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The Gender Gap in Mathematics: Evidence from Low- and Middle-Income Countries
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ABSTRACT

We establish the presence of a gender gap in mathematics across many low- and middle-income countries using detailed, comparable test score data. Examining micro level data on school performance linked to household demographics we note that first, the gender gap appears to increase with age. Indeed, the gap nearly doubles when comparing 4th grade and 8th grade test scores. Second, we test whether commonly proposed explanations such as parental background and investments, unobserved ability, and classroom environment (including teacher gender) explain a substantial portion of the gap. While none of these explanations help in substantially explaining the gender gap we observe, we show that boys and girls differ significantly in perceptions about their own ability in math, conditional on math test scores. Girls are much more likely to state that they dislike math, or find math difficult compared to boys. We highlight differences in self-assessed ability as areas for future research that might lead to a better understanding of the gender gap in math.

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1 Introduction

Throughout much of the developing world, women tend to be disadvantaged in terms of job opportunities and wages (Sen, 1999). This gap is at least partially due to a significant gender gap in educational levels which remain large in many countries (World Development Report 2012), although it is reversed in the US for recent cohorts (Goldin, Katz, and Kuziemko (2006) and Fortin, Oreopoulos, and Phipps (2012)). This gap is also potentially due to difference in the types of human capital women and men have even conditional on the same level of education. For example, there is substantial evidence of a strong correlation between math test scores, math based curriculum, mathematical majors in college and future income earned,[1] suggesting that observed differences in math skills across genders can explain part of the wage gap. It is therefore important for research to address the differences in the development of math skills and the determinants of math related specializations and the role played by myriad factors starting from early childhood, such as parental investments, preferences, expectations and innate ability. Understanding when and how differences between men and women begin to develop in the process of human capital accumulation is crucial to understand the gender gap in wages and job opportunities later in life.

In this paper, we document the early emergence of a math gender gap (by fourth grade) which grows over time across a large sample of low and middle income countries. We then examine different hypothesis as to why math scores differ between boys and girls to try to understand the roots of this gap in the spirit of Fryer and Levitt (2010), but add key insights to their work using a unique administrative dataset from Chile.

Our analysis begins by looking at a series of comparable data across low and middle income countries that were part of the PISA-OECD test score data, administered to children around the age 15. Like others before us, we first show that cross country variables do little to mitigate this gap. Next, within countries, we examine the effect of individual-, family-, and school-level characteristics on the gender gap. We show a substantial gap in mathematical test scores open-

[1] See (Paglin and Rufolo, 1990; Murnane, Willett, and Levy, 1995; Grogger and Eide, 1995; Altonji and Blank, 1999; Weinberger, 1999, 2001; Murnane, Willett, Duhaldeborde, and Tyler, 2000) for evidence on math scores and wages and see Altonji, Blom, and Meghir (2012) for a review on math curriculum and college major.

ing up as low as the median level and getting larger towards the top of the distribution in all countries we consider that are included in the PISA - individual, family and school characteristics do little to alter this gap. This means that the median boy and girl perform differently at age 15, with boys doing better than girls by twenty percent of a standard deviation. The gender gap is quite large at the top quantiles, so that the 90th and 95th percentile scores for a boy are respectively about 0.31 and 0.32 of a standard deviation larger than for a girl. Another way to look at this gap is that there are about 1.5 boys per girl in the top ten percent of the distribution. For example, Figure 1 shows the size of the gender gap across different quantiles of the distribution of math scores for ten developing countries, plus the US as a comparison. For seven of the eight countries (the eighth being Thailand), the gender gap is already present at the median and increases for higher quantiles. Thus, while the median boy may have a higher test score than the median girl, this disparity becomes especially pronounced at higher quantiles.[2]

We further explore dynamics of the gender gap, and more detailed explanations for the gap using administrative data from Chile. A similar gap in math scores is also present in the Chilean SIMCE data (the SIMCE is a national test which is administered to all 4th and 8th graders in the country). In the SIMCE scores at age nine and ten (grade four) we see already a sizable gap in the mean and median achievement. At the same time we note that these gaps expand substantially, nearly doubling by ages 13 and 14 (grade eight). Further, for the top 5 percent the gap continuously increases across grades, i.e. the ratios of boys to girls is 1.9 and 2.2 for grade four and eight respectively. The detailed nature of the data from Chile allows us to explore some more possibilities along the broad categories of individual, parental and school characteristics that are not available in the PISA data, and also some that were not explored by Fryer and Levitt (2010).[3]

[2]The gender gap in this figure is the coefficient on a dummy variable for being male in a quantile regression of standardized PISA math scores on "Male" and a set of control variables for the fiftieth, seventy-fifth, ninetieth, and ninety-fifth percentiles. The PISA data will be described more in the data section.

[3]This study is closely related to the recent paper by Fryer and Levitt (2010). Using data from the US, Fryer and Levitt (2010) establish that while the gender gap does not appear to be present at the beginning of school going age, boys perform better in math by the end of the first six years of school. A host of explanatory variables are unable to account for the gap in their setting. Our paper expands on and complements the work of Fryer and Levitt (2010). We examine the gender gap in different countries and at different grade ranges. We are able to control for a rich set of individual and family characteristics (for example, by examining differences within twins) and at the same time attempt to account for classroom composition, teacher gender and other related factors. Moreover, our

In terms of individual level characteristics, we examine factors such as birth weight and gestational age in the determination of test scores. Early childhood health has been shown to be important determinant of a host of later life outcomes like income, school performance and health (Black, Devereux, and Salvanes, 2007; Bharadwaj, Loken, and Neilson, 2011). If there are differences in early childhood health across genders, then perhaps some of this gap is driven by these "health endowments". We are also able to explore gender gaps within twin pairs, given the richness of the data from Chile. A twins fixed effect in this setting attempts to control for a large portion of genetic characteristics, as well as unobserved family background and parental investment variables which twins share. Even within twins, we see a sizable gender gap in math.

