THE INTERGENERATIONAL TRANSMISSION OF MATH CULTURE

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ABSTRACT. We study the relationship between three different aspects of math attitude and children's scores accounting for the endogeneity problem that arises when studying attitude and performance. The first aspect we investigate is the parental belief about the importance of math for the future of children in terms of placement in the job market (parental attitude). The second is the student belief that making an effort in mathematics is worth it because it is an useful instrument to find a good job (student instrumental motivation). The third is the student math anxiety. We instrument math attitude with the fact that one of the member of the student's family is working in a math-related career. Our results show that an increase of 1 standard deviation in the parental attitude increases the student performance by more than 40 score points, an increase of 1 standard deviation in the student instrumental motivation increases her score by more than 60 score points, and a decrease of 1 standard deviation in anxiety increases her performance by more than 100 score points. These are large effects, considering that the equivalent of one year of schooling is 40 score points.

JEL Classification: I21, J13, O15

Keywords: Parental beliefs, Math-related career, Math performance, Math Anxiety, Motivations.

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, the students' family background and the interactions between them.

In this literature there is an increasing agreement that the family background' category includes, together with education and income, several *intangible* factors. In comparison with parental income and education tangibility, inherited traits, beliefs and cultural values are factors classified as *intangible*. As example, 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 (Bisin and Verdier, 2001), 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). In the psychology literature, the investigation on how the dimensions of parenting are linked to academic efforts, performances and occupational aspirations of students is quite established, through the adoption of alternative models. One of the basic hypothesis of these models is that parents' values and beliefs are expected to be related with youths' values and beliefs either directly or indirectly via their behaviors. In the first case, parents who value academics should have children who think studying is important. In the second case, parents should translate their values and beliefs into behaviors that help transmitting values and beliefs. A second hypothesis is that in case of a positive identification with one's parents, i.e. when children view one's parent as positive role model, adolescents are more likely to internalize parental values (e.g.Jodl et al. (2001)).

Scholarly attention has primarily been devoted to the attitude toward science and math because of the worldwide emphasis on their importance for technological development and global economic competition (Tucker-Drob, Cheung, and Briley, 2014). According to OECD, an improvement of one-half standard deviation in mathematics and science performance at the individual level implies, by historical experience, an increase in annual growth rates of GDP per capita of 0.87 per cent (OECD (2010), pag. 17). In particular, when looking at the role played by parental attitude toward math on their children performance and aspirations the multifaceted nature of the math attitude construct should be considered. Math attitude has been defined as the cluster of beliefs and affective orientations related to math, such as anxiety, math gender stereotypes, math self-concepts, and attributions and expectations for success and failure in math (Gunderson et al., 2012). Parents and teachers are both considered the primary means for the intergenerational transmission of all these aspects, and attention of scholars has primarily been devoted to the gender gap (Gunderson et al., 2012). In the vast literature on the math gender gap, there is a general agreement that environmental factors are crucial in the development of gender-math attitudes, as well as that the lower performance of girls are linked to a lack of confidence, which can be 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)). Independently from the sex of the students, not only the students' math anxiety but also that of the adults have reach an increasing attention in this debate. Gunderson et al. (2012) and Casad, Hale, and Wachs (2015) have shown that adults' own math anxieties and their beliefs that math ability is a stable trait may have significant impacts on children's development of math attitude. Furthermore, randomized experiments have been conducted and there is first evidence that short numerical problems, delivered through an iPad app, significantly increased children's math achievement across the school year compared to a control group, especially for children whose parents are anxious about math (Berkowitz et al., 2015). Finally, based on a multivariate genetic analysis of two samples of monozygotic and dizygotic twins, there is evidence that mathematical ability has highly specific heritability(Kovas et al., 2007), and that math anxiety has a genetic source (Wang et al., 2014).

In this paper, we investigate the mechanism trough which having parents working in a math-related career contributes to explain children' math performance by affecting intangible factors like parental attitude, children' motivations and anxiety toward math. Our working hypothesis is that parents who are in a math-related career may ease their children approach toward math through at least three channels. First, parents who are in a math-related career may assert that math is important for the future of their children in terms of placement in the job market. In this case, the belief about the relevance of math is not necessarily shared by the children. Second, parents who are in a math-related career might succeed in transmitting this belief, so that children - if asked - would assert that math is an instrument to find a good job. Third, the fact that parents might appear to be more self-confident and relaxed about math when working in a math-related career, might help reducing math anxiety in their offsprings. In all these cases, these beliefs and feelings might encourage children in studying the subject.

