Let the Girls Learn!
It is not *Only* about Math…
It's about Gender Social Norms

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Abstract

Using PISA test scores from 11,527 second-generation immigrants coming from 35 different countries of ancestry and living in 9 host countries, we find that the positive effects of country-of-ancestry gender social norms on girls' math test scores relative to those of boys expand to other subjects (namely reading and science). We further find that gender norms shaped by beliefs on women's political empowerment and economic opportunity affect the gender gaps in test scores in general. Interestingly, gender norms do not seem to particularly influence math-related stereotypes, but instead, preferences for math. Finally, the evidence indicates that these findings are driven by cognitive skills, suggesting that social gender norms affect parent's expectations on girls' academic knowledge relative to that of boys, but not on other attributes for success--such as non-cognitive skills. Taken together, our results highlight the relevance of general (as opposed to math-specific) gender stereotypes on the math gender gap.

Keywords: Gender gap in math, reading and science, beliefs and preferences, second-generation-immigrants, cognitive and non-cognitive skills, culture and institutions.

JEL Codes: I21, I24, J16, Z13

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"Maybe it means telling your sons that it's okay to cry, and your daughters that it's okay to be bossy. Maybe it means encouraging your daughters, not just your son, to study math and science and sign up for the football team. And if there isn't a team for girls, maybe it means asking why not.

That's how all of you will begin to break down those old stereotypes and biases. That's how you'll change the way that women and girls are seen. And that's the kind of work that we need to be doing around the world – the work of changing culture. The work of changing expectations and standards that we have for women and girls."

First Lady of the United States of America, Michelle Obama at the "Let the Girls Learn" conference in Madrid, June 30, 2016

1. Introduction

It has been widely documented that, by the end of elementary school, boys begin to outperform girls in math tests in many industrialized countries and that this gap persists over time—see Bedard and Cho (2010) for a literature review in OECD countries. Much of the evidence has focused on the United States with some recent studies suggesting that the average gender gap in math test scores among teenagers has been narrowing (Hyde and Mertz 2009), and others documenting persisting large differences in the average performance of girls relative to boys (Fryer and Levitt 2010; Penner and Paret 2008). Yet, there is a wide consensus that substantial differences persist at the top of the distribution (Ellison and Swanson 2010; Hyde and Mertz 2009) and that the fraction of males to females who score in the top 5 percent of the distribution in high-school math has remained constant at two to one over the past 20 years (Xie and Shauman 2003).[1] Using PISA data from 40 countries and focusing on students in the upper-half of each country's socio-economic status, Guiso et al. (2008) also document that "*girls' math scores average 10.5 (or 2 percent) lower score points than those of boys"*. Using TIMMS data, Fryer and Levitt (2010) find similar results across 41 different countries.[2]

Aiming at explaining the math gender gap, several studies have found a positive association between the measures of gender equality across countries or regions and the relative performance of girls in mathematics, suggesting the important role of the environment behind the math gender gap (Guiso et al. 2008

[1] Similarly, Cobb-Clark and Moschion (2017) find that, in Australia, boys' stronger performance is most evident in the top half of the achievement distribution and driven by families with high socio-economic status.
[2] Only 17 of 41 countries are included in both TIMMS and PISA datasets.

and Fryer and Levitt 2010; Pope and Sydnor 2010; and González de San Román and de la Rica 2012).[3] Most recently, Nollenberger, Rodríguez-Planas, and Sevilla (2016)—henceforth, NRS 2016—go a step further by providing causal evidence on the importance of "*values and beliefs about women's role in society transmitted from generation to generation*" in determining the gender gap in math test scores, and disentangling the role of gender social norms versus that of a country's institutions and formal practices.[4]

In this paper, we address a different but highly critical and policy-relevant question for the cognitive performance of girls. We analyze the extent to which gender social norms just affect gender gaps in math, or also in other fields. Evidence of the latter would underscore the relevance of general gender stereotypes as opposed to math-specific stereotypes on girls' relative test performance. Examples of general gender stereotypes include: "the best women are stay-at-home moms", "women are supposed to make less money than men", "women are not politicians", "girls have to work hard to learn in school, whereas boys are naturally gifted", or "women are nurses, not doctors". In contrast, examples of math-specific gender stereotypes include: "math is for boys, reading is for girls", "boys are good at math, girls are good at writing", or "it is always men who work at science, engineering and technical fields".

To examine whether gender social norms can explain gender differences in test performance, we follow the same approach as in NRS 2016 and focus on second-generation immigrants who are exposed to the same host country's labor market, regulations, laws and institutions, but are also influenced by the different cultural beliefs of their parents.[5] Evidence that gender equality in the immigrant´s country of ancestry can explain test scores of second-generation immigrants living

[3] Many alternative or complementary explanations have been proposed for gender gaps in test scores as explained in the literature review in Cobb-Clark and Moschion (2017).

[4] NRS 2016 do so by focusing on second-generation immigrants who share the institutions and culture of the country they were born in and raised, but are also influenced by the social norms and beliefs of their parents' country of origin. They find that greater gender equality in second-generation immigrants' country of ancestry decreases the gender gap in math test scores in the country where they were born in and live.

[5] In this paper, second-generation immigrants are defined as individuals born in country they live in to parents (both of them) born in a different country. Throughout the paper, we will refer to the country where each individual is born and lives as their "host country". Given that they are second-generation immigrants, the country where they were born and live is actually the host country of their parents.

in a particular host country would suggest that the preferences and beliefs of the immigrant's ancestors matter and have been transmitted to them by their parents and/or their ethnic community.[6] To identify the effect of culture, we estimate whether the gender gaps in test scores for each immigrant group living in a particular host country is explained by measures of gender equality in the country of ancestry. For this purpose, we merge 2003, 2006, 2009 and 2012 data from PISA and the 2009 World Economic Forum's gender gap index (Hausmann, Tyson, and Zahidi 2009), which reflects economic and political opportunities, education and well-being for women in the country of ancestry.[7]

Using close to 12,000 second-generation immigrants from 35 different countries of ancestry and living in 9 host countries, we first analyze the effect of culture on reading (where girls outperform boys in our sample) and science (where the gender gap is small and not statistically significantly different from zero in our sample).[8] Evidence that the effects of culture expand beyond math suggests that gender social norms are affecting female academic performance more broadly. As shown by Figure 1, which plots gender gaps in test scores in the country of residence against the gender gap index (GGI hereafter) in the country of ancestry, we find that second-generation immigrant girls whose parents come from more gender-equal countries gain an absolute advantage over boys on reading and science, (as well as in math), suggesting that beliefs about women's role in society

[6] Using a similar approach, several studies have examined the effect of culture on different socio-economic outcomes, including savings rates (Carroll, Rhee, and Rhee 1994), fertility and female labor force participation (Antecol 2000; Fernández 2007; Fernández and Fogli 2006, 2009), living arrangements (Giuliano 2007), the demand for social insurance (Eugster *et al.* 2011), preferences for a child's sex (Almond, Edlund, and Milligan 2013); the math gender gap (Nollenberger, Rodríguez-Planas, and Sevilla 2016); divorce (Furtado, Marcén, and Sevilla 2013); and the gender smoking gap (Rodríguez-Planas and Sanz-de-Galdeano 2016).

[7] This is the same index used by Guiso et al. (2008); Fryer and Levitt (2010); Nollenberger, Rodríguez-Planas, and Sevilla (2016); and Rodríguez-Planas and Sanz-de-Galdeano (2016).

[8] A recent study by Cobb-Clark and Moschion (2017) finds that third-grade Australian boys score 9 points lower (the equivalent of 3 months of normal academic progression) in reading than their female classmates and that this underperformance is explained by a relative lack of school readiness and literacy skills in kindergarten. Even though girls' better reading skills are well known in the literature (Buchmann, DiPrete, and McDaniel 2008; Guiso et al. 2008), less is known about gender relative performance and science-test scores. Most of the research on science gender gaps has focused on explaining gaps in science course taking or degree pursuit (see, for example, Ost 2010; Turner and Bowen 1999). Most recently, Quinn and Cooc (2015) find that there is a relatively stable science gender gap in the US between 3rd and 8th grade, which averages -0.19 standard deviations and is slightly larger than the math gender gap (in their sample, -0.12 standard deviations at 8th grade).

affect girls' relative test performance of different subjects alike.[9] More specifically, we find that a one standard deviation increase in the country-of-ancestry GGI is associated with an *increase* of 0.31, 0.34 and 0.29 standard deviation in the reading, science, and math gender gaps, respectively.[10] Because our approach cannot rule out that differences in parental characteristics (unrelated to social gender norms) drive the results, it is certainly comforting that our results do not change much as parental education, labor force participation and home possessions are added to the model. They are also robust to different specification strategies, selective migration, adjustments of standard errors, alternative measures of gender equality, and changes in sample criteria.

Consistent with the hypothesis that more general stereotypes (as opposed to math-specific gender stereotypes) are at play, we find suggestive evidence that country-of-ancestry institutions related to women's political empowerment and economic opportunity (as opposed to education, health and survival) are driving all three gender gaps.

As further evidence that these gender norms effects are driven by general gender stereotypes, we present a math-focused analysis analyzing whether cultural beliefs on the role of women in society affect girls' *beliefs* in their own math abilities ("as I am a girl, I am not good at math"); their beliefs in the institutional constraints she may face ("as I am a girl, math will not help my career prospects");[11] their anxiety on performing in math ("as I am a girl, I am told math is not for me, which generates anxiety and reduces my performance in math"); or their *preferences* regarding math ("as I am a girl, I dislike math") relative to those of boys. We find that girls hold similar beliefs in their *ability* to do math and report similar anxiety when performing math than boys *irrespective* of cultural background. However, we find that girls whose parents come from more gender-equal countries have higher *preferences* for math; to put it differently, they just like math more.

[9] Figure 1 displays the raw relationship between the gender gap in each test score and the Gender Gap Index (GGI) from the World Economic Forum. This relationship persists even after adjusting the gender gap in each test score by individual characteristics and the GDP of the country of ancestry as shown in Appendix Figure A.1.
[10] The math result replicates findings in NRS 2016.
[11] Expected institutional constraints may be driven by actual constraints in the country of ancestry. Note that this is still a story about beliefs, even though beliefs and institutions are closely intertwined.

As we find that parents' gender stereotypes may well affect how much parents push their daughters to learn relative to boys, a different and complementary question is the extent to which our results are driven by cognitive versus non-cognitive skills. Non-cognitive factors, such as an individual's motivation, eagerness to succeed, agreeableness, or ambition, have been recently found to affect human capital accumulation (Cunha, Heckman, and Schennach 2010) as well as labor market outcomes, engagement in risky behaviors and health outcomes (Heckman, Pinto, and Savelyev 2013; Heckman and Rubinstein 2001). Following methodology first introduced by Borghans and Schils (2012), we first measure non-cognitive skills by the rate of decline in performance over the course of the PISA test, and find no evidence that our results are driven by non-cognitive skills. Then, we measure non-cognitive skills as item non-responses on the PISA test (following Hitt, Trivitt, and Cheng, 2016; Zamarro et al. 2016; Zamarro, Hitt, and Mendez 2016), and find no evidence that gender social norms affect girls' non-cognitive skills relative to boys'. Taken together, these findings suggest that social gender norms affect parent's expectations on girls' learning cognitive skills, but not necessarily on other attributes for success.

Our work contributes to findings from NRS 2016 in that we show that gender equality affects female performance in math not necessarily through its effects on female math-related gender identity, but instead through its effects on general gender stereotypes, and (possibly) through its direct effects on girls' preferences. To put it differently, our findings reveal that the positive effects of gender social norms on girls' math test scores relative to those of boys found by NRS 2016: (1) expand to other subjects (namely reading and science), (2) are shaped by beliefs on political empowerment and economic opportunity, and these beliefs also shape girls' relative performance in other subjects, (3) are driven by parents' influencing their children (especially their girls') preferences for math, and (4) are not driven by non-cognitive skills.

Our work also complements earlier findings from Guiso et al. (2008) and Pope and Sydnor (2010). Using PISA data from 40 countries, the former find that, in more gender-equal societies, girls close the gender gap by becoming better at both math and reading. In contrast, Pope and Sydnor (2010) find the opposite result by exploiting regional variation in the US. More specifically, they find that: "*areas which have smaller gender-disparities in stereotypically-male dominated* *tests of math and science, also tend to have smaller disparities in stereotypically female-dominated tests of reading."* The authors conclude that: "*variation across states in test scores disparities is not simply a reflection of some states improving the performance of females relative to males. Rather, some states appear to be more gender equal across all tests and adhere less to gender stereotypes in both directions*."

While our findings are closer to Guiso et al. (2008), they also use the same data source *and* exploit cross-country variation as opposed to cross-regional variation within one country as in Pope and Sydnor (2010). In contrast with our work, Guiso et al. (2008) include natives as well as first- and second-generation immigrants, and hence, relate country-of-residence gender equality measures with the math and reading gender gap in the country of residence. Thus, their findings fail to distinguish the role of country-of-residence's institutional constraints from country-of-residence's gender social norms in influencing gender gaps in test scores. Moreover, they are silent on the direction of the causality or the role of parental transmission of beliefs.

Our work also exploits findings from a recent literature that views survey and tests as performance tasks (in addition to a measure of knowledge). This literature shows that the rate of decline in performance in tests or item nonresponse in survey questionnaires are proxies of agreeableness, motivation and ambition, but not to cognitive performance (Borghans and Schils 2012); and conscientiousness (Hitt, Trivitt, and Cheng 2016; Zamarro et al. 2016). Borghans and Schils (2012) and Zamarro, Hitt, and Mendez (2016) find that between one fifth and one third of the between country variation in PISA scores is driven by these non-cognitive skills measures. Our contribution to this literature is to explore whether country-of-ancestry gender social norms are related to gender differences in non-cognitive skills and whether these non-cognitive skills are driving the results that second-generation girls coming from more gender-equal countries of ancestry outperform their male counterparts in math, reading and science. With our measures of non-cognitive skills, we find no evidence of this.

The remainder of this paper is organized as follows. Sections 2 and 3 describe the empirical strategy, and the data and sample selection, respectively. Section 4 presents the main results on the reading, science, and math gender gap. Section 5 analyzes which country-of-ancestry institutional channels shape the gender cultural attitudes that ultimately improve girls' relative test performance. Section 6 presents results on self-reported beliefs on math performance. Section 7 analyses whether the effect of social gender norms on gender test gaps is driven by cognitive or non-cognitive skills, before concluding in section 8.

2. Empirical Strategy

We use OLS to estimate the following baseline specification:

$$E_{ijkt} = \alpha_1 female_i + \alpha_2 (female_i GE_j) + X'_{ijkt}\beta_1 + (X'_{ijkt} female_i)\beta_2 + \sum_j J'_j\lambda_j + \sum_k K'_k\lambda_k + \sum_t T'_t\lambda_t + \sum_k (K'_k female_i)\delta_k + \varepsilon_{ijkt} \quad (1)$$

where E_{ijkt} is the test score of second-generation immigrant i who lives in host country k at time t and is of ancestry j. To identify the differences in test scores between girls and boys, the variable $female_i$ is an indicator equal to one if the individual is a girl and zero otherwise. GE_j is a measure of gender equality from the individual i's country of ancestry j, such that a higher value is associated with a more gender-equal culture. The vector X_{ijkt}, includes a set of individual characteristics that may affect test scores for reasons unrelated to gender equality, and that vary with the specification considered. These individual characteristics are also interacted with the female indicator. J_j, K_k, and T_t are a full set of dummies that control for the country of ancestry j, the host country k, and the PISA cohort t. Country-of-ancestry fixed effects (J_j) control for the gender equality (GE_j) in the country of ancestry, and for any other factors that affect the test scores of boys and girls in the same way. Year fixed effects (T_t) account for cohort differences and other time variation. Following Alesina and Giuliano (2010 and 2011), Luttmer and Singhal (2011), and NRS 2016 who also look at immigrants living in multiple host countries, we include host-country fixed effects (K_k) in our specification to account for the host country's characteristics that may be related to test performance. Most importantly, host-country dummy variables (K_k) are interacted with $female_i$ to account for variation in the host country's test-scores gender gaps that may arise from cross-country differentials in cultural or institutional channels.

