Immigrant Students' Performance in Maths:

Does it Matter Where One is From?

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Abstract

Using PISA 2012, which measures the cognitive achievement of 15 year olds, we address two questions. First, we ask whether immigrant students have a lower performance in Maths than their non-immigrant school mates. Second, we ask whether first (second) generation students coming from (whose parents come from) countries with higher performance in Maths fare better than their immigrant peers coming from lower ranked countries. Our sample is composed by around 13,000 immigrant students whose average immigrant-native score gap in Maths amounts to around -12 score points. For each immigrant student, we know the country of origin, and for the origin countries assessed by PISA, we know the corresponding national average score in Maths. Controlling for a wide set of variables, we estimate the relationship between the immigrant-native score gap in the school attended by the immigrant student and the national average score in Maths of the immigrant's country of origin. Our multiple imputation estimates show that students coming from higher ranked origin countries have a significantly lower score gap in absolute terms, thus being relatively less disadvantaged. This result is robust across different specifications. For example, coming from a country in the top quintile in Maths and having attended school there for at least one year, improves the absolute score gap by nearly 33 score points, the highest coefficients among the variables that reduce the disadvantage such as parental education and socio-economic condition.

Keywords: Students' mathematical skills, Immigrant-native score gaps, Immigrants' origin countries, multiple imputation, PISA 2012

JEL: I21, I25, J15, J24

1. Introduction

Integration of immigrant students is becoming a central concern in many countries. It is widely recognized that the chances of social and economic integration would be increased if immigrants' children were guaranteed equal opportunities of education. Research on students' school achievements provides evidence of a widespread performance gap between immigrant and native students that varies considerably across countries. Immigrant students underperformance may be due to a multiplicity of factors, such as socio economic differences (Ammermueller 2007, Rangvid 2007), linguistic barriers (Akresh and Akresh, 2011), ethnicity and its transmission to children through parental influence (Gang and Zimmermann, 2000), age at arrival in the country of immigration (van Ours Veenman, 2006; Böhlmark, 2008), educational institutions (Schneeweis, 2011), excessive concentration in schools (Cortes, 2006) and educational tracking (Lüdemann and Schwerdt, 2013).

At the same time, the scholars' interest on students' performance in Maths has been always growing. The focus on Maths is motivated by the belief that mathematical skills are crucial for individuals' employment, productivity and earnings (Hanushek and Kimko, 2000), as well as for social mobility (Martins and Veiga, 2005). On the contrary, the estimated effect of students' performance in Math on economic growth is an open debate, especially if the so-called Asian Tigers are –or are not- considered in the cross-country analysis (e.g. Hanushek and Kimko, 2000; Ramirez et al. 2006). As far as score gaps are concerned, beside the generalized evidence of gender score gaps in Maths in favour of males, the emphasis is now on assessing the relative importance of biological and cultural explanation (Guiso et al. 2008; Reilly, 2012; Stoet and Geary, 2013; Weber et al. 2014).

While the literature on immigrant students' achievements has predominantly concentrated on language performance gaps, in this paper our focus is on Maths and on the role played by performance in Maths of the origin countries. Our research hypothesis is that language barriers to learning Maths may be lower than to learning how to read and write in a different language. As a consequence, Maths would be a more portable skill than others, and the disadvantage of immigrant students with respect to natives reduced, especially when the former come from countries that are highly ranked in Maths. In other words, immigrant students may take advantage of a performance in Maths of their origin countries which is higher, or equivalent, to that of the countries of destination. This advantage may come indirectly, from their family influence, if they are second generation immigrants. For first generation immigrants, the advantage may come directly from schooling in the country of origin, if students started to go to school there, and also indirectly from their family influence, if they started to go to school in the country of immigration because students' age at arrival was lower than schooling age. Parental influence would always be there, and may increase immigrant students' advantage if parents come from highly performing countries in Maths.

Using PISA 2012, we first measure immigrant students' performance gap in Maths with respect to their native classmates, and then investigate whether the disadvantage is reduced when they come from highly ranked countries in Math performance. Two pieces of evidence are relevant for this research. The first one, is the well-documented fact that immigrant students experience severe difficulties in subjects that are, too a large extent, indissolubly linked to language skills. As emerging from both PISA 2000 and PISA 2009 surveys, in some countries the estimated disadvantage in reading skills of immigrants is of about one year of school less (around 40 score points) than natives (OECD, 2012). In the entire 2012 PISA sample, the immigrant-native score gap in Math is on average -6.26 score points, while in reading it amounts to -9.68 score points.[1] This descriptive evidence supports the supposition that mathematical skills are indeed more portable than language skills.

The second relevant piece of evidence is that the average performance in Maths of some countries of origin of the emigration is better than that of some countries of destination of

[1] Our calculation on PISA 2012 using the OECD definition of first and second generation immigration.

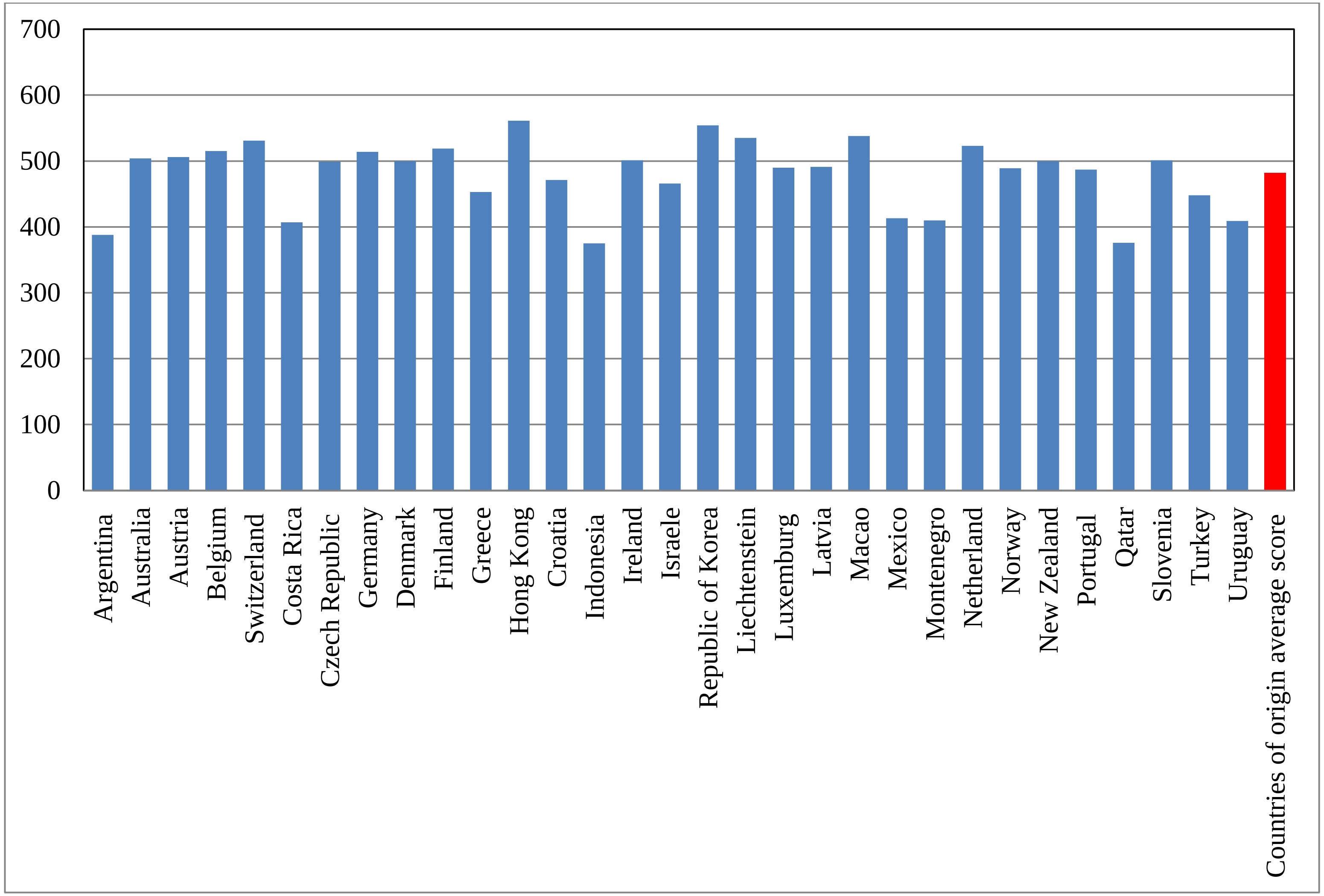
immigrants. Graph 1 shows the average scores in Math by country of destination (the blue bars) compared with the overall average Math score of the countries of origin of immigrant students (the red bar). The overall average of the Math scores of the countries of destination is 482, slightly higher than 480 , which is the overall average Math score of the countries of origin. Symmetrically, Graph 2 shows the average scores in Math by country of origin (the blue bars), while the last bar illustrates the overall average Math score of the countries of destination of immigrant students.[2]

