Immigrant-gender gaps in education in Italy. An empirical investigation based on PISA data.

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Abstract. Gender and migratory background are widely accepted in the economics of education literature as factors highly correlated with educational outcomes. However, little attention has been devoted so far to the interaction of these two dimensions. We use Italian data from PISA 2015 to investigate potential immigrant-gender gaps in school assessment (differences in scores between immigrants and natives and between girls and boys). In line with previous work, we find that girls outperform boys in reading and are outperformed by them in math and science, and that immigrant students' test scores are persistently below those of natives. Interestingly, however, immigrant girls are less at a disadvantage in math and science relative to immigrant boys, than native girls are with respect to native boys. Moreover, the immigrant girls' advantage in reading relatively to immigrant boys is wider than that of native girls with respect to native boys. Overall, we find the stronger disadvantage is that of immigrant boys in reading-related fields. Language spoken at home is one of the main factors affecting this result, while family background strongly influences immigrant girls' performances. Targeted policies should therefore be implemented.

Introduction

The existence of persistent gender and immigrant gaps in schooling (differences in scores between girls and boys and between immigrants and natives) across countries and time clearly emerges from several waves of the Program for International Student Assessment (PISA) and other surveys on students' performances. PISA data (OECD, 2016a), which investigate fifteen year old performances in reading, mathematics and science, show that – except for a few countries – fifteen-year-old girls perform below boys in mathematics and above them in reading. Relative performances in science are more heterogeneous. In addition, the scores of immigrant students tend to be below those of natives in the three areas. Less known and explored are the joint effects of gender and immigrant status on schooling performances. However, these stylized facts do suggest some questions. One is whether being female and immigrant leads to stronger disadvantages in mathematics than those corresponding to each of the two characteristics taken separately. Similarly, another is whether being male and immigrant widens the gap in reading. This paper attempts to measure immigrant-gender gaps in mathematics, reading and science, specifically focusing on the case of Italy. To this end, we estimate an educational production function using data from the 2015 PISA survey.

Several waves of PISA data from Italy show that the country is characterized by persistently negative gaps of girls in math and in science, and positive ones in reading. The negative girls' gaps are slightly wider than the OECD average, while their advantage in reading is narrower. Moreover, the performance of immigrant students is below average in all areas (OECD, 2016a).

The economic and sociological literature has thoroughly documented the importance of education, especially regarding workers' human capital formation and access to the labour market (among others: Heckman and Mosso, 2014). Moreover, the capability approach highlights the central role of schooling in enabling capabilities to develop (Addabbo, Di Tommaso, Maccagnan, 2016; Terzi, 2007). In general, there is a positive and robust correlation between wages in the labour market and workers' education, especially with their mathematical knowledge (Machin and Puhani, 2003). Few empirical studies focus on the possibly interactive nature of gender and immigration background, and most do so with respect to labour market outcomes (see, among others, Zaiceva, 2010).

Many cross-country studies in education confirm the importance of gender and immigrant status on schooling performance (OECD, 2015a, 2015b; Azzolini, Schnell and Palmer, 2012). They show that the relative disadvantage of immigrant students tends to be related to families' economic and social resources and to the country's school system

(Murat and Frederic, 2015; OECD, 2015b), while the negative girls' gap in mathematics is also correlated with social norms and gender inequalities within countries (Guiso *et al.*, 2008, Nollenberger *et al.*, 2016). Rodríguez-Planas and Nollenberger (2018) extend the analysis to science and reading.

Also in Italy family background plays a key role among the determinants of educational achievements (Bratti, Checchi and Filippin, 2007; Giambona, Porcu, 2015). Further, Italy is generally characterized by a high degree of regional heterogeneity in students' educational achievements, with better performances in the Northern regions of the country, matched with regional disparities in the quality of the school system (Agasisti and Vittadini, 2012; Quintano, Castellano and Longobardi, 2012; INVALSI, 2017). The school attended affects results because the Italian school system is characterized by early tracking (at the age of 14) between general (lyceums) and vocational schools, and because of differences in curricula between schools of the same type. Students enrolled in general education tend to perform better than those enrolled in vocational schools (INVALSI, 2017).

Immigrant students tend to attend vocational rather than general schools, and are more concentrated in the Northern and richer regions of the country. In turn, girls tend to attend schools with fewer hours of math and science. Bratti, Checchi and Filippin (2007) find that the socioeconomic conditions of students' households affect the choice of school, but other factors also matter for the higher propensity shown by immigrant students to attend vocational schools (Barban and White, 2011).

To test the effects on test performance of gender, immigrant status, and the interaction between the two, we use an educational production function that includes several inputs. Among them are students' demographic characteristics, the socioeconomic conditions of their families, the language spoken at home, the types of schools attended, the regions of residence and, for immigrant students, the age of arrival.

As expected, we find that girls perform better than boys in reading and worst in math and science, while immigrant students perform persistently below natives. More interestingly, the interaction between the immigrant and gender dimensions reveals that negative gender gaps are more severe within native population rather than among immigrant students and positive gaps are wider among immigrant students. More specifically, immigrant girls are less at a disadvantage with respect to immigrant boys in math and science and more advantaged in reading than what could be anticipated by the separate performances of the two categories. Overall, the widest disadvantage is that of male immigrant students in reading. Other results are that immigrant and gender gaps are strongly affected by the school attended, the age of immigrants' arrival in Italy, family economic and social conditions ad language spoken at home. The remainder of the paper is as follows. The next section reviews the survey data used and present some descriptive statistics; then the empirical strategy and the results are presented and, finally, the last section concludes.

Data and descriptive statistics

Data

To test our hypothesis, we use the 2015 wave of PISA assessment, focusing on the sample of Italian schools and using information from both the Student Questionnaires and the individual test scores. The full sample includes 11,583 students enrolled in over 450 schools, representative of the Italian population of 15 years old students. The Italian PISA dataset (as for most of the other participating countries) is the result of a two-stage stratified design, where, first, individual schools are sampled, and secondly, students are sampled within sampled schools. All throughout the paper we make use of the final student weights, which allow us to scale the sample up to the size of the Italian population and take into account the oversampling of specific Italian regions (Lombardy and Campania) and provinces (Trento and Bolzano). The number of students in the nationally defined target population that our analytical sample represents is 480,600, covering over 95% of the desired national population.

Several variables present a number of observations inferior to the full sample, as a small percentage of students did not provide all the necessary information asked by the Background Questionnaire. Because of our specific interest in assessment gaps by gender and immigrant status, we restricted the sample to those students that can be classified according to our immigrant variables. Moreover, we excluded from the analysis individuals with missing information on the set of other relevant covariates, such as ESCS and grade repetition. Hence, our final sample consists of 11,205 observations, where about 3% of the initial full sample was dropped.[1] The weighted means and standard deviations of the scores and the variables used in the analysis are in Table A1 in the Appendix. The Table shows that girls constitute about 51% of the sample employed in our study, while the proportion of immigrants is about 8% (and immigrant girls are about half of the immigrant population).