Our coefficient of interest on the interaction between the GE_j and the female indicator, α_2, captures the role of gender equality in explaining the gender differences in test scores of second-generation immigrant boys and girls. A positive and significant α_2 would suggest that more gender-equal attitudes in the immigrant's country of ancestry are associated with a higher relative test performance of second-generation immigrant girls over boys, and thus a *smaller* gender gap if the initial gap is negative (as it is in math), but a *greater* gender gap if the initial gap is non-negative (as is the case in reading and science).

3. Data and Sample

Program for International Student Assessment (PISA) Data

Our main data set uses the 2003, 2006, 2009 and 2012 student-level data from the Program for International Student Assessment (*PISA*), an internationally standardized assessment conducted by the Organization for Economic Cooperation and Development (OECD) and administered to 15-year olds in schools every three years since 2000. PISA assesses a range of relevant skills and competencies in three main domains: mathematics, reading, and science. To do so, PISA randomly distributes the participating students into booklets, which differ (also randomly) in type and order of questions. The PISA test has an average of 60 questions across the three different subjects and is expected to last about 2 hours.

The purpose of PISA is to test whether students have acquired the essential knowledge and skills for full participation in society near the end of compulsory education. These skills include whether they can analyze, reason and communicate effectively. According to the OECD (2003), the PISA math test assesses "*the capacity to identify and understand the role that mathematics plays in the world, to make well-founded judgments and to use and engage with mathematics in ways that meet the needs of that individual's life as a constructive, concerned and reflective citizen*". At the same time, the PISA reading test assesses "*the capacity to understand, use and reflect on written texts in order to achieve one's goals, to develop one's knowledge and potential, and to participate in society*", and the PISA science test assesses "*the capacity to use scientific knowledge, to identify scientific questions and to draw evidence-based conclusions in order to understand and help make decisions about the natural world and the changes made to it through human activity*". In addition, students and school principals also answer questionnaires to provide information about the students' background, school and learning experience, as well as the broader school system and learning environment. Appendix Table A.1 presents a detailed description of all PISA variables used in the analysis, as well as basic descriptive statistics.

Our analysis begins in 2003 because questions entering the math scores are not comparable before and after that year. PISA tests are mainly paper and pencil tests, and assess the performance in each subject using a broad sample of tasks with differing levels of difficulty to represent a comprehensive indicator of the continuum of students' abilities. The PISA program presents the tests scores in standardized form, whereby they have a mean of 500 test-score points and a standard deviation of 100 test-score points across the OECD countries. In our sample of second-generation immigrants living in 9 different countries (most but not all OECD countries), the mean is around 480 test-score points with a standard deviation between 104 and 108 (see Panel A of Appendix Table A.1).

Even though PISA aims at measuring students' skills in a three subject areas (science, math and reading), it also aims at keeping the test manageable, which implies that it lasts at most two hours. Hence, students do not complete all questions but instead, they are *randomly assigned* to complete one booklet (out of thirteen possible booklets) with four different collection of questions (known as clusters) lasting 30 minutes each. Thus, students only answer a limited number of questions from the total test item pool and, thus, they are not necessarily tested in all three subjects.[12] Because students are randomly assigned to booklets, and thus to test questions, "*the missing data for the questions they have not been asked to answer can be treated as Missing Completely at Random. Consequently, multiple imputation is used (by PISA) to create test scores for each pupil in each subject areas regardless of whether they have answered questions on that particular domain or not*" (Jerrim et al. 2017). Using a statistical imputation model, PISA creates for each student five separate test scores in each subject area (also known as "plausible values" hereinafter PV). As is standard in this literature and

[12] For example, in PISA 2006 there were 108 science, 31 reading, and 48 math questions divided into seven science, four mathematics and two reading clusters. From these clusters, a total of 13 test booklets were formed. Of these, one included only science questions. The others included questions in two different subjects: reading and science, or science and math. And four booklets (B2, B7, B9 and B11) contained questions in three different subjects (see Table 4 in Jerrim et al. 2017).

recommended by the OECD, we use PV in all of our analysis that involves test scores. Hence, we estimate one regression for each set of PV and, subsequently, report the arithmetic average of these estimates.

PISA sample is stratified at two stages: first, schools are randomly selected; and second, students at each school are randomly assigned to carry out the test in all three subjects. A minimum participation rate of 65% of schools and 80% of students from the original sample is required for a country to be included in the international database. Following OECD recommendations, we apply the Fay's Balanced Repeated Replicated (BRR) methodology to estimate standard errors that will take into account PISA's stratified, two-stage sample design. Results are robust to clustering standard errors at the country-of-ancestry level.

Gender Equality Measures

To measure gender equality in an immigrant's country of ancestry, we follow Guiso et al. (2008), Fryer and Levitt (2010), NRS 2016, and Rodríguez-Planas and Sanz-de-Galdeano (2016) and use the Gender Gap Index (GGI hereafter) from the World Economic Forum (Hausmann, Tyson, and Zahidi 2009). The GGI measures the relative position of women in a society taking into account the gap between men and women in economic opportunities, economic participation, educational attainment, political achievements, health and well-being. The GGI is an un-weighted average of the four subindex scores (described in the next paragraph): economic participation and opportunity subindex, education attainment subindex, political empowerment subindex, and health and survival subindex.

To explore which country-of-ancestry institution shape the beliefs that end up mattering the most and test the robustness of our results to alternative measures of gender equality, we also use other measures of gender equality from the World Economic Forum, namely an index of ***economic participation and opportunity*** based upon: (1) female labor force participation over male, (2) wage equality between women and men to similar work, (3) female earned income over male, (4) female legislators, senior officials and managers over male, (5) female professional and technical workers over male; an index on ***educational attainment*** based upon: (1) female literacy rate over male, (2) female net primary level enrollment over male value, (3) female net secondary level enrollment over male,

(4) female gross tertiary level enrollment over male value; an index on ***political empowerment*** based upon: (1) the ratio women to men with seats in parliament, (2) the ratio of women to men in ministerial level, and (3) the ratio of the number of years with a women as head of state to the years with a man; and an index on ***health and survival*** based upon: (1) the gap between women and men's healthy life expectancy and, (2) the sex ratio at birth, which aims to capture the phenomenon of "missing women". All these indexes range from 0 to 1, with larger values indicating a better position of women in society.[13]

Information on the GGI is available from 2006 on. In this year, 115 countries were included, in 2007 128, in 2008 130, and in 2009 134. In order to maximize the number of countries in our sample, we focus on the year 2009 as NRS 2016. The use of contemporaneous measures of gender equality rather than those observed at the time parents migrate is a common practice in the literature. First, it is reasonable to expect that countries' aggregated preferences and beliefs about the role of women in society change slowly over time. Second, as Fernández and Fogli (2009) point out, "*one could argue that the values that parents and society transmit are best reflected in what their contemporaneous counterparts are doing in the country of ancestry*".

Sample

Our sample comprises second-generation immigrants who were born and reside in a participating host country but whose parents (both of them) were born in another country. Interestingly, 85 percent of our sample have parents who emigrated from the same country. Choosing second-, rather than first-generation immigrants, is preferred by the epidemiological literature as it minimizes the role of institutions in the country of ancestry for immigrant's outcomes. In particular,

[13] Each of the four subindex scores is calculated as a weighted average of the variables within each subindex. As Hausmann, Tyson, and Zahidi (2009) explain: "*Averaging the different variables would implicitly give more weight to the measure that exhibits the largest variability or standard deviation. Hence, the variables are first normalized by equalizing their standard deviations. Then it is determined what a 1% point change would translate to in terms of standard deviations by dividing 0.01 by the standard deviation for each variable. These values are then used as weights to calculate the weighted average of each of the variables used for each subindex. This way, each variable has the same relative impact on the subindex (....) Hence, a country with a large gender gap in primary education (a variable where most countries have achieved near-parity between men and women) will be more heavily penalized.*"

second-generation immigrants were born and raised in their parents' host country and hence, did not attend school in their parents' country of birth. Furthermore, the probability to return to the country of ancestry of second-generation immigrants is much lower than the probability of first-generation immigrants.[14] We pool the 2003, 2006, 2009 and 2012 PISA waves to have the larger variation possible in terms of both host countries and countries of ancestry. To determine the students' country of ancestry, we need specific information on their parents' country of birth. This question is not consistently asked among participating countries. For instance, when asking about the country of origin, the US only provided the options "United States of America" and "another country". Consequently, only data from those participating countries providing detailed information about the parents' birth place were used in the analysis.[15]

Based upon Blau et al. (2013), who find that the effect of mother's country of origin on second-generation immigrants girls tend to be stronger than the effect of the father's country of origin when parents come from different countries, we assign the mother's country of origin.[16] We restrict our sample to those individuals for whom we observe gender equality measures for both their country of ancestry and their host country, focusing our analysis on host countries with immigrants from at least four countries of ancestry.[17] We also drop second-

[14] The concern here would be that, if there were gender discrimination in the home country, those immigrant females planning to return may end up investing less in scholarly activities than their male counterparts. In that case, we would be picking up the effect of country-of-ancestry institutions instead of country-of-ancestry culture. Because the odds of returning to the country-of-ancestry are small for second-generation immigrants, we prefer to focus on them than to include first-generation immigrants.

[15] These are Australia, Austria, Belgium, Denmark, Finland, Germany, Greece, Latvia, Liechtenstein, Luxembourg, New Zealand, Norway, Portugal, Switzerland and Scotland in 2003, 2006, 2009 and 2012 PISA; Argentina, Czech Republic, Israel, Netherlands and Qatar in 2009 and 2012 PISA; and China, Costa Rica and Turkey in 2012. Notice that we lose countries such as the United States of America or Canada because they do not collect detailed information on the parents' country of birth. They only inform on whether the parents were born in that country or abroad.

[16] Only 15% of our sample have parents who emigrated from two different countries.

[17] The lack of gender equality measures for all countries implies losing the following countries of ancestry: Afghanistan, Bosnia and Herzegovina, Cape Verde, Occupied Palestine, Iraq, Lebanon, Liechtenstein, Netherlands Antilles, Somalia, Somoa and Serbia-Montenegro (4,345 observations) and the host country of Liechtenstein (or 135 observations). In any case, most of the countries of ancestry we lose are from conflictive zones, which are commonly excluded from this kind of analysis (see Fernández and Fogli 2009, and Furtado, Marcén, and Sevilla 2013). In addition, by limiting our analysis to host countries with at least four different groups of immigrants we lose 3,983 observations from the following ten host countries (Costa Rica, China, Denmark, Germany, Greece, Latvia, Norway, Portugal, Qatar and Turkey), and seven countries of ancestry (Brazil,

generation immigrants whose country of ancestry has fewer than 15 observations in a given host country.[18] In the robustness section, we explore the robustness of our results to changes in sample criteria.

Our final sample has 11,527 second-generation migrants from 35 different countries of ancestry and living in nine host countries (as shown in Appendix Table A.2). Host countries are mainly OECD countries, whereas countries of ancestry are from various continents and levels of development. For instance, the countries of ancestry in our sample cover all continents, with many European (14 countries) and some transition economies (Albania, Poland and Russia), several countries in the Americas (Bolivia, Chile, Paraguay, Suriname, United States and Uruguay), some in Asia (China, India, Korea, Malaysia, Philippines and Vietnam), Africa (Ethiopia, Morocco and South Africa) and Oceania (Australia, Republic of Fiji and New Zealand). Second-generation immigrants whose country of ancestry is Portugal, Turkey or Italy represent 49% of the sample. Host countries with the highest sample of second-generation immigrants are Switzerland, Australia and Luxembourg (immigrants living in these countries represent 71% of the sample). Potential concerns of selection of immigrants are dealt with in the robustness section.[19]

Descriptive Statistics

Appendix Table A.3 presents summary statistics of the outcome variables and the key explanatory variables for our sample of second-generation immigrants by country of ancestry.[20] The first three columns show the average gap in different test scores of second-generation immigrant girls relative to boys. This gap is

Bulgaria, Belarus, Jordan, Egypt, Nicaragua and Yemen). Most importantly, our results are generally robust to relaxing this restriction.

[18] This is a common practice in the literature. For instance, Fernández and Fogli (2009) eliminate those countries of ancestry with fewer than 15 observations. Given that our regressions are ran at the individual level, whether we include these small numbers of observations does not affect our results. With this adjustment, we lose 201 individuals and 11 different countries of ancestry (Argentina, Bangladesh, Colombia, Czech Republic, Denmark, Hungary, Iran, Panama, Slovenia, Sweden and Thailand).

[19] We have checked with OECD data on immigrant stocks in 2010 and have found that the proportion of immigrants from each nationality in our sample (within a given host country) seems to be in line with that of second-generation immigrant population. An exception is immigrants from Turkey, which seem to be over-represented in our sample for a variety of host countries, and immigrants from Russia to Israel (results available from authors upon request).

[20] Descriptive statistics for the other covariates used in the analysis can be found in Appendix Table A.1.

calculated from estimating a linear regression using the PV provided by the PISA data sets as LHS variable and a female indicator as RHS (we estimated one regression for each PV and present the average of the five coefficients estimated). Hence, a negative gap means that boys over perform girls while a positive gap means that girls over perform boys. The first, second, and third columns show the average gap in math, reading, and science test scores of second-generation girls relative to boys, respectively.

Countries of ancestry are ordered from the more math gender biased countries to the least. Column 1 shows a large variation in the gender gap in math scores across countries of ancestry. On average, the difference in math score between girls and boys across our sample is -15.70, the equivalent to 4.5 less months of schooling. In contrast, we find that, on average, girls outperform boys in reading test scores (Column 2). The difference in reading score between girls and boys across our sample is +30.16), the equivalent to 9 more months of schooling. Column 3 shows that even though, on average, boys outperform girls in science, the average difference (-6.37) is considerably smaller than in math.

It is important to highlight that these gender gaps in test scores are quite similar to those observed among all second-generation immigrants and natives living in the host countries included in our analysis, and are not too distant from those shown when all countries participating in PISA assessments are considered (see Appendix Table A.4).

Panel A in Appendix Figure A.2 presents the relationship between the raw math and reading gender gaps among second-generation immigrants, by country of ancestry. Panel B and C do the same for math and science and for reading and science, respectively. The test scores gender gap were obtained from estimating a linear regression using the plausible values provided by PISA as LHS variable and a female indicator as RHS variable. We estimated one regression for each PV for each country and present the average of the five coefficients estimated. Panel A in Appendix Figure A.2 shows that second-generation immigrant girls from a given country of ancestry who perform better in math than their male counterparts also tend to perform relatively better in reading. Panel B also shows that second-generation immigrant girls who have a higher score in math relative to their male counterparts also have a relative higher score in science. Panel C shows a similar relationship between reading and science test scores.