Our multiple imputation estimates show that performance in Maths of the countries of origin contributes to reduce both first and second generation students immigrant-native score gap in absolute value, particularly of students that come from highly ranked countries. This result holds true controlling for students' characteristics, household socio economic condition, language spoken at home, years spent in education in the origin countries, schools fixed effects and level of economic development of the origin country.

The structure of the paper is the following. Section 2 overviews the background literature. Sections 3 presents the empirical strategy. Section 4 describes the data, the sample and the variables. Section 5 presents the results and Section 6 concludes.

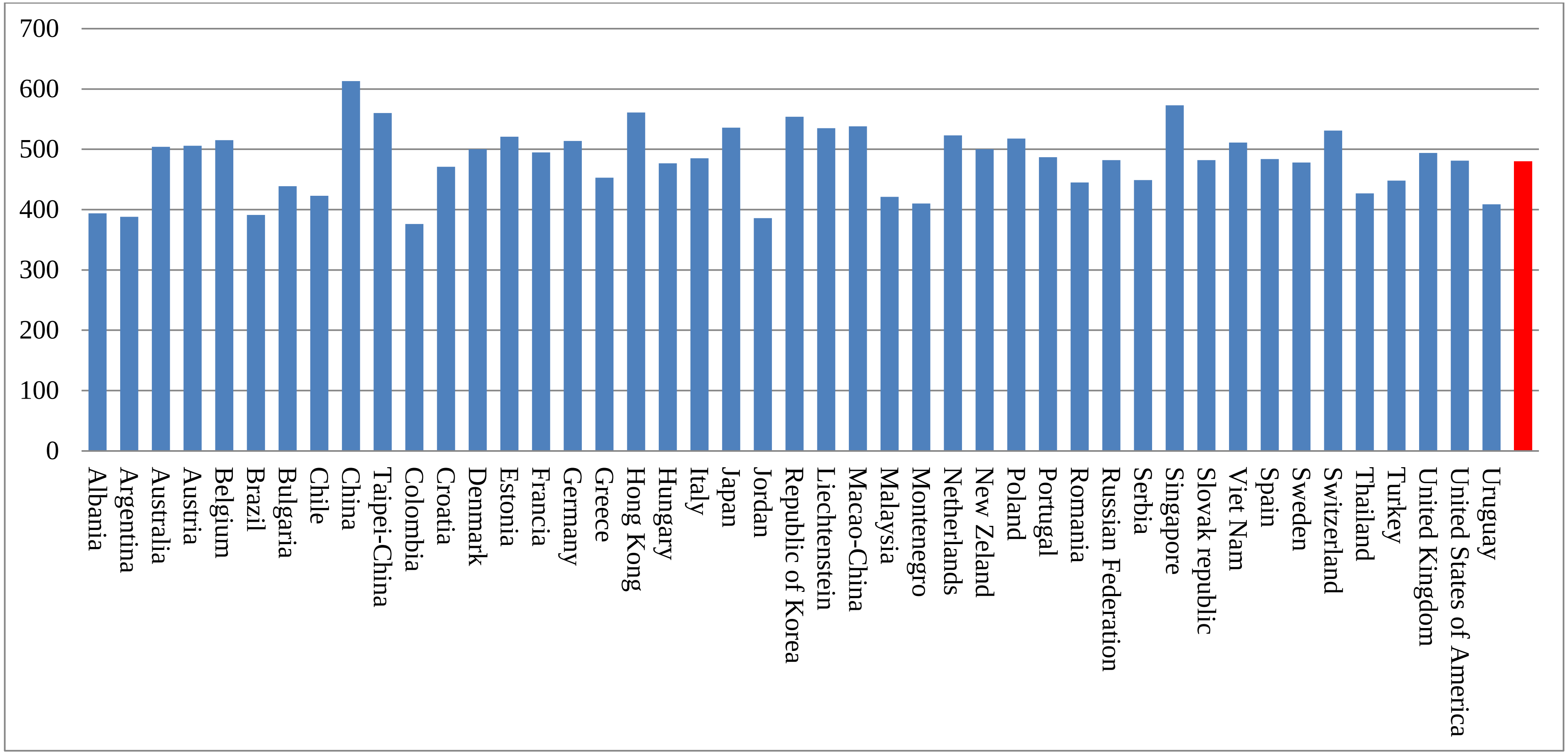
[2] Details on the sample of countries are in Section 4.

Graph. 1: Math scores of the countries of destination of immigrant students and average score of the countries of origin



Source: Our elaboration on PISA 2012.

Graph. 2: Math scores of the countries of origin of immigrant students and average score of the countries of destination.



Source: Our elaboration on PISA 2012

2. Background literature

The study of the achievement of immigrant students in different countries and school systems exploits the growing set of data collected at the individual level in different surveys (e.g. PISA, PIRLS, TIMMS)[3] and the recent empirical methodologies for handling plausible values. In fact, student ability is unknown and should be inferred from the observed items responses.[4] The topic has been approached both from the perspective of a specific country of destination and in a comparative perspective. In studies of the score gap in a specific country of destination, the explanatory power of individual characteristics of immigrant students (such as family background, the language spoken at home, attitude to study, being a first or second generation immigrant) is tested jointly with aspects related to the educational system of the country of destination (such as grade retention, public vs. private financing of schools, the socio-economic profile of classes and schools, the segregation of immigrants, or the level of formal comprehensiveness -or differentiation- of the curricula). The aim is to disentangle the role of individual characteristics from the functioning of the school system in the final outcomes of immigrant students. On the contrary, in comparative works the research questions frequently focus on only one aspect, which can be related to the individual characteristics of the students (for example, family background) or to the education system (grade retention), with the aim of discovering in which country immigrant students achieve better.

[3] Progress in International Reading Literacy (PIRL); Trends in International Mathematics and Science Study (TIMSS).

[4] Plausible values are estimates of student ability. More precisely, in PISA there are five plausible values for each subject (Reading, Maths and Science). Plausible values are imputed values that look like individual test scores. They are estimated to have approximately the same distribution as the latent trait being measured. Plausible values were developed starting from Rubin's work on multiple imputations (see Rubin, 2004) to obtain consistent estimates of population characteristics in assessments where individuals are administered too few items to allow precise estimates of their ability.

In the perspective of single country analysis, i.e. the studies of test score gaps between natives and immigrants from the perspective of the destination country, it is shown that one factor that explains the lower performance of immigrant students with respect to natives is a less favourable family background (e.g. Schnepf 2007; Ammermueller 2007; Schneeweis 2011). Family background not only means the education level of parents or their economic condition, but also the home environment for learning, as indicated by the number of books, the language spoken at home, or the academic expectations of parents for their children (Schnepf, 2007; Entorf and Lauk, 2008). Together with the family background, the role of the school system is crucial in explaining gaps in test scores, both in terms of school quality and peer composition (Rangvid 2007).

