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ABSTRACT

Immigrant Student Performance in Math: Does It Matter Where You Come From?*

The performance gap in math of immigrant students is investigated using PISA 2012. The gap with respect to non-immigrant schoolmates is first measured. The hypotheses that first (second) generation students coming from (whose parents come from) countries with a higher performance in math fare better than their immigrant peers coming from lower-ranked countries are then tested on a sample of about 13,000 immigrant students. The estimated average immigrant-native score gap in math amounts to -12 points. The results show that immigrant students coming from higher-ranked origin countries have a significantly lower score gap, and are thus relatively less disadvantaged. For example, coming from a country in the top quintile for math and having attended school there for one year improves the absolute score gap by nearly 39 points, the highest coefficient among the variables that reduce the gap, such as parental education and socio-economic status.

JEL Classification: I25, J15, O15

Keywords: mathematical skills, migration, countries of origin

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1. Introduction

The 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 immigrant children were guaranteed equal education opportunities. Research on student school achievement provides evidence of a widespread performance gap between immigrant and native students that varies considerably across countries. The underperformance of immigrant students may be due to a multiplicity of factors, such as socio-economic differences (Ammermueller 2007, Rangvid 2007), linguistic barriers (Akresh & Akresh, 2011), ethnicity and its transmission to children through parental influence (Gang and Zimmermann, 2000), age on 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 & Schwerdt, 2013).

In parallel, growing attention is being paid to performance in math. The focus on math is motivated by the belief that mathematical skills are crucial for employment, productivity and earnings (Hanushek & Kimko, 2000), as well as for social mobility (Martins & Veiga, 2005). The estimated effect of student performance in math on economic growth, however, remains an open debate (Ramirez, Luo, Schofer & Meyer, 2006). As far as performance gaps are concerned, the generalized evidence of gender score gaps in math in favor of males has stimulated research on assessing the relative importance of biological and cultural explanations (Guiso, Monte, Sapienza & Zingales, 2008; Reilly, 2012; Stoet & Geary, 2013; Weber, Skirbekk, Freund & Herlitz, 2014).

While the literature on immigrant student achievement has predominantly concentrated on language performance gaps, in this paper our focus is on math and on the role played by performance in math of countries of origin. Our research hypothesis is that language barriers to learning math may be lower than those to learning how to read and write in a different language. As a consequence, math would be a more portable skill than others, and the disadvantage of immigrant students with respect to natives would be less, especially when the former come from countries that are highly ranked for math. In other words, immigrant students may take advantage of a performance in math of their origin countries which is higher than, or equivalent to, that of the countries of destination. This advantage may come indirectly, from 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 they had some schooling there, and indirectly from family influence. Parental influence would always be there, and may increase the advantage of immigrant students if their parents come from highly performing countries for math.

Using PISA 2012, we first measure the performance gap of immigrant students in math with respect to their native schoolmates, and then investigate whether the disadvantage is reduced when they come from highly-ranked countries for math performance. Two pieces of evidence are relevant for this research. The first 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 emerges from both the PISA 2000 and PISA 2009 surveys, in some countries the estimated disadvantage in reading skills of immigrants is of about one school year (around 40 points) compared to natives (OECD, 2012a). In the entire 2012 PISA sample, the immigrant-native score gap for math is on average -6.26 points, while in reading it amounts to -9.68 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 for math of some countries of origin is better than that of some countries of destination. Graph 1 shows average scores in math by country of destination (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 (blue bars) while the last bar illustrates the overall average math score of the countries of destination of immigrant students.[2]

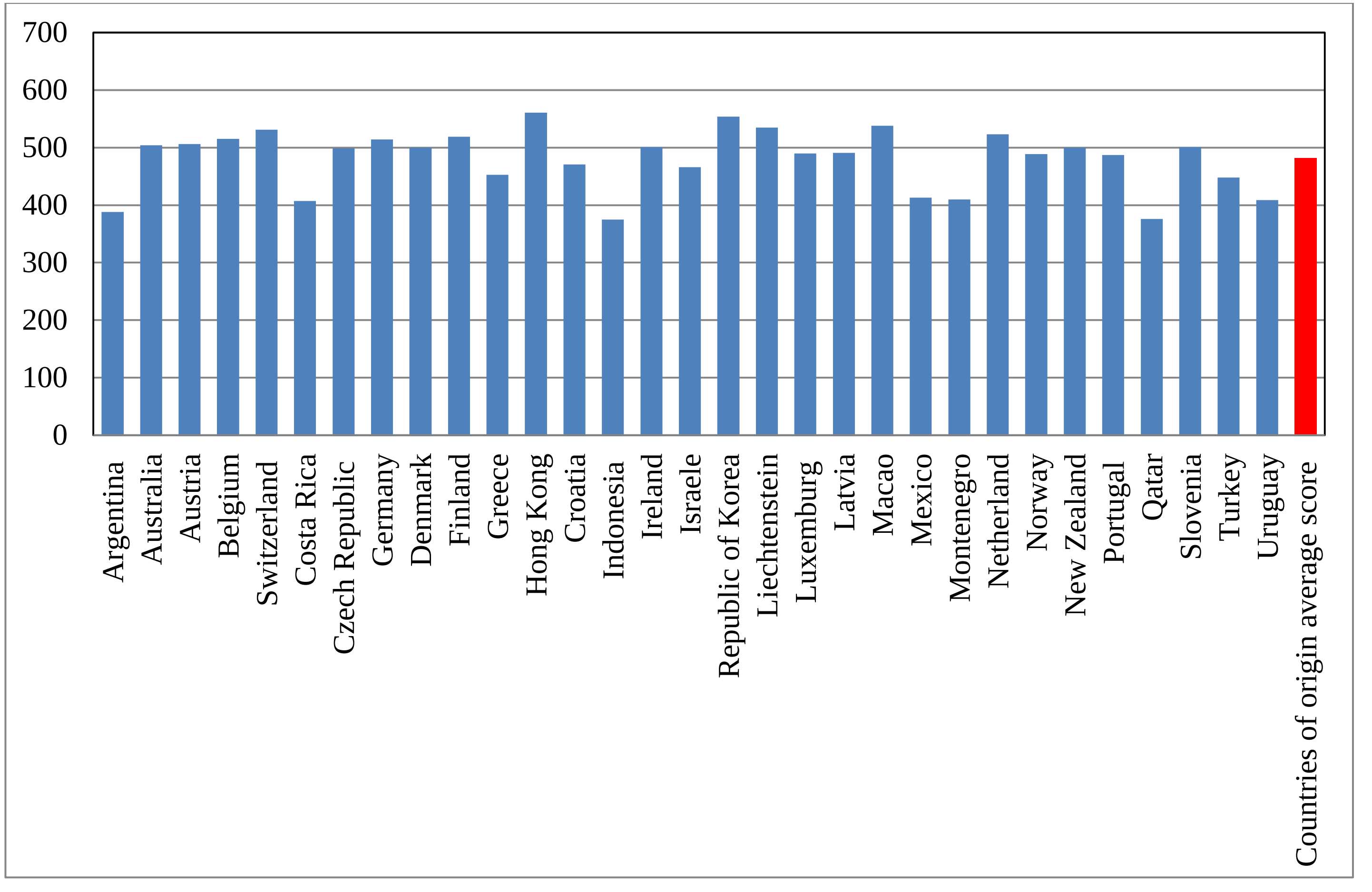
Our estimates show that performance in math of the countries of origin contributes to reducing both first- and second-generation students' immigrant-native score gap in absolute value, particularly of students that have attended school in highly-ranked countries. This result holds true when controlling for student characteristics, household socio-economic status, language spoken at home, school fixed effects, and level of economic development of the country of origin.