Columns 9 to 12 in Appendix Table A.3 show the value of different gender-equality measures by country of ancestry. Our main variable, GGI, averages 0.69 with a standard deviation of 0.05, varying from 0.58 in Turkey to 0.79 in New Zealand. Further detail on the other indices of gender equality is provided in Section 5 below.

4. Main Results

Replicating NRS 2016

Prior to presenting our analysis, we replicate NRS 2016's results for the math gender gap. Column 1 in Table 1, which only controls for the female indicator and the year, country-of-ancestry and host-country fixed effects, reveals that second-generation immigrant girls underperform boys in math by, on average, 14.77 score points within host country, country of ancestry, and survey year. Column 2 in Table 1 replicates NRS 2016's main result: if a girl's parents, originally from a country with an "average" GGI, had instead come from a country with a GGI one standard deviation above the mean, her math test score in the host country would have increased by 7.47 score points relative to that of a male counterpart, the equivalent of a reduction in the math gender gap of 0.29 standard deviation.[21] To put estimate α_2 into context: if immigrants from Turkish descent, whose country of ancestry has a GGI of 0.58 and who present a gender gap in math scores of -13.77 score points, were characterized by the mean gender equality in our sample (GGI = 0.69), the statistical model would suggest that the mean score performance in mathematics of second-generation Turkish girls relative to boys would increase by 16.45 score points, thus reversing the gender gap.[22]

Gender Social Norms and the Reading and Science Gender Gaps

Column 3 in Table 1 reveals that second-generation immigrant girls outperform boys in reading by, on average, 32.25 score points within host country, country of ancestry, and survey year. Since the average reading test score is 465 among second-generation boys, this implies that second-generation girls' reading test

[21] This is calculated as $\frac{\alpha_2 * GGI_{StDev}}{Gap\ in\ Math_{StDev}} = \frac{149.55*0.05}{26.04} = \frac{7.47}{26.04} = 0.29$

[22] This is calculated as $(GGI_{AVG} - GGI_{TUR}) * \alpha_2 = (0.69 + 0.58) * 149.55 = 0.11 * 149.55 = 16.45$

scores are, on average, 7 percent higher than those of boys. Column 5 in Table 1 shows that there is no statistically significant difference in science test scores between second-generation immigrant girls and boys.

Columns 4 and 6 in Table 1 estimate equation (1) using reading and science test scores as the LHS variable. Column 4 shows that second-generation immigrant girls whose country of ancestry is more gender equal also have higher reading scores relative to boys, and hence the girls' reading advantage *widens*. Similarly, Column 6 shows that second-generation girls coming from more gender-equal countries of ancestry outperform their male counterparts also in science. According to these estimates, one standard deviation increase in the GGI is associated with an *increase* of 0.30 (0.36) standard deviation in the reading (science) gender gap, which is very close to the magnitude of effect on the math gender gap (0.29 standard deviation *decrease* of the math gender gap). At the bottom of Table 1, we test whether the impacts on the relative reading (or science) scores are statistically different from those on the scores in math, and find that we cannot reject the null hypothesis that the coefficients of the interaction between the GGI and the female dummy (α_2) are equal across test scores.

While the effect of immigrants' language skills on reading test scores is well known, Isphording, Piopiunik, and Rodríguez-Planas (2016) have recently shown that language skills also have a causal impact on math test scores. Hence, to address concerns that parents from countries with lower GGI values may have systematically worse (or better) host country language skills, and that these language skills may differ by gender, we exploit information in PISA on whether each student's family speaks the test language at home or not, and reestimate our main specification adding a dummy variable equal to 1 if the family does not speak the test language at home and zero otherwise, and its interaction with the female dummy (shown in the even columns in Appendix Table A.5). While those students who speak another language (different to the test language) at home underperform in all domains (math, reading and science), we observe no statistically significant gender differences, suggesting that boys and girls are equally affected by parents' language skills. Most importantly, the effect of the gender culture on the three gender gaps remains practically unchanged.

Hence, we find that second-generation immigrant girls whose parents come from more gender-equal countries perform better relative to immigrant boys in *both* math, reading and science, suggesting that cultural beliefs on the role of women in society are *not* specific to math skills, but instead more general as they also apply to reading and science skills. While these findings are closer to Guiso et al. (2008) than Pope and Sydnor (2010), we use the same data source and exploit cross-country variation as the former, whereas the latter focuses on cross-regional variation in the US, and hence our results and those of Pope and Sydnor (2010) are not necessarily comparable. As explained in the introduction, Guiso et al. (2008) do not use the epidemiological approach but estimate instead correlates between country-of-residence gender equality measures and the math and reading gender gaps, being silent on the role of parental transmission of beliefs. Most importantly, our contribution to this literature is that the *transmission of cultural beliefs on the role of women in society* (not societal factors generally defined) affects girls' relative test performance in subjects different from math, namely reading and science.

Other Determinants of the Gender Gaps and the Transmission of Culture

Appendix Tables A.6 and A.7 present different robustness checks of our reading and science results.[23] While Column 2 presents our baseline specification, Column 1 displays a specification that omits the interaction between country-of-ancestry GDP per capita and the female dummy. The reason for doing so is to explore how sensitive our results are to *only* controlling for the interaction between country-of-ancestry GGI and the female dummy. Although doing so slightly reduces the effect of culture on both the reading and science gender gaps, the effect of culture on the test gender gaps remains large and statistically significant at the 0.05 level or higher, suggesting that this concern is not affecting our main results.

As our baseline specification includes country-of-ancestry fixed effects, it precludes us from observing the direct effect of country-of-ancestry GGI or GDP per capita on second-generation immigrants reading and science test scores. Column 3 presents a specification that replaces country-of-ancestry fixed effects with country-of-ancestry GGI and GDP per capita. It shows that more gender equality in the country-of-ancestry is associated with higher reading and science

[23] Results are also robust to using math test scores as the LHS variable as shown in Table 1 in NRS 2016.

test scores among second-generation immigrants (both boys and girls, albeit the effect is greater for the latter) and that higher GDP per capita in the country of ancestry is also associated with higher science test scores (but has no effect on reading). Note, however, that this alternative specification leaves our main estimates of culture practically unchanged.

Columns 4 to 6 take a closer look at the relationship between gender social norms and the reading and science gender gaps by sequentially adding covariates. The aim here is to observe how our coefficients of interests vary with the inclusion of additional covariates and to shed some light on the mechanisms through which the relationship between gender social norms and the gender reading and science gaps operates. Most importantly, doing so enables us to assess the relevance of various potential sources of omitted variable bias and how they may affect our conclusions. Note, however, that some of the additional characteristics that we will sequentially include (such as, for instance, parental education and work status as well as school type) may well be affected by culture. Therefore, by including some of the controls we will introduce below, we are limiting the avenues through which culture is allowed to operate, and estimate the direct effect of culture beyond the indirect ways in which these additional variables could affect such gender gaps through these variables. This is arguably a very demanding test of the relevance of culture. Note also that, by comparing outcomes across second-generation immigrants whose parents came to the host country from different countries of origin, the epidemiological approach is prone to underestimating the true effect of culture for two additional motives. First, cultural transmission is restricted to parents (or parents' social networks). Second, assimilation to the host country's culture is likely to weaken the impact of the country of ancestry's culture.

Column 4 adds to the baseline specification mother's and father's highest education level attained and their interaction with the female dummy. Doing so has little effect on the estimate of culture on the reading gender gap, and slightly increases the estimate of culture on the science gender gap. Not surprisingly, having more educated parents increases reading and science test scores for both girls and boys.

Column 5 adds to the specification in Column 4 controls for mother's and father's work status, as well as a variable measuring the household's possessions, and these variables' interaction with the female dummy. Having parents' work or more household possessions is positively associated with higher reading and science test scores for both boys and girls. While having more home possessions seems to have a larger effect on girls' science test scores than on boys', the opposite is true for having a working mother (father) on reading and science (science) test scores. Crucially, adding these controls increases the estimate of culture, which remains positive and statistically significant at the 0.01 level.

In addition to the covariates in Column 5, Column 6 adds school controls and their interaction with the female dummy. As discussed earlier, to the extent that parents choose which schools (or neighborhoods) their children enroll (or live in), these variables are endogenous. Including them reduces the size of the coefficient of culture on reading by about 10% and that of science by about 5%. Nonetheless, both coefficients remain large, positive, and statistically significant at the 0.01 level. Estimates from Column 6 indicate that attending schools with a higher proportion of girls improves girls' science and reading test scores relative to those of boys.[24] In contrast, attending schools in metropolitan areas is more beneficial for boys than for girls.

Additional Robustness Checks

A common concern within the epidemiological approach is that immigrants may "self-select" in some areas in a given country. While most of epidemiological papers focus the analysis in one country, our analysis looks at immigrants not only coming from different countries of ancestries, but also going to multiple destination countries. As the form of selection is likely to differ across different destination countries, this approach potentially limits the scope for selection bias (see Alesina and Giuliano 2011; and Luttmer and Singhal 2011). To address concerns that parents who care more about their girls' success choose to move from ancestry countries with low gender-equality culture to areas in the host

[24] The concern here is that girls from more gender-equal countries may do relatively better (with respect to boys) than girls from less gender-equal countries not because of gender norms but, instead, because they attend schools where there is a higher proportion of girls. Indeed, Bordalo, Gennaioli, and Shleifer 2014 develop a theory to rationalize the empirical findings that a higher proportion of girls may boost women's confidence and, subsequently, improve their math performance relative to boys as shown by Gneezy, Niederle and Rustichini 2003, Booth 2009, Booth and Nolen 2012, and Anelli and Peri 2013, among others. If that were driving our results, our coefficient of interest would go to zero when including controls for proportion of girls in the school. We find no evidence of this.

country with high-gender equality, Panel B in Appendix Table A.8 controls for local geographic variation in markets and institutions *within* our host countries by including regional fixed-effects (instead of the host-country dummies) and their interaction with the female indicator. Doing so accounts for variation in the host-country region's educational gender gaps that may arise from cross-regional differentials in cultural or institutional channels as a result from immigrants self-selecting in particular areas of the host country. Again, the effect of culture on the three gender gaps remains robust to this specification change.

Panel C in Appendix Table A.8 also shows that our results remain practically unchanged when we adopt a more flexible specification where each year fixed-effect is interacted by the female indicator to allow different gender gaps by the cohort assessed in different PISA waves. Finally, Panel D shows that our results are robust to clustering the standard errors at the host country level, as opposed to using Fay's BRR methodology to account for the double stratification of the sampling design employed by PISA as explained in the Data Section.

Changes in Sample Criteria

Appendix Table A.9 shows that our results are not driven by the main group of immigrants (the Portuguese) or the host country with the largest sample of immigrants (Switzerland)--shown in panels B and C, respectively. Panel D also shows that the effect remains when only one host country is used (although the coefficient is no longer statistically significant in the case of Switzerland). Panel E shows that the results also hold when we drop countries that send migrants to only one host country. By construction, we defined second-generation immigrants as those with two foreign-born parents. Panel F replicates the analysis for the three test scores using second-generation immigrants with one or two foreign-born parents. Our findings are robust to this sensitivity analysis.

Heterogeneity

In this section we explore whether the transmission of cultural beliefs on the role of women in society varies across different subgroups of second-generation immigrants. First, we explore how much of the culture effect on the test-score gender gaps is explained by the effect of gender social norms on girls' versus that on boys' test scores. To put it differently, do gender social norms improve girls' test scores exclusively? Do they improve girls' test scores more than those of boys? Or do they have a detrimental effect on boys' test scores that could also potentially explain the converging results found earlier? Then, we explore whether the effect of social norms on second-generation immigrants varies depending on the concentration of immigrants from the same ethnicity in the school.[25]

Panel A in Table 2 estimates the effect of GGI on girls' and boys' test scores separately. Interestingly, we observe that the coefficient on the GGI is positive and statistically significant for both boys and girls, suggesting that youth whose parents come from more gender-equal societies perform better in exams regardless of gender or subject type. However, we find that the effect of culture on test scores is more than twice as large for girls than for boys (again regardless of the subject type).[26] Hence, gender social norms seem to be beneficial for all, but more so for girls than boys. In all three subjects, we reject the null hypothesis that the effect of culture on girls' and boys' test scores is the same.

Panel B in Table 2 explores whether culture has a differential effect on girls' test scores relative to boys' according to the concentration of immigrants from the same ethnicity. To do so, we calculate the proportion of first- and second-generation immigrants in each school from PISA following Schnepf (2007) (see definition in Appendix Table A.1). Even though we cannot reject that the effect of culture differs across the two groups, the effect of culture on the girls' test scores relative to those of boys is considerably larger and (frequently estimated with greater precision) for second-generation immigrants attending schools with a high concentration of immigrants from the same ethnicity. Fernández and Fogli (2009) and Luttmer and Singhal (2011) also find that the

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[25] We also checked whether the transmission of culture depends on the proportion of girls in the school, finding that only in the case of science, the effect of gender social norms is positive and statistically significant. At the same time, we find no evidence that the transmission of culture depends on parents' characteristics (mother labor status, or mother (or father) level of education), which is consistent with the literature that looks at the influence of parental characteristics on girls performance relative to boys in math or in STEM fields (Cheng, Kopotic, and Zamarro 2017; Fryer and Levitt 2010).

[26] Note that for the three test scores, the standard deviation across countries of ancestries is almost the same for boys and for girls (around 64 score points for boys and around 63 score points for girls). Therefore, a one standard deviation increase in the GGI leads to an increase in girls' test score that more than doubles that of boys'. The finding that culture had a greater beneficial effect on girls than boys was also revealed in the specification in column 3 in Appendix Tables A.6 and A.7 that replaced the country-of-ancestry fixed effects with country-of-ancestry GGI.

impact of culture is stronger for immigrants who have a greater tendency to cluster with their ethnic community. One possible interpretation is that horizontal transmission of culture through peers may constitute a potential mechanism of the transmission and maintenance of cultural beliefs. As in previous studies, however, to the extent that parents may be sorting into neighborhoods or schools, the stronger cultural effects for this subgroup may be a further consequence of vertical cultural transmission rather than a genuine peer effect.

By construction, our sample of second-generation immigrants have both parents foreign born. In Panel F in Appendix Table A.9, we saw that including individuals born in the host country to only one foreign-born parent does not change our results. However, one would expect the effect of culture to be smaller for those with only one foreign-born parent. We explore this in Panel C in Table 2. Not surprisingly, we find that the effect of culture is less than half the size (and lacks statistical significance) for individuals with one native parent relative to that of individuals with two foreign-born parents. Nonetheless, we cannot reject that the size of both estimates is the same.

5. Institutional Channels from the Country of Ancestry Shaping Culture

An alternative and complementary exercise to explore whether general stereotypes (as opposed to only math-gender stereotypes) are at play is to identify what types of institutional channels in the country of ancestry are shaping the gender cultural attitudes that ultimately affect the math gender gap. Columns 1 to 4 in Table 3 re-estimate our baseline math gender gap specification replacing the GGI with alternative measures of gender equality that focus on specific areas of society, namely political empowerment (column 1), economic participation and opportunity (column 2), educational attainment (column 3), and health and survival (column 4).

