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Gianna Giannelli and Chiara Rapallini

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PARENTAL OCCUPATION AND CHILDREN'S SCHOOL OUTCOMES IN MATH

GIANNA C. GIANNELLI[1,2], CHIARA RAPALLINI[1]

[1] DEPARTMENT OF ECONOMICS, UNIVERSITY OF FLORENCE, ITALY

[2] IZA, BONN, GERMANY

ABSTRACT. We find a positive relationship between math attitude and students' math scores using data obtained from PISA 2012 and a 2SLS model. Math attitude is approximated by three subjective measures: parental attitude and student instrumental motivation, which assess beliefs about math importance for the job market, and student math anxiety. The presence of one family member in a math-related career is our instrumental variable. Regardless of the proxy that is used for math attitude, an increase of one standard deviation increases the student score by at least 40 points, the equivalent of one year of schooling. (JEL I21, J13, J24)

Keywords: Parental attitude toward math, Student instrumental motivation, Math anxiety, Math-related career, Math scores.

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Corresponding author: Gianna Giannelli, giannelli@unifi.it

I. Introduction

Recent studies of the determinants of educational achievements aim to isolate the effects of the intangible components of family background, such as inherited traits, beliefs and cultural values, from the effects of other determinants, such as parental education and family income (Björklund and Salvanes, 2011). For example, intelligence and personality - respectively referred to as *hard* and *soft* skills - are inherited traits that are 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 exert self-control, that have been shown to differ across cultures and explain school outcomes (Figlio et al., 2016).

In the psychology literature, numerous studies have investigated how the dimensions of parenting are linked to the academic efforts, performances and occupational aspirations of students using both survey data and field experiments. These studies hypothesize that parents aim to transmit their values and beliefs to children through parental behavior. According to this view, in conversations with their children, parents may assert that studying math is relevant for the future and might encourage their children to put more effort into the study of math (Harackiewicz et al., 2012). Another way of transmitting this belief rests on the hypothesis that children internalize values through a positive identification with ones parents, i.e., ones parent is perceived as a positive role model (Jodl et al., 2001).

Among the different school subject areas, scholarly attention has primarily been devoted to attitudes 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 the OECD, an improvement of one-half standard deviation in mathematics and science performance at the individual level implies, by historical experience, an increase in the annual growth rate of GDP per capita of 0.87 percent (OECD, 2010). In particular, the multifaceted nature of math attitude should be considered when analysing its effect on student performance. Math attitude has been defined as the cluster of beliefs and affective orientations related to math, such as math self-concepts, and attributions and expectations for success and failure, math anxiety and math gender stereotypes (Gunderson et al., 2012). Parents and teachers are both considered the primary means for the intergenerational transmission of all these aspects, and the attention of scholars has primarily been devoted to the gender gap (Gunderson et al. (2012); Thompson (2017)). In the vast literature on the math gender gap, scholars generally agree that environmental factors are crucial in the development of gender-math attitudes and that the lower performance of girls is linked to a lack of confidence, which can be measured by means of questions evaluating the self-efficacy, self-concept and anxiety of students when they approach the subject (OECD, 2015a; Saarela and Karkkainen (2014)). Independent from the sex of the student, not only the students' math anxiety but also that of the adults have received 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, some evidence from randomized experiments shows that short numerical problems delivered through an iPad application significantly increases 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 is highly heritable (Kovas et al., 2007), and math anxiety has a genetic source (Wang et al., 2014).

In this paper, we investigate the mechanism through which having parents who work in a math-related career contributes to explaining children's math performance by affecting intangible factors such as parental attitude, children's motivations and anxiety toward math. Our working hypothesis is that parents who are in a math-related career may ease their children's approach to math through at least three channels. First, parents who are in a math-related career in their conversations 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 their children. Second, parents who are in a math-related career might succeed in transmitting this belief, so that the 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 reduce math anxiety in their children. In all these cases, these beliefs and feelings might encourage children to study the subject.

From a methodological perspective, studies on 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/low scores in this subject. The same problem emerges when studying the relationship between student attitudes and their performance. For example, students may declare that math will help them find a good job in the future because they are influenced by their scores. Likewise, student anxiety may be affected by their scores. To address this endogeneity issue, the instrument we adopt for our identification strategy is whether at least one of the student's family members is in a math-related career. We expect this variable to be exogenous with respect to the children's scores.

The data we use are obtained 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 they are in a math-related career. Thus, our result is robust to the endogeneity between parental attitudes and children's outcomes. Similarly, we find that student instrumental motivation positively predicts their performance in math as well as lower levels of math anxiety.

One might argue that when parents possess 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 - for example, 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 this contemporary influence with school fixed effects, we are not able to control how teachers and peers have affected past school experiences.