In trying to establish which educational system is more successful in facilitating immigrant students' educational integration, comparative analysis complements single country analysis. Indeed, comparative studies confirm the relevance of the education level of parents in reducing the immigrant score gaps, with huge differences across countries. The comparison of European and non-European traditional countries of immigration shows that the highest effect of family education on scores is in Germany, in the UK and in the US, whereas intergenerational transmission of educational attainment is less likely in the Scandinavian countries and in Canada. Immigrant students' performance differ also according to the immigration policies adopted by different countries of destination (Entorf and Minoiu, 2005). Evidence on second-generation immigrants in thirteen European countries shows that, not only individual student characteristics matter for academic achievements, but also the macro-characteristics of the country of destination, like the average educational level and the naturalization policies (Dronkers and Fleischmann, 2010). A comparative analysis on ten European countries focusing on the organization of the education systems, shows that grade retention, where applied, broadens the gap between immigrant children and natives (Park and Sandefur, 2010). A comparison among countries with public educational systems and comprehensive curricula with countries with market-oriented educational systems and differentiated curricula, shows that segregation is favoured by differentiated curricula and market-oriented systems (Alegre and Ferrer-Esteban, 2010).

More recently, attention has also been paid to the characteristics of origin countries (Dronkers and Fleishmann, 2010). Three analytical strategies have been adopted. First, examining multiple origin countries within one single destination country; second, looking at different destination countries of a single origin group; third, considering both the destination and the origin countries. Following the first approach, one study on the three main Danish groups of immigrants, namely, Turks, Lebanese people and the Pakistanis, shows that second generation Turks maintain the disadvantage with respect to natives, while this is not true for the Pakistanis and for Lebanese. Besides, the gap between immigrants and natives is bigger in reading and writing than in Maths (Rangvid, 2010).

Within the second approach, evidence on Turkish immigration shows that in many countries the test scores of children of Turkish immigrants, although being lower than that of their native peers, are higher than those of students of their cohort in the home country, irrespective of parental background (Dustmann et al., 2012). The explanation of this result is that the higher school and peer quality relative to that in the home country is a main determinant of the educational advantage of immigrant students.

Finally, following the third approach, evidence shows that both origin and destination countries characteristics help explain the differences in achievements of immigrant students. For example, strict immigration laws explain immigrant students' higher educational performance in traditional immigrant-receiving countries, such as Australia and New Zeeland, because of the selection at entry of immigrants with a better socio economic condition. In addition, the origin countries' level of economic development can positively affect immigrants' educational performance. Furthermore, immigrant students from more politically stable countries perform better at school and the socioeconomic status of the immigrant community, as well as the dimension, positively affects immigrant students' school achievement (Levels et al., 2008). Some features, such as the education, political, economic and religious systems of both the destination and origin country, have been included in the individual level analysis with macro indicators at the country level. Education systems may be compared according to the parameters of differentiation, standardization and resources devoted to teaching and learning (Dronkers and de Heus, 2012). The differentiation parameter refers to early tracking and also to the use of ability grouping internal to each track. The standardization parameter refers to the nationally established set of standard rules to which educational institutions should comply. The resource parameter can be measured with time devoted to teach and learn assuming that they are positively correlated. Within this methodological approach, it has been demonstrated that comprehensive educational systems have a positive influence on immigrant students' performance, but this is only the case for higher class students. If one looks at the country of origin, the standardization in terms of compulsory period of education has a positive effect on immigrants' performance. As for the resource parameter, the teacher shortage has a negative effect on immigrant students' performance (Dronkers and de Heus, 2012).

Our study contributes to this literature investigating how the performance in Maths of the origin country may affect the score gap with natives of immigrant students in the destination countries. Despite the growing interest on the role of Math skills in explaining different socio-economic developments across countries, when looking at immigrant students, the attention of scholars has been traditionally focused on language skills. Except for a comparative study that describes Math performance of immigrants as function of a multiplicity of variables (Levels et al. 2008), to our knowledge, so far no specific attention has been paid to the immigrant-native score gap in Maths with specific assumptions to test about its determinants.

3. The Empirical Strategy

The score gap in Maths of immigrant child i who is attending the school s in destination country d and is from origin country o , Y_{isod}, is our dependent variable. Y_{isod} is calculated as the difference between the immigrant score and the school native average score as follows:

$$Y_{isod} = y_{isod} - (\sum_{n=1}^{N_s} y_{ns})/N_s) \quad (1)$$

where y_{isod} is the score in Math of immigrant child i, enrolled in school s, coming from origin country o and assessed in destination country d, y_{ns} is the score of the native child n enrolled in school s, and N_s is the total number of natives in school s.

The equation we estimate is the following:

$$Y_{isod} = \alpha + \beta MATH_{io} + \mu IMMIG_i + \gamma X_i + \delta_{sd} + \varepsilon_{isod} \quad (2)$$

where $MATH_{io}$ is the national average score in Math in the origin country o from where the child i comes, $IMMIG_i$ is the immigration status of the child (whether first or second generation), X_i are other child and family characteristics, δ_{sd} is the school s of destination country d fixed effect, and ε_{isod} is a random error normally distributed.

As for the estimation method, we take into account that student proficiencies are not observed, i.e. they are missing data that must be inferred from the observed item responses (Mislevy, 1991 and Mislevy et al. 1992). There are several possible alternative approaches for making this inference and PISA uses the imputation methodology usually referred to as "Plausible Values" (PVs) (OECD, 2009). PVs are a selection of likely proficiencies for students that attained each score.

In order to account for the variability induced by plausible values, estimation is performed separately for each of the five plausible values available in PISA and then the results are combined by using Multiple Imputation (MI) formulas (Rubin, 2004)[5].

As in Ohinata and van Ours (2013), fixed effects allow us to take into account the unobserved heterogeneity among schools, such as the school peer effects (Micklewright et al. 2012) . Unfortunately, the PISA data do not allow us to conduct the analysis at the class level, being the school the lowest level of observation available. As it is well known in the economics of education literature, the composition of the class, and in particular the mix of natives and immigrants, may have significant effects on students' performance (Brunello and Rocco, 2013; Ohinata and van Ours, 2013; Jensen and Rasmussen, 2011; Geay et al. 2013). With the PISA data the only way to take this effect into account is to look at the composition within the school. Considering that schools may differ not only for their composition, but also for a lot of other unobservable characteristics, we choose a fixed effects model as our baseline.

As a robustness check, however, we also estimate the model with the school variables available in PISA, therefore replacing school fixed effects with destination country fixed effects. In this case, we can control for immigrant concentration with the ratio of immigrant student over total number of students in the school.

[5] The analysis is carried out using the "mixed" and "mi" commands of Stata (StataCorp, 2013).

4. Data and variables

As mentioned before, we use survey data drawn from the Programme for International Student Assessment (PISA) 2012 which measures the cognitive achievement of 15 year olds. The 2012 round is specifically targeted to mathematical skills, with several sections dedicated to this topic.

As for the sample selection, since we conduct our analysis at the micro level of immigrant students, we select only schools where immigrant students are present. Moreover, in order to answer our research question, we need to know the country of origin of each immigrant child, as well as of his/her parents, and its PISA average math score ($MATH_{io}$). PISA records the country of origin of immigrants only for a subset of the assessed countries, whereas, for the remaining countries, the immigrant origin country is generically indicated as "another country" with respect to the country where the assessment is conducted. Therefore, we have to first restrict our sample to the subset of assessed countries where the information on the immigrant students' origin countries is available. Secondly, not every origin country is assessed by PISA, so we have to further restrict our analysis to immigrants coming from countries assessed by PISA, so that we can attribute to each immigrant student i a $MATH_{io}$. After this selection, our sample is formed by 13,046 students who are assessed in 31 destination countries and come from 45 origin countries, those represented in Graph 1 and 2 respectively.

Table 1 shows the list of all variables used in the analysis and their descriptive statistics.

Insert Table 1 here

We calculate the math score gap for each immigrant student according to Equation (1).

