THE INTERGENERATIONAL TRANSMISSION OF MATH CULTURE

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ABSTRACT. We provide evidence that parents' beliefs about the value of math have a positive impact on children's math scores. This result is robust to the reverse causality that characterizes the relationship between parental attitude and children's performance. Our model is estimated on a sample drawn from PISA 2012 of second-generation students and first-generation students who migrated before starting primary education. We instrument parental attitude with the country of origin math performance. We find that one additional score point in the origin country performance in math increases student performance by 21 percent of one standard deviation of the student math score.

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INTRODUCTION

Over the past decade, the empirical economic literature has made considerable progress in isolating the factors explaining individual educational achievement, thanks to the adoption of increasingly robust identification strategies and richer data sets. These explanatory factors include the institutional characteristics of the educational system and the students' family background.

The funding of schools, the tracking system and the role played by teachers are among the most deeply investigated institutional features. For example, the effects on student achievements of the private or public funding of schools - or, rather, the consequences of the competition between the two systems - have been thoroughly investigated (Urquiola, 2016). Educational systems that adopt early tracking have been compared with those using the comprehensive system (Hanushek and Woessmann, 2006), and the interaction of the two approaches with the family background has been analyzed (Brunello and Checchi, 2007). Moreover, scholars have applied considerable scrutiny to the effect on student outcomes of the student-teacher ratio, together with the processes of teacher recruitment, evaluation, and experience (Rivkin, Hanushek, and Kain (2005); Rockoff (2004); Harris and Sass (2011); Jackson, Rockoff, and Staiger (2014)).

Regarding family background, some studies compare its importance to that of the organization of the school system (see, among others, Hanushek and Woessmann (2011), while some others compare the impact of different institutional arrangements on the intergenerational transmission of educational outcomes (e.g., Black, Devereux, and Salvanes (2005); Schütz, Ursprung, and Wößmann (2008); Hertz et al. (2007)). A family's socioeconomic background encompasses several aspects. Parental education and economic resources are the first factors to be taken into consideration. The higher the parents' level of education is, the more time they spend with their children in activities related to education, the greater their involvement in school activities, and the lower the psychological costs of children in coping with educational effort (Ho, 2010). Wealthier families are able to guarantee their children access to better

quality schools, and - throughout the educational career - their children are better able to borrow money or forgo income (Rothstein and Wozny (2013); Rouse and Barrow (2006)). The family background category includes, together with education and income, several *intangible* factors, such as inherited traits and cultural values, that have recently attracted the attention of researchers (Bisin and Verdier, 2001). Intelligence and personality - so-called *hard* and *soft* skills - are inherited traits that are both relevant for educational outcomes (e.g., Krapohl et al. (2014), Rustichini, Iacono, and McGue (2017)). Moreover, parents transmit different beliefs and values to their children, including the ability to delay gratification and to exert self-control, that have been shown to differ across cultures and to explain school outcomes (Figlio et al., 2016). The most recent analysis of the gender gap in math relies on the possible role played by *intangible* factors. The lower performance of girls has been linked to a lack of confidence, which has been measured by means of questions evaluating the self-efficacy, self-concept and anxiety of students in approaching the subject (OECD (2015); Saarela and Karkkainen (2014)). The idea behind this line of investigation is that self-beliefs have an impact on learning and performance at several levels: cognitive, motivational, affective and decision-making. Specifically, the most recent rounds of surveys on educational achievement, both national and international, contain questions related to students' self-confidence in different subjects of the curriculum and to *subjective norms*, meaning students' perseverance and aspirations. Only recently have a few surveys introduced questions regarding the beliefs and attitudes of parents toward school subjects. The availability of these new pieces of information has stimulated research on the role of these *intangible* factors in explaining the differences in students' outcomes. For example, (Jerrim, 2015) shows that the superior performance of children of East Asian descent in Australia, relative to children of Australian heritage, is in part associated with subjective norms and aspirations that seem to help the former to exert greater effort and achieve better outcomes. (Hsin and Xie, 2014) find that the Asian-American educational advantage, a well-documented phenomenon in the US, is primarily attributable to Asian students exerting greater academic effort and not to advantages in tested cognitive abilities or socio-demographics. Moreover, they