Although these different measures are correlated between them, they capture different aspects of culture, and hence may have independent power to explain the math gender gap.[27] For example, all variables may reflect, in part, the belief as to the appropriate role of women in society, but economic participation and opportunity may also capture some independent cultural preferences for the

[27] Correlations between the different measures of gender equality range between 0.23 and 0.77 and are displayed in Appendix Table A.10.

role of women in the labor market, the education index may also capture some independent cultural beliefs on education opportunities between men and women, and the political empowerment index may also capture some independent cultural beliefs on women's political representation.

Two of the four α_2 estimates shown in Table 3 are positive and statistically significant: the one on political empowerment and the one on economic opportunity, albeit the second one only at the 0.1 level. According to the estimates in Columns 1 and 2, beliefs transmitted to second-generation immigrants regarding women's political empowerment are those that matter the most, closely followed by those regarding women's economic opportunity. While an increase in the level of the political empowerment index by one standard deviation is associated with a reduction of 0.30 standard deviation in the math gender gap among second-generation immigrants, the reduction is 0.22 standard deviation for the economic-opportunities index. In comparison, an increase in the level of the education (health and survival) index by one standard deviation only reduces the math gender gap by a non-statistically significant 0.09 (0.11) standard deviations. To the extent that the transmission of beliefs is related to political empowerment and economic opportunity as opposed to education *per se* would suggest that more general stereotypes (as opposed to only math-gender stereotypes) are at play. Column 5 conducts a horse race by estimating a specification that controls for the four estimates of gender equality at the same time. While these two gender equality indices are the most relevant, and we reject the null hypothesis that all these coefficients are jointly equal to zero, we cannot reject the null hypothesis that they are all equal to each other.

Table 4 also shows that, as in math, cultural attitudes regarding women's political empowerment and economic opportunity in the country of ancestry matter in determining the reading and science gender gaps of second-generation immigrants in the host country. Except for economic opportunity in the science equation, which is statistically significant at the 0.1 level, the other three coefficients are statistically significant at the 0.05 level. The magnitudes from the reading and science estimates in Columns 1 and 2 in Table 4 are similar to those found in math. A one standard increase in the economic opportunity or political empowerment indexes is associated with a 0.21 and 0.32 (0.25 and 0.36) *increase* in the reading (science) gender gap, respectively. These findings suggest that beliefs regarding economic opportunity and political empowerment affect girls' test performance relative to that of boys. When we do the horse race in Column 5, we observe that cultural attitudes regarding women's political empowerment in the country of ancestry matter the most for both the reading and science gender gaps. The estimates of this index are statistically significant at the 0.1 level and, in both cases, we reject the null hypothesis that all coefficients are jointly equal to zero at the 0.05 level. Although, again, we could not reject the null hypothesis that the different coefficients of gender equality are all equal to each other.

6. Cultural and Self-Reported Beliefs Regarding Math

As further evidence that the gender-norm effects are driven by general as opposed to math-specific gender stereotypes, we present a math-focused analysis further exploring the channels behind the relationship between gender social norms and the math gender gap.[28] Girls' relative underperformance in math could be the result of cultural beliefs on the role of women in society affecting girls' *beliefs* in their own math abilities ("as I am a girl, I am not good at math"); their beliefs in the institutional constraints she may face ("as I am a girl, math will not help my career prospects"); their anxiety on performing in math ("as I am a girl, I am told math is not for me, which generates anxiety and reduces my performance in math"); or girls' *preferences* regarding math ("as I am a girl, I dislike math").

To explore this, we estimate equation (1) using as left-hand-side (LHS) variable one of the following five PISA-constructed indices on self-reported beliefs or preferences regarding math, available *only* in waves 2003 and 2012, which are the waves that focus on mathematics (OECD 2013).[29] The first two indices capture students' beliefs on their math abilities. The *"math self-concept"* captures students' beliefs on their own math's abilities, including whether they believe they are good and fast at *learning* math;[30] whereas the *"math self-efficacy"*

[28] While we would like to perform a similar analysis for reading and science, PISA information on reading and science self-beliefs is limited and only available for one of the four waves, reducing the precision of our estimates due to small sample sizes.

[29] The main finding that culture affects the gender gap in math generally holds when estimating the effect using the subsample for whom each of the self-beliefs was reported (see column 1 in Appendix Table A.11), albeit we lose precision as the sample size is smaller.

[30] This index is constructed using student responses to a question over the extent they strongly agree, agree, disagree or strongly disagree with the following statements when asked to think about studying mathematics: "I am just not good at mathematics; I get good grades in mathematics; I

index captures the extent to which students believe in their own ability to *handle mathematical tasks* effectively and overcome difficulties.[31] The higher the value of the index, the higher self-concept or self-efficacy a student has, respectively. The third index, the *"instrumental motivation to learn math"* index, captures students' perception on how useful math may be in their professional future, with a higher value of the index indicating higher instrumental motivation to learn math.[32] The *"math anxiety"* index captures thoughts about doing math, such as feeling of helplessness and stress when dealing with mathematical problems, with a higher index indicating higher anxiety.[33] Finally, the "*intrinsic motivation to learn math"* index includes several questions on enjoyment from doing math. More specifically, the student is asked to strongly agree, agree, disagree or strongly disagree to a series of statements, when asked to think about his or her views on mathematics: "I enjoy reading about mathematics; I look forward to my mathematics class; I do mathematics because I enjoy it; I am interested in the things I learn in mathematics." The higher the value of the index, the more intrinsic motivation the student has.[34]

Columns 3, 5, 7, 9 and 11 in Table 5 explore whether there is a differential gender pattern across these different index variables by estimating a regression with a female indicator, and country-of-ancestry, host-country and year fixed

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learn mathematics quickly; I have always believed that mathematics is one of my best subjects; in my mathematics class, I understand even the most difficult work".

[31] This index is calculated based on how confident students report to be at performing the following mathematics tasks: "Using math to work out how long it would take to get from one place to another; calculating how much cheaper a TV would be after a 30% discount; calculating how many square meters of tiles you need to cover a floor; understanding graphs presented in newspapers; solving an equation like 3x+5=17; finding the actual distance between two places on a map with a 1:10,000 scale; solving an equation like 2(x+3)=(x+3)(x-3); calculating the petrol consumption rate of a car".

[32] The index is constructed using students' responses over the extent they strongly agree, agree, disagree or strongly disagree to a series of statements, when asked to think about their views on mathematics: "Making an effort in mathematics is worth it because it will help me in the work that I want to do later on; learning mathematics is worthwhile for me because it will improve my career; Mathematics is an important subject for me because I need it for what I want to study later on; I will learn many things in mathematics that will help me get a job".

[33] The index is constructed using students' responses to a question over the extent they strongly agree, agree, disagree or strongly disagree with the following statements when asked to think about studying mathematics: "I often worry that it will be difficult for me in mathematics classes; I get very tense when I have to do mathematics homework; I get very nervous doing mathematics problems; I feel helpless when doing a mathematics problem; I worry that I will get poor grades in mathematics".

[34] In PISA 2003, the index of intrinsic motivation to learn mathematics was named the index of interest and enjoyment in mathematics, but both 2012 and 2003 indices are based on the same questionnaire items.

effects. Columns 4, 6, 8, and 12 in Table 5 re-estimate equation (1) using these alternative LHS variables (instead of the math test score) with the objective of identifying whether country-of-ancestry gender social norms affect these different outcomes differentially for girls than for boys.[35]

Focusing in the odd columns first, we observe that second-generation immigrant girls believe that they are worse at learning math and handling math tasks effectively than their male counterparts (shown in columns 3 and 5, respectively). Second-generation girls are also more likely to report math anxiety than their male counterparts (column 9), and less likely to like math (column 11) and to perceive studying math as useful professionally in the future (column 7) than second-generation boys. All of these estimates are statistically significant at the 1 percent level.

Having girls perceive that their math skills, beliefs or preferences differ from those of boys does *not* necessarily help us better understand the relationship between cultural beliefs on gender roles and the math gender gap found by NRS 2016. For these self-reported skills, beliefs and preferences to be behind the cultural persistence explaining the math gender gap, they must also be related to country-of-ancestry gender social norms. We explore this in the even columns in Table 5. Interestingly, we find that α_2 is positive *and* statistically significant only in the case of *"intrinsic interest in mathematics"* (column 12). The other α_2 estimate that is large (albeit not statistically significant) is the *"instrumental motivation to learn math"* index. When the LHS variable is any of the other indices, the estimates of α_2 are considerably lower in magnitude and not statistically significant.

How much do gender cultural beliefs affect gender differences in math preferences? According to our estimates in Table 5, if a girl's parents, originally from a country with an "average" GGI, had instead come from a country with a GGI one standard deviation above the mean, her *"intrinsic interest in mathematics"* index in the host country would have increased by 1.53, reducing

[35] We use the same covariates as in NRS 2016 baseline specification, also shown in column 2, Table 1.

the gender differences in this index by 0.13 standard deviation.[36] This evidence is suggestive that beliefs on gender social norms are transmitted through parents (or parents' social network) from less gender-equal countries instilling to girls lower *preferences* for math relative to boys.[37]

7. Culture and Non-Cognitive Skills

So far, our analysis shows that parents' gender stereotypes may well affect how much parents push their daughters to learn relative to boys. A different and complementary question is the extent to which our results are driven by cognitive versus non-cognitive skills. Non-cognitive factors, such as an individual's motivation, eagerness to succeed, agreeableness, or ambition, have been found to affect human capital accumulation (Cunha, Heckman, and Schennach 2010) as well as labor market outcomes, engagement in risky behaviors and health outcomes (Heckman, Pinto, and Savelyev 2013; Heckman and Rubinstein 2001).

Recently several researchers have used subject tests questionnaires to measure non-cognitive skills following two distinct approaches. On the one hand, Borghans and Schils (2012) show that the rate of decline in performance over the course of the 2006 PISA test's administration is related to non-cognitive factors such as agreeableness, motivation and ambition, and is a good predictor of final levels of educational attainment. They also show that this decline in performance is not related to cognitive performance. Using 2009 PISA, Zamarro, Hitt, and Mendez (2016) expand the methods used by Borghans and Schils (2012), and find that the decline in test performance is a good predictor of international variation in test scores.[38]

On the other, Hitt, Trivitt, and Cheng (2016) have found that individuals' item non-response in survey questionnaires is also related with their performance

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[36] This is calculated as $\frac{\alpha_2 * GGI_{StDev}}{Gap\ in\ MIndex\ Gender\ Gap_{StDev}} = \frac{1.53*0.05}{0.59} = 0.13$

[37] Using PISA 2012, which is the only PISA in which information on time parents spend doing math with their children is available, we explore whether parents devote more or less resources on their daughters or their sons. While we find that they spend more resources on their sons relative to their daughters, the math gender gap remains even after controlling for parental resources spent. This analysis, available from the authors upon request, is performed on all students (including natives) residing in the 10 countries for which the information on parental time spent doing math is available.

[38] In another strand of this literature, Balart, Oosterveen and Webbink (2015) use the same methodology to decompose PISA test scores in cognitive and non-cognitive skills and estimate the association of each component with economic growth.

in school or in the labor market. Using six nationally-representative longitudinal datasets of American secondary school students, Hitt, Trivitt, and Cheng (2016) show that item-nonresponse rates predict students' educational attainment and employment outcomes as adults (even after controlling for cognitive ability measures), concluding that item non-response is a good proxy to measure character skills related to conscientiousness. Similarly, Zamarro et al. (2016) find that careless answering patterns in a nationally representative US survey is related to educational attainment, employment income, the likelihood of being employed in a high-skilled job, and self-reported measures of conscientiousness, even after controlling for cognitive ability. Most recently, Zamarro, Hitt, and Mendez (2016) use 2009 PISA students' survey questionnaire to build proxies of conscientiousness and diligence by measuring the amount of effort students put forward on the survey that accompanies the PISA test. Consistent with their findings on the decline in test performance, they find that survey item nonresponse is a strong predictor of international variation in test scores.

Below, we first explore whether our main finding, namely that country-of-ancestry gender social norms affect girls' test performance relative to that of boys, is driven by cognitive or non-cognitive factors. Second, we explore whether country-of-ancestry gender social norms are related to gender differences in non-cognitive skills. Finding that country-of-ancestry social gender norms affect the gender gap in test scores through both cognitive and non-cognitive skills would suggest that parents from less gender-equal societies care less about their daughters' success in life in general than their sons' success. Instead, evidence that country-of-ancestry social gender norms *only* affect the gender gap through cognitive skills may suggest that parents' gender stereotypes do not shape girls' non-cognitive skills relative to boys. To put it differently, believing that "the best women are stay-at-home moms", "women are supposed to make less money than men", "women are not politicians", "girls have to work hard to learn in school, whereas boys are naturally gifted", or "women are nurses, not doctors" may well affect how much parents push their daughters to learn relative to boys, without affecting parents' expectations on their daughters' motivation, ambition or agreeableness relative to that of their sons. However, because we only have crude measures on non-cognitive skills, lack of evidence on the relevance of non-cognitive skills needs to be taken with caution.

We follow Borghans and Schils (2012) and use the information on the decline of students' performance in the PISA achievement tests to disentangle the effects of cognitive versus non-cognitive skills on gender gaps in test scores. These authors exploit the randomization in the order of PISA questions to identify the cognitive versus the non-cognitive factors behind the PISA achievement test.

Applying their methodology to our analysis, we use OLS to estimate the following specification:

$$Y_{iqjkt} = \alpha_0 + \alpha_1 female_i + \alpha_2(female_i GE_j) + \gamma_1 order_{iq} + \gamma_2(female_i order_{iq}) + \gamma_3(order_{iq} GE_j) + \gamma_4(female_i order_{iq} GE_j) + X'_{ijkt}\beta_1 + X'_{ijkt} female_i \beta_2 + \sum_j J'_j\lambda_j + \sum_k K'_k\lambda_k + \sum_t T'_t\lambda_t + \sum_q Q'_q\lambda_q + \sum_k (K'_k female_i)\delta_k + \varepsilon_{ijkt} \quad (2)$$

Where Y_{iqjkt} is 0 if the answer of participant i who lives in host country k at time t and of ancestry j on question q is wrong, 0.5 if the answer is partially right and 1 if the answer is right.[39] The variable $order_{iq}$ indicates the sequence number of the test question q for individual i, rescaled such that the first question is numbered as 0 and the last question as 1. Question fixed effects, Q_q, control for unobserved characteristics of the question such as clarity, difficulty, subject (math, reading, or science), and nature (multiple choice versus an open question). See equation 1 for an explanation of the other covariates.[40]

The coefficient γ_1 shows the pattern of the test performance drop, that is the variable of interest in Borghans and Schils (2012). A significant and negative γ_1 coefficient would reveal a decline in performance from the first to the last question of the test. The coefficient on the interaction between $order_{iq}$ and the female indicator, γ_2, captures whether there is a gender differential decline in performance along the test. The coefficient on the interaction between $order_{iq}$ and the GE_j, γ_3, captures whether there is a differential decline in performance along the test among those second-generation immigrants whose parents come

[39] Following Borghans and Schils (2012), questions that have not been reached by the student are classified as missing, and those that have been skipped are classified as wrong.

[40] To identify the effect of cognitive skills, we assume that non-cognitive skills do not affect the answer on a test in the beginning of the test. This is a normalization that defines cognitive skills as the performance at the first question. Borghans and Schils (2012) show that there is no strong correlation between the decline in performance and the performance on the first question.

from more (or less) gender equal countries. And the coefficient on the interaction between $order_{iq}$, the female dummy, and the GE_j, γ_4, captures whether the decline in performance along the test differs between second-generation immigrant girls and boys whose parents come from more (or less) gender equal countries.