Given that each participating student in PISA survey answers a limited amount of questions taken from the total test item pool, OECD provides ten test scores (known as plausible values), which can be interpreted as multiple imputed values of students' performance based on students' answers to the test and their background questionnaires. The difficulty of each item represents a weight, used to compute the weighted averages of correct responses. This approach

[1] Our tests show that dropping observations with missing information causes a slight upward bias in test scores. However, such a small percentage of dropped observations should not significantly affect results, even if the selection on missing variables may not have happened at random.

allows having a measure of an individual’s proficiency for each student in each subject area, regardless of the questions actually answered. We employ the recommended OECD strategy for estimation of coefficients and their variances, making use of all ten plausible values all throughout the main analysis.

Descriptive statistics

Italian PISA data provide an interesting base for analysing potential immigrant-gender gaps in education, first for their representativeness of the Italian student population, and secondly because marked and significant gender and immigrant imbalances in Italy have been registered over different cross-sections of the survey. According to PISA 2015, Italian girls on average do better than boys in reading-related skills by 16 points and worse than boys in science and math by about 17 and 20 points respectively. The latter is one of the largest gender gaps across PISA-participating countries.

Regarding inequalities by immigrant status, the interest of Italy resides on the rapid growth of its immigrant population, which has determined a doubling of the share of immigrant students on the total students’ population (OECD, 2016b). This crucially enhances the role of the educational system in easing the integration process (Barban and White, 2011). Immigrants in Italy tend to perform persistently below natives in all fields, but – differently from the gender gap – this disadvantage has narrowed along the last decade. (OECD, 2016b).

[Table 1 about here]

In math there is a significant and wide gender gap in favour of boys and a a similar gender gap at the disadvantage of girls in the field of Science, without appreciable improvements in the last decade. Girls perform better than boys in reading, but their advantage is lower than that of the OECD average. There is also a significant gap linked to the origin of the students (scores of immigrant children minus those of natives), negative for immigrant students, both first and second generation. Figures 1 (a) - (d) in the Appendix illustrate these gaps. Figure A1 (a) shows a shift of the Math test scores distribution to the right, in favour of boys, and the opposite for the scores of reading test scores. The differences appear more marked if we focus on the dimension of the student's immigrant status. Distributions in Figure 1(b) in fact show a disadvantage for immigrant students especially in readings with wider gender gaps than for natives ones (Figures 1, c-d).

The descriptive statistics by gender and immigrant status show the immigrants' disadvantage in the test scores of all subjects, with a larger gap for boys in reading (Table 1) (mean values in test scores for the whole student population, in Table A1 in the Appendix, confirm the higher average girls' achievement in reading and higher boys' achievement in mathematics and science). The occurrence of repeated grade is higher for immigrants, with immigrant boys registering the highest share (38%), followed by immigrant girls (23.8%), native boys (17%) and native girls (10%). Turning to the language spoken at home, a language different from Italian is spoken more frequently in immigrant students' households, with percentages of about 62% for immigrant boys and 55% of immigrant girls, 15% for native boys and 10% for native girls. Table 1 also shows a higher presence of immigrant students in Lombardy than in Campania, which is in line with the overall higher presence of immigrants in the Northern and central part of the country.

Empirical strategy

We seek to test gender and immigrant gaps in PISA test scores for the three main subject areas – mathematics, reading and science – by using the following base specification:

$$\mathrm{T_{ij}} = \alpha + \beta_1 \mathrm{Female_{ij}} + \beta_2 \mathrm{Immig_{ij}} + \beta_3 (\mathrm{Female} * \mathrm{Immig})\mathrm{ij} + \gamma \mathrm{Xij} + \delta \mathrm{Sj} + \varepsilon \mathrm{ij} \qquad (1)$$

where $\mathrm{T_{ij}}$ is the test score of student i within school *j*, standardized for each subject to have a mean of zero and a variance equal to one. At the individual level, besides gender, immigration status and the interaction between the two, we include information about age, grade repetition, an index of socio-economic status of the students' family, *ESCS*, and a set of dummies concerning the (immigrant's) age of arrival into the country. A dummy takes value 1 if the main language spoken at home is not Italian and zero otherwise. OLS specifications include geographical variables for some regions and provinces (those for which data are available in PISA 2015), and a dummy for the school type attended, which, following PISA 2015, can only be vocational or general. In FE specifications, we include $\mathrm{S_j}$, a full set of school dummies. ε_{ij} is the individual error term, estimated with a Huber-White adjustment to take the clustering of students within schools into account.

The coefficients of interest are β_1, β_2 and β_3, related to the gender, immigration and immigration-gender variables. Ideally, we would like to observe the country of origin of immigrant students, but this information is not available from Italian PISA data. Hence, our variable is a dummy taking value one for students who were either born abroad or had both parents of foreign origin, and zero otherwise. In this classification, native students have at least one parent of Italian origin. We estimate equation (1) separately for each PISA subject. In each estimation process, we use students' sampling weights, replicate weights and the ten plausible values of students' scores present in 2015 data. The school fixed effect specification is our preferred one, as it allows taking into account the great heterogeneity of the Italian schooling situation across regions, school types and curricula. Relatively to the OLS specification, it shows whether school effects influence coefficients on gender, origin, their interaction, socio-economic background and other cofactors.

In a second part of the analysis, we test marginal effects in the full specification of equation (1). They show the scores of students of each type – natives, immigrants, girls and boys – as deviations from the means, and hence the gaps in performance within groups. Secondly, we test the specification of equation (1) on the two separate female and male subsamples. This allows to measure how immigrant students perform relatively to peers of the same gender and to analyse the incidence of cofactors within each group. Subsequently, we use the Oaxaca-Blinder decomposition (Oaxaca, 1973; Blinder, 1973) to disentangle the part of gender gaps that can be explained by differences in observed variables from the part that remains unexplained.

$$\Delta\overline{\mathrm{T}} = (\alpha_{\mathrm{M}} - \alpha_{\mathrm{M}}) + (\beta_{\mathrm{M}} - \beta_{\mathrm{F}})\,\overline{\mathrm{X_F}} + \beta_{\mathrm{M}}(\overline{\mathrm{X_M}} - \overline{\mathrm{X_F}}) \quad (2)$$

where $\beta_{\mathrm{M}}(\overline{\mathrm{X_M}} - \overline{\mathrm{X_F}})$ concerns the observed part, regarding students' characteristics and other household's and school related variables, and $(\alpha_{\mathrm{M}} - \alpha_{\mathrm{M}}) + (\beta_{\mathrm{M}} - \beta_{\mathrm{F}})\,\overline{\mathrm{X_F}}$ relates to differences in the returns of each variable included in the model, or to unobserved variables affecting reading, mathematics and science scores.