II. BACKGROUND

Over the past decade, the empirical economic literature has made considerable progress in isolating the factors explaining individual educational achievement due to the adoption of increasingly robust identification strategies and the use of 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 of the private or public funding of schools - or, rather the consequences of the competition between the two systems - on student achievement have been thoroughly investigated (Urquiola, 2016). Educational systems that adopt early tracking have been compared with those using a 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 of the student-teacher ratio on student outcomes as well as teacher recruitment, evaluation, and experience (Rivkin, Hanushek, and Kain (2005); Rockoff (2004); Harris and Sass (2011); Jackson, Rockoff, and Staiger (2014)).

Some studies compare the importance of family background to that of the organization of the school system (see, among others, Hanushek and Woessmann (2011)), while 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 considered. 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 is, 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 their educational career - their children are better able to borrow money or forgo income (Rothstein and Wozny (2013); Rouse and Barrow (2006)). The family background includes education and income and 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 - respectively referred to as *hard* and *soft* skills - are inherited traits that are 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 exert self-control, that have been shown to differ across cultures and explain school outcomes (Figlio et al., 2016).

In the psychology literature, using a sample of North American adolescents, Jodl et al. (2001) provide evidence that in the academic domain, parental values predict youth values directly rather than indirectly through their behaviors. In addition, the study shows that positive identification was directly related to adolescents values, and parents values predict 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. The most recent rounds of surveys on educational achievements, both national and international, contain questions related to student self-confidence in different subjects of school curricula, and *subjective norms* which refer to students' perseverance and aspirations. Only recently, a few surveys have introduced questions regarding the beliefs and attitudes of parents toward school subjects. The availability of this new information has stimulated research on the role of these *intangible* factors in explaining the differences in student 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 rather than advantages in tested cognitive abilities or socio-demographics. Moreover, they show that the greater academic effort exerted by Asian-American students is due parental attitudes toward their children's academic efforts. DeBacker and Routon (2017) establish a causal link between parental expectations regarding education and the educational attainment of children by using a panel data and considering the different household socio-economic backgrounds. In particular, they find that children from lower socio-economic background households are less likely to attain high school and college degrees, but they reject the hypothesis that this is driven by the low subjective expectations of educational success. This is because parents in more disadvantaged households are too optimistic about the educational outcomes of their children, while parents in more advantaged households have more realistic expectations.

Thus far, attention has primarily been devoted to science and math attitudes because of the worldwide emphasis on their importance for technological development and global economic competition (Tucker-Drob, Cheung, and Briley, 2014). There is growing evidence that parental attitudes toward science, in terms of how much parents value the subject and 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 there is little evidence of an intergenerational transfer of preferences for science careers. Similarly, in all but four countries of the PISA 2006 survey, 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, 2017). Sikora and Pokropek (2012) analyze the same data with the aim of comparing different hypotheses related to the intergenerational transfer of preferences, and they conclude that in many nations, paternal employment enhances sons' interest in science careers regardless of their field, while maternal employment inspires daughters in fewer countries, and this influence 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 are more likely to graduate from college with a science degree, emphasizing the importance of early encouragement (Tai et al., 2006).

For 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 to explain the score gap between Chinese and US students. Harackiewicz et al. (2012) find that an intervention designed to help parents convey the importance of math and science courses to their high schoolaged children lead them to take more math and science courses in high school. Math anxiety, either of the parents or of the children, is probably the factor that has received the most attention in the most recent literature (Gunderson et al. (2012); OECD, 2015b; Saarela and Karkkainen (2014); Casad, Hale, and Wachs (2015)); Berkowitz et al. (2015); Wang et al. (2014)).

III. Methods

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 parental attitude toward math. To address the endogeneity problem that occurs because 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 has a math-related career.

The dependent variable, Y_{is}, is the math score 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:

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

$MathPaAtt_{is}$ is our index of the attitude toward math of the parents of student i in school s, and in the next section we describe the information obtained from PISA that is used to build it. X_{is} represents student and family characteristics, δ_s represents the school fixed effects and ϵ_{is} is a normally distributed random error. $Mathcareer_{is}$ is the IV, a dummy variable equal to 1 if one of the members of the family works in a math-related career. Having a math-related career implies that the parents have quite a high level of math skill, since PISA defines a math-related career jobs that require studying a math course at a university level. The question in the parental questionnaire reads as follows: ”Does anybody in your family (including you) work in a mathematics-related career?” [1]. Examples of such jobs 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 influence parents to consider math skills as a means for guaranteeing higher levels of incomes and job satisfaction to their offspring. Our assumption is that having parents that have a job in a math-related career can affect students' motivation regarding the importance of math for finding a good job in the labor market. However, parental attitude *per se* does not necessarily imply that children share the belief about the relevance of math. As another test of our hypothesis, therefore, we substitute parental attitude toward math with students' instrumental motivation toward math. This variable is constructed using the responses to 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:

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

[1] While we know that the parental questionnaire is completed by one or both parents, we do not know which family member has a math-related career. For the sake of simplicity, in the paper, we refer to ”parents have a math-related career” since the role played by another family member can be comparable.