From a methodological perspective, investigating the relationship between these intangible factors and children's school achievements may suffer from an endogeneity problem because the former can be influenced by the latter. In other words, parents could claim that math is important for the future of their children merely because their children have high scores in this subject. The same problem emerges when studying the relationship between the student attitudes and their performance. As example, students may declare that math will help them in finding a good job in the future simply because they enjoy the subject. Likewise, if students feel anxious, the scores are doomed to decrease, while anxiety is doomed to increase. To tackle this reverse causality issue, the instrument we adopt for our identification strategy is whether at least one of the student's family member is in a math-related career.

The data we use are from the Programme for International Student Assessment (PISA) 2012, which measures the cognitive achievement of 15 year olds specifically targeting mathematical skills, with several sections dedicated to this topic.

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 fact of being in a math-related career. Thus, our result is robust to the endogeneity between parental attitudes and children's outcomes. Similarly, we find that the students' instrumental motivations positively predict their performance in math, as well as lower levels of math anxiety. One might argue that when parents hold a rather high level of math skill, they are more capable of helping their children with their math homework. In this case the effect on math scores would be conveyed through this channel. We control for this effect and our results continue to hold.

One limitation of our analysis is that children's school outcomes are certainly affected by other unobserved elements such as inherited traits -like personality and intelligence- that parents also transmit. Another limitation is that children's outcomes are not only affected by parents, but also by teachers and peers. While we can control for the latter with school fixed effects, we are not able to control how teachers and peers have affected past school experiences.

Background literature

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, beliefs and cultural values, that have recently attracted the attention of economists (e.g. Rustichini, Iacono, and McGue (2017) and 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).

In the psychology literature, using a sample of North American adolescents, Jodl et al. (2001) give evidence that in the academic domain, parents values predicted youths values directly rather than indirectly through their behaviors. In addition, they show that positive identification was directly related to adolescents values and that parents values predicted adolescents occupational aspirations, via both direct and indirect pathways.

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. Coherently, 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.

As mentioned in the introduction, attention has primarily been devoted to the attitude toward science and math because of the worldwide emphasis on their importance for technological development and global economic competition (Tucker-Drob, Cheung, and Briley, 2014). There is a 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)), while the is little evidence of an intergenerational transfer of preferences for sciences careers. From 2006 PISA data emerges that, among participating countries, only a minority of students who reported that they expected to be working in a science-related career at age 30 also reported having at least one parent in a science-related career. Similarly, in all but four countries the majority of students with parents in a science-related career reported that they did not expect to pursue a science-related career themselves. Students occupational expectations with regard to occupations in science-related areas seem to be largely uninfluenced by whether or not their parents work in science (Oecd, 2007). Sikora and Pokropek (2012) look at these data with the aim of comparing different hypotheses of intergenerational transfer of preferences, and they conclude that in many nations, relevant paternal employment enhances sons' interest in science careers regardless of their field, while maternal employment inspires daughters in fewer countries and this influences tends to be limited to careers in biology, agriculture and health. There is also evidence that young adolescents who expect to have a career in science will be more likely to graduate from college with a science degree, emphasizing the importance of early encouragement (Tai et al., 2006).

In the context of math, the role of parental attitudes has been investigated 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. As said, looking at the role played by parental attitude toward math on their children performance and aspirations requires taking into account the multifaceted nature of the math attitude construct that includes beliefs and affective orientations related to math, such as anxiety, math gender stereotypes, math self-concepts, and attributions and expectations for success and failure in math (Gunderson et al., 2012). Math anxiety, either of the parents or of the children, is probably the factor that has received the largest attention in the most recent contributions of the literature (Gunderson et al. (2012); OECD (2015); Saarela and Karkkainen (2014); Casad, Hale, and Wachs (2015)); Berkowitz et al. (2015); Wang et al. (2014)).

EMPIRICAL STRATEGY

Our benchmark is 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. To address the endogeneity problem due to the fact that parents' attitudes may be affected by their children's observed math performance, we instrument the parental attitude with a dummy variable that indicates whether one of the parents works in a math-related career.