Turning to our main variable of interest, as already explained, our working hypothesis is that those countries with a higher performance in Maths provide a more valuable portable human capital asset not only to future immigrant students in their destination countries, but also to their parents, who will be more able to help their children in the new school systems. We therefore introduce $MATH_{io}$, either the level or the quintile ranking (i.e. four quintile dummies), to approximate the success of a country in Math performance. More specifically, in the first specification (Table 3), $MATH_{io}$is the average Math score of the origin country imputed to each immigrant child of our sample. In the second and third specification (Table 4 and 5), the origin countries are ranked in five groups, from bottom to top, according to their average score in Math. In this case the variable is represented by four dummy variables which record in which quintile of the Math ranking the origin country of each immigrant child is classified. In the last specification, the top fourth and fifth quantiles are interacted with the number of years of school attendance in the country of origin for first generation students.

As for the child immigration status, our focus is on both first generation and second generation immigrant students. For testing our working hypothesis that the advantage of coming from a highly ranked origin country may be direct and indirect, we need a detailed definition that takes account of the different family types of the students with a migration background. As illustrated in Table 2, we distinguish among twelve groups, three for natives and nine for immigrants. We run the regressions on immigrant students, while native students are needed to compute the dependent variable, namely, the immigrant-native score gap as in (1). Table 2 also describes the rules we have adopted to impute $MATH_{io}$. In details, we select students for whom we have information on the country of birth of both parents or at least of the mother.[6] Furthermore, when the parents' birth places are different, we take the mother's birth place into account for our imputation. This choice is justified by the observation that, in several research fields, school success has been considered to be more strongly linked to the role of mothers than that of fathers. Even if there is no robust evidence supporting the assumption that mothers' education is more important than fathers' education for children's school attainment,[7] it is a stylized fact emerging from time use surveys (e.g. HETUS, ATUS and MTUS)[8] that mothers spend more time than fathers with their children.

Insert Table 2 here

Following these criteria, native children are those who are born in the country of the test, as well as their parents or their mothers. They can be distinguished into three groups: the 1st includes children born in the country of the test as well as their parents; the 2nd includes children who are born in the country of the test and for whom information about the father is missing; the 3th includes children born in the country of the text from a mixed couple in which the mother is from the country of the test. As already said, the scores of native students are used to calculate the score gap, when they are in the same school of immigrant children, while they are not included in the regression's sample. The second generation immigrant children are those who are born in the country of the test and have at least the mother who is born abroad. They can be divided in three groups too: group 4 includes children born in the country of the test from a mixed couple, in which

[6] Note that this selection rule implies that mothers have to be present, while fathers may be absent.

[7] For example, Chevalier et al. (2013), using the UK Labour Force Survey, find that OLS estimation reveals larger effects of maternal education than paternal education, and stronger effects on sons than on daughters. Using IV to simultaneously model the endogeneity of parental education and income, the maternal education effect disappears, while paternal education remains significant but only for daughters.

[8] Harmonized Time Use Survey (HETUS, OECD); American Time Use Survey (ATUS, US Bureau of Labor Statistics); Multinational Time Use Study (MTUS; Center for Time Use Research, University of Oxford, UK).

the mother is born abroad and the father in the country of the test; group 5 comprises children born in the country of the test and for whom it is known that the mother is born abroad, while information about the father is missing. Group 6 includes children born in the country of the test from a couple of parents both born abroad. The $MATH_{io}$ given to the second generation immigrant children is that of the mother's country. Our definition of immigrant students is broader than that used by the OECD, according to which only those in group 6 are second generation students. Finally, first generation immigrant children are those who are born abroad and whose parents can be born either abroad or in the country of the test. Group 7 includes children born abroad from a couple of parents born in the country of the test; group 8 includes children born abroad with the mother born in the country of the test and information on the father missing, while group 9 includes children born abroad as well as their father, while the mother in born in the country of the test. Groups 10, 11 and 12 include children born abroad from a mother born abroad and a father either born in the country of the test, or abroad or missing. To all the first generation students so defined, the attributed $MATH_{io}$ is that of the child's country of birth. The OECD definition of first generation immigrant students only includes those of our group 12. Table 1 shows that the immigrant students encompassed by the OECD definition only corresponds to 64 per cent (group 6 plus group 12) of students encompassed by our comprehensive definition.

In our control strategy, three groups of variables are included: the student characteristics, the household characteristics and the GDP per capita of the origin country. Among the first, there are the age, sex and immigration status of the student. In addition PISA records the number of years spent in pre-school, and years since migration (for the first generation), that allows us to calculate the number of years of school attendance in the country of origin. As for the household characteristics, we control for parents' ISCED levels of education and employment status together with the language spoken at home, the number of books and the presence of a computer at home. Finally, we control for the GDP per capita of the county of origin in order to be sure that the effect of the highly ranked countries of origin on immigrant students' performance is not attributable to the economic development of these countries.[9]

Our sample selection has required to discard immigrant children for whom the origin country was not specified. In order to check the implication of this selection, the last column of Table 1 shows the means of the variables calculated on the full sample of immigrants (around 70,000 children, using our definition, more comprehensive than the OECD definition). The values are remarkably similar for the main individual (sex, age) characteristics, and also rather similar for other household characteristics like language spoken at home and parents' labor market position. The main difference with our sample consists in the different proportion of first and second generation children. In our sample the proportion of second generation students is much lower (27 vs 37 per cent). This difference is likely to be due to the fact that, for the second generation it is probably more problematic to record the specific country of origin of the mother than that of the child for the first generation. Second generation students have less disadvantage (the lower immigrant-native score gap in absolute value of the full sample in Table 1 is an indication of this) and come from households with a better socio-economic background (higher ESCS and parental education the full sample). Therefore, our results must be interpreted with the caveat that second generation students are underrepresented.

[9] However, there is no robust evidence of a positive relationship between a country's wealth or expenditure and its performance in Maths (see OECD; 2012d).

5. Results

As mentioned in the Introduction, in PISA 2012 the disadvantage that immigrant students experience in Maths is lower than the disadvantage they experience in reading. This result is confirmed in our data: the average immigrant-native score gap in Math is -11.90 score points, while in reading it is equal to -14.54 score points (Table 1).

Table 3 shows the estimated coefficients of equation (2). In both specifications (column (1) and (2)) we control for immigration characteristics, student characteristic and school fixed effects, while in column (2) we add household characteristics. In order to interpret the value of the coefficients, it is useful to keep in mind that the equivalent of one year of schooling is 40.8 score points on the PISA mathematics scale.[10] Furthermore, for interpreting the value of the coefficients it should be born in mind that the gap is -on average- a negative number. Therefore the larger is its absolute value, the larger is the disadvantage of the student. A positive coefficient reduces the absolute value of the gap and, thus, it has to be interpreted as a reduction of the disadvantage. In the first specification (column (1) of Table 3), just controlling for basic child characteristics,[11] immigration status and years of school attended in the country of origin, shows that the coefficients of $MATH_{io}$ is positive and statistically significant. Ten score points more in the origin country make the disadvantage to decline by 3.3 score points. In the second specification (column (2) of Table 3), where we introduce household and family characteristics, the coefficient remains positive and significant.

The immigration status reveals that, compared to students of group 12, i.e. those born abroad as well as both their parents, (which correspond to the OECD definition for first

[10] "The equivalent of almost six years of schooling, 245 score points on the PISA mathematics scale, separates the highest and lowest average performances of the countries that took part in the PISA 2012 mathematics assessment." OECDd, 2013, p. 6.

[11] We show the first specification, col. (1), and then add household characteristics in col. (2) in order to better appreciate the weight of family variables in changing the size and significance of the coefficients of the child characteristics.

generation immigrants), all other groups are less disadvantaged with respect to natives. This is true except for group 5 (in column (2) of Table 3) who are students born in the country of the test, with the mother born abroad, while no information are available for the father. The most advantaged are the second generation students whose mother was born abroad and whose father is born in the country of the test (around +11 score points, group 4, col. 2) and the first generation whose mother was born in the country of the test and whose father was born abroad (around +15 score points, group 9, col. 2). This evidence shows that when the mother is born in the country of the test integration is easier. The number of years of school attended in the origin country, instead, is significant and decreases the absolute value of the score gap by one score point.[12]

Other variables that reduce the disadvantage are age, being male (in line with most of PISA evidence), having attended more than two years of pre-school, having a computer at home and number of books at home, the mother employed part-time and the mother and the father with the highest levels of education. Quite strangely, as for as the father level of education, having the first level of education helps more than reaching the intermediate levels). Instead, the only household variable that increases the disadvantage is father working part-time, probably because father's work position acts as a proxy of income.