[1] Our calculation on PISA 2012 using the OECD definition of first- and second-generation immigrants.
[2] Details of the sample of countries are in Section 4.

A limitation of our analysis is related to the unobserved heterogeneity implicit in the use of PISA data. In particular, the main sources of this heterogeneity are the pre-migration socio-economic situation of the students' families, and the school career and school characteristics of immigrant students in the countries of origin.

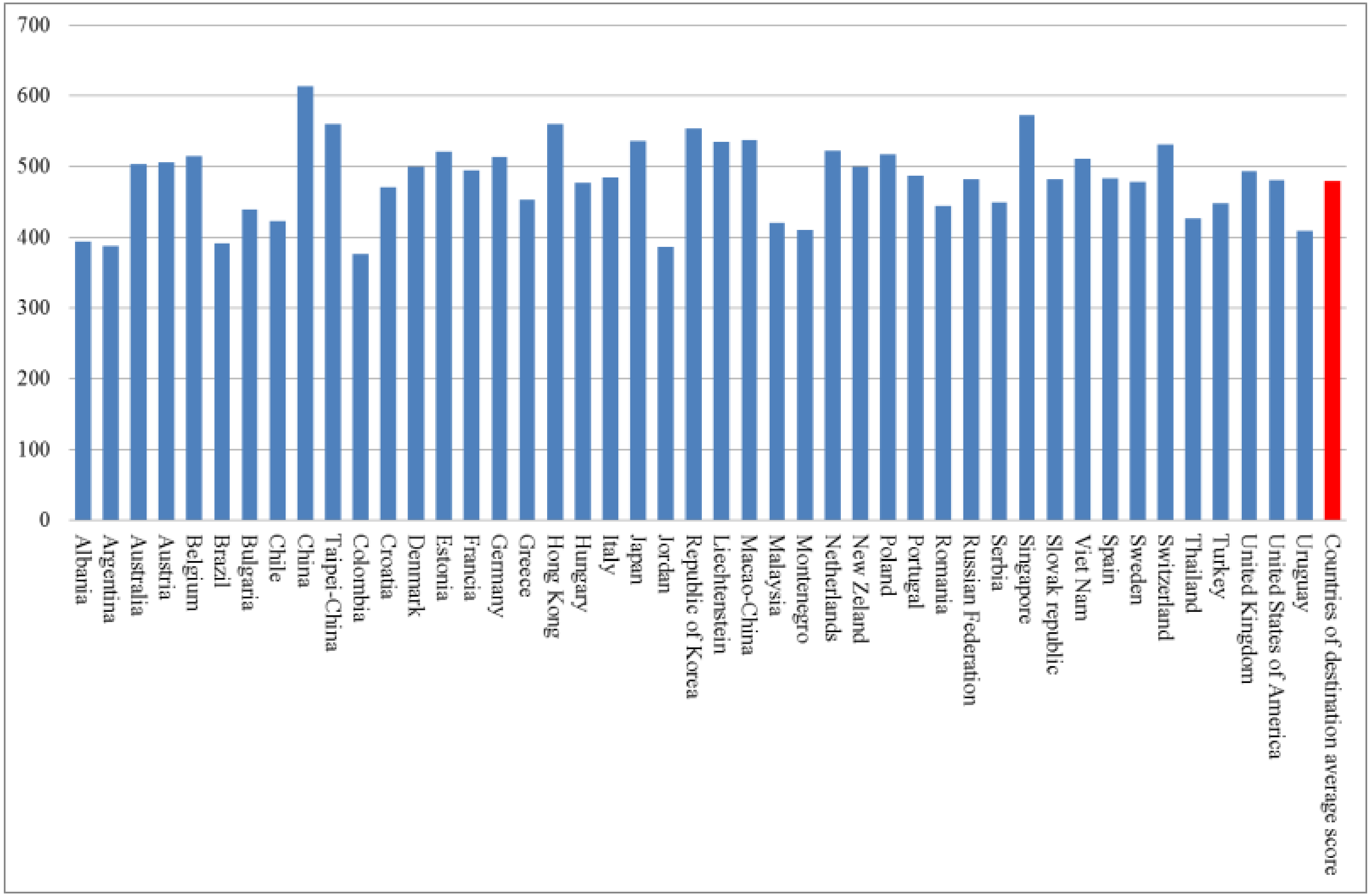
The structure of the paper is the following. Section 2 overviews the background literature. Sections 3 presents the empirical strategy. Section 4 describes the data, the sample and the variables. Section 5 presents the results, and Section 6 concludes.