We then examine the school and class environment. Given the population of school students observed in Chile, we can examine how gender composition of the classroom and classroom size affects performance in math. The motivation for examining this comes from an influential literature suggesting that girls and boys perform differently in competitive environments. We can also test the role that teacher gender plays in mitigating or exacerbating the gender gap in math. Dee (2007) and Carrell, Page, and West (2010) find that gender of the teacher matters for female performance on science and math. While we cannot account for selection via random assignment of teachers, controlling for gender of the math teacher does little to close the gap. We also examine the role played by schools in influencing the gender gap by using school fixed effects in various countries.

Finally we examine parental characteristics which is a critical part of the hypothesis related to sibling competition and differential resources within the household. In addition, we study the role of parental investments and student perceptions regarding their own math abilities. Using survey data where parents report time spent on various activities, we note that parents are more likely to devote time spent with math homework if the child is male. We find that students also have differential perceptions by gender regarding their own math abilities. Even conditional on math score, we find that boys tend to be more optimistic about their math ability.

data on math ability perception and parental investments is unique in this setting and allows us to further pursue relevant hypothesis regarding the emergence of the gender gap in math skills.

For example, boys are much more likely to say that they are good at math than girls. However, it is not the case that girls are pessimistic about everything - while answering questions about general ability in school, the differences between boys and girls is much smaller. These gaps in perceptions appear to arise specifically in the context of mathematics ability. While we do not use data on perceived ability as an explanatory variable, the differences appear to suggest that this would be an important area for future research in this area to focus on.

Taken together with the results of Fryer and Levitt (2010), it is apparent that not only is there a well established gender gap in math scores across many parts of the world, but that a host of potential explanations do little to explain this gap. The evidence we present suggests a combination of differential parental investments and also perceptions may play a role. Future research should focus on these aspects to further shed light on this issue.

2 Data

2.1 PISA Data

This paper uses data from the 2006 and 2009 PISA (Programme for International Student Assessment) tests. The PISA is designed by the OECD to produce student outcomes that are comparable across countries and to provide information about the characteristics of successful students, families, schools, and national educational systems. It is administered to students who are between the ages of fifteen years and three months and sixteen years and two months. Four waves of the PISA have been carried out (2000, 2003, 2006, and 2009), but we use only the two most recent because previous waves do not contain as many countries, especially the developing countries we focus on in this paper.

The PISA data includes four distinct components: student, parent and school questionnaires, and the results of three tests, for mathematics, science, and reading. We use primarily the student questionnaire responses and test results. The parental questionnaire was not administered for many of the countries in our set of countries of interest, but much of the information on parental education, occupation, wealth, and migrant status is available in the student questionnaire as well.

Students take a two hour test that includes both multiple choice and handwritten long-form answers. Each student is tested on only a portion of the available test modules, so the raw scores are scaled using the Rasch model of item response theory to reflect this fact. We further standardize the scores by country so that they have a mean of zero and a standard deviation of one. We focus on the results for mathematics, but also include some comparative analysis using the reading test results. The reading questions test primarily reading comprehension, while the math questions are in such areas as algebra, geometry, and interpretation of graphs, especially as they relate to solving real-world problems.

The PISA data also includes information on parents' education, migration status, and classification of their occupation into lower or upper white- or blue-collar. Since parental education (measured using the standard ISCED levels) and migration status are very closely correlated, we use only the values for the mother in our regressions. Though the data does not contain a direct measure of assets or income, it does include a wealth index generated using a Warm estimate process as a combination of the presence of various goods, including a dishwasher, an unshared room, educational software, and a link to the Internet, as well as the number of cellular phones, television sets, computers, automobiles, and bathrooms in a household. We also use the results of a question asking how many books a household has as a proxy for the importance of education and information to a household.

For the portions of this paper that use PISA data from multiple countries, we focus on a set of 10 countries (plus the US) that fulfill all the following criteria:

1. The country has a 2010 per capita purchasing power parity (PPP) adjusted GDP of $16,000 or less.

2. The country is not in Europe.

3. The country is not and is not a part of a former or current Communist country.

4. Data exists for the country for both the 2006 and 2009 waves of PISA.

Criterion 1 is imposed so as to focus the analysis on middle- and low- income countries. Criteria 2 and 3 are used to exclude countries with a different historical and institutional context than we are interested in. Criterion 4 is to ensure that the necessary data exists. The countries that fulfill all these criteria are Argentina, Brazil, Chile, Colombia, Indonesia, Mexico, Thailand, Tunisia, Turkey, and Uruguay. We also include the United States in the set of countries under analysis to allow us to make comparisons with a more economically developed country.[4] Notice that we also run our analysis with the entire set of countries available as in Table A.7.

Tables A.1, A.2, and A.3 contain descriptive statistics for the variables of interest in the PISA dataset for these countries. Table A.4 includes data by sex from UNESCO (2010) on survival rates to grade five (the percentage of students that eventually finish fifth grade) and the secondary school net enrollment rate (the percentage of people who are in the age range for secondary school that are actually enrolled in secondary school). It should be noted that the secondary school enrollment rates given here would underestimate the relevant enrollment rates for our analysis as we focus on grade 10 and below for most countries in the analysis, which is below compulsory schooling age for a regular schooling path.