Results

Base specification

Tables 2, 3 and 4 show the OLS regression coefficients in columns 1 and 8 and school FE regression coefficients in columns 2 to 7 and 9. Results evidence some main patterns. First, as expected, coefficients on our first variable of interest, *Female*, are positive and significant in reading and negative and significant in math and science. Second, coefficients on the *Immigrant* variable are always negative, in all specifications for the three subjects. Third, the coefficient on the interacted variable, *Female*Immigrant*, is always positive, although significance is below 10%. Hence, immigrant girls perform better than what could be anticipated, given the double characteristics of being immigrant and female (the latter for math and science). More specifically, negative gender gaps in math and science are smaller within the immigrant group than within natives, and the positive gender gap in reading is wider among immigrants, as emerge even more clearly in the marginal effects reported in Table 5. In general, we observe from Table 5 that the biggest disadvantage is experienced not by immigrant girls in math and science, as expected, but by immigrant boys in reading. Male students with an immigration background experience a disadvantage which is almost equal to 2/3 of a school year in reading (-0.20, column 5, Table 5). Following Woessmann (2016), across PISA-OECD countries, a school year corresponds to about 0.33 standard deviations.

Another result worth nothing relates to the gender gap among immigrant and native populations. Table 5 shows that the score differential between girls and boys is more favourable to girls within the immigrant group than within natives, across all subject areas. More specifically, the female advantage in reading is larger among immigrant students (0.15, in column 6, Table 5, versus 0.09 among natives), and the girls' disadvantage in math and science is more severe among Italian students (-0.23 and -0.22, and -0.15 and 0.13, respectively among immigrant students). Hence, immigrants are disadvantaged at school, but immigrant girls perform above expectations in all subjects.

These results may depend on several factors. Some we cannot test because of lack of data. Among these are culture, gender norms, institutions and school systems of the countries of origin, all of which can influence the school performance of immigrant girls and boys in the country of residence (Nollemberger *et al.*, 2016). The motivation to exert effort in certain subjects and the interest in succeeding at school can also differ among immigrants and natives and among boys and girls. However, our data allows the analysis of other important cofactors, which are considered in the following Tables.

[Table 2 about here]

[Table 3 about here]

[Table 4 about here]

[Table 5 about here]

A result common to the three fields is that immigrant gaps significantly shrink when school effects are included into the regressions. This emerges from comparing columns 1 and 2 in the three Tables, and concerns especially math and science. Column 2, by including school fixed effects, controls for school types and different curricula in schools of the same type. As immigrant students are relatively more present in technical and vocational schools, which exhibit on average lower performances than general schools, within schools the immigrant disadvantage is smaller than across them.

Coefficients associated to the immigrant status shrink further when the age at arrival in Italy is considered: we observe a particularly negative effect for students who arrived in the country after the school starting age, i.e. 6 years. The age effect is especially strong in reading and science-related skills and lower and less significant in math.

Other cofactors tend to be correlated with the immigrant score gap; among them, *Language at home*, *Repeated grade* and *ESCS*. This is not surprising when we consider that the proportion of immigrant students not speaking Italian at home and repeating a grade is substantially higher than that of natives, and that their socioeconomic condition is generally below average (Table A1). Coefficients on *Language at home* and *Repeated grade* are negative, wide in magnitude and significant at the 1% level in the three subjects (columns 5 Tables 2-4). In particular, repeating a school year leads to lower scores by about 0.45 standard deviations in reading, 0.53 in mathematics and 0.42 in science. Another factor strongly affecting results is the economic and social status at home, *ESCS*.

Column 8 (OLS) includes these variables, the attendance of general rather than vocational schools, and fixed effects for the provinces of Trento and Bolzano, and the regions of Lombardy and Campania. Specifically, the average school performance of students in Lombardy, Bolzano and Trento, located in the Northern part of the country, are strongly and significantly above average in all fields, while that of students in Campania, in the South of Italy, is significantly below. Moreover, attending a general rather than a vocational school increases reading and science scores by about 0.6 standard deviations, and the score in mathematics by 0.46 (significance at 1% in the three cases). Hence, attending a general rather than a vocational school implies an advantage in mathematics corresponding to more than a school year (Woessmann, 2016). With these controls, coefficients on Immigrant in the three fields – reading, math and science – lose their significance.

Compared to columns 8, the introduction of school FE in the full models of columns 9 tends to increase the magnitude of coefficients on *Immigrants* and, in the case of reading and science, also their significance. Hence, when all cofactors are controlled for, there is still a significant within-schools disadvantage of immigrant students in reading and science. At least partially, this can be related to the geographic distribution of immigrant students across the country. The immigrant student population is proportionally higher in the productive provinces and regions of the North-Centre of Italy, where school outcomes and native students' socioeconomic characteristics are above average. Beyond Lombardy, Trento, and Bolzano, which are high performing regions, regions such as Emilia-Romagna, Veneto, Piedmont and Tuscany (not separately identifiable in PISA 2015), also register above average scores, together with a substantial presence of immigrant students and a more favourable students' ESCS on average. Hence, once school fixed effects and all the included regressors 'absorb' this provincial and regional distribution, immigrant students of rich and high performing regions score below natives within schools (column 9), but across schools they have a good performance relatively to students in the Southern and poorer regions. In the country as a whole, this is captured by the smaller and less significant OLS coefficients of columns 8.

Specifically, the within-school immigrant gap in reading is wide and significant at the 5% level (column 9, Table 2); it is narrower in science, but still significant, at the 10% level (column 9, Table 4); and it is still negative in mathematics, but not significant (column 9, Table 3). This suggests that factors such as immigration background and culture may slow down the learning of the language, literature and history of the host country – and in a lesser degree of science –, but have a lower influence on math, which is comparatively more 'culture-free'. Similar results can be found in Murat (2012).

Another result worth noting is that the introduction of school fixed effects significantly affects also girls' scores relatively to boys' in the three subjects, but especially in math. Coefficients on *Female* shrink from column 8 to column 9 in all three subjects. The differences between the two coefficients are statistically significant at the 1% level in math and science, and at the 10% in reading. These differences can be explained by the relatively higher presence of girls in general schools, comprising curricula with fewer hours of math and science. Moreover, once schools and all cofactors are considered, the girls' disadvantages in mathematics and science more than compensate their advantage in reading (columns 9, Tables 2-4).

Female and male immigrant gaps

This Section tests the immigrant gap in reading, math and science on the two separate subsamples of female and male students. In Table 6, we use the complete OLS and FE models (corresponding to columns 8 and 9). Coefficients on the *Immigrant* variable report the difference in scores between native and immigrant students of the same gender.