The dependent variable, Y_{is}, is the score in math of student i who is attending school s. The equation (second stage) we estimate is therefore:

$$Y_{is} = \alpha + \beta MathPaAtt_{is} + \gamma X_{is} + \delta_s + \epsilon_{is} \tag{1}$$

where the first stage is:

$$MathPaAtt_{is} = a + bMathcareer_{is} + cX_{is} + u_{is} \tag{2}$$

$MathPaAtt_{is}$ is our index of the attitude toward math of the parents of student i in school s and in the next section we will detail the information used by PISA OECD to build it. $Mathcareer_{is}$ is the IV, a dummy variable equal to 1 if one of the members of the family works in a math-related career, X_i are student and family characteristics, δ_s are the school fixed effects and ϵ_{is} is a normally distributed random error.

Our aim is to measure the influence of parents' relationship with math on children's math outcomes. As for the choice of our instrument, holding a math-related career implies a quite high level of math skill on the part of parents, since PISA defines as math-related those jobs that require studying a math course at a university level. [1] Examples of such careers include math teachers, economists, financial analysts and computer scientists. They also include many science-related careers, such as engineers, weather forecasters, and medical doctors. These are generally good quality jobs, that might shape parental attitudes towards math as a means for guaranteeing higher levels of incomes and job satisfaction to their offspring. Coherently with our line of reasoning, it is also natural to assume that the fact that parents holding a job in a math-related career can affect students' motivation as to the importance of math as an instrument for finding a good job in the labour market. In this case parental attitude would act through the transmission of a 'work role model' that children would imitate. As an alternative test of our hypothesis, we therefore substitute parental attitude toward math with students' instrumental motivation towards math. This variable is constructed using questions asked to students regarding their beliefs about the value of math for placement in the labor market. The model therefore becomes:

$$Y_{is} = \alpha + \beta InstMot_{is} + \gamma X_{is} + \delta_s + \epsilon_{is} \tag{3}$$

where $InstMot_{is}$ is instrumented with $Mathcareer_{is}$ as follows:

$$InstMot_{is} = a + bMathcareer_{is} + cX_{is} + u_{is} \tag{4}$$

We expect that the coefficient of $InstMot_{is}$ might be even larger than the coefficient of $MathPaAtt_{is}$ because $InstMot_{is}$ is more directly correlated with the effort put by children in the study of math.

[1]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.

Finally, we estimate a third alternative model where our focal variable proxying math attitude is a measure of student math anxiety. At variance with the other two measures that might be positive or negative, math anxiety is a characteristic of personality that refers to a negative attitude toward math. We use the same instrument, since, in this case, the fact that parents might appear to be more self-confident and relaxed about math when working in a math-related career, might help reducing this negative feeling in their offsprings. We expect the coefficient of this variable to be the largest one, since anxiety has to do with the sphere of emotions that, in adolescents, might often prevail on rationality.

One may argue that when parents hold a high level of math skill, they are more capable of helping their children with their math homework. In this case the effect on math scores would be conveyed through this channel. To control for this problem, since PISA asks parents whether and how often they help their children with their math homework, we estimate the three alternative models on the sub-sample of children that are hardly ever helped with their math homework.

Student proficiency in the second stage, Y_{is}, 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).[2]

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. [3] 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

[2]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.

[3]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. [4]

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

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

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:

$$B = \frac{1}{m-1}[\sum_{pv=1}^{m} \hat{Q}_{pv} - \bar{Q}]^2 \tag{6}$$

$$\bar{U} = \frac{1}{m}[\sum_{pv=1}^{m} \hat{U}_{pv}] \tag{7}$$

$$T = \bar{U} + (1 + \frac{1}{m})B. \tag{8}$$

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.

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

DATA AND DESCRIPTIVE STATISTICS

The Programme for International Student Assessment (PISA) 2012, which measures the cognitive achievement of 15 year olds, specifically targets mathematical skills, with several sections dedicated to this topic. Our focus is on the variables that measure both parents and students math attitudes. The choice of the instrument, namely the variable recording whether parents have a math-related job, determines the sample selection. In fact this information, as well as parental attitude toward math, is collected in the *parents' questionnaire*, which is administered in a sub-sample of countries.[5] We are therefore obliged to select students for whom data from the parental questionnaire are available.