show that the greater academic effort exerted by Asian-American students is ascribable to the parental attitude toward their children's academic efforts. While some studies examine school program in broad terms, other studies focus on the role played by parental attitudes toward a specific subject. In particular, there is growing evidence that the parental attitude toward science, in terms of how much parents value the subject and of the importance they place on it, is relevant for the scientific literacy of their children (Sun, Bradley, and Akers (2012); Perera (2014)); Ho (2010); Ratelle et al. (2005)). In this literature, attention has primarily been devoted to the attitude toward science because of the worldwide emphasis on its importance for technological development and global economic competition (Tucker-Drob, Cheung, and Briley, 2014). In the context of math, to the best of our knowledge, the role of parental attitudes has been investigated only by (Wang, 2004), who includes - among other "home environment factors"- parents' aspirations for their children's math performance in explaining the score gap between Chinese and US students.

From a methodological perspective, however, the latter contributions may suffer from a reverse causality problem because the attitudes of parents can be influenced by the school achievements of their children. In other words, parents could claim that science, or math, is important for the future of their children merely because their children have high grades in these subjects. Similarly, parents may declare that they expect their children to continue studying math or science, and will work in related fields, simply because their children enjoy these subjects.

In this paper, we study the relationship between parental attitudes toward math and children's performance while accounting for this reverse causality problem. In particular, we adopt an original identification strategy based on two pillars. First, we estimate this relationship on a sample of immigrant students drawn from the Programme for International Student Assessment (PISA) 2012; second, we instrument parental attitude with the math performance of the parents'

country of origin, approximated by the PISA country average math score. Our working hypothesis is that parents with an immigrant background will value math according to the culture of their country of origin. Parents coming from countries with high performance in math would assert that this subject is important for the future of their children, e.g., in terms of placement in the job market and for securing a good job, while the same view would not be shared by parents belonging to countries with low performance in math. We focus on second-generation students and on first-generation students who migrated before starting primary education, as performance in math for the parents' countries of origin should not directly affect these students' performance. In fact, these children are born in the country of the test and/or have never attended the schools in the country of ancestry.

Our identification strategy is in line with the *epidemiological approach* (Fernandez, 2012) that studies the variation in outcomes across different immigrant groups residing in a given country. Immigrants presumably differ in their cultures but share a common institutional environment that - in our study - is the school. This circumstance allows one to separate the effect of culture from the institutional environment. This approach has been used to study a variety of issues, including female labor force participation, fertility, labor market regulation, redistribution, growth, and financial development. Similar to our investigation, (Nollenberger, Rodríguez-Planas, and Sevilla, 2016) explore the role of cultural attitudes toward women in determining educational gender gaps in math using this approach. To ascertain if culture matters, they test whether the math gender gap for each immigrant group living in a particular host country (and exposed to the same host country laws and institutions) is explained by measures of gender equality in the parents' country of ancestry. Their results show that the higher the degree of gender equality in the country of ancestry is, the higher the performance of second-generation immigrant girls relative to boys. In contrast to their study, where the degree of gender equality in the parents' country of origin is assumed to directly affect the gender gap in math, we use the math performance in the parents' country of origin to investigate the transmission mechanism of math culture from parents to children.

Our estimates show that parents' beliefs about the value of studying math are an explanatory factor of their children's scores. Parents' beliefs, in turn, are influenced by the average math performance in the country of origin. Thus, our result is robust to the endogeneity between parental attitudes and children's outcomes. Our finding holds after controlling for the school characteristics in the country of destination. This result also holds when we estimate our model to explain the score gap between immigrant and native students. A limitation of our analysis is that children's school outcomes are certainly affected by other unobserved elements, typical of each ethnic group, such as inherited traits, beliefs and values, that go beyond math culture, and that parents also transmit.

EMPIRICAL STRATEGY

We estimate a two-stage least squares (2SLS) model in which the dependent variable is the student's score in math and the main explanatory variable is the parental attitude toward math. As noted above, to address the potential reverse causality problem due to the fact that parents' attitudes may be affected by their children's observed math performance, we instrument the parental attitude. Moreover, we restrict the analysis to a sample of immigrant students who were born either in the country of the test (namely, second-generation students) or in the country of origin but migrated before being exposed to math teaching in the country of ancestry (namely, before primary school age).