[Table 6 about here]

The first general and interesting result is that immigrant girls do not experience a significant disadvantage with respect to native girls in any of the three subjects, both across (OLS) and within schools (FE), since the coefficients on *Immigrant* are not significant in the even columns (*Female*) of Table 6. On the other hand, immigrant boys register negative gaps with respect to native boys in the three subjects, wider and more significant when school effects are included into the regressions (*Male* columns). As above, wider gaps within schools can be related to the geographical distribution of immigrant students in the country and their self-selection in lower performing schools on average. Specifically, once school effects are considered, immigrant boys score below native boys by about 22 standard deviations in reading, by 16 in mathematics and by 24 in science (columns 3, 7 and 11 of Table 6). A comparison of immigrant gaps in the female and male subpopulations shows that the difference across the two groups is significant for math and science. The two coefficients on the *Immigrant* variable statistically differ at the 15% level for mathematics and at the 10% level for science. Hence, the school performance of immigrant girls in math and science is not very different to that of native girls, differently than that of immigrant boys, who exhibit a considerable disadvantage relative to native boys. In reading, where in the overall population girls outperform boys, immigrant boys experience a further disadvantage, as their scores are significantly below those of native boys (column 3, Table 6). On the other hand, the immigrant girls' performance in reading is not significantly below that of native girls.

The incidence of cofactors affecting girls and boys performances partially differs. Among these, the language spoken at home has a significantly stronger impact on the proficiency levels of boys. Moreover, the difference in coefficients on *Language at home* across the female and male samples is statistically significant in reading and math at the 10% level in the OLS regressions (columns 1-2 and 5-6), and in science at the 1% level (columns 9-10).

In all subjects and specifications, the economic and social condition of the student's family, *ESCS*, significantly affects results. However, it has a stronger impact on girls' performances. Differences in coefficients on *ESCS* between boys and girls (between columns 1 and 2; 5 and 6; 9 and 10; Table 6) are significant at the 5% level in the three subjects. They shrink for both girls and boys once schools attended are included into the regressions. This selection effect of schools, based on economic and social conditions at home, supports previous results (Agasisti and Vittadini, 2012; Bratti, Checchi and Filippin, 2007). We have estimated a Probit model that consistently shows a positive impact of a higher socioeconomic status on the probability of attending the general track (results available upon request). Once all cofactors have been considered, being girl increases the probability of attending a general – rather than vocational – school by 26 percentage points. The immigrant status does not significantly affect the probability of attending a general school, but talking at home a language different than Italian reduces by 12% the probability of attending general schools. Figure 2 in the Appendix shows estimated coefficients with regards to test scores of each group of students including schools fixed effects. As the results show the gender gap in Math and Sciences at the disadvantage of girls holds for both native and immigrant but the latter show a higher disadvantage with respect to native boys in Science.

Explaining the gender gap in test scores: Oaxaca-Blinder Decomposition

In this section we use the Oaxaca-Blinder (OB) decomposition of the differentials in reading, math, and science between the two subpopulations of boys and girls and, subsequently, of natives and immigrants. This implies decomposing the gap between the two groups into a part due to differences in the mean values of the independent variables within the groups, on the one hand, and group differences in the effects of the independents variables, on the other hand (O'Donnell *et al*. 2008; Jann, 2008).

The decomposition by gender is based on the FE models of Table 6 (columns 3-4; 7-8; 11-12) and is presented in Table 7. The predicted means in test scores in the different disciplines confirm the findings of a girls' disadvantage in mathematics and in science and a boys' disadvantage in reading: the gender net gap in education – controlling for all cofactors – is positive for girls in reading (0.17) and negative in mathematics (-0.23) and science (-0.21).

[Table 7 about here]

OB allows to decompose the gender gap in one part related to differences in the magnitude of the observed characteristics affecting test scores of girls and boys (explained part) and another part related to the difference in the effects of the factors and to unobserved variables (unexplained part). The part attributable to differences in the measured means of the observed characteristics for girls and boys in the three fields shows a better performance for girls. Overall, the Oaxaca-Blinder decomposition shows that the largest part of the gender gap in the educational achievements can be attributed to the differences by gender in the effects of the factors included in the model (-0.26 in mathematics, -0.23 in sciences and +0.15 in reading), but we cannot exclude that it can also be related to unobservable factors not included in our specification.

Table A2 in the Appendix uses the complete FE specification to replicate the above regressions on the two subsamples of natives and immigrants. Results confirm previous findings: both immigrant boys and girls have lower predicted average mean test scores in math, science and reading but immigrant girls do not perform significantly worse than immigrant boys in math and science. Moreover, interestingly, not only immigrant girls perform above immigrant boys in reading, but also their advantage is wider than that of native girls relatively to native boys. Gaps in reading are at the advantage of girls, respectively, 0.28 for immigrant girls and 0.17 for native girls.

[Table 8 about here]

The OB (Table 8) decomposition of the net test scores gap by gender between natives and immigrants confirms for each group a higher unexplained part of the differential related to the effects of the factors rather than to the difference in the magnitudes of the characteristics included in the model. An interesting result concerns the higher impact of observed differences in the characteristics at the advantage of girls, for immigrant, excluding reading where the unexplained part of the gap is higher amongst immigrant than natives. In *Science*, the contribution of the observed characteristics at the advantage of girls to the differential compensates the unexplained part of the differential for immigrant more than for natives, leading, on the whole, to a lower differential in scores.

Conclusions

Several waves of PISA and other surveys have shown that cross-country and through time girls tend to perform below boys in mathematics and above them in reading. In Italy, girls perform below average in math and science. At the same time, immigrants tend to have lower scores than natives. These stylized facts suggest that immigrant girls may experience a bigger disadvantage in education (at least in the areas of mathematics and science) or, more generally, that gender and immigration background may interact in affecting test scores.

Testing PISA 2015 data from Italy we found that, differently from what expected, immigrant girls are not disadvantaged relatively to immigrant boys in math and science, while significantly outperform them in reading. At the same time, immigrant boys appear to perform worse as compared to their native peers in the three fields, a disadvantage that we do not observe for immigrant female as compared to native girls. More specifically, across all specifications, immigrant boys struggle the most in reading. Within schools, and considering all cofactors, the immigrant boys' negative gap in reading corresponds to about two thirds of a school year. We also find significant heterogeneous effects across the gender dimension, with several factors affecting the performances of girls and boys differently. A language different from Italian being spoken at home has a stronger (negative) impact on boys, while the family's economic and social conditions especially influence the school performance of girls. For both immigrant groups, the age of arrival into the country plays a crucial role. Arriving after the age of compulsory schooling has a negative impact on scores: this affects performance especially in reading-related fields. Immigrants attend vocational school relatively more than native students, and immigrant boys do so more than immigrant girls. This partly explains the difference in scores between natives and immigrant, being narrower for girls as compared to guys. However, also within schools, the immigrant girls' gap is smaller and less significant than initially expected.