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



Source: Our elaboration on PISA 2012.

2. Background literature

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 various surveys (e.g. PISA, PIRLS, TIMMS)[3] and the recent empirical methodologies for handling plausible values. In fact, student ability is unknown and must be inferred from the observed item responses.[4] The topic has been approached both from the perspective of a specific country of destination and comparatively. 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, 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 students (for example, family background) or to the education system (grade retention), with the aim of discovering in which country immigrant students achieve better.

In the field of single country analysis, i.e. studies of test score gaps between natives and immigrants from the perspective of the destination country, it has been shown that one factor that explains the lower performance of immigrant students with respect to natives is a less favorable family background (e.g. Schnepf 2007; Ammermueller 2007; Schneeweis 2011). Family background not only means the education level of parents or their economic situation, 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

[3] Progress in International Reading Literacy (PIRL); Trends in International mathematics and Science Study (TIMSS). Neither survey records the country of origin of immigrant students. For this reason we could not use them to test our research hypothesis.

[4] Plausible values are estimates of student ability. More precisely, in PISA there are five plausible values for each subject (reading, math 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.

for their children (Schnepf, 2007; Entorf & Lauk, 2008). Together with 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 the educational integration of immigrant students, comparative analysis complements single country analysis. Indeed, comparative studies confirm the relevance of the education level of parents in reducing immigrant score gaps, with huge differences across countries. A comparison of traditional European and non-European countries of immigration shows that the highest effect of family education on scores is in Germany, the UK and the US, whereas intergenerational transmission of educational attainment is less likely in the Scandinavian countries and in Canada. The performance of immigrant students also differs according to the immigration policies adopted by the countries of destination (Entorf & Minoiu, 2005). Evidence on second-generation immigrants in thirteen European countries shows that not only do individual student characteristics matter for academic achievement, but also the macro-characteristics of the country of destination, such as the average educational level and naturalization policies (Dronkers & Fleischmann, 2010). A comparative analysis of ten European countries focusing on the organization of education systems shows that grade retention, where applied, broadens the gap between immigrant children and natives (Park & Sandefur, 2010). A comparison between countries with public education systems and comprehensive curricula with countries with market-oriented education systems and differentiated curricula shows that segregation is favored by differentiated curricula and market-oriented systems (Alegre & Ferrer-Esteban, 2010).

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

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

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

Our study contributes to this literature by investigating how the performance in math of the origin country may affect the score gap with natives of immigrant students in destination countries. Despite the growing interest in 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 the math performance of immigrants as a function of a multiplicity of variables (Levels & Dronkers, 2008), to our knowledge no specific attention has so far been paid to the immigrant-native score gap in math with explicit assumptions to test about its determinants.

3. Empirical Strategy

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

$$Y_{isod} = y_{isod} - \left(\sum_{n=1}^{N_s} y_{ns}\right)/N_s, \tag{1}$$

where y_{isod} is the score in math of immigrant child i from origin country o, enrolled in school s, and assessed in destination country d, y_{ns} is the score of 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:

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

where $MATH_{io}$ is the national average score in math in child i's origin country o, $IMMIG_i$ 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 normally distributed random error.

As for the estimation method, we take into account the fact 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, Beaton, Kaplan, & Sheehan, 1992). There are several possible alternative approaches for making this inference and PISA uses the imputation methodology usually referred to as "Plausible Values" (PVs) (OECDb, 2012). PVs are a selection of likely proficiencies for students that attain 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 school peer effects (Micklewright, Schnepf, & Silva, 2012). Unfortunately, the PISA data do not allow us to conduct the analysis at the class level, the school being the lowest level of observation available. As 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 student performance (Brunello & Rocco, 2013; Ohinata & Van Ours, 2013; Jensen & Rasmussen, 2011; Geay, McNally, & Telhaj, 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 in their composition but also in many 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, and thus replace school fixed effects with destination country fixed effects. In this case, we can control for immigrant concentration using the ratio of immigrant students to the total number of students in the school.

4. Data and variables

As mentioned, 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 at 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 only select 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 that of his/her parents, and its PISA average math score ($MATH_{io}$). PISA only records the country of origin of immigrants for a subset

[5] The analysis is carried out using the “mi” command in Stata (StataCorp, 2013).

of the assessed countries, while for the remaining countries the country of origin of immigrants 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’ countries of origin is available. Second, not every country of origin is assessed by PISA, so we have to further restrict our analysis to immigrants from countries assessed by PISA, so that we can attribute a $MATH_{io}$ to each immigrant student *i*. After this selection, our sample is made up of 13,046 students who are assessed in 31 destination countries and come from 45 origin countries – those represented in Graphs 1 and 2.