Our two coefficients of interest are: (1) the interaction between the GE_j and the female indicator, α_2; and (2) the interaction between $order_q$, the GE_j and the female indicator, γ_4. In equation 2, α_2 captures whether gender equality in the country of ancestry affects gender differences in test scores of second-generation immigrant boys and girls in the host country via the cognitive component. In contrast, γ_4 captures whether gender equality in the country of ancestry affects test scores via a non-cognitive component (such as agreeableness, motivation or ambition). A positive and significant α_2 would suggest that more gender-equal attitudes in the immigrant's country of ancestry are associated with a higher relative test performance of second-generation immigrant girls over boys because of its effect on cognitive skills. In contrast, a positive and significant γ_4 would suggest that more gender-equal attitudes in the immigrant's country of ancestry are associated with a higher relative performance of second-generation immigrant girls over boys via non-cognitive skills.

Column 1 in Table 6 explores whether there is a differential gender pattern in test performance drop by estimating a regression similar to equation 2 with only a female indicator, the $order_{iq}$ variable, their interaction, and country-of-ancestry, host-country, question, and year fixed effects. It is noteworthy that our estimate of the decline in test performance, γ_1, is very similar to that of Borghans and Schils (2012).[41] Moreover, we do not observe a gender differential in the performance decline as α_2 is zero and not statistically significant. The positive and statistically significant coefficient on the gender dummy, α_1, reflects that on average, second-generation girls perform better in the first question of the test.

Column 2 in Table 6 estimates equation 2. Interestingly, we find that the coefficient on the interaction between the GE_j and the female indicator, α_2, is positive and statistically significant, while γ_4 is negative, not statistically

[41] Borghans and Schils (2012) estimate a γ_1 coefficient ranging between 0.07 and 0.09 (shown in their Table 1). The intercept, which represent the average student's performance on the first question is also close to Borghans and Schils' (2012) estimate, which ranges between 0.46 and 0.50.

significant and close to zero. These findings suggest that the evidence that second-generation girls whose parents come from more gender-equal countries outperform their male counterparts in reading and science, as well as in math, is driven by cognitive factors.

Column 4 in Table 6 re-estimates equation 2 using more flexible specifications. In particular, it estimates equation 2 using an outcome variable that captures the deviation of each second-generation immigrant's response to each test question to the average response in his or her host country. More specifically, for each individual and each question, we estimated the difference between his or her actual score and the predicted value of his or her score in his or her host country. This predicted value was estimated separately for each host country and PISA wave using all individuals (including natives) but excluding the second-generation immigrant for whom we are predicting the answer. The covariates in the predicted model are $order_{iq}$ and question fixed effects. Concerns that specification 2 does not interact the host-country, year, order and question fixed effects are addressed in this more flexible specification. Results in column 4 resemble those of column 2.

An alternative and complementary question is whether second-generation girls put more or less effort in answering survey questionnaires than boys and whether country-of-ancestry gender social norms affect differentially non-cognitive skills of second-generation girls and boys. Estimates in columns 5 and 6 address these two questions by estimating equation 1 using as left-hand-side variable a measure of non-cognitive skills, namely item nonresponse on PISA students' surveys questionnaires. In a second specification (columns 7 and 8), we also control for cognitive abilities (math, reading and science test scores). Estimates from column 5 shows that second-generation girls' item non-response are lower than boys, suggesting that they are more conscientious when answering the students' questionnaires than their male counterparts. This difference, however, disappears after controlling for cognitive abilities (column 7).[42] Estimates from columns 6 and 8 provide no evidence that country-of-ancestry gender social norms affect this measure of non-cognitive skills, consistent with

[42] Note that test scores are endogenous. The intent here is not to claim causality, but to explore the gender differential in non-cognitive skills in the raw data (column 5) and conditioning on individual's test scores (column 7).

the results in columns 2, and 4. While Zamarro, Hitt and Mendez (2016) find that about one third of the between country variation in 2009 PISA scores is driven by similar measures of conscientiousness, we find no evidence that countries' gender social norms are driving these results.

10. Conclusion

Merging data from PISA and the World Economic Forum, this paper presents evidence that second-generation girls whose parents come from more gender-equal countries outperform their male counterparts in reading and science, as well as in math, suggesting that cultural beliefs on the role of women in society are not specific to math skills, but instead more general as they also apply to reading and science skills. We find weak evidence that it is the persistence of beliefs on women's political empowerment (and economic opportunities to a lesser extent) that seems to be driving these results. Our results are robust to a battery of sensitivity checks. These results are driven by a relatively larger effect of cultural beliefs about the role of women in society on test scores on girls than boys. We also find suggestive evidence for horizontal transmission of culture, as well as vertical transmission from parents to children. While our findings on non-cognitive skills suggest that non-cognitive skills are not driving our results, caution is needed as our measures of non-cognitive skills are only proxies. Further research on whether social gender norms also affect non-cognitive skills would be needed.

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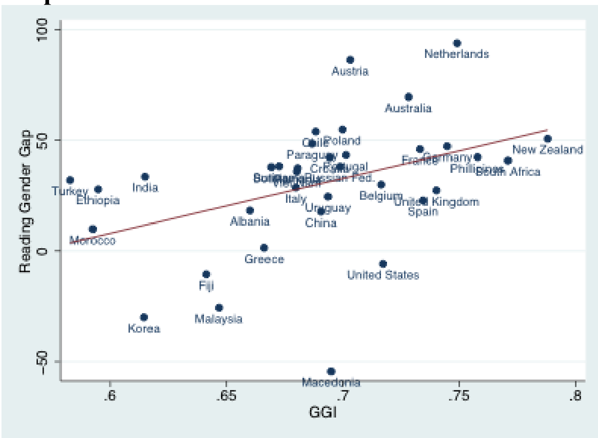
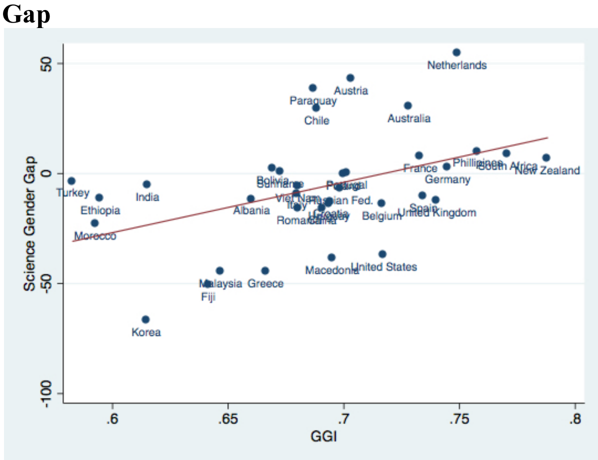
Figure 1. Gender Gap in Test Scores of Second-generation Immigrants and Gender Equality in Countries of Ancestry

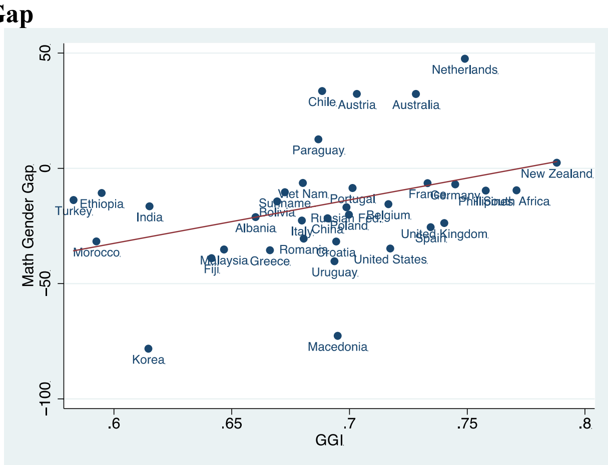
Panel A. Reading Gender Gap



Panel B. Science Gender Gap



Panel C. Math Gender Gap



Notes: These figures display the correlation between the raw average test scores gender gap among second-generation immigrants and the Gender Gap Index (GGI) in the country of ancestry. The fitted line is the prediction of running a linear regression of the gender gap on the test score on GGI. Panel A and B present the figures for reading and science test scores, respectively, whereas Panel C replicates Figure 1 presented in Nollenberger, Rodríguez-Planas, and Sevilla (2016) for math test scores. The test scores gender gap were obtained from estimating a linear regression using the plausible values provided by the PISA data sets as LHS variable and a female indicator as RHS variable. We estimated one regression for each PV for each country and present the average of the 5 coefficients estimated. We use individuals whose both parents were born in a foreign country from the 2003, 2006, 2009 and 2012 PISA datasets. The index of gender equality is the Gender Gap Index (GGI) from the 2009 World Economic Forum.

Table 1. Culture and Gender Gaps in Math, Reading, and Science Test Scores

	A. Math Test Scores		B. Reading Test Scores		C. Science Test Scores	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-14.77***	-177.15	32.25***	-339.29	-4.73	-343.57
	[2.74]	[298.18]	[3.18]	[517.76]	[3.19]	[519.63]
GGI×Female (α_2)		**149.55****		**179.27*****		**186.90*****
		[62.62]		**[68.25]**		**[65.67]**
Age of student		7.90		0.61		4.24
		[6.71]		[6.69]		[6.96]
Age×Female		6.07		17.86*		16.22
		[9.54]		[9.80]		[9.99]
Diff. grade		-13.82***		-13.79***		-14.00***
		[4.69]		[5.00]		[4.60]
Diff. grade×Female		-5.64		-9.12		-6.79
		[6.30]		[7.07]		[6.73]
GDP×Female		-3.94		-3.26		-5.02
		[3.30]		[4.01]		[3.74]
Constant	372.32***	243.53**	373.40***	360.49***	383.99***	306.93***
	[33.33]	[117.25]	[53.22]	[110.32]	[48.31]	[111.61]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country of ancestry FE	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE×Female	No	Yes	No	Yes	No	Yes
N	11,527	11,527	11,527	11,527	11,527	11,527
R^2	0.34	0.35	0.34	0.35	0.32	0.33
Null hypothesis:			H_0: α_2 [math] - α_2 [reading]=0		H_0: α_2 [math] - α_2 [science]=0	
F(1, 11,526)			1.34		2.40	
Prob > F			0.25		0.12	

Notes: Specification in odd columns include a female dummy, year and countries fixed-effects (for both ancestry and host countries). Specification in even columns add our variable of interest (GGI× Female) and control for individuals' age and dummies for any students who are in a grade different from the modal one in the country and its interactions with the female indicator, and the GDP per capita from the country of ancestry interacted by the female indicator. In all cases we use the five plausible values of math test scores provided by PISA datasets and report the average coefficient (Stata command *pv*). Standard Errors are adjusted following the Fay's BRR methodology using the 80 alternative weights provided by the PISA datasets. * p<0.1, ** p<0.05, *** p<0.01

Table 2. Subgroup Analysis

A. By gender	Math scores	Reading scores	Science scores
Boys			
GGI	96.13**	149.37***	138.65***
	[45.50]	[45.49]	[47.11]
Girls			
GGI	240.49***	327.38***	326.37***
	[39.61]	[39.65]	[42.02]
H_0: Equal GGI across samples (P-value)	0.02	0.00	0.00
B. By proportion of immigrants of same origin at school	**Math scores**	**Reading scores**	**Science scores**
Below median			
GGI×Female	88.20	115.48*	150.87**
	[69.21]	[69.42]	[72.46]
Above median			
GGI×Female	294.50***	235.16**	273.85**
	[105.29]	[106.83]	[112.78]
H_0: Equal GGIxFemale across samples (P-value)	0.10	0.35	0.36
C. By whether only one or both parents were born in a foreign country			
Only one parent foreign born			
GGI×Female	66.91	71.31	69.05
	[53.53]	[55.42]	[55.98]
Both parents foreign born			
GGI×Female	149.55***	179.27***	186.90***
	[57.08]	[57.53]	[59.74]
H_0: Equal GGIxFemale across samples (P-value)	0.29	0.18	0.15

Notes: Results from estimating our preferred specification (specification in column 2 of Table 2) with different samples. Note that in Panel A, the GGI interacted by gender is not included in the specification. The sample used in Panel C differs from our main sample in that now we also include those individuals with only one foreign-born parent. In this case, we assign as the individual's country of ancestry the country of birth of the immigrant parent. In all cases, we use the five plausible values of math, reading and science test scores provided by PISA datasets and report the average coefficient (Stata command *pv*). Standard Errors are adjusted following the Fay's BRR methodology using the 80 alternative weights provided by the PISA datasets. We report the p-value of a test about equality of coefficients (GGI or GGIxfemale) across different samples (we use the Stata command SUEST).

* p<0.1, ** p<0.05, *** p<0.01

Table 3. Effect of Gender Equality in the Country of Ancestry on the Math Gender Gaps, by Measure of Gender Equality

	Math Scores				
	(1)	(2)	(3)	(4)	(5)
Female	-100.90	-135.25	-139.99	-392.91	-140.25
	[154.09]	[155.37]	[158.73]	[344.62]	[365.51]
GGI Pol. Emp.×Female	71.72**				52.72
	[33.53]				[37.18]
GGI Ec. Opp.×Female		56.62*			61.61
		[29.58]			[42.82]
GGI Educ.×Female			38.83		-63.77
			[63.78]		[78.47]
GGI Health×Female				295.37	53.76
				[338.44]	[358.82]
Constant	242.38**	242.57**	242.70**	240.96**	241.36**
	[118.94]	[118.18]	[117.41]	[119.79]	[120.43]
Year FE	Yes	Yes	Yes	Yes	Yes
Country of ancestry FE	Yes	Yes	Yes	Yes	Yes
Host country FE	Yes	Yes	Yes	Yes	Yes
Host country FE×Female	Yes	Yes	Yes	Yes	Yes
N	11,527	11,527	11,527	11,527	11,527
R^2	0.35	0.35	0.35	0.35	0.35
H_0: All coefficients are jointly equal to zero (Prob>χ^2)					0.051

Notes: Results from estimating our baseline specification (specification in Column 2, Table 1) using alternative measures of Gender Equality (see Appendix Table A.1 for definitions and descriptive statistics of each measure). In all cases, we use the five plausible values of math test scores provided by PISA datasets and report the average coefficient (Stata command *pv*). Standard errors are adjusted following the Fay's BRR methodology using the 80 alternative weights provided by the PISA datasets.
p<0.1, ** p<0.05, *** p<0.01

Table 4. Effect of Gender Equality in the Country of Ancestry on the Reading and Science Gender Gaps, by Measure of Gender Equality

	A. Reading Scores					B. Science Scores				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Female	-246.77	-286.86*	-302.19*	-706.31**	-476.54	-248.28	-288.71*	-314.61**	-668.18*	-457.09
	[154.76]	[155.81]	[158.22]	[322.23]	[339.75]	[153.16]	[154.63]	[156.30]	[357.80]	[393.36]
GGI Pol. Emp.×Female	86.67**				68.33*	85.52**				68.94*
	[34.06]				[37.81]	[35.03]				[39.02]
GGI Ec. Opp.×Female		62.64*			43.80		65.34**			36.59
		[32.52]			[43.91]		[30.16]			[46.73]
GGI Educ.×Female			63.95		-18.32			87.32		16.88
			[73.02]		[87.99]			[69.61]		[93.95]
GGI Health×Female				472.93	242.05				430.18	203.32
				[337.17]	[353.08]				[358.58]	[390.03]
Constant	359.12***	359.26***	359.95***	357.13***	358.56***	305.45***	305.65***	306.91***	303.57***	305.82***
	[108.14]	[109.39]	[110.81]	[108.17]	[107.42]	[112.61]	[113.34]	[114.36]	[112.83]	[112.43]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country of ancestry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE×Female	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,527	11,527	11,527	11,527	11,527	11,527	11,527	11,527	11,527	11,527
R^2	0.34	0.34	0.34	0.34	0.35	0.33	0.33	0.33	0.33	0.33
H_0: All coefficients are jointly equal to zero (Prob>χ^2)					0.047					0.046