Considering the important role played by reading as a base to develop other skills and for the whole cognition and thinking process (Kern *et al.*, 2008), results on immigrant boys are interesting starting points to think about targeted integration policies. More generally, policy measures should especially address the economic and social conditions of boys and girls immigrants' families and the language spoken at home. The social integration and language education of parents would strongly improve the performance of immigrant students.

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Figure 1 (a-d) Standardized test scores distribution (average=0) in Reading, Math and Sciences by gender and immigrant status.

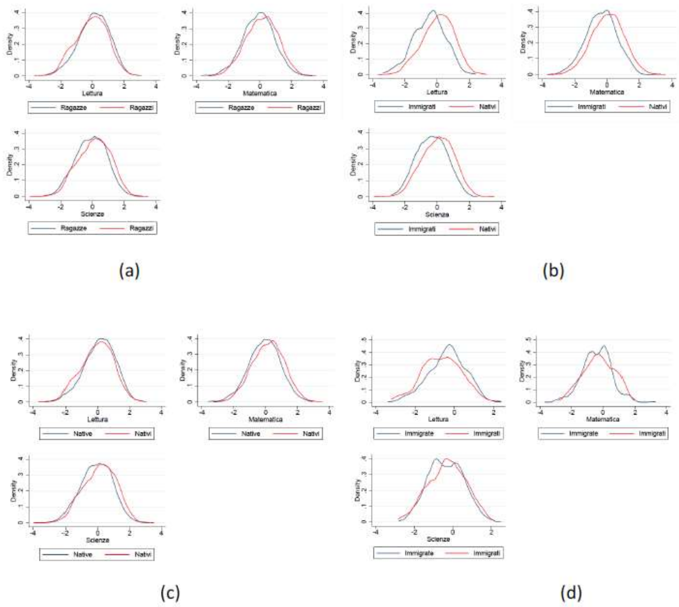

Figure 2 Estimated Coefficients on the Test Scores in Reading, Math and Sciences
by gender and immigrant status

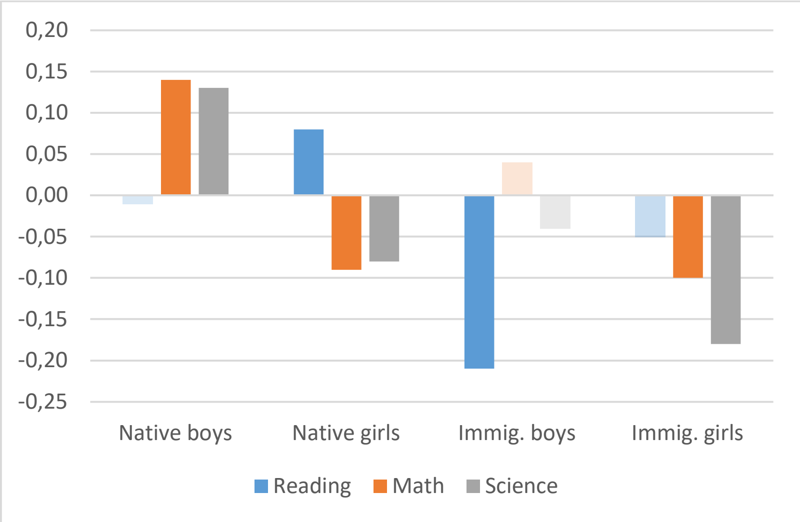

Table 1. Descriptive statistics by gender and by immigrant status

	Male		Female	
	Native	Immigrant	Native	Immigrant
Variable	(N=5,128)	(N=428)	(N=5,186)	(N=463)
Test score: read	483.16	427.276	497.846	454.196
	(3.559)	(7.617)	(3.697)	(6.755)
Test score: math	505.859	463.094	483.293	455.712
	(3.608)	(8.261)	(3.513)	(6.674)
Test score: science	494.266	456.025	475.512	449.225
	(3.224)	(6.462)	(3.646)	(6.165)
ESCS	0.30	-0.395	-0.087	-0.576
	(0.024)	(0.062)	(0.028)	(0.056)
Repeated grade	0.169	0.380	0.103	0.238
	(0.008)	(0.035)	(0.008)	(0.024)

Age	15.8	15.80	15.81	15.85
	(0.006)	(0.023)	(0.007)	(0.020)
Language at home	0.154	0.621	0.099	0.554
	(0.010)	(0.032)	(0.007)	(0.038)
School type: General	0.397	0.275	0.627	0.462
	(0.017)	(0.039)	(0.018)	(0.036)
Bolzano	0.010	0.012	0.011	0.009
	(0.000)	(0.001)	(0.000)	(0.001)
Trento	0.010	0.013	0.010	0.013
	(0.000)	(0.002)	(0.000)	(0.001)
Lombardy	0.153	0.247	0.152	0.208
	(0.010)	(0.032)	(0.011)	(0.036)
Campania	0.119	0.017	0.111	0.027
	(0.008)	(0.006)	(0.007)	(0.007)

Notes. The full sample of interest is employed. Immigrant students are both “II generation”, born in Italy from two parents born abroad and “I generation”, born outside the country. The mean of the test scores has been computed using all 10 plausible values. All results are weighted.

Table 2: Reading Scores (OLS and FE)

VARIABLES	(1) OLS	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE	(8) OLS	(9) FE
Female	0.169***	0.071**	0.072**	0.095***	0.049	0.070**	0.064**	-0.009	0.065*
	(0.050)	(0.035)	(0.034)	(0.035)	(0.034)	(0.035)	(0.034)	(0.047)	(0. 034)
Immigrant	-0.597***	-0.479***	-0.335***	-0.444***	-0.422***	-0.481***	-0.410***	-0.081	-0.188**
	(0.075)	(0.068)	(0.084)	(0.070)	(0.068)	(0.069)	(0.071)	(0.097)	(0.085)
Imm*Female	0.129	0.118	0.115	0.125	0.092	0.14	0.116	0.105	0.089
	(0.102)	(0.094)	(0.090)	(0.093)	(0.094)	(0.094)	(0.094)	(0.1110)	(0.087)
Arrival age 0-3			-0.165					-0.210	0.168
			(0.150)					(0.169)	(0.156)
Arrival age 4-6			-0.020					0.021	0.016
			(0.133)					(0.146)	(0.128)
Arrival age 7-9			-0.294*					-0.527**	-0.333*
			(0.176)					(0.239)	(0.184)
Arrival age 10-12			-0.429***					-0.508***	-0.450***
			(0.156)					(0.162)	(0.151)
Arrival age 13-15			-0.658***					-0.914***	-0.717***
			(0.197)					(0.198)	(0.207)
ESCS				0.099***				0.179***	0.086***
				(0.016)				(0.020)	(0.016)
Repeated grade					-0.447***			-0.597***	-0.446***
					(0.049)			(0.054)	(0.049)