In order to better disentangle the effects of $MATH_{i,oc}$, we transform it in quintiles. Table 4 shows the multiple imputation estimates of the effect of the Math ranking of the immigrant country of origin on the immigrant-native score gaps. In col. (1) around 51 score points (more than the one year of schooling, 40.8 score points on the PISA Math scale) and in col. (2) around 38 score points separate the students in the fourth quintile

[12]This is not such a small effect, since our sample includes second generation and first generation students who have left their country before their schooling age who will have a zero value for this variable.

from students in the lowest quantile. The coefficients of the other variables do not vary significantly with respect to the previous specification.

Insert Table 4 here

Even if the coefficient of the fifth quintile is lower than the coefficient of the fourth quintile, the F test for the equality of the coefficient cannot reject the hypothesis of equality of the two coefficients. In addition , we test the hypothesis that the advantage also depend on the number of years of school attended in highly ranked origin countries.[13] Thus, we have introduced the interaction of the top two Maths rank quantiles with the variables recording the number of years attended in the origin country. Table 5 shows the multiple imputation estimates of the effect of school attendance in top Math ranking countries of origin on the immigrant-native score gaps. This effect is positive and significant in for the top quantile (column 1 and column 2). Being in the fifth quintile and having attended school for one year in the origin countries, decreases the absolute value of the score gap by a coefficient ranging from around 43 score points (4.39 due to the interacted term plus 38.9 due to the coefficient of the dummy for the top rank, col. 1) to around 33 score points (3.32 due to the interacted term plus 29.7 due to the coefficient of the dummy for top rank, col. 2).[14]

Insert Table 5 here Finally, we try to disentangle the direct from the indirect advantage of coming from a highly ranked country in Maths. To this end, we have re-estimated the model on the subsamples of first generation students with no schooling in the origin country, first generation students with some schooling in the origin country and second

[13] Another reason might be that the ranking of the top countries is less variable. We have built the ranking on the whole data set, and therefore the distribution in our sample is not smooth.
[14] We also have estimated the model including the interaction among the variables Math score and Math rank with the immigration status dummies. Since no additional significant evidence has emerged, we do not present these results.

generation students. Table 6 shows the results. If one looks at the coefficients of the Math score of the origin country, the second generation students are indeed those who benefit more from coming from highly ranked countries of origin. Considering that these students have never studied in the country of origin, this result suggests that the indirect effect of the parental background is far from being negligible. The coefficients of the second specification (Table 6, lower panel) confirm this result: the coefficients of the quantiles are positive and statistically significant. Looking at the first generation, our results suggest that those who benefit more from coming from a highly ranked country in Math are those who have studied there. In other words, the direct effect is clear and evident for first generation students who studied in countries of origin ranked in the fourth and fifth quintiles. In particular, for the latter case, the coefficient is not only statistically significant but also the biggest in size (+63.7). Summing up, both the direct and the indirect positive effects of coming from a highly country ranked in Maths are present and sizeable.

Insert Table 6 here

To check for the problem of the sample selection due to the unavailability of the information about the country of origin for all immigrants, we have estimated equation (2) on the full sample of PISA immigrant students described in Table 1 (using the same independent variables, except, of course, for the score Math of the country of origin). As further evidence of the robustness of the results, the coefficients of the main independent variables remain significant and comparable in size with those of our baseline regression.[15]

[15] Data available upon request.

5. 1 Robustness checks

The PISA dataset is rich of information regarding the characteristics of the school. As a robustness check, we estimate our model using school variables instead of school fixed effects. .

With school variables, our estimated model becomes:

$$Y_{isod} = \alpha + \beta MATH_{io} + \mu IMMIG_i + \gamma X_i + \varphi S_{id} + \delta_d + \varepsilon_{isod} \qquad (2')$$

where S_{id} is a vector of characteristics of the school of immigrant *i* in the country of destination *d*. In this case, we can introduce the destination country fixed effects δ_d. Some of the school variables are general, while some other are specific for teaching Maths. The former group includes location (urban or rural) of the school, class size, total school enrolment, proportion of girls in the school, proportion of immigrants in the school, percentage of public funds in the funding of the school. In the latter group there are the student/math teachers ratio[16] and a dummy recording whether there exist ability grouping for Maths.[17] Since school characteristics are available for only a subset of students in PISA,[18] the number of observations available for estimating (2) is smaller with respect to those available for estimating (2'). Table 7 shows that the coefficients of our variables of interest remain significant. The coefficients measuring the Math teaching intensity in the school are not significant. [19]

Insert Table 7 here

[16] This was obtained by dividing the school size by the total number of mathematics teachers.
[17] See OECD 2013b, Annex A, PISA 2012 TECHNICAL BACKGROUND, p. 202.
[18] In order to avoid asking too many questions to all children, each set of questions regarding school characteristics is asked to different rotated sub-samples of children (see OECD.2012).
[19] Except the student/Math teacher ratio in the last specification, that has a counterintuitive sign.

The Pisa index of Economic, Social And Cultural Status (ESCS), provided by OECD, is a synthetic index that summarizes the socio-economic status of the family. We re-estimate our baseline model substituting this index to the household characteristics of the previous specifications. As expected, the coefficient of the ESCS index is positive and highly significant, meaning that a better household socio-economic status reduces the absolute value of the score gap. More relevant for our purpose, even if the ESCS index has been constructed to take account of additional aspects with respect to our previous specification (e.g. the household wealth of the time and resources devoted to cultural activities by the family), the coefficients of our variables of interest remain as significant as before.

Insert Table 8 here

Finally, we estimate our model using the OECD definition of immigration status, which is a subsample of our definition (see Table 2). Although the number of observations is much lower, our previous results continue to hold.

Insert Table 9 here

6 .Concluding remarks

In this paper we have investigated whether first (second) generation students coming from (whose parents come from) countries with higher performance in Math fare better than their immigrant peers coming from lower ranked countries. More specifically, if language barriers to learning Maths are lower than to learning how to correctly read and write in a different language, Maths would be a more portable skill than others, and the disadvantage of immigrant students with respect to natives reduced, especially when the former come from countries that are highly ranked in Maths. This advantage may come indirectly, from their family influence, if they are second generation immigrants. For first generation immigrants, the advantage may come directly from schooling in the country of origin, or indirectly from their family influence, if they are arrived in the country of destination before their schooling's age.

The supposition that mathematical skills are more portable than language skills, is confirmed either looking at the entire 2012 PISA sample (the immigrant-native score gap in Math is on average -6.26 score points while in reading it amounts to -9.68 score points), and the PISA sub-sample used in our analysis (the score gap in Math is -11.90 score points, while in reading it is equal to -14.54 score points).

Furthermore, multiple imputation estimation techniques allow us to show that students coming from higher score (highly ranked) origin countries have a significantly lower score gaps in absolute value, thus being relatively less disadvantaged. In more detail, coming from a country in the top quintile in Maths and having attended school there for at least one year, improves the absolute value of the score gap by nearly 33 score points. More noticeable, the size of the positive coefficients of the variables representing students coming from countries ranked in the fourth and fifth quintile are the highest among all the other variables that reduce the gap, such as being male, the years of preschool, the parents’ education as well as the more general socio-economic condition of the family.

Finally, a remarkable result is emerged comparing the direct effect of having attended schools in highly ranked countries with the indirect effect of having parents that are born in countries highly ranked in Maths. In fact, both effects are there but, above all, they are comparable in size. Among the explicative variables of the score gap in Maths, actually, the largest coefficient is that for immigrant students of the first generation, who studied in one of the countries of origin ranked in the fifth quintile. But the coefficient for the students of the second generation, the parents of whom they were born in highly ranked countries, follows closely.