2.1.1 Cross-Country Data

To explain the variance in the gender gap across countries, we follow the lead of several previous studies, including Chen (2004), Guiso, Monte, Sapienza, and Zingales (2008), Machin and Pekkarinen (2008) and Fryer and Levitt (2010), in carrying out regressions at the country level. For these cross-country regressions, we use the PISA data just described for the entire set of (about 65) countries involved in the 2009 survey to calculate the gender gap in normalized math test scores at the mean by country. Following Guiso, Monte, Sapienza, and Zingales (2008), we include among our regressors the 2011 Gender Gap Index, which is calculated by the World Economic Forum and has several subindices in the areas of economic opportunity and participation, educational attainment, political empowerment, and health and survival, which will

[4] An exception to the selection rule above is the exclusion of Jordan that would satisfy all of the above criteria, but we do not find the results on that country believable. In any case the inclusion of Jordan in the analysis changes the results very little.

also be included separately in our regressions. Guiso, Monte, Sapienza, and Zingales (2008) also include several variables from the World Values Survey (WVS) related to attitudes about gender equality; we will include several of these variables from the 2008 WVS (World Values Survey Association, 2009) for which there is sufficient coverage of the countries in the PISA sample. We include the average country response (on a scale of one to four (or three, for the first question) with one indicating the strongest level of agreement) to the following statements: "When jobs are scarce, men should have more right to a job than women," "Being a housewife is just as fulfilling as working for pay," "On the whole, men make better political leaders than women do," and "A university education is more important for a boy than for a girl." Thus, higher values of these variables indicate more egalitarian attitudes. From the World Bank, we use data on 2009 per capita GDP, 2009 cellular subscriptions per person (as per the finding of Chen (2004) that information and communication technologies can play an important role in promoting gender equality), 2009 population, and male and female literacy (from the period 2007-2009, as available). Availability of all these variables for the PISA sample of countries varies.[5]

2.2 Administrative Data from Chile

In addition to the picture that the PISA data provides us, we will also use detailed Chilean administrative data, including the SIMCE. The SIMCE (loosely translated as System for Measuring Educational Quality) is a national test administered annually in Chile for all fourth graders. On alternate years, eighth and tenth grade students are also given this test. We have data on the fourth grade SIMCE from 2002 and subsequently on a yearly basis from 2005 on. We use the eighth grade SIMCE as administered in 2007 and 2009. While there were waves of the eighth grade SIMCE administered prior to 2007, we do not use them, as the cohort that took those tests were born prior to 1992 and hence were not available in the vital statistics database.

The SIMCE test for fourth graders consists of reading, math, and a social science compo-

[5]More information on the specific countries in the sample available from the authors upon request.

nent.[6] These results are published at various levels to track performance of schools and (what would be the equivalent of) school districts.

The Chilean administrative data we use in this paper allows us, in several ways, to go beyond what is possible with the PISA data. First, the SIMCE data covers almost all children in the relevant grades over multiple years, which allows us to examine students who took the SIMCE in both fourth and eighth grades to see how the gender gap in math scores changes as students grow older while eliminating possible selection effects. At the same time, as we are dealing with population data, we can analyze the very top performers, such as the top 1% or the top 5%. According to UNESCO (2010), the survival rate to fifth grade in the 2007 school year was 96 percent, indicating that selection of students out of school is unlikely to bias the analysis for fourth grade. From the same source, the 2010 net enrollment rate for secondary school as a whole was 84 percent among boys and 87 percent among girls, indicating that differential dropout rates are similarly unlikely to bias the eighth grade results.

Because we are interested in understanding outcomes at the top end of the distribution, we should consider whether the SIMCE data does a better job than the PISA data of distinguishing students at the very top end of the distribution from one another. For example, can these tests tell us with some certainty that a student at the 99th percentile on a test is actually better at math than a student at the 95th percentile? Test design is an important issue when considering this question, as Ellison and Swanson (2010) show at length. Both the SIMCE and the PISA are designed to be broad-based tests that can be used at a national level (and an international level in the case of PISA) to compare regional performance and not to look at the performance of high achievers specifically. Both tests, however, do provide enough difficulty that very few students answer all the questions correctly, which increases our confidence that they can distinguish students at the top. Though both tests should be able to do a decent job, the SIMCE seems better able to address the gender gap at the top end of the distribution because of its structure and scope. The sample size of the SIMCE is much larger, so that we simply have more high achievers in the sample and can reduce the standard error of our estimates when dealing with

[6]For detailed information on the SIMCE and sample questions one can visit http://www.simce.cl/.

them. In addition, the SIMCE is better able to help us understand individual performance because it is longer and more uniform across individuals, while the PISA is shorter and uses different modules with different students, which allows for comparability across countries but does not give as much information about an individual student's performance as we would like.

Second, because we have the data for almost the entire relevant population of Chile for children born over a period of several years, we have a large number of sets of twins and of siblings, which allows us to control for family background, as well as unobserved school and neighborhood characteristics that they share. We cannot entirely control for genetic ability using this data - unlike studies that use genetically identical homozygotic twins - but the fact that twins of opposite gender share more genetic information, on top of identical prenatal care, than two randomly chosen students of opposite gender will help us understand the genetic component of the gender gap.

Third, this administrative data includes information on birth weight and gestational age (the time from when a child is conceived to when he or she is born). This data allows us to control for differential parental investment in boy children relative to girl children. It may also relate to some components of ability, if ability is considered to be the initial potential skill or genetic endowment a person has at birth. Electronic birth records were established in 1992 in Chile; detailed information is collected about every birth, such as birth weight, birth length, and gestational age, as well as basic parental characteristics, such as mother's age, education, and occupational status. The vital statistics used in this paper stem from the same data base as used in Bharadwaj, Loken, and Neilson (2011). That paper shows that the vital statistics records in the dataset match rather well to nationally published records on births and deaths by year. Under the guidance of the Ministries of Health and Education, the vital statistics data were matched with the educational records for each child. Again, Bharadwaj, Loken, and Neilson (2011) show that a large fraction of the population is observed with valid schooling data.