The dependent variable, Y_{isod}, is the score in math of immigrant student i from origin country o who is attending school s in destination country d. The equation (second stage) we estimate is the following:

$$Y_{isod} = \alpha + \beta MathPaAtt_{io} + \gamma X_i + \delta S_{id} + \epsilon_{isod} \tag{1}$$

The first stage of the model is the following:

$$MathPaAtt_{io} = a + bMath_{io} + cX_i + dS_{id} + u_{isod} \tag{2}$$

where $MathPaAtt_{io}$ is our index of the attitude toward math of the parents of student i, $Math_{io}$ is calculated as the national average math score of the origin country and represents the instrumental variable, X_i are student and family characteristics, S_{id} are characteristics of the school attended by the student in destination country d, and ϵ_{isod} is a normally distributed random error. The model is estimated by clustering the standard errors by country of destination to account for heteroskedasticity.

Student proficiency in the second stage, Y_{isod}, is not observed, i.e., it represents 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, 2012).[1]

PISA provides five PVs and, to account for the variability induced by PVs, estimation is performed separately for each of the five PVs. We proceed in two steps. First, we estimate the 2SLS model for each PV and save the coefficients and standard errors. [2] Second, these saved results are combined using Multiple Imputation formulae (see Rubin (2004). According to this technique, consistent estimates of the coefficients are obtained by simply averaging the

[1]PVs were developed from Rubin's work on multiple imputations (see Rubin (2004)) to obtain consistent estimates of population characteristics in assessments in which individuals are administered too few items to allow for precise estimates of their ability. PVs are estimates of student ability. Specifically, in PISA, there are five plausible values for each subject (reading, math and science). PVs are imputed values that resemble individual test scores. They are estimated to have approximately the same distribution as the latent trait being measured.

[2]We corrected the standard errors using the formulae in Baltagi (2011).

five 2SLS estimates of each coefficient and correcting standard errors by applying the Rubin formulae. [3]

Thus, for each explanatory variable, the final estimated coefficient is obtained with the following average:

$$\bar{Q} = \frac{1}{m}[\sum_{pv=1}^{m} \hat{Q}_{pv}] \tag{3}$$

where $\bar{Q}$ is the average of the $m = 5$ estimated coefficients, $\hat{Q}_{pv}$, derived from the 2SLS models of the 5 PVs pv of Y_{isod}. Then, the final standard error of each coefficient is obtained with the following formulae:

$$B = \frac{1}{m-1}[\sum_{pv=1}^{m} \hat{Q}_{pv} - \bar{Q}]^2 \tag{4}$$

$$\bar{U} = \frac{1}{m}[\sum_{pv=1}^{m} \hat{U}_{pv}] \tag{5}$$

$$T = \bar{U} + (1 + \frac{1}{m})B. \tag{6}$$

where B is the variance between the imputations, $\hat{U}_{pv}$ is the variance of the coefficient in each pv imputation, $\bar{U}$ is the average variance within the imputations, and T is the total variance (between plus within imputations). The final standard error is then obtained by taking the square root of the total variance T.

[3]We implement this procedure because the MI procedure in STATA is not applicable to 2SLS.

In the first stage, we derive the subjective variable for parental attitude ($MathPaAtt_{io}$) using the information uniquely provided in the 2012 PISA survey. In particular, we exploit a question - described in the next section - intended to ascertain how parents value math with respect to success in the labor market. The answer is articulated in four graded categorical measurements of parental attitude toward math according to which respondents indicate their level of agreement with each statement. We combine them to approximate the single latent factor $MathPaAtt_{io}$. To predict this latent factor, we use Item Response Theory (IRT) and implement a graded response model that uses ordered logistic regression (Samejima, 1969). [4]

DATA AND DESCRIPTIVE STATISTICS

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 specifically targets mathematical skills, with several sections dedicated to this topic. Regarding sample selection, as we conduct our analysis at the micro level of first- and second-generation immigrant students, we only select schools where immigrant students are present. Moreover, to test our research hypothesis, we need the following information: 1) the parental attitude toward math for each immigrant student ($MathPaAtt_{io}$); 2) the country of origin of the parents of each immigrant student, and 3) the PISA average math score of the country of origin ($Math_{io}$). PISA only records the country of origin of immigrants for a subset 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. Thus, first we have to 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, and hence, we have to further restrict our sample to immigrants from countries assessed by PISA to be able to attribute a $Math_{io}$ to each immigrant student. Third, PISA