Age						0.096**		0.074	0.103**
						(0.041)		(0.050)	(0.041)
Language at home							-0.148***	-0.174***	-0.113***
							(0.043)	(0.052)	(0.041)
School type: General								0.581***	
								(0.049)	
Bolzano								0.383***	
								(0.943)	
Trento								0.349***	
								(0.039)	
Lombardy								0.289***	
								(0.047)	
Campania								-0.293***	
								(0.063)	
Constant	-0.034	0. 717	0.731	0.717	0.739	-0.805	0.723	-1.309	-0.879
	(0.036)	(2.312)	(2.152)	(2.276)	(1.969)	(2.514)	(2.27)	(0.800)	(1.962)
School fixed effects	NO	YES	YES	YES	YES	YES	YES	NO	YES
Observations	11,205	11,205	11,205	11,205	11,205	11,205	11,205	11,205	11,205

Notes: Robust standard errors, clustered at the school level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1 All plausible values employed. All results are weighted and replication weights are taken into account.

Table 3: Math Scores (OLS and FE)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLE	OLS	FE	FE	FE	FE	FE	FE	OLS	FE

Female	-0.241***	-0.224***	-0.224***	-0.207***	-0.250***	-0.225***	-0.229***	-0.387***	-0.239***
	(0.046)	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)	(0.043)	(0.030)
Immigrant	-0.457***	-0.319***	-0.262***	-0.290***	-0.249***	-0.319***	-0.267***	-0.047	-0.118
	(0.082)	(0.071)	(0.089)	(0.071)	(0.066)	(0.071)	(0.072)	(0.104)	(0.086)
Imm*Female	0.162	0.122	0.125	0.125	0.090	0.116	0.119	0.126	0.093
	(0.108)	(0.095)	(0.091)	(0.094)	(0.092)	(0.094)	(0.094)	(0.102)	(0.086)
Arrival age 0-3			-0.050					-0.105	0.062***
			(0.165)					(0.204)	(0.018)
Arrival age 4-6			0.120					0.208	-0.072
			(0.166)					(0.181)	(0.175)
Arrival age 7-9			-0.075					-0.391*	-0.128
			(0.151)					(0.204)	(0.152)
Arrival age 10-12			-0.445***					-0.505***	-0.491***
			(0.167)					(0.165)	(0.156)
Arrival age 13-15			-0.188					-0.440**	-0.271
			(0.181)					(0.207)	(0.198)
ESCS				0.076***				0.166***	0.062***
				(0.019)				(0.022)	(0.018)
Repeated grade					-0.526***			-0.706***	-0.525***
					(0.048)			(0.050)	(0.048)
Age						0.108**		0.100*	0.116***
						(0.043)		(0.052)	(0.042)
Language at home							-0.107***	-0.143***	-0.084**
							(0.036)	(0.042)	(0.034)
School type: General								0.460***	

								(0.054)	
Bolzano								0.456***	
								(0.079)	
Trento								0.321***	
								(0.040)	
Lombardy								0.240***	
								(0.064)	
Campania								-0.355***	
								(0.058)	
Constant	0.172***	0.425	0.424	0.408	0.433	-1.299	0.412	-1.461*	-1.375
	(0.037)	(1.959)	(1.949)	(2.069)	(1.631)	(2.836)	(2.070)	(0.829)	(2.435)
School fixed effects	NO	YES	YES	YES	YES	YES	YES	NO	YES
Observations	11,205	11,205	11,205	11,205	11,205	11,205	11,205	11,205	11,205

Notes: Robust standard errors, clustered at the school level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1 All plausible values employed. All results are weighted and replication weights are taken into account

Table 4: Science Scores (OLS and FE)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	OLS	FE	FE	FE	FE	FE	FE	OLS	FE
Female	-0.205***	-0.208***	-0.207***	-0.192***	-0.229***	-0.209***	-0.212***	-0.359***	-0.220***
	(0.052)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0. 049)	(0.028)
Immigrant	-0.418***	-0.296***	-0.255***	-0.273***	-0.241***	-0.296***	-0.243***	0.041	-0.130*
	(0.068)	(0.067)	(0.077)	(0.067)	(0.065)	(0.067)	(0.067)	(0. 093)	(0.077)

Imm*Female	0.131	0.096	0.087	0.101	0.069	0.089	0.092	0.097	0.061
	(0.106)	(0.088)	(0.082)	(0.088)	(0.087)	(0.088)	(0.087)	(0.094)	(0.079)
Arrival age 0-3			-0.003					-0.078	-0.013
			(0.159)					(0.197)	(0.180)
Arrival age 4-6			0.224					-0.272*	0.246
			(0.143)					(0.152)	(0.137)
Arrival age 7-9			-0.146					-0.426**	-0.183
			(0.122)					(0.179)	(0.126)
Arrival age 10-12			-0.282*					-0.304**	-0.311**
			(0.145)					(0.147)	(0.145)
Arrival age 13-15			-0.478**					-0.711***	-0.535**
			(0.208)					(0.205)	(0.221)
ESCS				0.066***				0.162***	0.055***
				(0.014)				(0.019)	(0.014)
Repeated grade					-0.417***			-0.602***	-0.418***
					(0.042)			(0.048)	(0.042)
Age						0.118***		0.092*	0.121***
						(0.043)		(0.053)	(0.042)
Language at home							-0.111***	-0.154***	-0.090***
							(0.032)	(0.042)	(0.032)
School type: General								0.518***	
								(0.048)	
Bolzano								0.558***	
								(0.044)	
Trento								0.381***	
								(0.037)	

Lombardy								0.297***	
								(0.051)	
Campania								-0.297***	
								(0.057)	
Constant	0.150***	0.939	0.938	0.939	0.9451***	-0.938	0.930	-1.397*	-0.946
	(0.035)	(2.589)	(2.611)	(2.570)	(2.399)	(2.922)	(2.711)	(0.828)	(2.463)
School fixed effects	NO	YES	YES	YES	YES	YES	YES	NO	YES
Observations	11,205	11,205	11,205	11,205	11,205	11,205	11,205	11,205	11,205

Notes: Robust standard errors, clustered at the school level, in parentheses *** p<0.01, ** p<0.05, * p<0.1 All plausible values employed. All results are weighted and replication weights are taken into account.