As for the variable measuring how parents value math, we use the variable *PQMIMP* provided in the 2012 PISA survey. In particular, the variable exploits a question in the parents' questionnaire that intends to ascertain how parents value math with respect to success in the labor market[6] : "*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*". 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: 1) "*It is important to have good mathematics knowledge and skills in order to get any good job in today's world*"; 2) "*Employers generally appreciate strong mathematics knowledge and skills among their employees*"; 3) "*Most jobs today require some mathematics knowledge and skills*"; 4) "*It is an advantage in the job market to have good mathematics knowledge and skills*". The PISA variable *PQMIMP* combines them to approximate the single latent factor that we have used in our estimation for $MathPaAtt_{is}$. As for the variable measuring students instrumental motivation, we use the PISA variable *INSTMOT*. This variable exploits a question in the students' questionnaire that intends to ascertain how student value math with respect to success in the labor market, i.e. "*Thinking about your views on mathematics: to what extent do you agree with the*

[5]Belgium, Chile, Croatia, Germany, Hong Kong, Hungary, Italy, Korea, Macao-China, Mexico and Portugal

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

following statements?". The four graded categorical answers indicate their level of agreement with each statement: 1) "*Making an effort in mathematics is worth it because it will help me in the work that I want to do later on.*"; 2) "*Learning mathematics is worthwhile for me because it will improve my career*"; 3) "*Mathematics is an important subject for me because I need it for what I want to study later on*"; 4) "*I will learn many things in mathematics that will help me get a job*". The PISA variable *INSTMOT* combines them to approximate a single latent factor that we have use in our estimation as $InstMot_{is}$.[7]

As for the variable measuring students anxiety, we use the PISA variable *ANXMAT*. This variable exploits the following question in the students' questionnaire: "*Thinking about studying mathematics: to what extent do you agree with the following statements?*". The five graded categorical answers indicate their level of agreement with each of the following statements: 1)" *I often worry that it will be difficult for me in mathematics classes*"; 2) "*I get very tense when I have to do mathematics homework*; 3)"*I get very nervous doing mathematics problems*"; 4) "*I feel helpless when doing a mathematics problem*"; 5) "*I worry that I will get poor ¡grades¿ in mathematics*". *ANXMAT* combines the answers as in the previous two cases.

For all three variables, parents and students can grade each answer by choosing among the following four alternatives: "*strongly agree*", "*agree*", " *disagree*" and "*strongly disagree*".

To select the sub-sample of children who are never helped by their parents, we have used the answer to the question in the parents questionnaire "*How often do you or someone else in your home help your child with his/her mathematics homework?*". We have then created a dummy variable that takes value 1 when the answer is either "*Never or hardly ever*" or "*Once or twice a year*". The other possible answers are: "*Once or twice a month*", "*Once or twice a week*", "*Every day or almost every day*".

In our control strategy, three groups of variables are included: student characteristics, parents characteristics and household characteristics. Student characteristics are sex, the attendance of

[7] To predict both latent factors PISA uses the Item Response Theory (IRT) model.

the pre-school and whether the student is born abroad. As household characteristics, we control for the family Economic-Socio-Cultural Status (*ESCS*) index[8].

One may argue that the level of parental education might capture part of the effect of the parental attitude towards math. Parental education variables contribute to the synthetic index *ESCS*, but we can not appreciate their specific role in our estimated model. We therefore conduct a robustness check where we replace *ESCS* with Father with high education, Mother with high education, and control for all other variables that enter *ESCS*, with the aim of testing whether the coefficient of *PQMIMP* shows any significant change when introducing parental education explicitly. In a second robustness check we substitute to the two dummy variables with the continuous variable Parents' years of education, that is the sum of parents' number of years of education.

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 the linear model with school fixed effects in column (1); column (2) shows the estimated coefficients of equation 1, i.e. the IV model with school fixed effects, and column (3) shows the estimated coefficients of the IV estimation with school fixed effects for the sub-sample of students who declare that they never of hardly ever are helped with math homework by their parents.