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

Table 1. Descriptive statistics

	Mean	Max	Min	Std.Dev
	Immigrant students with recorded origin country			
Score gap (dependent variable)	-11.875	307.100	-337.642	82.483
Math score in the country of origin				
Average Math score in the country of origin	496.467	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	0.456
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; student born in the country of the test as the father, mother abroad (group 4 *)	0.202	1.000	0.000	0.402
Second-generation; student born in the country of the test, mother abroad, father missing (group 5)	0.004	1.000	0.000	0.066
Second-generation; student born in the country of the test, mother abroad as the father (group 6)	0.272	1.000	0.000	0.445
First-generation; student born abroad and parents born in the country of the test (group 7)	0.057	1.000	0.000	0.232
First-generation; student born abroad, mother in the country of the test, father missing (group 8)	0.001	1.000	0.000	0.036
First-generation; student born abroad, mother in the country of the test, father abroad (group 9)	0.030	1.000	0.000	0.171
First-generation; student born abroad, mother born abroad and father in the country of the test (group 10)	0.064	1.000	0.000	0.244
First-generation; student born abroad as well as the mother, father missing (group 11)	0.005	1.000	0.000	0.069
First-generation; student born abroad as well as the parents (group 12)	0.365	1.000	0.000	0.481
Second-generation (OECD definition)	0.275	1.000	0.000	0.447
First-generation (OECD definition)	0.370	1.000	0.000	0.483
Years of school attended in the country of origin	0.960	11.000	0.000	2.205
Interaction (Years of school attended in the country of origin)(country ranking 2)	0.039	9.000	0.000	0.477
Interaction (Years of school attended in the country of origin)(country ranking 3)	0.167	10.000	0.000	0.957
Interaction (Years of school attended in the country of origin)(country ranking 4)	0.351	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
Male student (yes=1, no=0)	0.492	1.000	0.000	0.500
One year or less of preschool (yes=1,no=0)	0.218	1.000	0.000	0.413
Two or more years of preschool (yes=1,no=0)	0.696	1.000	0.000	0.460
Household characteristics				
Computer at home (yes=1,no=0)	0.957	1.000	0.000	0.203
Computer connected with internet at home (yes=1,no=0)	0.952	1.000	0.000	0.213
Number of books at home (6 increasing alternatives between less than 10 and more then 500)	2.969	6.000	1.000	1.490
The language spoken at home is not that of the test (yes=1,no=0)	0.308	1.000	0.000	0.462
Mother in full-time job (yes=1,no=0) (ref. cat. unemployed)	0.471	1.000	0.000	0.499
Mother in part-time job (yes=1,no=0)	0.192	1.000	0.000	0.394
Father in full-time job (yes=1,no=0)	0.735	1.000	0.000	0.441
Father in part-time job (yes=1,no=0)	0.083	1.000	0.000	0.276
Mother education ISCED 2 (yes=1,no=0) (ref. cat. no education)	0.172	1.000	0.000	0.377
Mother education ISCED 3B (yes=1,no=0)	0.092	1.000	0.000	0.289
Mother education ISCED 3A (yes=1,no=0)	0.194	1.000	0.000	0.395
Mother education ISCED 5B (yes=1,no=0)	0.129	1.000	0.000	0.335
Mother education ISCED 5A (yes=1,no=0)	0.213	1.000	0.000	0.409
Father education ISCED 2 (yes=1,no=0) (ref. cat. no education)	0.160	1.000	0.000	0.366
Father education ISCED 2B (yes=1,no=0)	0.100	1.000	0.000	0.300
Father education ISCED 3A (yes=1,no=0)	0.177	1.000	0.000	0.382
Father education ISCED 5B(yes=1,no=0)	0.120	1.000	0.000	0.325
Father education ISCED 5A (yes=1,no=0)	0.226	1.000	0.000	0.418
Index of economic, social and cultural status of the household (ESCS)	-0.274	2.700	-4.220	1.070
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
Class size	26.306	53.000	13.000	8.103
School size	897.622	4925.000	23.000	589.965
Proportion of public funding over the total	88.140	100.000	0.000	22.497
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
External monitoring of teachers	0.287	1.000	0.000	0.453
Ratio of immigrant students in the school (over the total)	0.317	0.955	0.007	0.232
Number of observations**	13,046			

* See Table 2 for the definition of immigration groups.

* *The number of observations for school variables that are recorded for a subsample of the PISA and amounts to about 11,000.

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 math 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 better able to help their children in the new school systems. We therefore introduce $MATH_{io}$, as either an absolute level or a 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 in our sample. In the second and third specifications (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 the quintile of the math ranking in which the origin country of each immigrant child is classified. In the last specification, the top-rank quintiles 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- and second-generation immigrant students. To test our working hypotheses 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 adopt to impute $MATH_{io}$. In detail, 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' places of birth are different we take the mother's 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 the education level of mothers is more important than that of fathers for the school attainment of children,[7] it is a stylized fact emerging

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

[7] For example, Chevalier, Harmon, O'Sullivan, & Walker, (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.

from time use surveys (e.g. HETUS, ATUS and MTUS)[8] that mothers spend more time than fathers with their children.

Table 2. Immigration groups and imputed average math score according to the place of birth of the student and 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

* The OECD only defines as immigrants two groups: group 6 of second-generation immigrants; group 12 of first-generation immigrants.

Following these criteria, native children are those who (together with their parents or mothers) are born in the country of the test. They can be distinguished into three groups: group 1 includes children who both they themselves and their parents were born in the country of the test; group 2 includes children who were born in the country of the test and for whom information about the father is missing; group 3 includes children born in the country of the test from a mixed couple in which the mother is from the country of the test. As mentioned, the scores of native students are used to calculate the score gap when they are in the same school as immigrant children, while they are not included in the regression sample. Second-generation immigrant children are those who were born in the country of the test and whose mother, at least, was born abroad. They can also be divided into three groups: group 4 comprises children born in the country of the test from a mixed couple in which the mother was born abroad and the father in the country of the test;

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

group 5 contains children born in the country of the test and for whom it is known that the mother was born abroad, while information about the father is missing. Group 6 represents children born in the country of the test from parents who were both born abroad. The $MATH_{io}$ given to 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 were born abroad and whose parents may have been born either abroad or in the country of the test. Group 7 contains children born abroad from parents born in the country of the test; group 8 comprises children born abroad with the mother born in the country of the test and information on the father is missing, while group 9 represents children whose father and they themselves were born abroad, while the mother was born in the country of the test. Groups 10, 11 and 12 cover children born abroad from a mother born abroad and a father born in the country of the test, abroad or with missing information respectively. To all these so-defined first-generation students, the $MATH_{io}$ attributed is that of the child's country of birth. The OECD definition of first-generation immigrant students only includes those in our group 12. Table 1 shows that immigrant students identified by the OECD definition only correspond to 64 per cent (group 6 plus group 12) of the students covered by our comprehensive definition.