Notes: Results from estimating our baseline specification (specification in column 2, Table 1) using alternative measures of Gender Equality (see Table A.1 for definitions and descriptive statistics of each measure). In all cases, we use the five plausible values of math test scores provided by PISA datasets and report the average coefficient (Stata command *pv*). Standard errors are adjusted following the Fay's BRR methodology using the 80 alternative weights provided by the PISA datasets.
p<0.1, ** p<0.05, *** p<0.01

Table 5. Culture and Gender Gaps in Math, Math Preferences, Beliefs, and Anxiety

	Math Test Scores		Math self-concept		Math self-efficacy		Math improve career prospects		Anxiety doing math		Math interest	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female	-14.77***	-177.15	-0.33***	-1.58	-0.35***	-2.50	-0.25***	-0.74	0.30***	0.19	-0.28***	-3.43
	[2.74]	[298.18]	[0.04]	[2.53]	[0.04]	[2.09]	[0.05]	[2.64]	[0.05]	[2.67]	[0.03]	[2.75]
GGI×Female		**149.55****		**0.31**		**0.31**		**1.48**		**0.60**		**1.53****
		[62.62]		**[0.99]**		**[1.11]**		**[1.04]**		**[1.12]**		**[0.63]**
Age of student		7.90		0.05		0.13		-0.14		-0.10		-0.07
		[6.71]		[0.11]		[0.10]		[0.10]		[0.13]		[0.09]
Age×Female		6.07		0.11		0.16		0.06		-0.03		0.16
		[9.54]		[0.15]		[0.13]		[0.16]		[0.17]		[0.17]
Diff. grade		-13.82***		-0.01		0.06		-0.22***		0.02		-0.08*
		[4.69]		[0.06]		[0.06]		[0.07]		[0.05]		[0.05]
Diff. grade×Female		-5.64		-0.07		-0.10		0.17		0.08		0.01
		[6.30]		[0.10]		[0.07]		[0.10]		[0.09]		[0.07]
GDP×Female		-3.94		-0.09		-0.06		-0.20***		0.01		-0.06
		[3.30]		[0.05]		[0.05]		[0.06]		[0.06]		[0.06]
Constant	372.32***	243.53**	0.24	-0.83	-0.23	-2.44	0.39**	2.76*	0.43	1.88	0.40	1.72
	[33.33]	[117.25]	[0.41]	[1.71]	[0.14]	[1.54]	[0.16]	[1.61]	[0.27]	[2.02]	[0.50]	[1.34]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country of ancestry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE× Female	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	11,527	11,527	4,396	4,396	4,507	4,507	4,514	4,514	4,399	4,399	4,521	4,521
R^2	0.34	0.35	0.09	0.10	0.13	0.14	0.09	0.11	0.09	0.10	0.09	0.10

Notes: Results from estimating equation 1 using as LHS variable the PISA indices displayed in each column (refer to the main text for a definition of each index and Appendix Table A.1 for descriptive statistics). Specification in odd columns include a female dummy, year and countries fixed-effects (for both ancestry and host countries). Specification in even columns add our variable of interest (GGI× Female) and control for individuals' age and dummies for any students who are in a grade different from the modal one in the country and its interactions with the female indicator, and the GDP per capita from the country of ancestry interacted by the female indicator. These indices are only available in 2003 and 2012 PISA waves, which are focused in math. In Appendix Table A.5, we show the results from estimating the same specification using as LHS variable math scores over this reduced sample. Standard Errors are adjusted following the Fay's BRR methodology using the 80 alternative weights provided by the PISA datasets.
* p<0.1, ** p<0.05, *** p<0.01

Table 6. Culture and Gender Gaps in non-cognitive outcomes

Dep. variable:	*Score by question*		*Actual – Predicted Score by question*		*Item nonresponse rate to survey questionnaire*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.033***	-0.667***	0.000	-0.604***	-0.009***	0.036	-0.003	-0.078
	[0.010]	[0.102]	[0.004]	[0.113]	[0.004]	[0.194]	[0.005]	[0.184]
Order	-0.083***	-0.056	-0.086***	-0.041				
	[0.004]	[0.045]	[0.005]	[0.049]				
Order×Female	0.004	-0.080	0.009	-0.086				
	[0.006]	[0.062]	[0.007]	[0.068]				
GGI×Female (α_2)		0.226***		0.174***		-0.019		0.043
		[0.060]		[0.066]		[0.070]		[0.067]
GGI×Order×Female (γ_4)		-0.041		-0.068				
		[0.065]		[0.072]				
GGI×Order		0.125		0.143				
		[0.090]		[0.099]				
GDP×Female		-0.007***		-0.003		-0.002		-0.003
		[0.002]		[0.003]		[0.004]		[0.004]
Age of student		-0.001		0.001		-0.009		-0.009
		[0.004]		[0.005]		[0.009]		[0.008]
Age×Female		0.039***		0.035***		-0.002		0.004
		[0.006]		[0.007]		[0.012]		[0.011]
Diff. grade		-0.017***		-0.013***		0.023***		0.019***
		[0.003]		[0.003]		[0.006]		[0.005]
Diff. grade×Female		-0.015***		-0.021***		-0.006		-0.008
		[0.004]		[0.004]		[0.008]		[0.007]
Math score							0.0000	0.0000
							[0.0001]	[0.0001]
Reading score							-0.0002**	-0.0002**
							[0.0001]	[0.0001]
Science score							-0.0002**	-0.0002**
							[0.0001]	[0.0001]
Constant	0.285***	0.304***	-0.080**	-0.119	0.077***	0.198	0.207***	0.328***
	[0.030]	[0.073]	[0.033]	[0.081]	[0.028]	[0.132]	[0.031]	[0.126]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country of ancestry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE x female	Yes	Yes	No	Yes	No	Yes	No	Yes
Question FE	Yes	Yes	Yes	Yes	No	No	No	No
N	731,767	731,767	731,648	731,648	11,527	11,527	11,527	11,527
R^2	0.20	0.20	0.16	0.16	0.67	0.68	0.70	0.70

Notes: Columns 1 and 2 display the results from estimating equation (2) over the score the student achieved on each question of the test. Following Borghans and Schils (2012), we include the (random) question order to measure the decline in performance during the test, and its interaction with the female dummy (column 1), as well as the triple interaction with the GGI and the female dummy (column 2). In columns 3 and 4, we estimate the same model but using as dependent variable the difference between the actual score on each question and the score the student would achieve if his/her decline in performance during the test were the same than the average student in the host country where his/her lives. The predicted score comes from estimating the same model as in Borghans and Schils (2012) for each host country and PISA wave, excluding the student for whom we are predicting the answer. In columns 5 and 6, we estimate the equation 1 using as left-hand side variable the item nonresponse rate on PISA students' surveys questionnaires. In columns 7 and 8 we include also test scores to control for students' cognitive skills.

Appendix

Appendix Table A.1. Individual-level variables: Definition and Descriptive Statistics

Name	Definition	Mean	St. Dev. across countries of ancestry
A. Tests Scores			
Math test score	Performance in math, reading and science assessment, respectively. Average of the 5 plausive values on each domain provided by PISA program.	482.61	104.12
Reading test score		478.12	107.96
Science test score		478.21	108.33
B. Individual Characteristics			
Female	Dummy variable equal to 1 if the individual is a girl	0.52	0081
Age	Years and months	15.77	0.06
Different grade	Dummy equal to 1 if the current individual's grade is different from the modal grade at the children age in the host country and 0 otherwise.	0.35	0.17
C. Family characteristics			
Mother highest level of education (MISCED)	Index constructed by the PISA program based upon the highest education level of each parent. It has the following categories: (0) None; (1) ISCED 1 (primary education); (2) ISCED 2 (lower secondary); (3) ISCED Level 3B or 3C (vocational/pre-vocational upper-secondary); (4) ISCED 3A (upper-secondary) and/or ISCED 4 (non-tertiary post-secondary); (5) ISCED 5B (vocational tertiary); and (6) ISCED 5A, 6 (theoretically-oriented tertiary and post-graduate).	3.66	1.04
Father highest level of education (FISCED)		3.85	0.85
Mother works	Dummy equal to one if the mother (father) works, and zero otherwise. Due to the direct question about parents' labor status is not included in all PISA waves, we use students' responses about what is the mother (father) main work. The dummy takes the value of zero when the answer is housewife, student or social beneficiary (unemployed, retired, sickness, etc.) and one otherwise.	0.82	0.14
Father works		0.93	0.05
Index of home possessions (homeposs)	The PISA index of home possessions comprises all items on the indices of wealth, cultural possessions and home educational resources, as well as books in the home recoded into a four-level categorical variable (0-10 books, 11-25 or 26-100 books,101-200 or 201-500 books, more than 500 books). The index of wealth is based on the students' responses on whether they had a room of their own, a link to the Internet, a dishwasher, a DVD player, and three other country-specific items; and their responses on the number of cellular phones, televisions, computers, cars and the rooms with a bath or shower. The index of cultural possessions is based on the students' responses to whether they had the following at home: classic literature, books of poetry and works of art. The index of home educational resources is based on the items measuring the existence of educational resources at home including a desk and a quiet place to study, a computer, educational software, books to help with students' school work, technical reference books and a dictionary.	-0.04	0.53
D. School characteristics			
Percentage of girls	PISA index of the proportion of girls enrolled in each school derived from school principals' responses regarding the number of girls divided by the total of girls and boys at a school.	0.49	0.04
Private school	Dummy equal to 1 if school is private and 0 otherwise.	0.24	0.18
School location	Dummy equal to 1 if the school is in a metropolis or city and 0 if the school is in a town or village.	0.29	0.27
Percentage of immigrants from the same ethnicity	Number of immigrants from the same ethnicity (either first or second-generation) divided the total individuals by school. Own calculation based upon PISA samples by year, weighted by student final weight.	0.11	0.06

Appendix Table A.1 (cont.) Individual-level variables: Definition and Descriptive Statistics

Name	Definition	Mean	St. Dev. across countries of ancestry
E. Math-specific variables			
Mathematics self-concept	PISA index constructed using student responses to a question over the extent they strongly agree, agree, disagree or strongly disagree with the following statements when asked to think about studying mathematics: "I am just not good at mathematics; I get good in mathematics; I learn mathematics quickly; I have always believed that mathematics is one of my best subjects; in my mathematics class, I understand even the most difficult work".	-0.36	0.55
Mathematics self-efficacy	This index is calculated by the PISA program based on how confident students report to be at performing the following mathematics tasks: "Using math to work out how long it would take to get from one place to another; calculating how much cheaper a TV would be after a 30% discount; calculating how many square meters of tiles you need to cover a floor; understanding graphs presented in newspapers; solving an equation like 3x+5=17; finding the actual distance between two places on a map with a 1:10,000 scale; solving an equation like 2(x+3)=(x+3)(x-3); calculating the petrol consumption rate of a car".	-0.48	0.61
Math improve career prospects	PISA index constructed using students' responses over the extent they strongly agree, agree, disagree or strongly disagree to a series of statements, when asked to think about their views on mathematics: "Making an effort in mathematics is worth because it will help me in the work that I want to do later on; learning mathematics is worthwhile for me because it will improve my career; Mathematics is an important subject for me because I need it for what I want to study later on; I will learn many things in mathematics that will help me get a job".	-0.37	0.64
Mathematics anxiety	PISA index based on students' responses to a question over the extent they strongly agree, agree, disagree or strongly disagree with the following statements when asked to think about studying mathematics: "I often worry that it will be difficult for me in mathematics classes; I get very tense when I have to do mathematics homework; I get very nervous doing mathematics problems; I feel helpless when doing a mathematics problem; I worry that I will get poor in mathematics".	0.33	0.61
Math interest	PISA index based on students' responses to questions on enjoyment from doing math. The student is asked to strongly agree, agree, disagree or strongly disagree to a series of statements, when asked to think about his or her views on mathematics: "I enjoy reading about mathematics; I look forward to my mathematics class; I do mathematics because I enjoy it; I am interested in the things I learn in mathematics."	-0.35	0.59

Appendix Table A.2. Sample Size by Country of Ancestry and Host Country

		Host Countries									
		ARG	AUS	AUT	BEL	CHE	ISR	LUX	NLD	NZL	**Total**
Country of Ancestry											
1	Albania					132					**132**
2	Australia									36	**36**
3	Austria					46					**46**
4	Belgium							159			**159**
5	Bolivia	131									**131**
6	Chile	24									**24**
7	China		410						27	130	**567**
8	Croatia			77							**77**
9	Ethiopia						151				**151**
10	Fiji									35	**35**
11	France				102	203	67	242			**614**
12	Germany		21	38	41	176		116			**392**
13	Greece		46								**46**
14	India		158								**158**
15	Italy		88			739		256			**1,083**
16	Korea		31							15	**46**
17	Malaysia		34								**34**
18	Morocco								192		**192**
19	Netherlands				50						**50**
20	New Zealand		376								**376**
21	Paraguay	63									**63**
22	Philippines		240								**240**
23	Poland			47							**47**
24	Portugal					777		2,069			**2,846**
25	Romania			58							**58**
26	Russian Fed.						491				**491**
27	Viet Nam		291								**291**
28	South Africa		60								**60**
29	Spain					246					**246**
30	Suriname								107		**107**
31	Turkey			509	440	591			222		**1,762**
32	Macedonia			20							**20**
33	United Kingdom		651							168	**819**
34	United States		29				82				**111**
35	Uruguay	17									**17**
	Total	**235**	**2,435**	**749**	**633**	**2,910**	**791**	**2,842**	**548**	**384**	**11,527**

Notes: Final sample of second-generation immigrants from 2003, 2006, 2009 and 2012 PISA datasets. ARG=Argentina, AUS=Australia, AUT=Austria, BEL=Belgium, CHE=Switzerland, ISR=Israel, LUX=Luxembourg, NLD=Netherlands, NZL= New Zealand.