While these results are robust across different specifications, the limitation of our results is related to the unobserved heterogeneity implicit in the use of PISA data. In our study, the main sources of this heterogeneity are the pre-migration socio-economic condition of the students’ families and the school career of immigrant students in the origin country.

Finally, our results have some implications for policy. On one side, if immigrant students’ performance in Maths is less unequal than in reading and writing, education programs for integration should mainly concentrate their efforts on improving learning of language skills. On the other side, since the evidence we have presented seems to confirm the hypothesis of the “portability” of mathematical skill across countries, irrespective of the level of economic development, Maths may be also used to improve and speed up the integration process. Integration is, actually, the prerequisite of any learning process. To conclude, Maths is not only important for economic growth and for reducing the gender gap in the labour market, but also it may become a crucial tool for integrating immigrant students in the school life and in the society as a whole.

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Table 1. Descriptive statistics

	Mean	Max	Min	Std.Dev	Mean
	Selected sample				Full sample of immigrants+
Score gap (dependent variable)	-11.901	307.100	-337.642	82.496	-5.330
Math score in the country of origin					
Average Math score in the country of origin	496.435	613.000	376.000	57.158	-
Country math ranking 2 (yes=1, no=0)	0.133	1.000	0.000	0.339	-
Country math ranking 3 (yes=1, no=0)	0.304	1.000	0.000	0.460	-
Country math ranking 4 (yes=1, no=0)	0.276	1.000	0.000	0.447	-
Country math ranking 5 (yes=1, no=0)	0.197	1.000	0.000	0.398	-
Immigration characteristics					
Second generation, i.e. student born in the country of the test as the father, mother abroad (group 4 *)	0.203	1.000	0.000	0.402	0.229
Second generation, i.e. student born in the country of the test, mother abroad, father missing (group 5 *)	0.004	1.000	0.000	0.066	0.006
Second generation, i.e. student born in the country of the test, mother abroad as the father (group 6 *)	0.272	1.000	0.000	0.445	0.367
First generation, i.e. student born abroad and parents born in the country of the test (group 7 *)	0.057	1.000	0.000	0.232	0.042
First generation, i.e. student born abroad, mother in the country of the test, father missing (group 8 *)	0.001	1.000	0.000	0.036	0.011
First generation, i.e.student born abroad, mother in the country of the test, father abroad (group 9 *)	0.030	1.000	0.000	0.171	0.019
First generation, i.e. student born abroad, mother born abroad and father in the country of the test (group 10 *)	0.064	1.000	0.000	0.244	0.035
First generation, i.e. student born abroad as well as the mother, father missing (group 11 *)	0.005	1.000	0.000	0.069	0.003
First generation, i.e. student born abroad as well as the parents (group 12 *)	0.365	1.000	0.000	0.481	0.297
Second generation (OECD definition)	0.275	1.000	0.000	0.447	0.365
First generation (OECD definition)	0.370	1.000	0.000	0.483	0.290
Years of school attended in the country of origin	0.962	11.000	0.000	2.208	0.792
Interaction (Years of school attended in the country of origin)(country ranking 4)	0.354	11.000	0.000	1.484	-
Interaction (Years of school attended in the country of origin)(country ranking 5)	0.345	11.000	0.000	1.366	-
Student characteristics					
Age of the student	15.780	16.330	15.250	0.290	15.782
Male student (yes=1, no=0)	0.492	1.000	0.000	0.500	0.494
At least one year of preschool (yes=1,no=0)	0.218	1.000	0.000	0.413	0.239
Two or more years of preschool (yes=1,no=0)	0.696	1.000	0.000	0.460	0.623
Household characteristics					
Computer at home (yes=1,no=0)	0.957	1.000	0.000	0.203	0.934
Computer connected with internet at home (yes=1,no=0)	0.952	1.000	0.000	0.214	0.931
Number of books at home (6 increasing alternatives between less than 10 and more then 500)	2.969	6.000	1.000	1.490	2.896
The language spoken at home is not that of the test (yes=1,no=0)	0.308	1.000	0.000	0.462	0.303
Mother in full-time job (yes=1,no=0) *(ref cat unemployed)*	0.471	1.000	0.000	0.499	0.448
Mother in part-time job (yes=1,no=0)	0.192	1.000	0.000	0.394	0.145
Father in full-time job (yes=1,no=0)	0.735	1.000	0.000	0.441	0.723
Father in part-time job (yes=1,no=0)	0.083	1.000	0.000	0.276	0.086
Mother education ISCED 2 (yes=1,no=0) *(ref cat no education)*	0.172	1.000	0.000	0.377	0.140
Mother education ISCED 3B (yes=1,no=0)	0.092	1.000	0.000	0.289	0.070
Mother education ISCED 3A (yes=1,no=0)	0.194	1.000	0.000	0.395	0.223
Mother education ISCED 5B (yes=1,no=0)	0.129	1.000	0.000	0.335	0.138
Mother education ISCED 5A (yes=1,no=0)	0.213	1.000	0.000	0.409	0.273
Father education ISCED 2 (yes=1,no=0)	0.159	1.000	0.000	0.366	0.127
Father education ISCED 2B (yes=1,no=0)	0.100	1.000	0.000	0.300	0.079
Father education ISCED 3A (yes=1,no=0)	0.177	1.000	0.000	0.382	0.201
Father education ISCED 5B(yes=1,no=0)	0.120	1.000	0.000	0.325	0.126
Father education ISCED 5A (yes=1,no=0)	0.226	1.000	0.000	0.418	0.304
Index of economic, social and cultural status of the household (ESCS)	-0.274	2.700	-4.220	1.070	-0.129
Country of origin characteristics					
Log Gdp of the country of origin (ppp)	10.003	0.631	8.239	11.372	-
School characteristics					-
Located in a small town	0.217	1.000	0.000	0.412	-
Located in a town	0.340	1.000	0.000	0.474	-
Located in a city	0.240	1.000	0.000	0.427	-
Located in a large city	0.168	1.000	0.000	0.373	-
Student-mathematics teacher ratio	102.109	1581	2.595	84.516	-
Index of ability grouping in mathematics classes	0.206	1.000	0.000	0.405	-
Ratio of immigrant students in the school (over the total)	0.317	0.955	0.007	0.232	-

* See Table 2 for the definition of immigration groups

* *The number of observations is around 13,000 except for school variables that are recorded for a subsample of the PISA and amount to about 11,000.

\+ PISA sample of all immigrants including those whose with unspecified origin country ("another country"); around 70,000 observations.

Table 2. Categories of Immigration and Imputed Average Math Score according to the place of birth of the student or of its parents..

	Group of immigration	Student's Country of birth	Mother's Country of birth	Father's Country of birth	Imputed Average Math Score
Natives	1	Country of the test	Country of the test	Country of the test	Country of the test
	2	Country of the test	Country of the test	Missing	Country of the test
	3	Country of the test	Country of the test	Another Country	Country of the test
Second generation	4	Country of the test	Another Country	Country of the test	Mother's Country
	5	Country of the test	Another Country	Missing	Mother's Country
	6*	Country of the test	Another Country	Another Country	Mother's Country
First Generation	7	Another Country	Country of the test	Country of the test	Student's Country
	8	Another Country	Country of the test	Missing	Student's Country
	9	Another Country	Country of the test	Another Country	Student's Country
	10	Another Country	Another Country	Country of the test	Student's Country
	11	Another Country	Another Country	Missing	Student's Country
	12*	Another Country	Another Country	Another Country	Student's Country

* OECD definition: group 6 are second generation immigrants, while group 12 are the first generation.