Fourth, some parental time investment variables are available in this data. These come from questions asked to parents, such as whether they do homework with their child or read to their child. This data will help us understand the role of differential postnatal parental investment in boys and girls on the gender gap.

Fifth, the SIMCE data includes the school and classroom of each student in the sample, so that we can include school and classroom fixed effects to control for the influence of these environments on the student. We can also examine the effect of classroom size or the gender composition of the classroom on the size of the gender gap, which will be important if boys and girls perform differently in different classroom environments, perhaps because of different attitudes toward competition or because of the need for different teaching styles.

The descriptive statistics for the SIMCE and other Chilean administrative data used are in Table A.5. Some characteristics to note in the data are that the modal level of education for mothers that have children in the data set is high school, that most mothers do not work (and the majority were unmarried), and that about a quarter of twin pairs are mixed sex.

3 Empirical Analysis

In the empirical analysis we will first establish the main facts about the math gender gap in selected countries, as well as specifically for Chile. After we have done so, we will move into the analysis of why such a gap exists. We will spell out our hypotheses and testing strategy as we go.

We begin our analysis by estimating simple quantile or mean models of test scores where the gender gap is captured by a dummy for being male. We also run a parallel analysis on probability models for falling in various top quantiles of the distribution of test scores. The main specification is as follows:

$$y_{ihst} = \alpha + \beta Male_i + \gamma X_{ihst} + \epsilon_{ihst} \tag{1}$$

where y is the standardized (at the country level) test score in math, and the X variables are controls for characteristics at the level of the individual, family, school, etc. Controls are introduced to be consistent with the hypotheses we test. i indexes individuals, h households, s schools, and t is for the year or, more precisely, the cohort. Our main parameter of interest,

β, is meant to capture the gender gap. The quantile version of this specification would require some extra notation but is essentially the same. In addition to this, we also estimate a linear probability model for the probability of being in the top 25%, 10%, and so on of the distribution of test scores.

3.1 PISA-OECD Evidence

3.1.1 Existence of the Gender Gap

We start off with the pooled countries quantile regression. As we move from left to right in Table 1, we move across quantiles. For each quantile we have two columns, the first with the simple gap and the second with additional controls for household and school characteristics. The analysis in Table 1 always includes country and year fixed effects plus age and grade of the student.[7]

The median regression shows a substantial gap in mathematical test score: the median male score is about 25% of a standard deviation higher than for females. Such gaps increase monotonically along the distribution, and for the top ventile the gap is as high as 32% of a standard deviation. As we shall see later these aggregate estimates mask some substantial heterogeneity across countries.[8]

Another way to look at the gender gap is to compute the ratio of males to females at various quantiles of the distribution, while adding the same controls as in the quantile regressions. This is exactly what we do in Table A.6, where at the bottom of the table we present the male-female ratio for each regression. The main finding of this latter approach is that the gap between the proportion of those above a given quantile that are males and those that are females increases from 10% in the top half of the distribution to 74% in the top 5%.[9] These results do not appear to be sensitive to the selection of countries used, since Table A.7 performs the same analysis

[7] In the PISA-OECD analysis we do not present the results for the top percentile (1%) as in this case we would be dealing with a very small number of observations.

[8] The median gap is larger in magnitude than the class-size effect and other educational resources found in several studies.

[9] Although we present a linear probability model in Table A.6 the results from a probit model are essentially identical.

using all 65 countries available in the PISA-OECD sample and arrives at similar coefficient estimates and ratios.

3.1.2 Cross-Country Analysis

The results of our cross-country regressions for the PISA math gender gap are shown in Table 2, while results from comparable regressions for the reading gender gap are shown in Table A.8. The first column of each table shows the unconditional gender gap, while subsequent columns show specifications with different combinations of the explanatory variables described above. Observations are weighted by national population.[10]

In these regressions, the math gender gap is strongly correlated with the reading gender gap: countries where boys do well relative to girls in math tend to exhibit the same pattern in reading, and vice versa. Cellular subscriptions have a generally (though not invariably) negative association with the gender gap, especially for reading. GDP per capita also has a generally negative association with the gender gap, though with more variation across specifications. Literacy has an opposite effect from what we might expect: adult male literacy is associated with a reduction in the gap, while female literacy is associated with a larger gap. This reversal may have to do with selection effects caused as more literate populations attend school at higher rates, but with lower average performance. The WVS gender attitudes questions fail to display a clear pattern of association: though we would predict negative coefficients on these variables, which increase with stronger attitudes in favor of gender equality, several appear with positive coefficients.

An influential explanation for the existence of the gender gap is that of cultural norms, where more unequal societies in terms of treatment and beliefs regarding gender and the role of women in particular, should see large gaps in achievements that should close down as one looks at more gender equal societies. This explanation has been put forth and substantiated in Guiso, Monte, Sapienza, and Zingales (2008). However, the results from Table 2 does not

[10]Several countries or territories from the 2009 PISA sample are excluded from all the regressions because they could not be matched with the explanatory variables. Shanghai, China, is not included because accurate data does not seem to be available for several of the variables used and because it would be inaccurate to match up this metropolitan area's information with data describing China as a whole.

support their results.