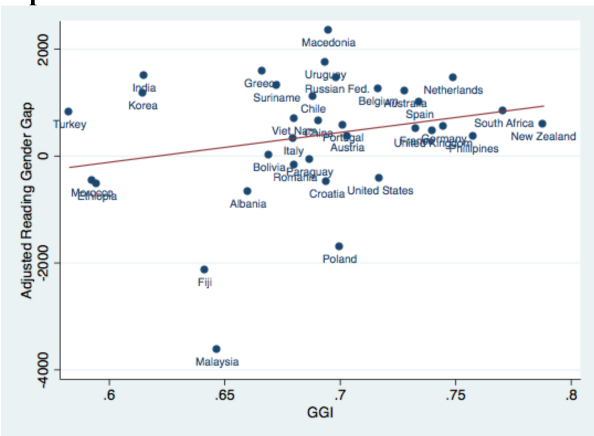
Appendix Table A.3. Gender Gap in Tests Scores and Gender Equality by Country of Ancestry

Country of ancestry	Math gender gap	Reading gender gap	Science gender gap	Math Self-concept gap	Math Self-effic. gap	Math career gap	Math anxiety gap	Math pref. gap	GGI	GGI Ec. Opp.	GGI Educ.	GGI Pol.	GGI Health
Korea	-78.24	-30.06	-66.90	0.06	-0.34	-0.47	0.59	-0.29	0.61	0.52	0.89	0.07	0.97
Macedonia	-72.64	-54.49	-38.52	-0.07	0.74	-0.54	-0.52	0.68	0.69	0.67	0.99	0.16	0.96
Uruguay	-40.31	24.55	-14.18	0.76	-0.47	0.67	-0.73	0.29	0.69	0.65	1.00	0.14	0.98
Fiji	-38.99	-10.64	-50.81	-0.61	-1.03	-0.44	0.17	-0.59	0.64	0.53	0.99	0.06	0.98
Greece	-35.53	1.44	-44.53	-0.16	0.07	-0.76	0.17	-0.49	0.67	0.61	0.99	0.09	0.98
Malaysia	-35.19	-25.68	-44.90	0.12	-0.71	-0.22	0.08	0.34	0.65	0.57	0.99	0.06	0.97
United States	-34.75	-5.90	-37.08	-0.09	-0.81	-0.20	0.11	0.49	0.72	0.75	1.00	0.14	0.98
Croatia	-31.74	42.24	-12.92	-0.13	0.34	0.67	0.77	0.12	0.69	0.65	0.99	0.16	0.98
Morocco	-31.70	9.92	-22.88	-0.35	0.20	0.00	0.35	-0.28	0.59	0.45	0.86	0.10	0.97
Romania	-30.52	37.49	-15.86	-1.08	-0.85	-0.76	0.70	-0.95	0.68	0.71	0.99	0.04	0.98
Spain	-25.55	22.78	-10.36	-0.33	-0.36	-0.26	0.42	-0.22	0.73	0.60	0.99	0.37	0.97
UK	-23.73	27.37	-12.32	-0.51	-0.45	-0.42	0.44	-0.28	0.74	0.71	1.00	0.28	0.97
Italy	-22.65	28.70	-9.18	-0.33	-0.34	-0.47	0.17	-0.29	0.68	0.59	1.00	0.16	0.97
China	-21.69	17.75	-15.95	-0.24	-0.57	0.01	0.20	-0.11	0.69	0.70	0.98	0.14	0.95
Albania	-21.16	18.23	-11.73	-0.23	-0.16	-0.46	-0.68	-0.39	0.66	0.65	0.99	0.04	0.96
Poland	-20.11	54.87	-0.59	-0.06	-1.55	-1.34	-0.79	-1.13	0.70	0.64	1.00	0.18	0.98
Russian Fed.	-16.88	38.20	-6.90	-0.45	-0.34	-0.06	0.44	0.02	0.70	0.74	1.00	0.08	0.98
India	-16.45	33.60	-5.31	-0.23	-0.64	0.25	0.57	-0.13	0.62	0.41	0.84	0.27	0.93
Belgium	-15.56	30.01	-13.81	-0.06	-0.77	-0.70	-0.22	-0.75	0.72	0.65	0.99	0.24	0.98
Bolivia	-14.36	37.98	2.02	-0.14	-0.33	-0.29	0.61	-0.54	0.67	0.59	0.97	0.15	0.97
Turkey	-13.77	32.04	-3.64	-0.35	-0.25	-0.31	0.05	-0.36	0.58	0.40	0.89	0.07	0.97
Ethiopia	-10.69	27.84	-11.48	-0.47	-0.57	0.06	0.52	0.11	0.59	0.60	0.70	0.11	0.97
Suriname	-10.39	38.32	0.43	0.02	-0.37	0.18	0.09	-0.15	0.67	0.57	0.99	0.16	0.97
Philippines	-9.66	42.40	9.93	-0.04	-0.08	-0.08	-0.02	-0.06	0.76	0.76	1.00	0.29	0.98
South Africa	-9.56	40.86	8.48	.	.	.	.	.	0.77	0.66	1.00	0.45	0.98
Portugal	-8.53	43.30	0.18	-0.57	-0.31	-0.59	0.39	-0.50	0.70	0.68	0.99	0.16	0.97
Germany	-6.96	47.27	2.59	-0.64	-0.58	-0.54	0.30	-0.77	0.74	0.70	1.00	0.31	0.98
France	-6.43	46.00	7.47	-0.69	-0.57	-0.28	0.73	0.06	0.73	0.66	1.00	0.29	0.98
Viet Nam	-6.34	35.92	-6.03	-0.28	-0.30	-0.08	0.43	-0.36	0.68	0.73	0.90	0.12	0.97
New Zealand	2.42	50.69	6.49	-0.46	-0.56	-0.28	0.48	-0.15	0.79	0.78	1.00	0.39	0.97
Paraguay	12.61	48.43	38.39	0.77	0.35	0.86	-0.01	-0.08	0.69	0.67	1.00	0.10	0.98
Australia	32.26	69.63	30.31	-1.07	-1.55	-0.48	1.03	-0.79	0.73	0.75	1.00	0.19	0.97
Austria	32.29	86.48	42.77	-2.24	-2.68	-1.55	2.18	-1.87	0.70	0.57	0.99	0.27	0.98
Chile	33.52	53.97	29.21	-1.57	-0.50	-2.69	1.94	-2.29	0.69	0.52	1.00	0.26	0.98
Netherlands	47.53	94.01	54.63	-0.39	-0.08	-0.83	0.45	-0.18	0.75	0.69	0.99	0.34	0.97
Mean	-15.70	30.16	-6.37	-0.36	-0.48	-0.37	0.33	-0.35	0.69	0.63	0.97	0.18	0.97
St. Dev.	26.04	30.03	26.10	0.55	0.61	0.64	0.61	0.59	0.05	0.10	0.06	0.11	0.01

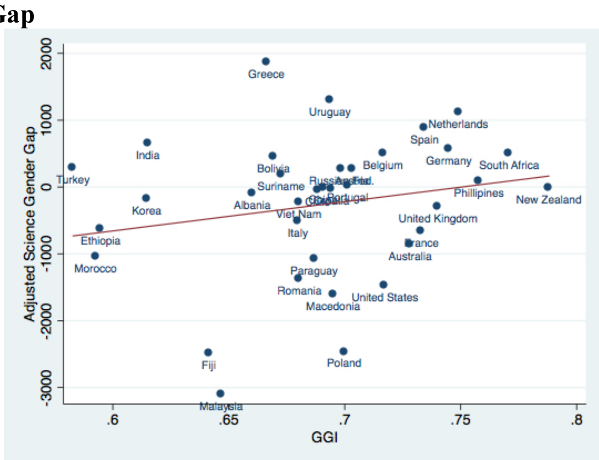
Notes: This table displays the means of test scores gender gaps, math indices and gender equality measures by country of ancestry estimated using our sample of second-generation immigrants from 2003, 2006, 2009 and 2012 PISA. Countries are ordered by the gender gap in math scores. The gap in test scores was obtained from estimating a linear regression using the plausible values provided by the PISA data sets as LHS variable and a female indicator as RHS (we estimated one regression for each PV and present the average of the 5 coefficients estimated). The last two rows display the mean and cross-country standard deviation.

Appendix Figure A.1. Adjusted Gender Gap in Test Scores of Second-generation Immigrants and Gender Equality in Countries of Ancestry

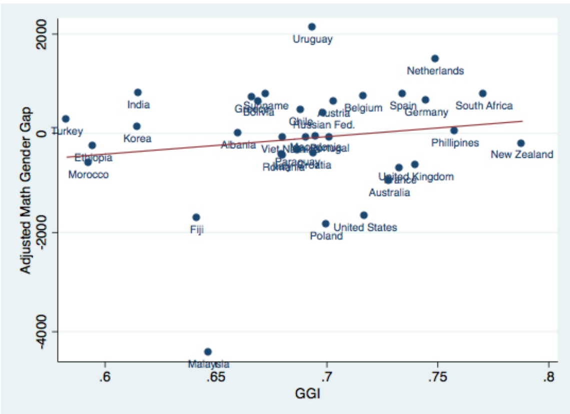
Panel A. Reading Gender Gap



Panel B. Science Gender Gap



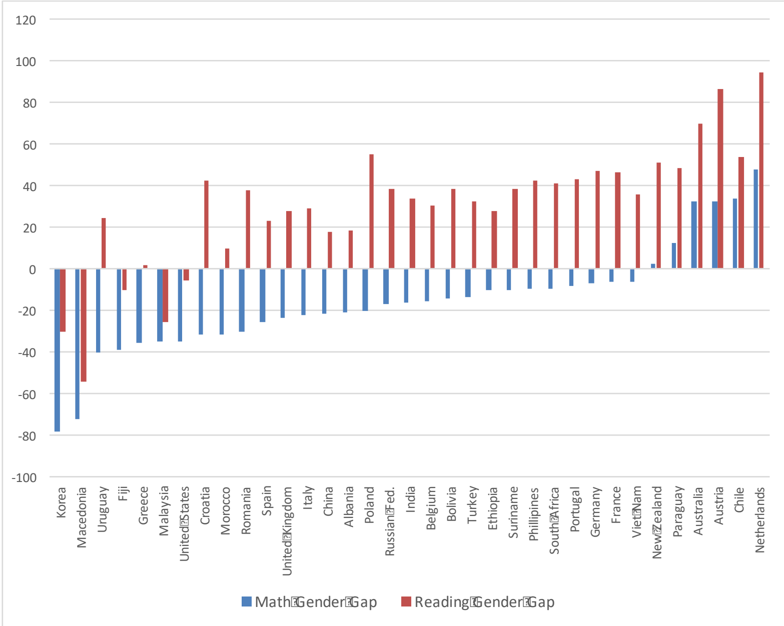
Panel C. Math Gender Gap



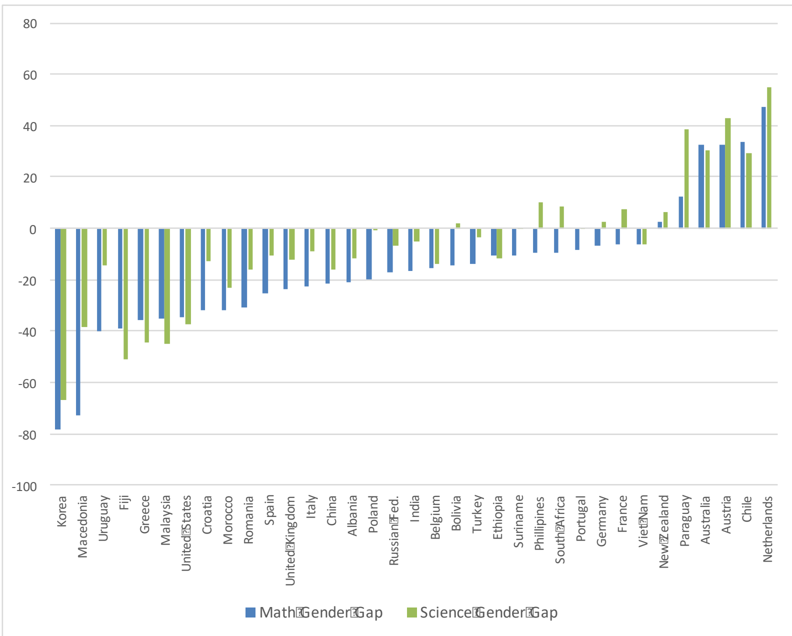
Notes: These figures display the correlation between the average test scores gender gap among second-generation immigrants and the GGI in the country of ancestry after adjusting the test scores gender gap by individual characteristics (age and dummies for being in a grade different from the modal one in the host country) and the GDP per capita of the country of ancestry. More specifically, we first estimate a linear regression using the individual plausible values provided by the PISA data sets as LHS variable and a female indicator, individual's controls and country of ancestry fixed effects as RHS variable. We then take the math gender gap of each country of ancestry resulting from the previous exercise and regress these coefficients on the GDP per capita of the country of ancestry and gender differences in the country of ancestry.

Appendix Figure A.2. Math, Reading and Science Test Scores of Second-generation Immigrants, by Country of Ancestry

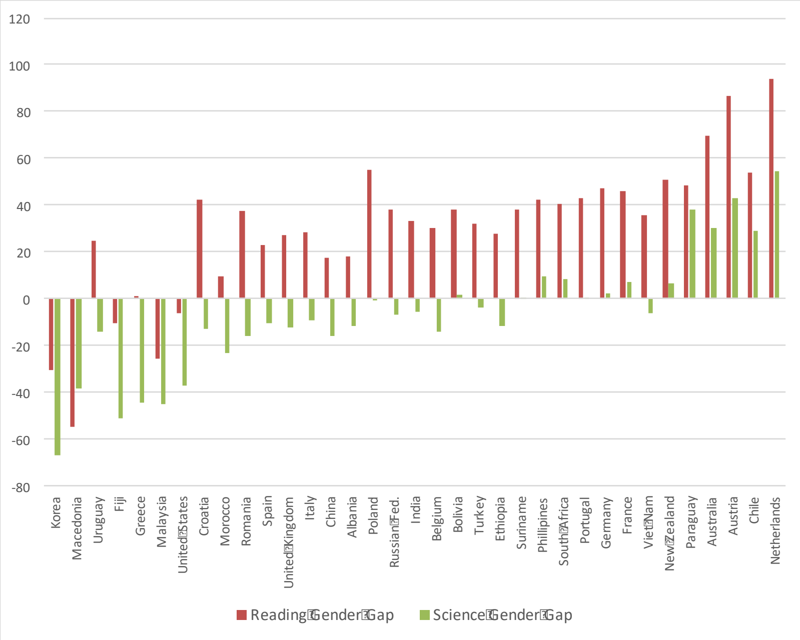
Panel. A Math and Reading Gender Gap



Panel. B Math and Science Gender Gap



Panel C. Reading and Science Gender Gap



Note: Panel A presents the relationship between the raw math and reading gender gaps among second generation immigrants, by country of ancestry. Panel B and C do the same for math and science and for reading and science, respectively. The test scores gender gap were obtained from estimating a linear regression using the plausible values provided by PISA as LHS variable and a female indicator as RHS variable. We estimated one regression for each PV for each country and present the average of the 5 coefficients estimated. We use individuals whose parents (both of them) were born in a foreign country from the 2003, 2006, 2009 and 2012 PISA datasets.

Appendix Table A.4. Gender Gap in Test Scores

	All Countries participating in PISA				Countries included in our 9 host countries					
	All individuals		Second-generation immigrants		All individuals		Second-generation immigrants		Second-generation immigrants (final sample)	
Math Scores	(1)		(2)		(3)		(4)		(5)	
Boys	460.13	[105.15]	470.02	[94.64]	488.95	[108.85]	494.46	[104.11]	493.51	[107.78]
Girls	447.70	[100.38]	459.79	[92.77]	473.21	[104.06]	476.00	[98.08]	477.81	[99.52]
Gender Gap	**-12.43**		**-10.23**		**-15.74**		**-18.46**		**-15.70**	
Reading scores										
Boys	441.18	[103.22]	453.67	[100.55]	460.94	[110.27]	465.93	[106.96]	464.69	[110.99]
Girls	472.29	[97.01]	487.64	[94.67]	494.40	[102.74]	495.82	[100.42]	494.84	[103.49]
Gender Gap	**31.11**		**33.97**		**33.46**		**29.89**		**30.16**	
Science scores										
Boys	465.41	[104.89]	469.74	[98.03]	486.28	[111.21]	484.21	[109.20]	483.79	[112.97]
Girls	461.75	[98.75]	466.39	[94.14]	483.32	[103.47]	476.53	[101.92]	477,42	[103.54]
Gender Gap	**-3.66**		**-3.35**		**-2.96**		**-7.67**		**-6.37**	
N	*1,676,363*		*84,426*		*222,082*		*22,910*		*11,527*	

Notes: Author's calculations based upon 2003, 2006, 2009 and 2012 PISA datasets. Mean and standard deviation in brackets. The nine (host) countries included in our sample are: Argentina, Australia, Austria, Belgium, Switzerland, Israel, Luxembourg, Netherlands, New Zealand. These countries collected information on the parents' country of birth in PISA and had at least four countries of ancestry among their second-generation immigrants.