Table 3

Immigrant-native Math score gap and Math score of the origin country

Multiple imputation fixed effects estimates, coefficients of the origin country Math score and of other controls displayed, standard errors in italic

	Coefficient (col.1)	*s.e*	Coefficient (col.2)	*s.e*
Origin country Math score	**0.332*** **	*0.038*	**0.237*** **	*0.037*
Immigration characteristics				
Second generation, Group 4	15.604***	*3.184*	10.71***	*3.228*
Second generation, Group 5	-11.342	*13.470*	-5.811	*13.233*
Second generation, Group 6	3.573	*2.715*	4.528	*2.771*
First generation, Group 7	14.325***	*5.508*	10.052*	*5.5*
First generation, Group 8	-3.633	*21.084*	4.920	*18.805*
First generation, Group 9	19.752***	*5.650*	15.147***	*5.597*
First generation, Group 10	8.805**	*3.507*	6.274*	*3.407*
First generation, Group 11 (ref. category Group 12)	-5.689	*10.626*	2.310	*10.607*
Years of school attended in the country of origin	0.827*	*0.494*	1.1**	*0.464*
Student characteristics				
Age	9.301***	*2.827*	9.867***	*2.829*
Male	18.655***	*1.903*	20.026***	*1.837*
At least one year of preschool	5.460	*3.860*	1.337	*3.838*
Two or more years of preschool	21.934***	*3.687*	15.711***	*3.632*
Household characteristics				
Computer at home			17.04***	*6.026*
Computer connected with internet at home			-1.026	*5.584*
Number of books at home (a)			12.042***	*0.752*
The language spoken at home is not that of the test			1.956	*2.370*
Mother in full-time job (ref. cat. unemployed)			1.279	*1.800*
Mother in part-time job			5.715**	*2.610*
Father in full-time job (ref. cat. unemployed)			1.969	*2.528*
Father in part-time job			-8.064**	*3.331*
Mother education ISCED 2 (ref. cat. no education)			4.343	*3.102*
Mother education ISCED 3B			4.287	*3.279*
Mother education ISCED 3A			6.457**	*2.964*
Mother education ISCED 5B			12.961***	*3.514*
Mother education ISCED 5A			9.4***	*3.412*
Father education ISCED 2 (ref. cat. no education)			3.154	*2.653*
Father education ISCED 2B			9.647***	*3.314*
Father education ISCED 3A			3.838	*2.909*
Father education ISCED 5B			6.021*	*3.299*
Father education ISCED 5A			12.943***	*3.254*
Origin Country GDP				
Log of GDP (ppp)	10.354***	*2.836*	3.741	*2.876*
School fixed effects (within regression)	ES (no. schools: 3362)		YES (no. schools: 3318)	
Constant	-459.157***	*55.319*	-415.165***	*56.438*
N. of observations	13029		12747	
Max no. of obs. per school (min.: 1)	152		148	
Rho (fraction of variance due to u_i)	0.44		0.44	

Notes. * 0.05<p<=0.1; ** 0.01<p<=0.05; *** p<=0.01. Robust (vce) standard errors in italic.

a) 6 increasing alternatives between less than 10 and more than 500.

Table 4
Immigrant-native Math score gap and Math ranking of the origin country
Multiple imputation fixed effects estimates, coefficients of the origin country Math score and of other controls displayed, standard errors in italic

	Coefficient (col.1)	*s.e*	Coefficient (col.2)	*s.e*
Math-rank 2 (ref.: Math-rank 1)	**13.583****	*6.751*	**11.431***	*6.589*
Math-rank 3	**26.099*****	*5.883*	**22.675*****	*5.662*
Math-rank 4	**50.759*****	*6.502*	**38.3*****	*6.253*
Math-rank 5	**43.762*****	*6.918*	**33.488*****	*6.840*
Immigration characteristics				
Second generation, Group 4	14.312***	*3.235*	10.077***	*3.294*
Second generation, Group 5	-10.505	*13.412*	-5.774	*13.210*
Second generation, Group 6	4.038	*2.965*	4.433	*2.984*
First generation, Group 7	14.354***	*5.550*	10.285*	*5.531*
First generation, Group 8	-3.401	*21.533*	5.463	*19.129*
First generation, Group 9	18.864***	*5.614*	14.756***	*5.582*
First generation, Group 10	8.133**	*3.500*	6.003*	*3.412*
First generation, Group 11 (ref. category Group 12)	-6.152	*10.667*	1.834	*10.601*
Years of school attended in the country of origin	0.795	*0.497*	1.053**	*0.467*
Student characteristics				
Age	9.668***	*2.805*	10.086***	*2.811*
Male	18.695***	*1.892*	20.044***	*1.834*
At least one year of preschool	5.139	*3.830*	1.273	*3.809*
Two or more years of preschool	21.525***	*3.648*	15.644***	*3.597*
Household characteristics				
Computer at home			17.039***	*6.025*
Computer connected with internet at home			-0.738	*5.560*
Number of books at home (a)			11.933***	*0.746*
The language spoken at home is not that of the test			3.601	*2.442*
Mother in full-time job (ref. cat. unemployed)			1.420	*1.800*
Mother in part-time job			5.554**	*2.610*
Father in full-time job (ref. cat. unemployed)			2.196	*2.537*
Father in part-time job			-7.925**	*3.323*
Mother education ISCED 2 (ref. cat. no education)			4.326	*3.109*
Mother education ISCED 3B			3.377	*3.294*
Mother education ISCED 3A			5.629*	*2.960*
Mother education ISCED 5B			12.255***	*3.507*
Mother education ISCED 5A			8.859***	*3.401*
Father education ISCED 2 (ref. cat. no education)			3.035	*2.647*
Father education ISCED 2B			9.587***	*3.330*
Father education ISCED 3A			3.488	*2.894*
Father education ISCED 5B			5.608*	*3.300*
Father education ISCED 5A			12.746***	*3.256*
Origin Country GDP				
Log of GDP (ppp)	-0.199	*3.000*	-3.821	*2.959*
School fixed effects (within regression)	YES (no. schools: 3362)		YES (no. schools: 3318)	
Constant	-226.66***	*52.273*	-250.648***	*53.600*
N. of observations	13029		12747	
Max no. of obs. per school (min.: 1)	152		148	
Rho (fraction of variance due to u_i)	0.44		0.43	

Notes. * 0.05<p<=0.1; ** 0.01<p<=0.05; *** p<=0.01. Robust (vce) standard errors in italic.
a) 6 increasing alternatives between less than 10 and more than 500.

Table 5

Immigrant-native Math score gap and interaction of Math rank with years attended in the origin country

Multiple imputation fixed effects estimates, coefficients of the origin country Math score and of other controls displayed, standard errors in italic

	Coefficient (col.1)	*s.e*	Coefficient (col.2)	*s.e*
Math-rank 2 (ref.: Math-rank 1)	**13.972****	*6.727*	**11.687***	*6.570*
Math-rank 3	**26.204*****	*5.867*	**22.688*****	*5.659*
Math-rank 4	**50.289*****	*6.502*	**38.168*****	*6.245*
Math-rank 5	**38.922*****	*7.118*	**29.679*****	*7.045*
Years of school attended in the country of origin*Math-rank 4	**1.362**	*1.172*	**0.695**	*1.148*
Years of school attended in the country of origin*Math-rank 5	**4.389*****	*1.153*	**3.32*****	*1.191*
Immigration characteristics				
Second generation, Group 4	12.24***	*3.146*	8.366***	*3.178*
Second generation, Group 5	-12.381	*13.391*	-7.483	*13.221*
Second generation, Group 6	2.066	*2.887*	2.862	*2.881*
First generation, Group 7	13.163**	*5.489*	9.16**	*5.460*
First generation, Group 8	-4.009	*21.623*	4.663	*19.247*
First generation, Group 9	17.754***	*5.598*	13.741**	*5.575*
First generation, Group 10	8.204**	*3.496*	6.042*	*3.408*
First generation, Group 11 (ref. category Group 12)	-5.872	*10.648*	1.784	*10.585*
Years of school attended in the country of origin	-1.413*	*0.823*	-0.513	*0.837*
Student characteristics				
Age	9.548***	*2.802*	9.962***	*2.809*
Male	18.747***	*1.890*	20.088***	*1.832*
At least one year of preschool	4.603	*3.782*	0.880	*3.767*
Two or more years of preschool	21.169***	*3.609*	15.451***	*3.558*
Household characteristics				
Computer at home			16.734***	*6.016*
Computer connected with internet at home			-0.519	*5.586*
Number of books at home (a)			11.878***	*0.750*
The language spoken at home is not that of the test			3.550	*2.424*
Mother in full-time job (ref. cat. unemployed)			1.456	*1.799*
Mother in part-time job			5.68**	*2.607*
Father in full-time job (ref. cat. unemployed)			2.080	*2.544*
Father in part-time job			-8.051**	*3.335*
Mother education ISCED 2 (ref. cat. no education)			4.233	*3.111*
Mother education ISCED 3B			3.497	*3.289*
Mother education ISCED 3A			5.615	*2.964*
Mother education ISCED 5B			12.119***	*3.499)*
Mother education ISCED 5A			8.834***	*3.405*
Father education ISCED 2 (ref. cat. no education)			3.000	*2.647*
Father education ISCED 2B			9.461***	*3.311*
Father education ISCED 3A			3.114	*2.875*
Father education ISCED 5B			5.277	*3.300*
Father education ISCED 5A			12.453***	*3.244*
Origin Country GDP				
Log of GDP (ppp)	1.188	*3.030*	-2.621	*3.009*
School fixed effects (within regression)	YES (no. schools: 3362)		YES (no. schools: 3318)	
Constant	-236.073***	*52.810*	-258.192***	*54.067*
Max no. of obs. per school (min.: 1)	152		148	
N. of observations	13029		12747	
Rho (fraction of variance due to u_i)	0.42		0.43	