The coefficient of the parental attitude is statistically significant and equal to 4.43 in the OLS model with fixed effects, while in both the instrumented specifications it amounts to approximately 43 score points. Not having been helped in math homework doesn't change the coefficient significantly. The comparison between the OLS and the IV coefficients reveals a large underestimation of the role of the parental attitude in the former model.

The estimated coefficient, b, of the dummy variable indicating that at least one member in the family works in a math-related career in the first stage is equal to 0.19 in the specification of column (2), and 0.18 in that of column (3), and it measures the effect of being in a math-related

[8]This synthetic index is provided by PISA.

career on the parental attitude. A possible 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. [9] Since parental attitude is a standardized variable (see Table 1), an increase of 1 standard deviation of this variable increases the math score of about the equivalent one year of school.

All the control variables have the expected signs. Being male has a positive and significant effect on the math score around 20 points (see column (2) and (3) of Table 2). Having been enrolled in a pre-school for two or more years has a positive effect on the math score between 12.23 and 10.68 points. To be a student with an immigration background reduces the score by more than 9 points. *ESCS* has a positive and statistically significant coefficient.

Our results confirm that parental attitude is 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 Cragg-Donald F statistics being greater than 16.38, which is the critical value according to the Stock and Yogo (2005) second characterization of weak instruments (see the statistics in Table 3).

As Table 4 illustrates, the parental attitude toward math is not a substitute to the parents' education variables. In other words, the effect that we have captured by using the parental attitude toward math variable is different from taking into account either the fact that the mother or/and the father have a high education level (column (1) of Table 4), or their total years of education (column (2) of Table 4).

Table 5 shows the estimated coefficients of equation 3 in column (2) and (3), while column (1) reports the coefficients of the OLS model with school fixed effects. As expected, if the student believes that making an effort in mathematics is worth it because it will help in her future work,

[9] 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).

the positive effect on her score is grater than in the case in which this is a parental belief, not necessarily shared by the child. In fact, in this case the coefficient is equal to 67.20 for the entire sample and 66.77 for the sample of those students who are never or hardly ever helped with math homework, both coefficients being statistically significant and not statistically different. As shown by Table 3, the instrumental motivation variable is endogenous to the math score, and the instrumental variable that we have chosen is not a weak instrument.

As said, the means of transmission of the student instrumental motivation may include, together with the parents, the teachers and the peers too. Said differently, there may exist some unobservable characteristics of the teachers and/or of the peers that contribute -positively or not- to the formation of student's belief, thus affecting her score. Assuming that this effect is equal for all the students of the same school, the adoption of a school fixed effects model allows us to take it into account.

Finally, the estimation of the model in which the main explanatory variable is the measure of the student math anxiety confirms the expected outcome: the estimated coefficient is the grater in size (see Table 6). The sign is negative because the reduction in this feeling predicts the increase in the performance. Comparing column (2) with column (3) of Table 6, one may verify that this is true including or not the students who are never or hardly ever helped with math homework by their parents. Our findings show that math anxiety is the most important channel in explaining the scores of the students. A limitation of our analysis is that we are not able to disentangle the mechanisms trough which a parent in a math-related career may help her child in approaching math with less anxiety. In fact, there are at least three reasons explaining this phenomenon: the first is that the parents themselves are less anxious, thus transmitting a positive feeling in approaching math; second, the positive identification with one or both parents can help the child in being less anxious; third, the transmission of the math anxiety may have a genetic source.

Considering the great interest of scholars in the math gender gap, in Table 7 we show our three main estimations for the different samples of the male and female students. We find that the effects of the parental attitude, of the student instrumental motivation and of the math anxiety hold in both samples. In all cases, however, the effects for male students are larger than those for female students.

Concluding remarks

In this paper, we investigate the relationship between math attitude and student performance. Our results show 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 standard deviation in parental belief has a positive effect on student performance of more than 40 score points. This finding is robust to the endogeneity issue arising when using parents' beliefs to study children's school outcomes, thanks to the adoption of an identification strategy that relies on the fact that at least one member of the student's family is working in a math-related career. Adopting the same identification strategy, we find that an increase of 1 standard deviation in the student belief that making an effort in math helps in the labor market increases her score by more than 60 score points. Finally, we find that a decrease of 1 standard deviation of anxiety increases the score by more than 100 score points. To conclude, with this study we provide evidence on the role played by several *intangible factors* in explaining children's school outcomes, a particular aspect of the intergenerational transmission of math culture that had to be studied.