We explore this connection further using more recent PISA-OECD data from 2006 and 2009 as well as including some of the countries excluded from the Guiso, Monte, Sapienza, and Zingales (2008) analysis. We run regressions that are very similar to those in the original paper, though our findings are somewhat discouraging as we do not find a robust relation between the mathematical test score gender gap and the Gender Gap Index, which is one of the major measures of gender equality used by Guiso, Monte, Sapienza, and Zingales (2008).[11] As shown in Table A.9, we get similar results to Guiso, Monte, Sapienza, and Zingales (2008) when using the set of countries used in the original paper (column (1)), in that more gender equality improves the relative performance of female students[12], but these results are very dependent on the set of countries used.[13] We find similar outcomes in the 2009 data in Table A.10. When we pool both data waves as we do in Table A.11, controlling for the survey year and GDP, we find little evidence that the gap closes for countries with more gender equality. In fact for the overall sample (column (3)) the coefficient is not significant and with the wrong sign. As before the results are also highly dependent on the sample chosen, as we can see if we compare this result with columns (4) and (5), which produce coefficients with very different magnitudes but still have the wrong sign. We therefore tend to dismiss the likelihood of "culture" being a fundamental explanation for the existence of gender gaps.

3.1.3 Parental Background and School Characteristics

Two of our proposed explanations for the gender gap in math are (i) family background and (ii) school characteristics. It is possible that boys or girls are more likely to be present in

[11]This measure is produced by the World Economic Forum and includes several components of gender equality, such as economic opportunity and participation, education, political participation, and health. The GGI is larger for more equal societies. We choose this measure to focus on from Guiso, Monte, Sapienza, and Zingales (2008) because it has updated data to use with the 2009 PISA-OECD data and includes a variety of components relating gender equality.

[12]Note that, for this analysis, we use measures of the outcome variable, i.e. the gender gap in math, that are equivalent to the Guiso, Monte, Sapienza, and Zingales (2008) measures but differ from the normalized scores we use in the rest of the paper, so that the coefficient in these regressions indicates the relative improvement in non-normalized female test scores relative to male associated with going from zero to one on the GGI.

[13]Column (2) in Tables A.9 and A.10 has the full sample of countries that we were able to find all the data for and Columns (3) and (4) of these tables exclude the countries from the analysis that have the highest and lowest test score gaps in 2006 and 2009, respectively.

specific households because of gender selective fertility and abortion (for a recent review of the literature, see Pörtner, 2010). At the same time, it is also possible that boys and girls are found in different schools. We therefore test for such hypotheses by adding additional controls to the simple mean or quantile differences discussed so far. The results of this exercise are presented in the even columns of Tables 1 and A.6. The previous findings remain unaltered as we add parental background controls such as mother's education, parental occupation category, immigration status, wealth, number of books at home, and so on. To reiterate, the test score gaps increase from 25% to about 32% of a standard deviation as we move from the middle to the top 5% of the distribution.[14]

Such statistics, however, mask some substantial heterogeneity across the countries considered; in fact, that heterogeneity emerges quite clearly in Figure 1, where one can see that the male-female ratios range, for the highest ventile, from 1.2 to 3. As mentioned, all these results also hold true when school fixed effects are included in individual country regressions, though these are not included in the pooled regression for computational reasons.

As we mentioned, proposed explanations include differential backgrounds between boys and girls and self-selection into schools and classes. We provide evidence in this section against family background and school selection as the main causes of such a gap. When we control for school as well as family background characteristics (such as education of the parents, wealth, occupation, and number of books in the household), as we do in each second column within each quantile in Tables 1 and A.6, we find that the gap remains unaltered from the mere "unconditional" gap found in the odd columns of the same tables. The take-home message of this analysis is that one should look beyond parental background and school selection in the attempt to uncover the roots of such an achievement gap.[15]

[14]In the reported tables we do not use father's education, as that is not available for the Chilean administrative data. Adding this control does not change the results.

[15]Another point worth reporting is that the achievement gap is not closing between the two years we use for the study, 2006 and 2009. If we run an interaction model between them, we cannot reject the equality of the gaps for the two years, though this is admittedly a very limited time frame.

3.1.4 Family Composition

We can test the hypothesis that boys have higher math scores than girls because of competition among siblings by examining family composition and how this affects test scores. If parents have a preference toward their male children, we would expect that female students would receive less parental investment if they have one brother and no sisters than if they have one sister and no brothers. If girls perform worse than boys do when placed in competition with male siblings, we should observe lower test scores for girls with brothers than boys with brothers or girls with no brothers. Unfortunately, we do not have random variation and full data on family composition and we have no data on birth order within the family, but the 2009 PISA data set does have questions in the student questionnaire asking whether the respondent has at least one sister living at home and whether they have at least one brother living at home, which will allow us to make some conclusions about the effects of family composition.

Using this data, we perform a quantile regression of test scores on the "male" dummy and the controls from the other quantile regressions, along with dummy variables that capture the different sibling situations we can distinguish among (at least one brother and no sisters at home, at least one sister and no brothers at home, at least one brother and one sister at home, and no brothers or sisters at home, which will be the excluded category) along with interactions of these with "male." The results of this are in Table 3. The inclusion of these sibling variables reduces the coefficient on "male," indicating that these variables play some role in the gender gap. The base "no brother, no sister" category produces the lowest test scores, followed by "brother and sister," "no brother, sister" and "brother, no sister," categories, in order; this means that girls do the best with a brother and no sister, which is not consistent with either the parental investment or the inter-sibling competition hypothesis. The outcomes for boys follow the same ranking, however, with all the effects being larger for them, so that boys appear to be more sensitive to family composition than girls but to be affected similarly. The size of these effects is also increasing for higher quantiles for girls, indicating a larger role for family composition for higher-scoring students, but the stronger effects for boys do not carry through to the ninetieth or ninety-fifth quantiles. The overall ranking of these outcomes does not seem to follow a consistent story about why parental investment or inter-sibling competition would work this way, so probably the most we can say from this data is that family composition matters for test scores, though not in a simple way. In particular, the competition story would predict that a girl with a brother should do worse than a girl with no brother (or just a sister), but the findings do not support this prediction: a girl with a brother (and no sister) does better than a girl with only sisters, no siblings or both a brother and a sister.