Table 5: Marginal effects of gender and immigrant status (School FE)

	(1)	(2)	(3)	(4)	(5)	(6)
	Native girls	Native boys	Gender gap, Natives	Immig. girls	Immig. boys	Gender gap, Immigrants
Reading	0.08***	-0.01	0.09**	-0.05	-0.20***	0.15**
	(0.013)	(0.014)		(0.052)	-0.058	
Math	-0.09***	0.14***	-0.23**	-0.07	0.08*	-0.15**
	(0,015)	(0.015)		(0.054)	(0.054)	
Science	-0.09***	0.13***	-0.22**	-0.09*	0.04	-0.13
	(0.013)	(0.012)		(0.06)	(0.054)	
Cofactors	YES	YES	YES	YES	YES	YES
Observations	11,205	11,205		11,205	11,205	

Notes: Robust standard errors, clustered at the school level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1, +p<0.15. First plausible value employed. All results are weighted and replication weights are taken into account.

Table 6: Scores by gender (OLS and FE)

	Reading						Math						Science					
Variable	Male OLS	Female OLS	Diff	Male FE	Female FE	Diff	Male OLS	Female OLS	Diff	Male FE	Female FE	Diff	Male OLS	Female OLS	Diff	Male FE	Female FE	Diff
	(1)	(2)		(3)	(4)		(5)	(6)		(7)	(8)		(9)	(10)		(11)	(12)	
Immigrant	-0.100	-0.018		-0.225**	-0.105		-0.001	0.025		-0.164*	0.018	+	-0.105	0.051		-0.241**	-0.050	*
	(0.121)	(0.071)		(0.106)	(0.066)		(0.125)	(0.087)		(0.088)	(0.056)		(0.116)	(0.079)		(0.100)	*(0.057)*	
Repeated grade	-0.583***	-0.635***		-0.410***	-0.479***		-0.656***	-0.737***		-0.458***	-0.583***	+	-0.570***	-0.628***		-0.364***	-0.452***	
	(0.063)	(0.048)		(0.056)	(0.060)		(0.050)	(0.054)		(0.064)	(0.070)		(0.064)	(0.050)		(0.068)	(0.067)	
Language at home	-0.213***	-0.087	*	-0.102**	-0.101**		-0.184***	-0.068	*	-0.079***	-0.051		-0.246***	-0.072	***	-0.113***	-0.075**	
	(0.057)	(0.059)		(0.051)	(0.050)		(0.040)	(0.056)		(0.029)	(0.043)		(0.044)	(0.055)		(0.036)	(0.037)	
Years 0-3	-0.126	-0.244		-0.016	-0.230		-0.191	-0.032		-0.017	-0.081		0.075	-0.118		0.132	-0.021	
	(0.242)	(0.191)		(0.237)	(0.170)		(0.296)	(0.169)		(0.304)	(0.143)		(0.334)	(0.156)		(0.293)	(0.178)	
Years 4-6	-0.119	-0.069		-0.060	-0.040		0.219	0.095		0.268**	0.067		0.449**	0.205		0.443***	0.180	
	(0.208)	(0.121)		(0.157)	(0.143)		(0.195)	(0.171)		(0.127)	(0.144)		(0.223)	(0.178)		(0.148)	(0.191)	

Years 7-9	-0.388	-0.584**		-0.286	-0.296*		-0.445	-0.230		-0.112	0.033	-0.258	-0.521***		-0.059	-0.255**
	(0.274)	(0.234)		(0.182)	(0.174)		(0.268)	(0.215)		(0.171)	(0.218)	(0.230)	(0.175)		(0.147)	(0.101)
Years 10-12	-0.502***	-0.492***		-0.387***	-0.366***		-0.631***	-0.642***		-0.470**	-0.713***	-0.339**	-0.278*		-0.274**	-0.286**
	(0.174)	(0.157)		(0.143)	(0.122)		(0.214)	(0.164)		(0.178)	(0.163)	(0.159)	(0.165)		(0.119)	(0.140)
Years 13-15	-1.004***	-0.761***		-0.762***	-0.426*		-0.687**	-0.198		-0.438**	-0.168	-0.932**	-0.627***		-0.739**	-0.448**
	(0.350)	(0.171)		(0.268)	(0.233)		(0.303)	(0.251)		(0.213)	(0.186)	(0.381)	(0.176)		(0.338)	(0.186)
ESCS	0.155***	0.223***	**	0.083***	0.123***	+	0.122***	0.190***	**	0.037*	0.073***	0.134***	0.199***	**	0.051***	0.075***
	(0.020)	(0.027)		(0.021)	(0.015)		(0.021)	(0.026)		(0.019)	(0.020)	(0.019)	(0.028)		(0.017)	(0.020)
Age	0.118*	0.016		0.163***	0.065		0.142**	0.054		0.159***	0.118**	0.101	0.061		0.140***	0.104**
	(0.062)	(0.060)		(0.050)	(0.045)		(0.066)	(0.059)		(0.044)	(0.053)	(0.068)	(0.067)		(0.040)	(0.045)
School type: General	0.590***	0.542***					0.505***	0.424***				0.504***	0.490***			
	(0.058)	(0.072)					(0.059)	(0.071)				(0.060)	(0.081)			
Bolzano	0.484***	0.306***	**				0.449***	0.331***				0.607***	0.498***			
	(0.055)	(0.057)					(0.046)	(0.053)				(0.053)	(0.057)			
Trento	0.390***	0.285***					0.315***	0.296***				0.415***	0.338***			

	(0.053)	(0.044)			(0.048)	(0.046)			(0.052)	(0.051)		
Lombardy	0.299***	0.281***			0.273***	0.220***			0.281***	0.278***		
	(0.062)	(0.065)			(0.068)	(0.082)			(0.064)	(0.072)		
Campania	-0.255***	-0.284***			-0.352***	-0.377***			-0.369***	-0.377***		
	(0.064)	(0.069)			(0.057)	(0.068)			(0.066)	(0.070)		
Constant	-2.019**	-0.364	-3.935***	-0.716	-2.150**	-1.082	-3.022***	-1.652*	-1.512	-1.248	-2.433***	-0.844
	(0.998)	(0.948)	(0.798)	(0.771)	(1.042)	(0.936)	(0.692)	(0.976)	(1.078)	(1.058)	(0.625)	(0.724)
School FE	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Observations	5,556	5,649	5,556	5,649	5,556	5,649	5,556	5,649	5,556	5,649	5,556	5,649

Notes: Robust standard errors, clustered at the school level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1, +p<0.15. Diff. provides the statistical significance of the difference between the coefficients in the model by gender. First plausible value employed. All results are weighted and replication weights are taken into account.