[4]We use the STATA command GSEM with the OLOGIT option. Traditionally, IRT models are used in educational testing, where responses to test items can be viewed as indirect measures of latent ability. Item response models also apply equally for measurement of other latent traits, such as the parental attitude in our case (Zheng and Rabe-Hesketh, 2007).

collects information on how parents value math with a question with a few statements in the *parents' questionnaire*.[5] Thus, we have to further restrict our sample to students for whom data from the parental questionnaire are available. After this selection, our sample comprises 1,092 students who are assessed in 8 destination countries [6] and come from 18 origin countries. [7]

The variable *Parental attitude toward math* is estimated with the IRT model using the following question from the parental questionnaire[8]: "*We are interested in what you think about the need for mathematics skills in the job market today. How much do you agree with the following statements*":

- "*It is important to have good mathematics knowledge and skills in order to get any good job in today's world*";
- "*Employers generally appreciate strong mathematics knowledge and skills among their employees*";
- "*Most jobs today require some mathematics knowledge and skills*";
- "*It is an advantage in the job market to have good mathematics knowledge and skills*".

Parents can answer by choosing among the following four alternatives: "*strongly agree*", "*agree*", " *disagree*" and "*strongly disagree*". In the IV estimation, this is the variable that we instrumented with the average math score of the parental origin country imputed to each immigrant student.

For student immigration status, our definition of first- and second-generation is different from that adopted by OECD, which defines a student as an immigrant if both parents are present and

[5]This questionnaire should be completed by a parent (or jointly by both parents) of the student, but the information regarding who has effectively answered is not provided. Note that the PISA *students' questionnaire* also asks children how much they think their parents' value math. We prefer to use the answers to questions asked directly to parents to reduce misreporting, which has been shown to be present when children report parental education levels ((Kreuter et al., 2010)).

[6]Belgium, Germany, Hong Kong, Croatia, Korea, Macau-China, Mexico, Portugal.

[7]Brazil, Turkey, the Czech Republic, Greece, Croatia, the USA, Italy, Portugal, France, Ireland, Vietnam, Germany, Canada, the Netherlands, Japan, Macau-China, China-Taipei, Hong Kong China.

[8]This question is placed in Section G of the parents' questionnaire: Mathematics in child's career and job market, question PA14.

were born abroad. As illustrated in the Appendix, we distinguish among eighteen groups, three for natives and fourteen for immigrants. In detail, we select students for whom we have information on the country of birth of one or both parents. Furthermore, when the parents' places of birth differ, we impute the mother's country math score to the immigrant student. This choice is justified by the observation that in several research fields, school success has been considered to be more strongly tied to the role of mothers than to the role of fathers. [9] In the Appendix, we describe the rules we have adopted to impute $Math_{io}$. Our estimation sample includes second-generation immigrants, thus children in categories from 4 to 8, and first-generation students who never studied in the country of origin, i.e., categories 12 and 14 to 17. Actually, PISA records the number of years since migration, which allows us to calculate the number of years of school attendance in the country of origin and to isolate the group of children who migrated before primary school age.

In our control strategy, three groups of variables are included: student characteristics, household characteristics and school characteristics. Student characteristics are age, sex and the distinction between first- and second-generation immigrants. In particular, to check whether being born in the origin country has some effect even if the child has no years of primary schooling in that country, we introduce the dummy *Student born abroad*, which takes value 1 if the child has migrated before primary school age. Moreover, first-generation students may have been enrolled in the pre-school of the country of ancestry. To control for the potential effect of attending pre-school in the country of origin, we also interact *Student born abroad* with the variables for pre-school attendance.

As household characteristics, we control for the family's Economic-Socio-Cultural Status (*ESCS*) index[10] and whether the language spoken at home is that of the test. In the robustness

[9]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, it is a stylized fact emerging from time use surveys (e.g., HETUS, ATUS and MTUS) that mothers spend more time with their children than do fathers.
[10]This synthetic index is provided by PISA.

checks, we replace the *ESCS* index with some of its components such as the parents' employment and education, and the number of books, the presence of a computer and an internet connection in the home. In addition, we are able to control for whether parents work in a math-related job.