Notes. * 0.05<p<=0.1; ** 0.01<p<=0.05; *** p<=0.01. Robust (vce) standard errors in italic.

a) 6 increasing alternatives between less than 10 and more than 500.

Table 6

Sub samples of first and second generations

Multiple imputation fixed effects estimates, coefficients of the origin country Math score and of other controls displayed, standard errors in italic

	Coefficient	*s.e*	Coefficient	*s.e*	Coefficient	*s.e*
	First generation no school in origin country		First generation some school in origin country		Second generation	
First specification:						
Origin country Math score	0.195**	0.076	0.325**	0.141	0.471***	0.09
Years of school attended in the country of origin	-	-	2.264**	0.977	-	-
Second specification:						
Math-rank 2 (ref.: Math-rank 1)	2.879	19.300	22.228	32.359	27.812*	15.456
Math-rank 3	9.579	9.071	37.552	24.977	40.141**	16.149
Math-rank 4	37.306***	12.759	55.544*	29.061	57.022***	16.801
Math-rank 5	21.880	18.108	63.702**	29.247	52.366***	16.723
Years of school attended in the country of origin	-	-	1.872*	1.112	-	-
Immigration characteristics	YES		YES		YES	
Student characteristics	YES		YES		YES	
Household characteristics	YES		YES		YES	
Log of GDP (ppp)	YES		YES		YES	
School fixed effects (within regression)	YES		YES		YES	
Constant	YES		YES		YES	
N. of observations	3783		2613		6351	

Notes. * 0.05<p<=0.1; ** 0.01<p<=0.05; *** p<=0.01. Robust (vce) standard errors in italic.

Table 7

Robustness checks

Immigrant-native Math score gap and Math teaching effort in schools

Multiple imputation fixed effects estimates, coefficients of the origin country Math score and of other controls displayed, standard errors in italic

	Coefficient	*s.e*	Coefficient	*s.e*	Coefficient	*s.e*
	(col.1)		(col.2)		(col. 3)	
Origin country Math score	**0.250*** **	*0.057*				
Math-rank 2 (ref.: Math-rank 1)			**15.421***	*2.600*	**15.524***	*5.832*
Math-rank 3			**34.208*** **	*6.220*	**34.023*** **	*5.748*
Math-rank 4			**43.356*** **	*5.170*	**42.607*** **	*8.816*
Math-rank 5			**39.408*** **	*5.240*	**34.123*** **	*8.299*
Years of school attended in the country of origin*Math-rank 4					**1.377**	*1.313*
Years of school attended in the country of origin*Math-rank 5					**4.300***	*1.635*
Student-mathematics teacher ratio	**0.020**	*0.010*	**0.021**	*0.010*	**0.022***	*0.010*
Index of ability grouping in mathematics classes	**-2.589**	*3.001*	**-2.922**	*3.005*	**-3.153**	*-1.050*
Other school characteristics	YES		YES		YES	
Immigration characteristics	YES		YES		YES	
Student characteristics	YES		YES		YES	
Household characteristics	YES		YES		YES	
Log of GDP (ppp)	YES		YES		YES	
Destination country fixed effects (within regression)	YES		YES		YES	
Constant	-364.443***	*71.349*	-196.871***	*81.555*	-201.629***	*84.341*
N. of observations	10741		10741		10741	
Max no. of obs. per country (min.: 9)	1703		1703		1703	
Rho (fraction of variance due to u_{i})	0.110		0.113		0.115	

Notes. * 0.05<p<=0.1; ** 0.01<p<=0.05; *** p<=0.01. Robust (vce) standard errors in italic.

Table 8
Robustness checks
Immigrant-native Math score gap and Index of the economic, social and cultural status of the household

Multiple imputation fixed effects estimates, coefficients of the origin country Math score and of other controls displayed, standard errors in italic

	Coefficient (col.1)	*s.e*	Coefficient (col.2)	*s.e*	Coefficient (col. 3)	*s.e*
Origin country Math score	**0.269***	*0.037*				
Math-rank 2 (ref.: Math-rank 1)			**14.986***	*6.666*	**15.292***	*6.640*
Math-rank 3			**26.482*****	*5.795*	**26.578*****	*5.780*
Math-rank 4			**43.425*****	*6.400*	**43.019*****	*6.409*
Math-rank 5			**39.474*****	*6.843*	**35.550*****	*7.064*
Years of school attended in the country of origin*Math-rank 4					**1.406**	*1.160*
Years of school attended in the country of origin*Math-rank 5					**3.724****	*1.163*
Index of economic, social and cultural status of the household	**14.243*****	*1.012*	**13.816*****	*1.016*	**13.628*****	*1.017*
Immigration characteristics	YES		YES		YES	
Student characteristics	YES		YES		YES	
Household characteristics	NO		NO		NO	
Log of GDP (ppp)	YES		YES		YES	
School fixed effects	YES		YES		YES	
Constant	-370.445***	*55.388*	-187.689***	*52.621*	-195.665***	*53.179*
N. of observations	12907		12907		12907	
Max no. of obs. per school (min.: 1)	149		149		149	
Rho (fraction of variance due to ui)	0.429		0.426		0.427	

Notes. * 0.05<p<=0.1; ** 0.01<p<=0.05; *** p<=0.01. Robust (vce) standard errors in italic.

Table 9
Robustness checks
Immigrant-native Math score gap and the OECD definition of immigration

Multiple imputation fixed effects estimates, coefficients of the origin country Math score and of other controls displayed, standard errors in italic

	Coefficient (col.1)	*s.e*	Coefficient (col.2)	*s.e*	Coefficient (col. 3)	s.e
Origin country Math score	**0.222*****	*0.047*				
Math-rank 2 (ref.: Math-rank 1)			**10.906**	*8.090*	**11.037**	*8.118*
Math-rank 3			**21.123*****	*6.217*	**21.202*****	*6.238*
Math-rank 4			**39.372*****	*7.313*	**39.768*****	*7.275*
Math-rank 5			**36.493*****	*8.681*	**32.026*****	*8.789*
Years of school attended in the country of origin*Math-rank 4					**0.010**	*0.939*
Years of school attended in the country of origin*Math-rank 5					**2.797**	*1.361*
Student characteristics	YES		YES		YES	
Household characteristics	NO		NO		NO	
Log of GDP (ppp)	YES		YES		YES	
School fixed effects	YES		YES		YES	
Constant	-408.818***	*71.005*	-246.744***	*70.935*	-111.704***	*71.291*
N. of observations	8167		8167		8167	
Max no. of obs. per school (min.: 1)	131		131		131	
Rho (fraction of variance due to ui)	0.465		0.460		0.462	

Notes. * 0.05<p<=0.1; ** 0.01<p<=0.05; *** p<=0.01. Robust (vce) standard errors in italic.