We get similar results, which are shown in Table A.12, from including the sibling variables in a linear regression for the probability of being in the top percentiles of the distribution.[16]

3.2 Analysis from Chilean Administrative Data

The addition of our Chilean administrative data allows us to go well beyond what is possible using the PISA-OECD data alone. As mentioned in Section 2, the Chilean data are extremely rich in many respects, including (i) population data (among other things we are now able to look at the top 1% of achievement), (ii) family background variables, (iii) a large sample of twins (iv) birth outcomes like birth weight and gestational age, (v) post birth parental investment measures and (vi) self assessed math ability.

3.2.1 Existence of the Gender Gap

Table 4 has simple OLS regressions that use the standardized SIMCE math test scores as the dependent variable, with fourth grade scores being used in the first through third columns and eighth grade scores in the fourth through sixth columns. The first and fourth columns report the results of the most basic, "unconditional" regression of test score on a dummy variable for whether a student is male. We will discuss the remaining columns in the next sections.

The most important result of this exercise is that the coefficient on "male", which measures the gender gap, remains substantially the same as these control variables are added, at around 0.08 of a standard deviation for fourth grade and around 0.2 of a standard deviation for eighth grade, suggesting that the gender gap is not the result of boys' and girls' having systematically

[16]Probit results are also similar.

different family, classroom, or school environments.[17] It is also striking to observe that the gender gap more than doubles between fourth and eighth grade. This doubling also occurs when the sample of students is limited to those for whom we have both fourth grade and eighth grade scores, so that selection is not a plausible cause of this phenomenon. Fryer and Levitt (2010) find a similar pattern among US schoolchildren, noting that "[t]here are no mean differences between boys and girls upon entry to school, but girls lose more than two-tenths of a standard deviation relative to boys over the first six years of school" (p. 210). In the Chilean data, for computational reasons, we do not run quantile regressions, but we still investigate the distributional gap through the probability model (the linear probability model and the probit model produce very similar results, so we omit the probit here). The main findings from the probability model are that the unconditional male-female ratios increase from about 1.3 to 1.9 for 4th graders between the top 10% and the top 1% (Table 5). What is again striking is a large jump in the gaps for older children: for 8th graders the male-female ratios jump to 1.4 and 2.6 for the top 10% and 1% respectively (Table 5).[18]

This gender gap in test scores may influence later wage differentials by gender. At the very least, the description of the math test score gender gap from the previous paragraph is consistent with the form that the wage gender gap among adults takes on. Ñopo (2006), for example, finds that the unexplained gender gap in wages in Chile is at around twenty-five percent of average female wages with an increasing gap by wage percentile: "While for the lowest percentiles of the wage distribution, males tend to earn an unexplained premium of 10 percent to 20 percent over comparable females, at the top of the distribution this premium increases to 40 percent to 80 percent, depending on the set of matching characteristics" (p. 31).

Despite the gender gap in test scores, women receive more years of school than men on average in Chile, which one could hypothesize would compensate for some of the test score difference. Ñopo (2006) shows that, over the period from 1992 to 2003, women had 1.6 more

[17]One reassuring outcome is that the results of this regression with regard to the eighth grade gender gap are very similar to what the regression using the PISA data for Chile produces for students who are only a year or so older.

[18]One would also have to consider the possibility that the 4th grade test is not able to capture the very top performances as well as the 8th grade test.

years of schooling on average than men in rural areas and 0.5 years more in urban areas. Interestingly, the gender gap in wages was nonexistent in rural areas and quite large in urban areas, and the largest gender gap in wages by far was among college graduates. Education levels were increasing throughout this period. Nevertheless, women had relatively low, though increasing, rates of labor force participation during this period, around 35 percent.

3.2.2 Family Background, School and Class Characteristics

In order to test whether family background and school and class characteristics are crucial in explaining the gap, we first add control variables able to capture such confounders, such as birth weight and gestational age of the student and the education, employment, marital status, and age of the student's mother. The second and fifth columns also include school fixed effects, while columns 3 and 6 have classroom fixed effects instead.

Once again, columns 2, 3, 5, and 6 of Table 4 confirm the previous "unconditional" findings reported in columns 1 and 4. The average gender gap can be explained neither on the basis of the maternal characteristics included nor on classroom and school selection. Looking at the control variables in Table 4, the children of more educated women had much better test scores, while the children of older mothers and married mothers did somewhat better. The log of birth weight also has a statistically significant impact of about 0.25 standard deviations on both fourth grade and eighth grade test scores, indicating that a student who had a birth weight that was ten percent higher could expect a math test score 0.025 standard deviations higher.

We can look at the right tail of the distribution by using the probability analysis technique used above on the PISA data, with the results shown in Table 5. We examine how the probability of being in the top 1, 5 or 10% relates to the dummy variable for being male and the same set of control variables used in Table 4. In order to have a consistent basis of comparison as the base percentage changes, as for the PISA-OECD analysis, we also calculate the predicted male-to-female ratio. We find that, as in the PISA data, the gender gap increases at higher scores: for the fourth grade specification with class fixed effects, there are predicted to be 1.27 male students for every female in the top 10%, 1.35 males per female in the top 5%, and 1.86

males per female in the top 1%, while–consistent with the increase in coefficient in the OLS regression above–these ratios are 1.41, 1.50 and 2.33 among eighth graders. These results are not sensitive to the use of fixed effects at the school instead of the class level.[19]

We additionally performed exactly the same analysis for the twins sample both on the continuous (mean) test outcome as well as on the top end of the distribution. For a detailed discussion on the twins sample and how it relates to the general population see Bharadwaj, Loken, and Neilson (2011). The findings of this analysis are presented in Table 6. This specific cut of the data is meant to address several of the proposed explanations for the gender gap. In this section, however, the focus is on parental background, which twins typically share. As is clear from the table, if anything the gap is larger across the board for twins.