As school characteristics, we control for the proportion of math teachers in the total staff and for school size in terms of the number of students. Table 1 shows the list and the descriptive statistics of all the variables used in the analysis.

RESULTS

Table 2 shows the estimated coefficients of equation 1. In both specifications (columns (1) and (2)), we control for student characteristics, household characteristics and immigration status, while in column (2), we add school characteristics in the country of the test. In the first specification (column (1) of Table 2), the coefficient of parental attitude is equal to 64.77 and statistically significant.

The estimated coefficient, b, of the math score of the parents' country of origin in the first stage is equal to 0.010, and it measures the effect of an increase of 1 score point on the parental attitude. The estimated coefficient, β, of the parental attitude is equal to 64.77. If we substitute equation 2 into equation 1, we obtain an increase of 0.64 score points, which is the result of multiplying $\beta * b$. To appreciate this result, we can multiply this effect by 1 standard deviation of the math score of the parents' country of origin, i.e., 44.07 score points. We obtain a final effect of 28.54 score points, which is 28 percent of 1 standard deviation of the student math score (102.56; see Table 1). In the second specification (column (2) of Table 2), although we control for school characteristics in the destination country, this effect continues to hold, and it is equal to 21 percent of 1 standard deviation of the student math score. For an indirect transmission mechanism through parents' math culture, this can be considered a quite substantial effect. An alternative interpretation of the value of the coefficients may rely on the fact that the equivalent

of one year of schooling is 40.80 score points on the PISA mathematics scale. [11] Thus, an increase of 0.64 score points is equal to 1.56 percent of one year of school, a non-negligible effect, as the standard deviation of the math score of the country of origin - in our sample - is equal to 44.07 score points.

All the control variables have the expected signs. Being male has a positive and significant effect on the math score equal to 20.15 points (see column (2) of Table 2). Having been enrolled in a pre-school for two or more years has a positive effect on the math score of approximately 70 score points. Instead, neither *Student born abroad* nor its interaction with pre-school enrollment is ever statistically significant.[12] The latter findings show that the effect of the parental attitude is not differentiated by generation of immigration and that pre-school attendance in the country of origin has no effect.

ESCS has a positive and statistically significant coefficient, while *Language spoken at home* decreases the math score of the student by 34 score points. Among the school characteristics, only *School size* has a positive and statistically significant effect.

Our results allow us to accept our working hypothesis, i.e., that parental attitude could be endogenous to the math score of the children. In fact, the Durbin (1954) and Wu-Hausman (Wu (1974); Hausman (1978)) tests reject the null hypothesis of exogeneity (see the statistics in Table 3). Moreover, the Wald test allows us to reject the null of a weak instrument for the math score of the parental country of origin, with the F statistics being equal to 16.38, i.e., greater than 10, which is the critical value according to the Stock and Yogo (2005) second characterization of weak instruments (see the statistics in Table 3).

We also conducted several checks to verify the robustness of this result. [13] As a first robustness check, we re-estimate the model using the score gap between immigrant and native students

[11]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 (2012).

[12]Data available upon request.

[13]These checks are performed with a simplified procedure exploiting only one of the five PVs provided by PISA. A comparison of the coefficients and standard errors yielded by the multiple imputation procedure described in the Section *Empirical Strategy* with those estimated with only one of the five PVs shows that the differences are minimal. The data are available upon request.

in each school. One might be concerned that the way in which the parental attitude shapes the score of the children differs according to the country of destination of the student, namely where he/her took the test. A possible way to address this concern is to estimate a model with country fixed effects. Unfortunately, we cannot implement this strategy because in our sample there are three countries, out of eight, for which there is a single parental country of origin. This feature of the data entails multicollinearity.[14] Using the score gap is an alternative that allows us to take into account the characteristics of the country of the test. In other words, using the gap, we consider the characteristics of the country of the test via the natives' scores. Specifically, the score gap in math of immigrant student i from origin country o who is attending school s in destination country d, $ScoreGap_{isod}$, is calculated as the difference between immigrant student i's score and the average math score of native students in the school as follows:

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

where $ScoreGap_{isod}$ measures the immigrant-native student score gap, y_{ns} is the score of native student n enrolled in school s, and N_s is the total number of natives in school s. As Table 4 shows, the change in the dependent variable with the adoption of the score gap confirms our result. This result indicates that for 1 standard deviation of the math score of the origin country, the effect amounts to 14.5 percent of 1 standard deviation of the score gap.