TABLE 1. **Descriptive statistics**

Variable	Mean	Std. Dev.	Min	Max
Dependent variable				
Math score of the student	480.62	95.51	194.35	821.16
Instrument				
Parents in a math-related career	.46	.50	0	1
Explanatory variables				
Parental attitude toward math	.06	.98	-3.17	1.30
Student instrumental motivation	-.01	.99	-2.30	1.59
Math anxiety	.29	.85	-2.37	2.55
Students' characteristics				
Student sex (male=1)	.49	.50	0	1
One year of pre-school or less	.14	.35	0	1
Two or more years of pre-school	.79	.41	0	1
Student born abroad	.09	.29	0	1
Parents' characteristics				
Father has a full-time job (a)	.72	.45	0	1
Mother has a full-time job (a)	.41	.49	0	1
Father with tertiary education (b)	.59	.49	0	1
Mother with tertiary education (b)	.60	.49	0	1
Highest years of education	12.45	3.65	3	18
Households' characteristics				
ESCS (c)	-.45	1.17	-4.61	3.01
Computer at home	.86	.35	0	1
Internet at home	.82	.39	0	1
Number of books at home (d)	2.79	1.47	1	6
N	33,138			

(a) Reference categories: part-time job, not working but looking for a job, other (e.g., home duties, retired). (b) Reference categories: all other levels of education and no education. (a) Information drawn from the parents' questionnaire. (c) OECD Index of the Economic, Socio and Cultural Status of the family. (d) Categories ranging from 1 to 6 indicating from fewer than 10 to more than 500 books.

TABLE 2. **Student math score and parental attitude toward math**

	(OLS) (1)	(IV) (2)	(IV) (3)
Parental attitude toward math	**4.34*****	**42.67*****	**43.32*****
	(0.41)	(5.17)	(7.01)
Male student (=1)	23.27***	19.99***	21.26***
	(0.81)	(1.11)	(1.48)
One year of pre-school	6.70**	8.53***	8.24***
	(1.88)	(2.35)	(3.17)
Two years or more of pre-school	13.61***	12.23***	10.68***
	(1.73)	(2.14)	(2.99)
ESCS	7.35***	8.36***	10.24***
	(0.47)	(0.62)	(0.89)
Immigrant student (=1)	-6.24**	-9.63***	-9.51***
	(2.15)	(2.38)	(3.13)
School fixed effects	YES	YES	YES
First stage: Parental attitude toward math			
Parents in a math career		0.19***	0.18***
		(0.01)	(0.02)
N	32,548	32,316	18,321

*$p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors in parenthesis clustered by school and calculated with Rubin's correction. Estimation of Column (3) refers to the sub-sample of students who are never or hardly ever helped with math homework by their parents.

TABLE 3. **Endogeneity and identification tests**

Endogeneity tests				
Parental attitude toward math				
Hensen J statistics chi2(1)	72.32	(p = 0.00)		
Student instrumental motivation				
Hensen J statistics chi2(1)	64.96	(p = 0.00)		
Student math anxiety				
Hensen J statistics chi2(1)	57.50	(p = 0.00)		
Weak identification test				
Parental attitude toward math				
Cragg-Donald F Statistic	259.15			
Student instrumental motivation				
Cragg-Donald F Statistic	106.66			
Student math anxiety				
Cragg-Donald F Statistic	51.80			
Stock-Yogo (2005) critical values				
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. **Robusteness checks: parental education**

	(1)		(2)	
	(Coeff.)	(S.E.)	(Coeff.)	(S.E.)
Second stage: Math score of the student				
Parental attitude toward math	43.85***	(5.29)	44.85***	(5.36)
Male student (=1)	21,07***	(1.12)	21,00***	(1.13)
One year of pre-school	6.81**	(2.38)	7.04**	(2.42)
Two years or more of pre-school	12.10***	(2.16)	11.96***	(2.19)
Father with a full time job	1.37*	(1.18)	1.69**	(1.20)
Mother with a full time job	0.95	(1.00)	1.26	(1.02)
Father with high education	3.76***	(1.28)		
Mother with high education	4.15***	(1.41)		
Parents' years of education			0.56***	(0.19)
Computer at home	8.40***	(2.00)	9.36***	(2.02)
Internet at home	-2.42	(1.99)	-2.16	(2.00)
Books at home	8.63***	(0.41)	8.72***	(0.42)
Immigrant student (=1)	-8.44***	(2.38)	-8.21***	(2.42)
School fixed effects	YES		YES	
N	31,736		31,382	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors clustered by school and calculated with Rubin's correction.