In our control strategy, three groups of variables are included: student characteristics, household characteristics and the GDP per capita of the country of origin. The first of these 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), which allows us to calculate the number of years of school attendance in the country of origin. As for 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 the performance of immigrant students is not attributable to the economic development of these countries.[9]

5. Results

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

As mentioned in the Introduction, in PISA 2012 the disadvantage that immigrant students experience in math 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 points (Table 1), while in reading it is equal to -14.54 points.

Table 3 shows the estimated coefficients of equation (2). In both specifications (columns (1) and (2)) we control for immigration characteristics, student characteristics 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, to interpret the value of the coefficients it should be born in mind that on average the gap is a negative number. Therefore, the larger its absolute value, the larger 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 coefficient of $MATH_{io}$ is positive and statistically significant. Ten score points more for the country of origin make the disadvantage decrease by 4 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 in group 12, i.e. those both of whose parents and they themselves were born abroad, (which correspond to the OECD definition of first-generation immigrants), all the other groups are less disadvantaged with respect to natives. This is true except for group 5 (in column (2) of Table 3), who are the students born in the country of the test with the mother born abroad and no information is available for the father. The most advantaged are the first-generation students whose mother was born in the country of the test and whose father was born abroad (around +13 score points, group 9, col. 2). This evidence shows that when the mother is born in the country of the test integration is easier. One year of school attended in the country of origin decreases the absolute value of the score gap by 2.5 score points.

[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." OECD b, 2013.

[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.

Other variables that reduce the disadvantage are age, being male (in line with most of the 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. Instead, the only household variable that increases the disadvantage is the father working part-time, probably because the father's work position acts as a proxy for income.

In order to better disentangle the effects of $MATH_{i,oc}$, we transform it in quintiles. Table 4 shows the estimates of the effect of the math ranking of the country of origin on the immigrant-native score gaps. In col. (1) around 47 score points (more than the one year of schooling, 40.8 score points on the PISA math scale), and in col. (2) around 36 score points separate the students in the fifth quintile from those in the lowest quintile. The coefficients of the other variables do not vary significantly with respect to the previous specification.

In addition, in Table 5 we test the hypothesis that the advantage also depends on the interaction of the math rank quintiles with the number of years attended in the country of origin. These interaction terms have positive and significant coefficients for the top quintiles (column 1 and column 2). Being in the fifth quintile and having attended school for one year in the country of origin decreases the absolute value of the score gap by a coefficient ranging from around 55 points to around 52.

Table 3

Immigrant-native score gap in math and math score of the country of origin

Fixed effects estimates.

	Coefficient (col.1)		*s.e*	Coefficient (col.2)		*s.e*
Math score of the country of origin	**0.400**	***	*0.068*	**0.298**	***	*0.064*
Immigration characteristics						
Second-generation, Group 4	10.339	*	*5.172*	3.848		*5.113*
Second-generation, Group 5	-15.084		*22.022*	-7.015		*19.345*
Second-generation, Group 6	4.232		*3.820*	4.471		*3.990*
First-generation, Group 7	6.145		*8.080*	0.536	*	*8.7*
First-generation, Group 8	-7.130		*27.008*	3.843		*23.036*
First-generation, Group 9	17.770	**	*8.904*	13.136		*8.739*
First-generation, Group 10	6.919		*5.025*	6.077		*4.968*
First-generation, Group 11 (ref. category Group 12)	-11.135		*11.795*	2.455		*13.598*
Years of school attended in the country of origin	2.587	***	*0.702*	2.509	***	*0.680*
Student characteristics						
Age	12.210	***	*4.125*	12.359	***	*4.276*
Male	19.295	***	*2.742*	21.134	***	*2.651*
One year or less of preschool	-0.787		*5.823*	-5.776		*5.723*
Two or more years of preschool	22.867	***	*5.478*	15.190	***	*5.193*
Household characteristics						
Computer at home				13.596	*	*6.925*
Computer connected with internet at home				0.494		*7.601*
Number of books at home (a)				11.635	***	*1.195*
The language spoken at home is not that of the test				10.470	***	*3.116*
Mother in full-time job (ref. cat. unemployed)				0.726		*2.540*
Mother in part-time job				2.948		*3.837*
Father in full-time job (ref. cat. unemployed)				3.404		*3.560*
Father in part-time job				-9.947	**	*4.837*
Mother education ISCED 2 (ref. cat. no education)				-0.706		*3.734*
Mother education ISCED 3B				5.126		*4.736*
Mother education ISCED 3A				7.833	*	*4.024*
Mother education ISCED 5B				15.849	***	*5.376*
Mother education ISCED 5A				13.665	***	*4.937*
Father education ISCED 2 (ref. cat. no education)				8.158	**	*3.455*
Father education ISCED 2B				10.147	**	*4.759*
Father education ISCED 3A				7.735	*	*4.061*
Father education ISCED 5B				6.861		*5.111*
Father education ISCED 5A				7.318		*4.838*
GDP of the country of origin						
Log of GDP (ppp)	11.755	***	*3.929*	7.081	*	*3.904*
School fixed effects (within regression)	YES (no. schools: 3362)			YES (no. schools: 3318)		
Constant	-551.46	***	*83.888*	-514.886	***	*85.106*
N. of observations	13029			12747		
Max no. of obs. per school (min.: 1)	152			148		
Rho (fraction of variance due to u_i)	0.41			0.42		

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.