As a second robustness check, we re-estimate the model including a dummy variable that controls for parents working in a mathematics-related career. This might have an effect on parental attitudes.[15] As shown in Table 5, this variable positively affects the math score of the child, but the effect related to the parental attitude toward math is still present, and the positive and statistically significant coefficient does not change in magnitude with respect to the main specification presented in Table 3.

[14]The destination country fixed effect is collinear with the national math score of the country of origin in those countries where immigrants have a single origin.

[15]The question reads as follows: "Does anybody in your family (including you) work in a mathematics-related career?"; Section H: Academic and Professional Expectations in mathematics, question PA15.

As a third robustness check, we re-estimate our model substituting detailed household characteristics for the synthetic index ESCS. These characteristics are the parents' employment status, i.e., if the mother and the father are in full-time employment. In addition, to take into account the role that the level of education of the parents may exert on their attitude toward math, we add a dummy for parents having a tertiary education. As Table 6 illustrates, parents' education and employment variables are not significant.

Finally, we performed some robustness checks using alternative specifications of the instrumental variable. First, we re-estimate by adopting a different strategy for instrumenting the parental attitude. Column 1 of Table 7 illustrates the coefficients of the second-stage estimation using two instrumental variables, i.e., the country of origin GDP per capita (in PPP) and the country of origin math score. In column 2 of Table 7, we show estimates when employing as an instrumental variable only the country of origin GDP per capita. In so doing, we seek to verify that our result is not due to the potential positive correlation between a country's performance in math and its economic development. The comparison between columns 1 and 2 allows us to reject the hypothesis that the origin country's economic development is a general indicator of school quality that affects the outcomes of immigrant students in their countries of destination. In fact, parental attitude is still a positive and significant explanatory factor of the children's scores in math in the specification that adopts the country of origin GDP as a second instrumental variable (column 1). On the contrary, it loses its explanatory power in the specification that uses only the country of origin GDP as the instrumental variable (column 2). Note that the first-stage coefficients of GDP are never significant.

Second, one might argue that parental attitude depends on the origin country's performance in math at the time when the parents attended school. The only way to test this hypothesis would be to use the average math performance reported in past PISA surveys, i.e., 2009, 2006, 2003 and 2000, that are plausibly nearer in time to parents' school attendance. Unfortunately, we cannot perform this check because the number of origin countries of parents assessed in PISA

decreases the older the survey is, thereby drastically reducing our sample: e.g., if we use average scores of origin countries in 2000, we are left with approximately 400 observations. As an alternative, we checked that the average math performance values of the origin countries in our sample do not change significantly over time with respect to 2012. This evidence is somewhat reassuring.

CONCLUDING REMARKS

In this paper, we investigated whether parental attitude toward math influences children's performance in this subject. Our results have shown that children's math scores increase if parents believe that it is worth studying math because of its usefulness in the labor market. In particular, an increase of 1 score point in the country of ancestry performance in math has a positive effect on the parental attitude that increases student performance by 21 percent of 1 standard deviation of the student's math score. This finding is robust to the reverse causality issue arising when using parents' beliefs to study children's school outcomes, thanks to the adoption of an original twofold identification strategy. This strategy relies, first, on generations of immigration that have not being exposed to math teaching in the origin country and, second, on instrumenting the parental attitude with math performance in the origin country. Our result continues to hold if we measure this effect in relative terms, namely, on the immigrant-native score gap. With this study, we have provided evidence on the role played by an *intangible factor*, i.e., parental beliefs about the value of a specific competence, in explaining children's school outcomes, a particular aspect of the intergenerational transmission of culture that had to be studied.