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 exerted by children in the study of math.

Finally, we estimate a third model where our focal variable proxying math attitude is a measure of student math anxiety. Compared with the other two measures, this variable may be either positive or negative because math anxiety is a characteristic of personality that refers to a negative attitude toward math. We use the same instrument, since parents that work in a math-related career might appear to be more self-confident about math, thus reducing this negative feeling in their children. We expect the coefficient of this variable to be the highest, since anxiety has to do with the sphere of emotions that, especially during adolescence, might prevail on rational motivations.

The model therefore becomes:

$$Y_{is} = \alpha + \beta AnxMath_{is} + \gamma X_{is} + \delta_s + \epsilon_{is} \tag{5}$$

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

$$AnxMath_{is} = a + bMathcareer_{is} + cX_{is} + d_s + u_{is} \tag{6}$$

One may argue that when parents possess 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 possibility, 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 who were 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, estimations are 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 the multiple imputation formulae (see Rubin (2004)). According to this technique, consistent estimates of the coefficients are obtained by simply averaging the 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:

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

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

$$B = \frac{1}{m-1}[\sum_{pv=1}^{m} \hat{Q}_{pv} - \bar{Q}]^2 \tag{8}$$

$$\bar{U} = \frac{1}{m}[\sum_{pv=1}^{m} \hat{U}_{pv}] \tag{9}$$

$$T = \bar{U} + (1 + \frac{1}{m})B. \tag{10}$$

[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).

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

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.

IV. DATA

PISA 2012, which measures the cognitive achievement of 15 year olds, specifically targets mathematical skills and includes several sections dedicated to this topic. Our focus is on variables that measure the math attitudes of both parents and students. The choice of the instrument, namely the variable indicating 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.

To measure how parents value math, we use the variable *PQMIMP* provided by PISA 2012 which we rename $MathPaAtt_{is}$. 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, and the 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*"; and 4) "*It is an advantage in the job market to have good*

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

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

mathematics knowledge and skills". The PISA variable *PQMIMP* combines these responses to approximate the single latent factor we use in our estimation.[7] 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 students 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 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*"; and 4) "*I will learn many things in mathematics that will help me get a job*". The PISA variable *INSTMOT* combines these responses to approximate a single latent factor that we use in our estimation of $InstMot_{is}$.

To measure student anxiety, $AnxMath_{is}$, 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*"; and 5) "*I worry that I will get poor grades in mathematics*". *ANXMAT* combines the answers as in the previous two cases.

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

To control for the possibility that parents may help their children with math homework, we select the sub-sample of those who were never helped using the following question in the parents questionnaire: "*How often do you or someone else in your home help your child with his/her mathematics homework?*". We then create a dummy variable that takes the value of 1 when the answer is either "*Never or hardly ever*" or "*Once or twice a year*". The other possible answers

[7]To predict a latent factor, PISA uses the item response theory (IRT) model. For scale reliabilities regarding the attitudes toward mathematics indices in PISA 2012 countries, see OECD (2015).

are: "*Once or twice a month*", "*Once or twice a week*", and "*Every day or almost every day*". In our control strategy, three groups of variables are included: student's characteristics, parents' characteristics and household characteristics. Student characteristics include sex, the attendance of pre-school and whether the student is born abroad. For household characteristics, we control for the family's Economic-Socio-Cultural Status (*ESCS*) index[8]. One may argue that the level of parental education plays a crucial role in the determination of parental attitude toward math. Parental education variables contribute to the synthetic index *ESCS*, but we do not evaluate their specific role in our estimated model. We therefore conduct a robustness check where we replace *ESCS* with two dummy variables for having a "Father with tertiary education" or a "Mother with tertiary education" and control for all the other variables in *ESCS*, with the aim of testing whether the coefficient of $MathPaAtt_{is}$ shows any significant change when explicitly introducing parental education. In a second robustness check, we substitute the two dummy variables with the continuous variable "Parents' years of education", which is the sum of the parents' number of years of education. Table 1 lists the variables used in the analysis and their descriptive statistics.

V. 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 their parents never or hardly ever helped them with math homework.

The coefficient of 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. A possible interpretation of the size of the IV coefficients of parental attitude may be that the equivalent of one year of schooling is 40.80 score points on the PISA mathematics scale (OECD, 2012). Since parental attitude is a standardized variable (see Table 1), an increase in this variable of 1 standard deviation increases the math score of about the equivalent of one year of school. Not receiving help with math homework does not significantly change the coefficient. The

[8]This synthetic index is provided by PISA.