Estimation is performed separately for each of the five plausible values. The results are then combined with Multiple Imputation.

Estimations are weighted using school weights.

Table 4. Immigrant-native score gap in math and math-rank of the country of origin

Fixed effects estimates

	Coefficient (col.1)		*s.e*	Coefficient (col.2)		*s.e*
Math-rank 2 (ref.: Math-rank 1)	**10.068**		*9.507*	**10.121**		*9.449*
Math-rank 3	**12.513**		*7.982*	**12.813**	*	*7.679*
Math-rank 4	**43.689**	***	*10.003*	**35.302**	***	*9.309*
Math-rank 5	**47.324**	***	*12.542*	**36.993**	***	*12.207*
Immigration characteristics						
Second-generation, Group 4	11.096	**	*5.184*	4.604		*5.157*
Second-generation, Group 5	-9.845			-3.833		*18.903*
Second-generation, Group 6	8.455	**	*4.197*	6.928		*4.282*
First-generation, Group 7	7.383		*8.079*	1.241		*8.720*
First-generation, Group 8	-4.966		*26.725*	4.378		*23.224*
First-generation, Group 9	18.466	**	*8.945*	13.639		*8.758*
First-generation, Group 10	6.959		*5.024*	6.264		*4.981*
First-generation, Group 11 (ref. category Group 12)	-11.953		*11.881*	1.429		*13.471*
Years of school attended in the country of origin	2.748	***	*0.705*	2.620	**	*0.686*
Student characteristics						
Age	12.513	***	*4.090*	12.704	***	*4.227*
Male	19.296	***	*2.697*	21.128	***	*2.616*
One year or less of preschool	-1.663		*5.837*	-6.076		*5.685*
Two or more years of preschool	21.843	***	*5.393*	14.777	***	*5.097*
Household characteristics						
Computer at home				13.944	**	*6.925*
Computer connected with internet at home				0.824		*7.567*
Number of books at home (a)				11.524	***	*1.175*
The language spoken at home is not that of the test				12.619	***	*3.319*
Mother in full-time job (ref. cat. unemployed)				1.751		*2.522*
Mother in part-time job				3.614		*3.850*
Father in full-time job (ref. cat. unemployed)				3.945		*3.595*
Father in part-time job				-9.404	*	*4.802*
Mother education ISCED 2 (ref. cat. no education)				-1.288		*3.730*
Mother education ISCED 3B				3.637		*4.800*
Mother education ISCED 3A				6.202		*4.082*
Mother education ISCED 5B				13.799	**	*5.474*
Mother education ISCED 5A				11.696	**	*4.991*
Father education ISCED 2 (ref. cat. no education)				7.362	**	*3.448*
Father education ISCED 2B				9.349	**	*4.748*
Father education ISCED 3A				6.945	*	*4.021*
Father education ISCED 5B				6.229		*5.132*
Father education ISCED 5A				5.865		*4.885*
GDP of the country of origin						
Log of GDP (ppp)	-0.947		*4.180*	-1.905		*4.040*
School fixed effects (within regression)	YES (no. schools: 3362)			YES (no. schools: 3318)		
Constant	-254.588	***	*75.354*	-303.032	***	*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)	0.40			0.41		

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.
Estimation is performed separately for each of the five plausible values. The results are then combined with Multiple Imputation.
Estimations are weighted using school weights.

Table 5.

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

Fixed effects estimates.

	Coefficient (col.1)	*s.e*	Coefficient (col.2)	*s.e*
Math-rank 2 (ref.: Math-rank 1)	**6.108**	*9.847*	**5.875**	*9.810*
Math-rank 3	**7.144**	*8.315*	**7.434**	*7.906*
Math-rank 4	**37.932** ***	*9.924*	**30.092** ***	*9.428*
Math-rank 5	**40.296** ***	*12.591*	**30.568** **	*12.283*
Years of school attended in the country of origin*Math-rank 2	**5.193**	*3.599*	**5.317**	*3.695*
Years of school attended in the country of origin*Math-rank 3	**6.891** **	*3.069*	**6.753** **	*3.142*
Years of school attended in the country of origin*Math-rank 4	**6.444** *	*3.179*	**5.523**	*3.196*
Years of school attended in the country of origin*Math-rank 5	**9.862** ***	*3.081*	**8.642** **	*3.127*
Immigration characteristics				
Second-generation, Group 4	9.112	*5.458*	3.094	*5.388*
Second-generation, Group 5	-11.374	*20.964*	-5.132	*19.033*
Second-generation, Group 6	6.671	*4.268*	5.711	*4.321*
First-generation, Group 7	6.063	*8.218*	0.203	*8.835*
First-generation, Group 8	-7.345	*26.700*	2.267	*23.483*
First-generation, Group 9	17.241 *	*9.001*	12.554	*8.862*
First-generation, Group 10	6.957	*5.028*	6.257	*4.972*
First-generation, Group 11 (ref. category Group 12)	-12.012	*12.028*	0.893	*13.607*
Years of school attended in the country of origin	-5.311 *	*2.716*	-4.580	*2.711*
Student characteristics				
Age	12.244 ***	*4.089*	12.482 ***	*4.232*
Male	19.347 ***	*2.683*	21.187 ***	*2.601*
One year or less of preschool	-2.120	*5.766*	-6.451	*5.649*
Two or more years of preschool	21.460 ***	*5.396*	14.524 ***	*5.120*
Household characteristics				
Computer at home			13.832 *	*7.007*
Computer connected with internet at home			1.255	*7.549*
Number of books at home (a)			11.460 ***	*1.190*
The language spoken at home is not that of the test			12.530 ***	*3.335*
Mother in full-time job (ref. cat. unemployed)			1.892	*2.516*
Mother in part-time job			3.663	*3.829*
Father in full-time job (ref. cat. unemployed)			3.381	*3.646*
Father in part-time job			-9.632 **	*4.834*
Mother education ISCED 2 (ref. cat. no education)			-1.205	*3.741*
Mother education ISCED 3B			3.862	*4.804*
Mother education ISCED 3A			6.171	*4.126*
Mother education ISCED 5B			13.666 **	*5.481*
Mother education ISCED 5A			11.611 **	*5.056*
Father education ISCED 2 (ref. cat. no education)			7.292 **	*3.445*
Father education ISCED 2B			9.816 **	*4.707*
Father education ISCED 3A			6.765 *	*3.994*
Father education ISCED 5B			6.293	*5.121*
Father education ISCED 5A			5.582	*4.822*
GDP of the country of origin				
Log of GDP (ppp)	0.900	*4.192*	-0.380	*4.112*
School fixed effects (within regression)	YES (no. schools: 3362)		YES (no. schools: 3318)	
Constant	-261.876 ***	*75.630*	-308.188	*76.774*
Max no. of obs. per school (min.: 1)	152		148	
N. of observations	13029		12747	
Rho (fraction of variance due to u_i)	0.40		0.41	