TABLE 1. **Descriptive statistics**

Variable	Mean	Std. Dev.	Min	Max
Dependent variables, second stage				
Math score of the student	491.65	102.56	207.60	795.15
Immigrant-native score gap in math	-10.63	74.57	-257.92	230.30
Instruments				
Math score of parents' country of origin	494.30	44.07	391.00	561.00
GDP origin country (per capita, PPP, 1000 dollars)	34.95	17.12	9.08	86.34
Parents' characteristics				
Parental attitude toward math (a)	.61	2.98	-3.97	9.47
Mother with tertiary education (b)	.19	.39	0	1
Father with tertiary education (b)	.21	.41	0	1
Mother has a full-time job (c)	.43	.50	0	1
Father has a full-time job (c)	.74	.44	0	1
Parent in a math-related career (d)	.46	.50	0	1
Students' characteristics				
Student sex (e)	.48	.50	0	1
Student age	15.78	.30	15.00	16.33
One year of pre-school or less	0.11	.31	0	1
Two or more years of pre-school	.82	.38	0	1
Student born abroad (f)	.10	.30	0	1
Households' characteristics				
ESCS (g)	-.33	1.07	-3.74	2.43
Language spoken at home (h)	.22	.41	0	1
Computer at home	.93	.26	0	1
Internet at home	.91	.28	0	1
Number of books at home (i)	2.75	1.41	1	6
School characteristics				
Proportion of math teachers in the school staff	.17	.11	0.00	1.00
School size	885.58	630.39	50	6,800
Number of observations	1,087			

(a) Our calculations, estimated with GSEM (ologit) using information drawn from the parent's questionnaire. (b) Reference categories: all other levels of education and no education. (c) Reference categories: part-time job, not working but looking for a job, other (e.g., home duties, retired).(d) Information drawn from the parents' questionnaire. (e) Percentage of boys. (f) Percentage of first-generation children in the sample (i.e., those who were born abroad but migrated before primary school age). (g) Index of the Economic, Socio and Cultural Status of the family. (h) Percentage of students for whom the language spoken at home is different from that of the test. (i) Categories ranging from 1 to 6 indicating from fewer than 10 to more than 500 books.

TABLE 2. **Student math score: IV estimated model**.

	(1)		(2)	
Second stage: Math score of the student				
Parental attitude toward math	64.77**	(20.34)	45.42***	(7.53)
Student age	0.01	(0.01)	0.00	(0.00)
Student sex (a)	17.12	(9.61)	20.15**	(8.05)
One year of pre-school	58.57*	(29.66)	26.64	(29.57)
Two years or more of pre-school	80.12**	(29.29)	69.86**	(24.73)
Student born abroad	11.31	(20.18)	21.43	(13.38)
ESCS	16.50	(10.25)	20.68**	(7.63)
Language spoken at home	-52.10	(32.42)	-34.11	(23.55)
Proportion of math teachers			190.98	(119.69)
School size			0.03***	(0.05)
First stage: Parental attitude toward math				
Math score of the country of origin	0.010*	(0.005)	0.011**	(0.005)
N	1,087		974	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Dependent variable: math score (mean of the coefficients of the five plausible values). Linear model with IV: parental attitude instrumented with the PISA math score of the country of origin. Standard errors clustered by country of destination and calculated with Rubin's correction.

TABLE 3. **Tests for endogeneity and for weakness of the instrument**

Test of endogeneity					
Durbin (score) chi2(1)	= 79.5393	(p = 0.0000)			
Wu-Hausman F(1,1077)	= 85.0295	(p = 0.0000)			
First-stage regression summary statistics					
Variable	R-sq.	Adjusted R-sq	Partial R-sq.	F(1,1078)	Prob>F
Parental attitude	0.036	0.029	0.020	21.60	0.000
Weakness of the instrument					
2SLS relative bias	10 per cent	15 per cent	20 per cent	25 per cent	
Wald test	16.38	8.96	6.66	5.53	

TABLE 4. **Robustness check: score gap in math**.

Parental attitude toward math	22.28*	(10.22)
Student age	0.00	(0.00)
Student sex	21.14**	(7.84)
One year of pre-school	-2.73	(20.17)
Two years or more of pre-school	10.42	(18.53)
ESCS	3.80	(4.91)
Language spoken at home	-37.10*	(15.86)
Proportion of math teachers	90.24	(91.89)
School size	0.00	(0.00)
Constant	-49.93*	(22.70)
N	974	
$RootMSE^2$	98.40	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Dependent variable: score gap (coefficients of the first plausible value). Linear model with IV: parental attitude instrumented with the PISA score math of the country of origin. Standard errors clustered by country of destination.

TABLE 5. **Robustness check: math score. Controlling for parent in a math-related career**.