OLS coefficient of parental attitude is much smaller than the IV coefficient. A possible interpretation of the underestimation of the OLS coefficient is that since parental attitude is endogenous, it might be negatively correlated with unobserved student characteristics that positively affect the score. Therefore, parental attitude *per se* would increase the score, but the OLS coefficient is reduced by the fact that parental attitude also captures the effects of student characteristics that negatively affect the math score. In other words, the underestimation would suggest that parents declare that math is important when children do not demonstrate much interest or skill in math.

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 career on parental attitude.

All the control variables have the expected signs. Being male has a positive and significant effect on math scores by around 20 points. 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. Being 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 one of the family members in a math-related career because the Cragg-Donald F statistics is higher than 16.38, which is the critical value according to the Stock and Yogo (2005) second characterization of weak instruments.

The explicit introduction of the parents' education level does not significantly change the coefficient of the parental attitude variable (see Table 4). In other words, the effect that we captured by using the parental attitude toward math variable is independent from the fact that the mother or/and the father have a high education level.

Table 5 shows the estimated coefficients of equation 5 in column (2) and (3), while column (1) reports the coefficients of the OLS model. As expected, if the student believes that making an effort in mathematics is worth it because it will help in her future work, the positive effect on her score is greater than in the case in which this is a parental belief, which may 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 were never or hardly ever helped with math homework. Both coefficients are statistically significant and not statistically different. As shown in Table 3, student instrumental motivation is endogenous to the math score, and the instrumental variable that we have chosen is not a weak instrument.

As already noted, the transmission mechanism of the student instrumental motivation includes not only parental attitude but also the attitudes of teachers and peers. Said differently, there may exist some unobservable characteristics of teachers and/or peers that contribute to the formation of the students' beliefs, thus affecting their scores. Assuming that this effect is equal for all the students of the same school, the introduction of school fixed effects allows us to control for it.

Finally, the estimation of the model in which the main explanatory variable measures student math anxiety confirms the expected outcome: the estimated coefficient is the highest (see Table 6). This result holds whether or not the students who were never or hardly ever helped with math homework by their parents are included. One limitation of our analysis is that we are not able to disentangle the mechanisms through which a parent in a math-related career may help her child approach 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 reduce the anxiety of the child; and 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 male and female students. We find that the effects of parental attitude, student instrumental motivation and math anxiety hold in both samples. In all cases, however, the effects for male students are higher than those for female students.

VI. 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 because of the adoption of an identification strategy based 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 in anxiety of 1 standard deviation increases the score by more than 100 score points. To conclude, with this study, we provide evidence on the relevance of some previously unexplored *intangible factors* for explaining children's school outcomes.

TABLE 1. **Descriptive statistics**

Variable	Mean	Std. Dev.	Min	Max
Dependent variable				
Math score of the student (Y_{is})	480.62	95.51	194.35	821.16
Instrument				
Parents have a math-related career ($Mathcareer_{is}$)	.46	.50	0	1
Explanatory variables				
Parental attitude toward math ($MathPaAtt_{is}$)	.06	.98	-3.17	1.30
Student instrumental motivation ($InstMot_{is}$)	-.01	.99	-2.30	1.59
Math anxiety ($AnxMath_{is}$)	.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 has tertiary education (b)	.59	.49	0	1
Mother has tertiary education (b)	.60	.49	0	1
Highest years of education	12.45	3.65	3	18
Household 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 or retired). (b) Reference categories: all other levels of education and no education. (c) OECD Index of the Economic, Socio and Cultural Status of the family. (d) Categories 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 have a math-related 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 appear in parenthesis, are clustered by school and are calculated with Rubin's correction. The estimation of Column (3) refers to the sub-sample of students who were never or hardly ever helped with math homework by their parents. The first stage coefficients refer to the first plausible value.

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 has a full time job	1.37*	(1.18)	1.69**	(1.20)
Mother has a full time job	0.95	(1.00)	1.26	(1.02)
Father has tertiary education	3.76***	(1.28)		
Mother has tertiary 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 are clustered by school and calculated with Rubin's correction.

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

	(OLS) (1)	(IV) (2)	(IV) (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 have a math-related 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 appear in parenthesis, are clustered by school and are calculated with Rubin's correction. The estimation of Column (3) refers to the sub-sample of students who were never or hardly ever helped with math homework by their parents. The first stage coefficients refer to the first plausible value.

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

	(OLS)	(IV)	(IV)
	(1)	(2)	(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 have a math-related 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 appear in parenthesis, are clustered by school and are calculated with Rubin's correction. The estimation of Column (3) refers to the sub-sample of students who were never or hardly ever helped with math homework by their parents. The first stage coefficients refer to the first plausible value.

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 have a math-related 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 are clustered by school and calculated with Rubin's correction.

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