TABLE 5. **Student math score and student instrumental motivation**

	(OLS)	(IV)	(IV)
	(1)	(2)	(3)
Student instrumental motivation	**10.33*** **	**67.19*** **	**66.77*** **
	(0.45)	(9.13)	(12.13)
Male student (=1)	20.80***	13.04***	14.93***
	(0.80)	(1.73)	(2.54)
One year of pre-school	6.52***	8.23***	8.11***
	(1.89)	(2.63)	(3.57)
Two years or more of pre-school	14.11***	16.32***	13.61***
	(1.73)	(2.40)	(3.39)
ESCS	7.15***	6.53***	7.31***
	(0.47)	(0.66)	(0.90)
Immigrant student (=1)	-6.84***	-12.15***	-11.80***
	(2.15)	(2.71)	(3.48)
School fixed effects	YES	YES	YES
First stage: Student instrumental motivation			
Parents in a math career		0.12***	0.12***
		(0.01)	(0.02)
N	32,548	32,316	18,321

$*p < 0.05$; $** \; p < 0.01$; $*** \; p < 0.001$. Standard errors in parenthesis clustered by school and calculated with Rubin's correction. Estimation of Column (3) refers to the sub-sample of students who are never or hardly ever helped with math homework by their parents.

TABLE 6. **Student math score and student math anxiety**

	(OLS) (1)	(IV) (2)	(IV) (3)
Student math anxiety	**-26.17*** **	**-107.00*** **	**-101.22*** **
	(0.47)	(15.33)	(19.18)
Male student (=1)	22.00***	1.50***	1.73***
	(0.77)	(3.24)	(4.85)
One year of pre-school	5.37**	3.01	0.03*
	(1.79)	(2.87)	(4.06)
Two years or more of pre-school	12.71***	9.99*	5.07*
	(1.66)	(2.64)	(3.74)
ESCS	6.70***	4.86	5.17*
	(0.44)	(0.76)	(1.07)
Immigrant student (=1)	-6.27**	-7.77	-6.84
	(1.99)	(2.47)	(3.15)
School fixed effects	YES	YES	YES
First stage: Student math anxiety			
Parents in a math career		-0.07***	-0.08***
		(0.01)	(0.02)
N	32,548	32,316	18,321

*$p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors in parenthesis clustered by school and calculated with Rubin's correction. Estimation of Column (3) refers to the sub-sample of students who are never or hardly ever helped with math homework by their parents.

TABLE 7. **Student math score and math attitude by gender**

	Men	Women	Men	Women	Men	Women
Second stage						
Parental attitude	50.30***	34.26***				
	(10.13)	(6.31)				
Student instr. mot.			70.61***	62.16***		
			(15.93)	(12.66)		
Math anxiety					-108.40***	-103.20***
					(25.07)	(22.71)
1 yr of pre-school	4.20	7.15*	10.28*	4.59	2.40	1.97
	(3.78)	(3.29)	(4.17)	(3.56)	(4.43)	(4.02)
2 yrs or + pre-school	9.25*	14.76***	17.82***	14.44***	11.40**	8.06*
	(3.50)	(2.94)	(3.68)	(3.23)	(3.93)	(3.86)
ESCS	8.43***	8.37***	5.29***	7.35***	5.11***	4.41***
	(1.01)	(0.83)	(1.10)	(0.88)	(1.17)	(1.11)
Immigrant student (=1)	-4.83	-12.93***	-8.38	-17.13***	-3.10	-11.77***
	(4.14)	(2.96)	(4.68)	(3.43)	(4.05)	(3.38)
First stage						
Parents in a math career	0.16***	0.22***	0.11***	0.12***	-0.07***	-0.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
School fixed effects	YES	YES	YES	YES	YES	YES
N	15,812	16,504	15,812	16,504	15,812	16,504

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors clustered by school and calculated with Rubin's correction.

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