Parental attitude toward math	47.96***	(9.71)
Student age	-0.00	(0.00)
Student sex	20.67*	(8.76)
One year of pre-school	32.58	(37.23)
Two years or more of pre-school	68.83*	(28.16)
ESCS	16.96*	(8.27)
Language spoken at home	-38.92	(26.15)
Parent in a math-related career	38.79*	(16.47)
Proportion of math teachers	205.72	(135.26)
School size	0.03***	(0.00)
Constant	329.72***	(19.32)
N	964	
$RootMSE^2$	158.89	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Dependent variable: math score (coefficients of the first plausible value). Linear model with IV: parental attitude instrumented with the PISA math score of the country of origin. Standard errors clustered by country of destination.

TABLE 6. **Robustness check: math score.**
Details of the household socio-economic condition.

Parental attitude toward math	42.65***	(9.25)
Student age	0.00	(0.00)
Student sex	23.10**	(7.64)
One year of pre-school	33.87	(31.71)
Two years or more of pre-school	68.23**	(23.87)
Language spoken at home	-34.53	(23.09)
Mother with tertiary education	3.33	(10.00)
Father with tertiary education	-3.61	(18.66)
Mother full time job	9.46	(11.31)
Father full time job	-6.19	(13.45)
Computer at home	27.36	(18.44)
Internet at home	-31.54	(20.25)
Number of books at home	24.58***	(4.86)
Proportion of math teachers	170.07	(122.31)
School size	0.03***	(0.00)
Constant	291.73***	(46.38)
N	963	
$RootMSE^2$	145.41	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Dependent variable: math scores (coefficients of the first plausible value). Linear model with IV: parental attitude instrumented with the PISA math score in the country of origin. Standard errors clustered by country of destination.

TABLE 7. **Robustness check: math score. GDP as an alternative instrument**.

	(1)	(2)
Parental attitude toward math	45.04***	60.28
	(9.89)	(40.36)
Student age	-0.00	0.00
	(0.00)	(0.01)
Student sex	19.53*	23.48
	(10.16)	(13.28)
One year of pre-school	29.81	37.21
	(24.24)	(35.82)
Two or more years of pre-school	68.34**	70.40*
	(19.73)	(27.85)
ESCS	20.96***	20.17
	(4.65)	(10.57)
Language at home	-34.02*	-44.03
	(13.64)	(41.31)
Proportion of math teachers	184.20**	259.42
	(71.44)	(283.44)
School size	0.030***	0.03**
	(0.007)	(0.01)
Constant	352.987***	329.09***
	(24.477)	(71.20)
First stage: Parental attitude toward math		
Math score of the country of origin	0.014***	
	(0.003)	
GDP (PPP)	0.000	0.000
	(0.000)	(0.000)
N	974	974
$RootMSE^2$		190.07

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Dependent variable: math scores (coefficients of the first plausible value). Linear model with IV: parental attitude instrumented with the PISA math score of the country of origin and the GDP of the country of origin in (1) and with the GDP of the country of origin in (2). Standard errors robust in (1) and clustered by country of destination in (2).

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APPENDIX

TABLE 8. **Imputed average math score according to the student's and parents' countries of birth.**

Cat.	Student birth	Mother birth	Father birth	Imputed Math Score	In the sample
			Natives		
1	Test country	Missing	Test country	Test country	No
2	Test country	Test country	Test country	Test country	No
3	Test country	Test country	Missing	Test country	No
			Second generation		
4	Test country	Test country	Another country	Father country	Yes
5	Test country	Another country	Test country	Mother country	Yes
6	Test country	Another country	Missing	Mother country	Yes
7	Test country	Another country	Another country	Mother country	Yes
8	Test country	Missing	Another country	Father country	Yes
			First generation		
9	Another country*		*	-	No
10	Another country	Test country	Test country	Test country	No
11	Another country	Missing	Test country	Test country	No
12	Another country**	Test country	Another country	Father country	Yes
13	Another country	Test country	Missing	Test country	No
14	Another country**	Another country	Test country	Mother country	Yes
15	Another country**	Another country	Missing	Mother country	Yes
16	Another country**	Another country	Another country	Mother country	Yes
17	Another country**	Missing	Another country	Father country	Yes

* Students who started primary education in the origin country;

** Students who started primary education in the destination country.