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.

Estimation is performed separately for each of the five plausible values. The results are then combined with Multiple Imputation.

Estimations are weighted using school weights.

Finally, we try to disentangle the direct from the indirect advantage of coming from a country with a good performance in math. To this end, we re-estimate the model on the subsamples of first generation students with no schooling in the country of origin, first-generation students with some schooling in the country of origin, and second-generation students. Table 6 shows the results. Using the math score of the country of origin as regressor, second-generation students seem to be 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 math score of the country of origin of the mother is far from negligible. However, the coefficients of the specification with the math-ranks (Table 6, lower panel) are not statistically significant. This means that, when the effect of the math performance of the country of origin is only mediated by the mother's background, it can only be captured by the continuous math-score variable. Looking at the first generation, those who benefit more from coming from a highly-ranked country in math are those who have studied there (compare the coefficients of columns 1 and 2, Table 6, lower panel). 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, the coefficients are not only statistically significant but also the biggest in size (+70 and +65; the F test does not reject the null).

Table 6.

Sub samples of first- and second-generation immigrants

Fixed effects estimates.

	Coefficient		s.e	Coefficient		s.e	Coefficient		s.e
	First-generation: no school in the country of origin			First-generation: some school in the country of origin			Second-generation		
First specification:									
Math score of the country of origin	0.215	*	*0.111*	0.396	**	*0.181*	0.551	***	*0.196*
Years of school attended in the country of origin	-		-	3.544	***	*1.127*	-		-
Second specification:									
Math-rank 2 (ref.: Math-rank 1)	13.550		*27.980*	4.052		*35.690*	8.038		*16.634*
Math-rank 3	0.694		*11.446*	35.733		*22.590*	12.160		*18.128*
Math-rank 4	42.752	***	*15.867*	70.241	**	*27.239*	30.990		*19.838*
Math-rank 5	15.600		*33.873*	65.466	**	*29.151*	29.414		*22.656*
Years of school attended in the country of origin				3.625	***	*1.151*			
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.
Estimation is performed separately for each of the five plausible values. The results are then combined with Multiple Imputation.
Estimations are weighted using school weights.

5. 1 Robustness checks

The PISA dataset is rich in 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 attended by immigrant *i* in 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 others are specific for teaching math. 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, and percentage of public funds in the funding of the school. In the latter group are the student/math teacher ratio[12] and a dummy recording whether there is ability grouping for math. Since school characteristics are available for only a subset of students in PISA,[13] 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. [14]

Table 7. Robustness checks. Immigrant-native score gap in math and effort in teaching math in schools.

Fixed effects estimates.

	Coefficient (col.1)	*s.e*	Coefficient (col.2)	*s.e*	Coefficient (col. 3)	*s.e*
Math score of the country of origin	**0.254** ***	*0.056*				
Math-rank 2 (ref.: Math-rank 1)			**15.421** **	*5.933*	**14.901** **	*5.604*
Math-rank 3			**34.208** ***	*5.502*	**32.621** ***	*6.314*
Math-rank 4			**43.356** ***	*8.387*	**41.630** ***	*8.968*
Math-rank 5			**39.408** ***	*7.516*	**33.195** ***	*8.448*
Years of school attended in the country of origin*Math-rank 2					**0.773**	*3.560*
Years of school attended in the country of origin*Math-rank 3					**2.489**	*2.014*
Years of school attended in the country of origin*Math-rank 4					**3.101** *	*1.586*
Years of school attended in the country of origin*Math-rank 5					**6.020** **	*2.335*
Student-mathematics teacher ratio	**0.023** **	*0.011*	**0.021** *	*0.010*	**0.022** **	*0.010*
Index of ability grouping in mathematics classes	**-2.777**	*3.121*	**-2.922**	*3.005*	**-3.098**	*3.035*
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	-350.135 ***	*69.630*	-196.870 **	*81.550*	-204.656 **	*84.176*
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.
Estimation is performed separately for each of the five plausible values. The results are then combined with Multiple Imputation.
Estimations are weighted using school weights.