Table A.5. Culture, Test Gender Gaps, and Language Skills

	Math Score		Reading Score		Science Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-177.15	-156.79	-339.29	-345.93**	-343.57	-309.15*
	[298.18]	[175.20]	[517.76]	[174.72]	[519.63]	[173.47]
GGI × Female (α_2)	**149.55****	**155.64****	**179.27*****	**172.56****	**186.90*****	**192.74*****
	[62.62]	**[67.33]**	**[68.25]**	**[74.82]**	**[65.67]**	**[73.30]**
Age of student	7.90	3.75	0.61	-4.28	4.24	0.43
	[6.71]	[8.03]	[6.69]	[8.14]	[6.96]	[8.14]
Age×Female	6.07	2.88	17.86*	16.95	16.22	12.70
	[9.54]	[10.30]	[9.80]	[10.83]	[9.99]	[10.81]
Diff. grade	-13.82***	-17.45***	-13.79***	-14.97**	-14.00***	-16.46***
	[4.69]	[5.42]	[5.00]	[5.84]	[4.60]	[5.66]
Diff. grade×Female	-5.64	-1.66	-9.12	-8.45	-6.79	-4.27
	[6.30]	[6.91]	[7.07]	[7.74]	[6.73]	[7.69]
GDP×Female	-3.94	-1.39	-3.26	-0.19	-5.02	-3.11
	[3.30]	[3.42]	[4.01]	[4.48]	[3.74]	[4.05]
Do not speak test language at home		-15.95***		-20.56***		-19.73***
		[6.07]		[5.64]		[6.47]
Do not speak test language at home×Female		3.10		-4.01		4.63
		[7.35]		[7.30]		[7.23]
Constant	243.53**	357.21**	360.49***	435.38***	306.93***	373.94***
	[117.25]	[139.75]	[110.32]	[134.18]	[111.61]	[128.88]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country of ancestry FE	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE x female	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Results from estimating equation 1 on individuals' math, reading and science scores. Odd columns present our baseline specification. Specification in even columns add controls for language skill at home (and indicator variable equal to one if the family do not speak the language's test at home, and zero otherwise) and it interaction with the female indicator. In all cases we use the five plausible values of math test scores provided by PISA datasets and report the average coefficient (Stata command *pv*). Standard Errors are adjusted following the Fay's BRR methodology using the 80 alternative weights provided by the PISA datasets. * p<0.1, ** p<0.05, *** p<0.01

Appendix Table A.6. Reading Scores and the Gender Gap Index (GGI)

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-344.68**	-332.49**	-260.55	-352.55**	-311.83*	-317.96**
	[157.53]	[157.31]	[160.68]	[158.03]	[159.35]	[160.43]
GGI × Female (α_2)	**146.99*** **	**179.27*** **	**174.26** **	**172.93*** **	**192.23*** **	**173.91*** **
	[55.14]	**[68.25]**	**[67.91]**	**[63.46]**	**[64.31]**	**[64.81]**
Age of student	0.51	0.61	1.92	0.13	2.05	1.46
	[6.71]	[6.69]	[6.59]	[6.75]	[6.62]	[6.71]
Age×Female	17.98*	17.86*	13.92	19.24*	18.27*	17.75*
	[9.82]	[9.80]	[9.95]	[9.92]	[9.83]	[9.91]
Diff. grade	-13.68***	-13.79***	-16.83***	-13.65***	-11.77**	-11.36**
	[4.99]	[5.00]	[5.23]	[5.20]	[5.22]	[5.17]
Diff. grade×	-9.37	-9.12	-9.44	-6.99	-7.35	-7.45
Female	[7.03]	[7.07]	[7.37]	[7.16]	[7.09]	[6.89]
GDP×Female		-3.26	-3.81	-3.08	-3.62	-3.39
		[4.01]	[4.04]	[4.06]	[4.16]	[4.14]
Dad educ.				6.19***	5.10***	4.83***
				[1.45]	[1.48]	[1.47]
Dad educ.×				-1.05	-1.44	-1.38
Female				[2.30]	[2.40]	[2.36]
Mom educ.				3.80**	2.80*	2.55
				[1.59]	[1.61]	[1.59]
Mom educ.×				0.92	0.89	1.03
Female				[2.20]	[2.25]	[2.23]
Dad work					31.13***	30.75***
					[8.77]	[8.58]
Dad work×					-16.41	-16.15
Female					[10.92]	[10.95]
Mom work					20.68***	19.39***
					[5.42]	[5.42]
Mom work×					-18.86**	-16.63**
Female					[7.95]	[7.78]
Home possessions					9.21***	9.08***
					[2.66]	[2.65]
Home possessions					5.76	5.69
×Female					[3.92]	[3.86]
Proportion of girls						-15.44
at school						[14.02]
Prop. girls×						44.31**
female						[19.43]
Private school						12.39
						[7.89]
Private school×						-0.78
female						[9.13]
School is in a						23.40***
Metropolis						[5.87]
School is in a						-19.98**
Metro×Female						[8.44]
GGI			152.58***			
			[56.42]			
GDP			3.02			
			[3.12]			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country of ancestry FE	Yes	Yes	No	Yes	Yes	Yes
Host country FE	Yes	Yes	Yes	Yes	Yes	Yes
Host countryFE x female	Yes	Yes	Yes	Yes	Yes	Yes
N	11,527	11,527	11,527	11,527	11,527	11,527
R^2	0.35	0.35	0.30	0.38	0.39	0.40

Notes: Results from estimating equation 1 on individuals' reading scores. In all cases we use the five plausible values of math test scores provided by PISA datasets and report the average coefficient (Stata command *pv*). Following OECD recommendations, standard Errors are adjusted following the Fay's BRR methodology using the 80 alternative weights provided by the PISA datasets.

* p<0.1, ** p<0.05, *** p<0.01

Appendix Table A.7. Science Scores and the Gender Gap Index (GGI)

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-355.04**	-336.27**	-263.05	-361.59**	-324.46**	-339.57**
	[159.05]	[156.69]	[162.53]	[156.16]	[156.03]	[155.91]
GGI ×Female	**137.19****	**186.90*****	**183.14*****	**194.71*****	**212.52*****	**200.47*****
	[53.81]	**[65.67]**	**[67.03]**	**[61.61]**	**[61.48]**	**[61.46]**
Age of student	4.08	4.24	5.45	3.89	5.07	4.21
	[6.98]	[6.96]	[6.87]	[6.98]	[6.86]	[6.96]
Age×Female	16.40	16.22	12.33	17.50*	17.05*	16.83*
	[10.04]	[9.99]	[10.08]	[9.87]	[9.85]	[9.91]
Diff. grade	-13.84***	-14.00***	-16.94***	-13.77***	-12.51***	-12.11***
	[4.59]	[4.60]	[4.88]	[4.67]	[4.66]	[4.66]
Diff. grade× Female	-7.17	-6.79	-7.24	-4.88	-4.54	-4.42
	[6.72]	[6.73]	[7.14]	[6.78]	[6.73]	[6.48]
GDP×Female		-5.02	-5.85	-4.72	-5.77	-5.37
		[3.74]	[3.80]	[3.78]	[3.84]	[3.77]
Dad educ.				6.47***	5.29***	5.05***
				[1.45]	[1.47]	[1.46]
Dad educ.× Female				-0.32	-0.87	-0.79
				[2.26]	[2.30]	[2.27]
Mom educ.				5.69***	4.49***	4.28***
				[1.48]	[1.49]	[1.49]
Mom educ.× Female				-1.29	-1.45	-1.32
				[2.21]	[2.26]	[2.23]
Dad work					25.32***	25.00***
					[7.41]	[7.34]
Dad work× Female					-17.75*	-17.31*
					[10.26]	[10.38]
Mom work					19.01***	17.86***
					[5.22]	[5.11]
Mom work× Female					-14.76*	-12.12
					[7.97]	[7.86]
Home possessions					10.08***	9.90***
					[2.87]	[2.84]
Home possessions ×Female					8.24**	7.76*
					[4.12]	[4.09]
Proportion of girls at school						-8.34
						[15.23]
Prop. girls× female						38.76**
						[18.76]
Private school						16.72**
						[7.73]
Private school× female						0.42
						[8.55]
School is in a Metropolis						15.45**
						[6.10]
School is in a Metro×Female						-17.02**
						[7.48]
GGI			143.11**			
			[56.93]			
GDP			5.35*			
			[3.02]			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ancestry country FE	Yes	Yes	No	Yes	Yes	Yes
Host country FE	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE×Fem.	Yes	Yes	Yes	Yes	Yes	Yes
N	11,527	11,527	11,527	11,527	11,527	11,527
R^2	0.33	0.33	0.28	0.36	0.38	0.39

Notes: Results from estimating equation 1 on individuals' science scores. In all cases we use the five plausible values of math test scores provided by PISA datasets and report the average coefficient (Stata command *pv*). Standard Errors are adjusted following the Fay's BRR methodology using the 80 alternative weights provided by the PISA datasets.
* p<0.1, ** p<0.05, *** p<0.01.

Table A.8. Robustness Checks

	Math scores	Reading scores	Science scores
A. Baseline			
GGI×Female	149.55**	179.27***	186.90***
	[62.62]	[68.25]	[65.67]
N	11,527	11,527	11,527
R^2	0.35	0.35	0.33
B. Host-country regional FE			
GGI×Female	133.98**	166.16**	169.53**
	[62.69]	[69.46]	[66.60]
N	11,527	11,527	11,527
R^2	0.36	0.36	0.34
C. Adding Year FE × Female			
GGI×Female	150.13**	179.38***	187.37***
	[64.12]	[68.80]	[67.79]
N	11,527	11,527	11,527
R^2	0.35	0.35	0.33
D. Cluster SE at country-of-ancestry level			
GGI×Female	149.55***	179.27***	186.90***
	[45.98]	[49.70]	[43.99]
N	11,527	11527	11527
R^2	0.37	0.37	0.35

Notes: Results from estimating equation 1 using alternative specifications. In panel B, we control for host-country regional FE instead of countries FE. In Panel C, we add the interaction between year FE and the female dummy. Panel D presents estimates with standard errors clustered at the country of ancestry level. In all cases we use the five plausible values of math test scores provided by PISA datasets and report the average coefficient (Stata command *pv*). Except for Panel D, standard errors are adjusted following the Fay's BRR methodology using the 80 alternative weights provided by the PISA datasets.
* p<0.1, ** p<0.05, *** p<0.01

Table A.9. Sensitivity to Sample Selection

	Math scores	Reading scores	Science scores
A. Baseline			
GGI×Female	149.55**	179.27***	186.90***
	[62.62]	[68.25]	[65.67]
N	11,527	11,527	11,527
R^2	0.35	0.35	0.33
B. Dropping the most important country of ancestry (Portugal)			
GGI×Female	144.52**	173.54**	184.05***
	[65.15]	[70.81]	[67.56]
N	8,681	8,681	8,681
R^2	0.36	0.35	0.34
C. Dropping the most important host country (Switzerland)			
GGI×Female	148.77**	199.87**	185.84**
	[74.20]	[80.35]	[77.67]
N	8,617	8,617	8,617
R^2	0.38	0.37	0.36
D. Keeping only one host country			
Switzerland	163.12	85.42	184.09
	[136.34]	[137.45]	[149.98]
N	2910	2910	2910
R^2	0.12	0.16	0.14
Australia	199.01**	245.60***	235.03**
	[91.00]	[91.15]	[99.97]
N	2,450	2,450	2,450
R^2	0.16	0.12	0.11
E. Dropping those countries that send immigrants to only one host country			
GGI×Female	228.01**	154.40	194.15*
	[101.93]	[105.10]	[115.99]
N	8,240	8,240	8,240
R^2	0.29	0.32	0.32
F. Including individuals born in the host country to only one foreign-born parent (in addition to two foreign-born parents)			
GGI×Female	101.74**	118.61**	118.07***
	[42.96]	[49.45]	[42.86]
N	27,960	27,960	27,960
R^2	0.33	0.32	0.30

Notes: Results from estimating our preferred specification (Baseline) with different samples. In panel B we drop those second-generation immigrants whose ancestries come from Portugal (the country of origin with more observations in our sample). In panel C, we drop the host country with more observations in our sample (Switzerland). In panel D, we replicate our analysis using only one host country (Switzerland or Australia). In panel E, we drop those countries that send immigrants to only one host country. In panel, we include in the sample individuals born in the host country to only one foreign-born parent. In this case the GGI of the country of ancestry is the one of the foreign-born parent. In all cases we use the five plausible values of math test scores provided by PISA datasets and report the average coefficient (Stata command *pv*). Standard Errors are adjusted following the Fay's BRR methodology using the 80 alternative weights provided by the PISA datasets.
* p<0.1, ** p<0.05, *** p<0.01

Table A.10. Correlations Between Gender Equality Measures

	GGI	GGI Ec. Opp.	GGI Educ	GGI Pol. Emp.	GGI
GGI	1				
GGI Ec. Opp.	0.77†	1			
GGI Educ.	0.69†	0.48†	1		
GGI Pol. Emp.	0.73†	0.23	0.24	1	
GGI Health	0.36†	0.32†	0.39†	0.06	1

Notes: Table A.6 displays Pearson correlations between variables. †Indicates a correlation statistically significant at 5 percent.

Table A.11. Math Gender Gap and Culture with PISA Math Indexes Sub-Samples

Dep. Variable: Math scores	Sub-sample: 2003 and 2012 PISA	Sub-sample: no missing responses to each PISA math index below				
		Intrinsic motivation to learn mathematics	Instrumental motivation to learn mathematics	Mathematics self-efficacy	Mathematics self-concept	Mathematics Anxiety
GGI×Female	175.33*	204.01*	208.63**	205.23*	118.35	122.91
	[94.14]	[105.56]	[105.77]	[106.20]	[98.83]	[97.84]
N	5,850	4,521	4,514	4,507	4,396	4,399
% of missing		22.7%	22.8%	23.0%	24.9%	24.8%
R^2	0.36	0.33	0.33	0.32	0.34	0.35
Year FE		Yes	Yes	Yes	Yes	Yes
Country of ancestry FE		Yes	Yes	Yes	Yes	Yes
Host country FE		Yes	Yes	Yes	Yes	Yes
Host country FE x female		Yes	Yes	Yes	Yes	Yes

Notes: Results from estimating our preferred specification (specification in column 2 of Table 2) on the samples of respondents to the math indexes reported in each column. In all cases, we use the five plausible values of math test scores provided by PISA datasets and report the average coefficient (Stata command *pv*). Standard errors are adjusted following the Fay's BRR methodology using the 80 alternative weights provided by the PISA datasets.
p<0.1, ** p<0.05, *** p<0.01