3.2.3 Parental Investment

Prenatal Investment It has been hypothesized that parents have a preference for boys over girls and therefore they invest more in boys. This type of investment can happen quite early, such as in the womb or once the baby is born. We have a couple of ways to check whether the gender gap we found comes from very early investment in nutrition, health, and so on.

Studies have shown that boys typically tend to perform worse on early assessments of health such as APGAR scores (Gissler, Järvelin, Louhiala, Rahkonen, and Hemminki, 1999), even though they are typically born with higher birth weight. Moreover, in terms of early childhood cognitive achievement, females tend to perform better. Early studies such as Willerman, Naylor, and Myrianthopoulos (1970), using data from the US, show that females perform significantly better on tests such as the Bayley Motor Test (administered at an age of 8 months). According to the same study, females also perform better at the Binet IQ test administered at age 4. Simple correlations using data from the *Children of the NLSY* 1979 sample suggest that females do indeed perform better on early motor and social development skills tests (administered to children between the ages of 0 and 3). However, in tests such as the Peabody Picture and Vocabulary Test (PPVT) which is administered to children ages 3 and up, gender gaps ap-

[19]Once again because of standard concerns with predictions from a linear probability model like this (in the tails), we also ran the probit version of it, finding that the results are not substantially different.

pear in later ages, with males performing slightly better than females. Hence it appears that girls do better than boys along various health and cognitive measures in very early childhood.

The most convincing evidence we provide relies on the twins sample, since twins are subjected to the same investment or care in the womb. The richness of the data allows us to fully difference out prenatal investment and family background characteristics through the use of data on twins. This is not to say that twins are a representative sample of the population; in fact, they are quite clearly at the bottom end of the distribution in many respects including test scores.

Table 6 contains the results of OLS and probability regressions similar to those above with the sample restricted to twins. These results display the same trend of a gender gap that increases with age and at higher percentiles of the score distribution seen in previous tables. In fact, the twins results display an even larger gender gap than that in the overall sample. Twins are, of course, not average individuals, but the persistence of the gender gap among them does allow us to conclude that differential prenatal parental investment perhaps does not play a large role in creating this gap. As we can see from Table 6, girls fare worse than boys in math test scores even between twins.

Post-Natal Investment It is still possible that parents invest more into boys than girls, because of son preference (although this is unlikely in the case of Chile) or because of higher returns on the investment (wage differentials). We have some measures of parental investment in the Chilean data which can be summarized as mathematical or reading investments. For example, for the year 2002 data on 4th graders, the only year of data used in this part of the analysis, parents were asked: "How often do you pose math problems to your child?" They could reply in 5 categories from 1 (never) to 5 (very often). Similar questions were asked for reading investment.[20] We introduce such variables in our empirical model for the 4th grade test as continuous controls, the intuition being that if post-natal parental investment is the fundamental cause of the gender gap in math, once one controls for that (and other correlated

[20]The comparable reading related question is how often the parent reads to the child.

confounders) the gap should shrink or disappear.[21] Clearly parental investment is not a random event, so the analysis here is not able to make causal statements about the role of parental investments in the education production function. For our purposes, however, what we need to understand is whether parental investments are correlated with the gender of the child. We find that parents invest more in math in boys and the reverse is true for reading, although the magnitudes of these differences are very small (results not shown, available by request). As a result, when we control for parental investments as shown in Table 7, the gender gap remains relatively unchanged. As expected the direct effect of parental investments appears to have a large and positive effect on test scores

Even if our measures of parental investments do not capture the entire range of possible investments, we can turn to the evidence from the twins analysis, under the assumption that within twins the difference in investment is minimal. The twins evidence shows the existence of a large gap in math score between boys and girls.

The central message is that parental investment, measured as time spent challenging children in math and reading, has a positive and significant impact on the overall performance of boys and girls but does not explain the gender gap, while at the same time we do find some indication for differential investment between boys and girls. Hence, we believe that further research along this measure would be important. One drawback of our parental investment measure is that it only measures investments as a flow at a certain point in time, rather than a stock that has accumulated since birth. Perhaps differences in the stock of parental investments are much more important for explaining the gender gap.

3.2.4 Ability

We mentioned that a proposed explanation for the gender gap could be an innate ability difference between boys and girls in mathematical subjects in particular at the top of the distribution. Our analysis can indirectly speak to the ability explanation. First, we already mentioned that on many measures of health and cognitive ability girls tend to do better than boys at early ages.

[21] The large majority of the students, 93% of the 4th graders with valid SIMCE score, have valid parental investment information.

Our own simple analysis of correlations using data from the *Children of the NLSY* 1979 sample suggest that females do indeed perform better on early motor and social development skills tests (administered to children between the ages of 0 and 3). While boys tend to do better in the Peabody Picture and Vocabulary Test (PPVT), this is only apparent at later ages. Hence it appears that girls do better than boys along various health and cognitive measures in very early childhood.

As mentioned in the Chilean data we have the ability to look into the mixed-gender twins portion of the data. Following a very influential paper in the education literature (Ashenfelter and Krueger, 1994), we consider twins as sharing a large component of the genetic map, in addition to the same level of prenatal care and investment. We believe that the initial conditions of mixed gender twins are quite similar so that if those initial conditions were to be the fundamental reason for the gender gap we should see a negligible gap within mixed gender pairs of twins. As can be seen from Table 6, that prediction is not borne out by the data, and, in fact, the gap is larger for twins than for the rest of the population. As mentioned, we know that twins are located in the lower part of the test score (as well as health) distribution so that one cannot lightly draw implications from this sample. We also notice that in the lower part of the distribution there is not much of a gap for the general population so this finding would be a further reason for not finding any gap in the twins sample.