Table 7: Oaxaca-Blinder decomposition by gender (School FE)

	Math		Science		Reading	
VARIABLES	Diff	Decomp.	Diff	Decomp.	Diff	Decomp.
Male	0.134***		0.122***		-0.0662*	
	(0.0330)		(0.0332)		(0.0363)	
Female	-0.0917***		-0.0843**		0.105***	
	(0.0336)		(0.0379)		(0.0350)	
Difference (F-M)	-0.225***		-0.206***		0.171***	
	(0.0411)		(0.0466)		(0.0442)	
Explained		0.0330**		0.0274*		0.0221
		(0.0146)		(0.0142)		(0.0160)
Unexplained		-0.258***		-0.233***		0.149***
		(0.0372)		(0.0436)		(0.0397)
Observations	11,205	11,205	11,205	11,205	11,205	11,205

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 First plausible value employed. All results are weighted and replication weights are taken into account. Errors are robust and clustered at the school level.

Table 8: Oaxaca-Blinder decomposition by origin (School FE).

	Natives						Immigrants					
	Math		Science		Reading		Math		Science		Reading	
VARIABLES	Diff	Decomp.	Diff	Decomp	Diff	Decomp	Diff	Decomp	Diff	Decomp	Diff	Decomp
Male	0.167***		0.155***		-0.0205		0.284***		0.298***		-0.638***	
	(0.0335)		(0.0339)		(0.0367)		(0.0724)		(0.0648)		(0.0723)	
Female	-0.0641*		-0.0595		0.148***		-0.390***		-0.352***		-0.359***	
	(0.0345)		(0.0395)		(0.0358)		(0.0666)		(0.0556)		(0.0515)	
Difference(F-M)	-0.231***		-0.215***		0.169***		-0.106		-0.0544		0.279***	
	(0.0424)		(0.0492)		(0.0454)		(0.0883)		(0.0882)		(0.0830)	
Explained		0.0350**		0.0266*		0.0243		0.0679		0.0976**		0.0754
		(0.0142)		(0.0142)		(0.0153)		(0.0475)		(0.0459)		(0.0509)
Unexplained		-0.266***		-0.241***		0.144***		-0.174**		-0.152**		0.204**

		(0.0380)		(0.0456)		(0.0404)		(0.0778)		(0.0745)		(0.0780)
Observations	10,314	10,314	10,314	10,314	10,314	10,314	891	891	891	891	891	891

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 First plausible value employed. All results are weighted and replication weights are taken into account. Errors are robust and clustered at the school level.

Appendix

Table A1: Descriptive statistics

Variable	Obs	Mean	SD	Min	Max
Test score: reading	11,205	486.704	2.667	145.12	775.586
Test score: math	11,205	491.6585	2.893	140.802	822.637
Test score: science	11,205	482.2236	2.505	120.419	803.295
Female	11,205	0.508	0.015	0	1
Immigrant	11,205	0.079	0.005	0	1
Female*Imm	11,205	0.04	0.003	0	1
ESCS	11,205	-0.066	0.018	-4.4318	4.0683
Grade repeated	11,205	0.149	0.006	0	1
Age	11,205	15.807	.005	15.25	16.33
Language at home	11,205	0.163	0.163	0	1
Arrival age 0-3	11,205	0.011	0.002	0	1
Arrival age 4-6	11,205	0.013	0.002	0	1
Arrival age 7-9	11,205	0.009	.002	0	1
Arrival age 10-12	11,205	0.010	0.001	0	1
Arrival age 13-15	11,205	0.005	0.000	0	1
School type: General	11,205	0.502	0.012	0	1
Bolzano	11,205	0.010	0.000	0	1
Trento	11,205	0.010	0.000	0	1
Lombardy	11,205	0.158	0.006	0	1
Campania	11,205	0.108	0.004	0	1

Table A2: Test scores by origin and gender (School FE)

	Natives						Immigrants					
	Reading		Math		Science		Reading		Math		Science	
VARIABLES	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Repeated grade	-0.669***	-0.728***	-0.729***	-0.862***	-0.632***	-0.727***	-0.391**	-0.705***	-0.480***	-0.488***	-0.450**	-0.579***
	(0.0682)	(0.0632)	(0.0494)	(0.0645)	(0.0669)	(0.0651)	(0.149)	(0.126)	(0.142)	(0.114)	(0.173)	(0.121)
Language at home	-0.287***	-0.168**	-0.271***	-0.125*	-0.326***	-0.127*	-0.265*	-0.0315	-0.109	-0.0239	-0.188	-0.0270
	(0.0600)	(0.0706)	(0.0404)	(0.0657)	(0.0442)	(0.0645)	(0.157)	(0.107)	(0.148)	(0.106)	(0.167)	(0.0983)
ESCS	0.285***	0.329***	0.235***	0.276***	0.254***	0.299***	0.0780	0.211***	0.0718	0.178**	0.0148	0.175**
	(0.0236)	(0.0266)	(0.0223)	(0.0250)	(0.0226)	(0.0256)	(0.0861)	(0.0648)	(0.0780)	(0.0712)	(0.0731)	(0.0807)
Age	0.158**	0.0792	0.191***	0.0799	0.141**	0.0912	0.218	-0.360**	0.0447	0.0542	0.115	0.0415
	(0.0628)	(0.0684)	(0.0645)	(0.0670)	(0.0681)	(0.0722)	(0.269)	(0.152)	(0.313)	(0.176)	(0.264)	(0.178)

Arrival age 0-3							-0.114	-0.233	-0.204	0.0243	0.0243	-0.0755
							(0.233)	(0.211)	(0.258)	(0.170)	(0.315)	(0.177)
Arrival age 4-6							-0.189	-0.141	0.145	0.0240	0.349	0.115
							(0.215)	(0.116)	(0.181)	(0.182)	(0.231)	(0.172)
Arrival age 7-9							-0.199	-0.650***	-0.336	-0.325*	-0.137	-0.603***
							(0.278)	(0.224)	(0.254)	(0.193)	(0.236)	(0.184)
Arrival age 10-12							-0.519***	-0.559***	-0.672***	-0.661***	-0.402**	-0.329**
							(0.183)	(0.154)	(0.222)	(0.163)	(0.181)	(0.152)
Arrival age 13-15							-0.941***	-0.698***	-0.723***	-0.131	-0.935**	-0.557***
							(0.317)	(0.184)	(0.263)	(0.261)	(0.366)	(0.185)
Constant	-2.369**	-0.984	-2.694**	-1.203	-1.929*	-1.388	-3.543	5.888**	-0.535	-0.903	-1.752	-0.640
	(1.000)	(1.075)	(1.021)	(1.052)	(1.076)	(1.134)	(4.197)	(2.410)	(4.860)	(2.773)	(4.141)	(2.785)
School FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,128	5,186	5,128	5,186	5,128	5,186	428	463	428	463	428	463

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, +p<0.15. First plausible value employed. All results are weighted and replication weights are taken into account. Errors are robust and clustered at the school level.