The Pisa index of Economic, Social and Cultural Status (ESCS) provided by the OECD is a synthetic index that summarizes the socio-economic status of the family. We re-estimate our baseline model substituting this index for the household characteristics in 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 though the ESCS

[12] This was obtained by dividing the school size by the total number of mathematics teachers.
[13] In order to avoid asking all children too many questions, each set of questions regarding school characteristics is asked to different rotated sub-samples of children (see OECD 2012b).
[14] Except for the student/math teacher ratio, which has a counterintuitive sign.

index has been constructed to take account of additional aspects with respect to our previous specification (e.g. household wealth, and the time and resources devoted to cultural activities by the family), the coefficients of our variables of interest remain as significant as before.

Table 8. Robustness checks: Immigrant-native gap in performance in math and index of economic, social and cultural status of the household.

Fixed effects estimates.

	Coefficient (col.1)		*s.e*	Coefficient (col.2)		*s.e*	Coefficient (col. 3)		*s.e*
Math score of the country of origin	**0.337**	***	*0.061*						
Math-rank 2 (ref.: Math-rank 1)				**15.113**		*9.287*	**10.554**		*9.708*
Math-rank 3				**15.791**	*****	*8.052*	**9.995**		*8.481*
Math-rank 4				**40.237**	*******	*9.713*	**34.216**	*******	*9.756*
Math-rank 5				**45.772**	*******	*12.252*	**38.803**	*******	*12.351*
Years of school attended in the country of origin*Math-rank 2							**6.002**		*3.776*
Years of school attended in the country of origin*Math-rank 3							**7.116**	******	*3.122*
Years of school attended in the country of origin*Math-rank 4							**7.122**	******	*3.266*
Years of school attended in the country of origin*Math-rank 5							**9.581**	*******	*3.209*
Index of economic, social and cultural status of the household-ESCS	**12.546**	***	*1.431*	**11.468**	*******	*1.405*	**11.242**	*******	*1.405*
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	-460.058	***	*84.229*	-225.897	**	*76.846*	-230.908	**	*77.282*
N. of observations	12907			12907			12907		
Max no. of obs. per school (min.: 1)	149			149			149		
Rho (fraction of variance due to u_i)	0.406			0.400			0.427		

Notes. * 0.05<p<=0.1; ** 0.01<p<=0.05; *** p<=0.01. Robust (vce) standard errors in italic.
Estimation is performed separately for each of the five plausible values. The results are then combined with Multiple Imputation.
Estimations are weighted using school weights.

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

Table 9. Robustness checks. Immigrant-native gap in performance in math estimated using the OECD definition of first- and second-generation.

Fixed effects estimates.

	Coefficient (col.1)	*s.e*	Coefficient (col.2)	*s.e*	Coefficient (col. 3)	s.e
Math score of the country of origin	**0.279** ***	*0.072*				
Math-rank 2 (ref.: Math-rank 1)			**5.943**	*12.754*	**3.145**	*13.159*
Math-rank 3			**10.055**	*8.293*	**5.243**	*8.372*
Math-rank 4			**33.362** ***	*10.336*	**29.290** ***	*10.593*
Math-rank 5			**40.681** ***	*14.620*	**34.082** **	*14.331*
Years of school attended in the country of origin*Math-rank 2					**1.105**	*4.101*
Years of school attended in the country of origin*Math-rank 3					**5.717** *	*3.240*
Years of school attended in the country of origin*Math-rank 4					**3.862**	*3.382*
Years of school attended in the country of origin*Math-rank 5					**7.399** **	*3.228*
Student characteristics	YES		YES		YES	
Household characteristics	NO		NO		NO	
Log of GDP (ppp)	YES		YES		YES	
School fixed effects	YES		YES		YES	
Constant	-451.478 ***	*97.910*	-246.218 **	*94.139*	-251.337 **	*94.220*
N. of observations	8167		8167		8167	
Max no. of obs. per school (min.: 1)	131		131		131	
Rho (fraction of variance due to u_{ij})	0.439		0.432		0.435	

Notes. * 0.05<p<=0.1; ** 0.01<p<=0.05; *** p<=0.01. Robust (vce) standard errors in italic.
Estimation is performed separately for each of the five plausible values. The results are then combined with Multiple Imputation.
Estimations are weighted using school weights.

6 . Concluding remarks

In this paper we have investigated whether first (second) generation students coming from (whose parents come from) countries with a higher performance in math fare better than their immigrant peers coming from lower-ranked countries. More specifically, if language barriers to learning math are lower than to learning how to read and write correctly in a different language, math would be a more portable skill than others, and the disadvantage of immigrant students with respect to natives would be less, especially when the former come from countries that are highly ranked for math. This advantage may come indirectly, from 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 family influence if they arrived in the country of destination before starting school. The supposition that mathematical skills are more portable than language skills is confirmed both when looking at the entire 2012 PISA sample and at the PISA sub-sample used in our analysis.

Furthermore, our results show that students coming from higher score (ranked higher) countries of origin have significantly lower score gaps in absolute value, thus being relatively less disadvantaged. Coming from a country in the top quintile in math and having attended school there for at least one year improves the absolute value of the score gap by nearly 39 points. Moreover, the size of the positive coefficients of the fourth and fifth math ranking quintiles are higher than the coefficients of all the other variables that reduce the gap, such as being male, years of preschool, parental education level and the more general socio-economic status of the family. Those who benefit more from coming from a highly ranked country for math are those who have studied there. In particular, the absolute value of the score gap for first-generation students who studied in a country ranked in the fourth or fifth quintile improves by 70 and 65 points respectively.

Finally, our results have some implications for policy. On the one hand, if immigrant students' performance in math is less unequal than in reading and writing, education programs for integration should mainly concentrate on improving the learning of language skills. On the other hand, since the evidence we have presented confirms the portability of mathematical skill across countries, math may be a tool to improve and speed up the integration process. Integration is, in fact, a prerequisite for any learning process. To conclude, math is not only important for economic growth and for reducing the gender gap in the labor market, but it also may become crucial for integrating immigrant students into school life and into society as a whole.

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