs	20,341
School-by-Class FE	✓

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class level

Table 40: Preferences for Math

Variable	**(1)**
Like Italian	0.0835***
	(0.0150)
Female	-0.0679***
	(0.0119)
ESCS student	0.0149*
	(0.00792)
Obs	20,237
School-by-Class FE	✓

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class level

Table 41: Socio-emotional skills

Variable	(1) worried	(2) nervous	(3) wrong	(4) calm
Age	-0.00186**	0.00109*	-0.00168**	0.00109
	(0.000783)	(0.000660)	(0.000820)	(0.000804)
Distance	0.000169**	0.000435***	0.000391***	-0.000330***
	(8.00e-05)	(6.63e-05)	(8.28e-05)	(8.24e-05)
Female	0.127***	0.0202***	0.0635***	-0.117***
	(0.00683)	(0.00556)	(0.00697)	(0.00699)
ESCS student	-0.0274***	-0.0348***	-0.0453***	0.0407***
	(0.00455)	(0.00367)	(0.00468)	(0.00471)
School-by-class-by-cohort FE	✓	✓	✓	✓
Obs	74,074	74,027	73,821	73,771

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class-cohort level

Table 42: Socio-emotional skills

Variable	(1) worried	(2) nervous	(3) wrong	(4) calm
Age	-0.00179	-0.000290	-0.000897	0.00244*
	(0.00119)	(0.000983)	(0.00125)	(0.00125)
Distance	0.000354	-0.00293	0.00230	0.00297
	(0.00224)	(0.00190)	(0.00230)	(0.00229)
Age*Distance	-1.42e-06	2.58e-05*	-1.46e-05	-2.53e-05
	(1.72e-05)	(1.46e-05)	(1.76e-05)	(1.76e-05)
Female	0.127***	0.0202***	0.0635***	-0.117***
	(0.00683)	(0.00556)	(0.00697)	(0.00699)
ESCS student	-0.0274***	-0.0347***	-0.0453***	0.0406***
	(0.00455)	(0.00367)	(0.00468)	(0.00471)
School-by-class-by-cohort FE	✓	✓	✓	✓
Obs	74,074	74,027	73,821	73,771

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class-cohort level

Table 43: Posticipation of enrollment

Variable	**(1)**
Distance	0.000357***
	(2.63e-05)
ESCS student	-0.0112***
	(0.00144)
Female	-0.00832***
	(0.00214)
Obs	136,019
School-by-Class-by-Cohort FE	✓

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Clustered Standard Errors at the school-class-cohort level