3.2.5 Class Room Environment

Tables 8 and 9 explore the role of the class environment in explaining the gender gap. In some ways, this table explores various aspects of the classroom environment already captured by the classroom fixed effects regressions seen earlier. Hence, while it is useful to understand the extent to which individual classroom level variables matter for the gender gap, we do not expect these variables to explain the gap since the the classroom fixed effects regressions did not appear to matter much for changing the coefficient of interest.

Table 8 shows that adding teacher gender as an explanatory variable does not change the gender gap much. Approximately 20% of the fourth grade math teachers in Chile are male.

Typically, a teacher who teaches math in this grade also teaches other subjects like language and reading. While having a male teacher in general implies lower math scores, boys do slightly better in the presence of a male teacher (Column 3). However, the main message from these regressions is that selection issues aside, teacher gender does not appear to matter much in terms of explaining the gender gap.

A very influential experimental literature (Gneezy, Niederle, and Rustichini (2003), Niederle and Vesterlund (2007) and for a summary Niederle and Vesterlund (2010)) finds that females tend to shy away from competition and that such behavior can explain a substantial part of the gender gap in performance in many realms that involve a significant competitive element, such as taking tests in school. It would be very hard, however, to square these results in particular experiments with experiments that involve verbal competition tasks, where it appears that girls do better than boys. In order to investigate such an issue, we introduce amongst the control variables the classroom composition in terms of share of male students. The thought experiment is the following: as the fraction of males in the classroom increases, females would feel a higher competitive pressure, which might hamper their performance. If this is a principal cause of the gender gap, female students should perform the same as males in predominantly female classrooms.

To investigate the influence of the competitive environment in the classroom on boys and girls, we regressed fourth and eighth grade test scores on different combinations of the male dummy, the proportion of males in the student's fourth grade class, the number of students in the student's fourth grade class, and interactions of "male" with proportion male and class size. Table 9 reports the results of these regressions. We find that test scores go down for both boys and girls in fourth grade as the proportion of the class that is male increases, and that the effect is not significantly different by sex. For the eighth grade, we find that both sexes again do worse in the presence of more boys and that, in this case, boys experience this effect even more strongly than girls. Class size has a small negative effect on girls and a small positive effect on boys in fourth grade and a small positive effect on both sexes in eighth grade even controlling for school fixed effects. We might be concerned that a few outliers, classes which had almost all boys or almost all girls, are inordinately driving these results, so we also include the results of the regression excluding schools in which all students are of the same gender. This does not materially change the results. Thus, because we do not see a strong positive coefficient on the interaction of "male" and "fraction male," we learn from these class composition regressions that competition between boys and girls does not seem to be the main fact explaining the gender gap in math test scores either.[22]

The household composition regression using the PISA data is also relevant in this discussion, since siblings may compete within the household for resources as well as for grades and performances. As stated earlier, we found evidence that both sexes did better with certain combinations of siblings than others, but we did not find that the ordering of these outcomes supported the hypothesis of competition for household and parental resources or grades, especially because the ordering of outcomes was the same for both sexes.

3.2.6 Self assessed ability

A unique feature of the data from Chile is the ability to measure self assessed ability in math in boys and girls in 4th grade. In Table 10 we examine whether boys and girls differ in various aspects of how difficult they perceive math to be <u>conditional</u> on their math score. What is perhaps surprising is that even conditional on math scores, across the wide range of questions, girls are much more likely to be pessimistic about their math abilities. For example, boys are 10% more likely to say that they are "good at math", and 8% more likely to say that they get good grades in math without studying much. Conditioning on math score matters significantly for the coefficient on gender, suggesting that self assessed perceptions might go a long way towards explaining some of the gender gap in math.

The main empirical problem here is that it is unclear whether perceptions affect math scores or vice-versa, and hence, our analysis here is largely suggestive. However, we are able to provide some evidence that boys are not always more confident of their abilities than girls. In Table A.13 we examine whether boys and girls differ in other attitudes towards school not

[22]On a related note it would hard to explain why the competition explanation would hold for mathematical testing but not for reading, unless some further explanations are added on top of that.

related to math. While boys are still more likely to say that it is “important for me to get good grades”, relative to the mean response for this variable, the magnitude is quite small. Boys are less likely to agree that they “understand very little of what happens in class” but the magnitudes are small.

4 Concluding Remarks

A substantial gender gap in mathematical performance is found in several countries both in the middle and, more pronounced, at the top end of the distribution. It is also clear that while such gaps exist for a large number of countries, there are differences in the magnitudes of the gap and these differences are not explained away by country level variables. We also notice, from our Chilean data, that the gap increases over time so that smaller differences by grade 4 translate into larger differences by grade 8.

We attempt to explain where this gap is coming from. We examined detailed data at the cross country level, and then at the individual level, exploring the roles played by parents, classroom environments and individual characteristics of the students. None of those seems to be able to account for a substantial portion of such a gap. We conjecture that the evidence we provide points towards an explanation (or multiple ones) that is behavioral in nature and that appear to intervene (at least initially) between birth and the first reliable test we have, i.e. 4th grade. This could be, for example, stereotyping forces in society that lead girls to be less confident in their own math ability (even conditional on math score) as suggested by our data. This evidence is in line with the notion that parents spend more time on math investments with their sons, rather than with their daughters. While the magnitudes of these investment differences are very small, it is entirely likely that with a richer set of investment variables these will begin to play a role in explaining self assessed ability and eventually the gender gap. We therefore think that this is an important area for future research to explore.

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Figures and Tables

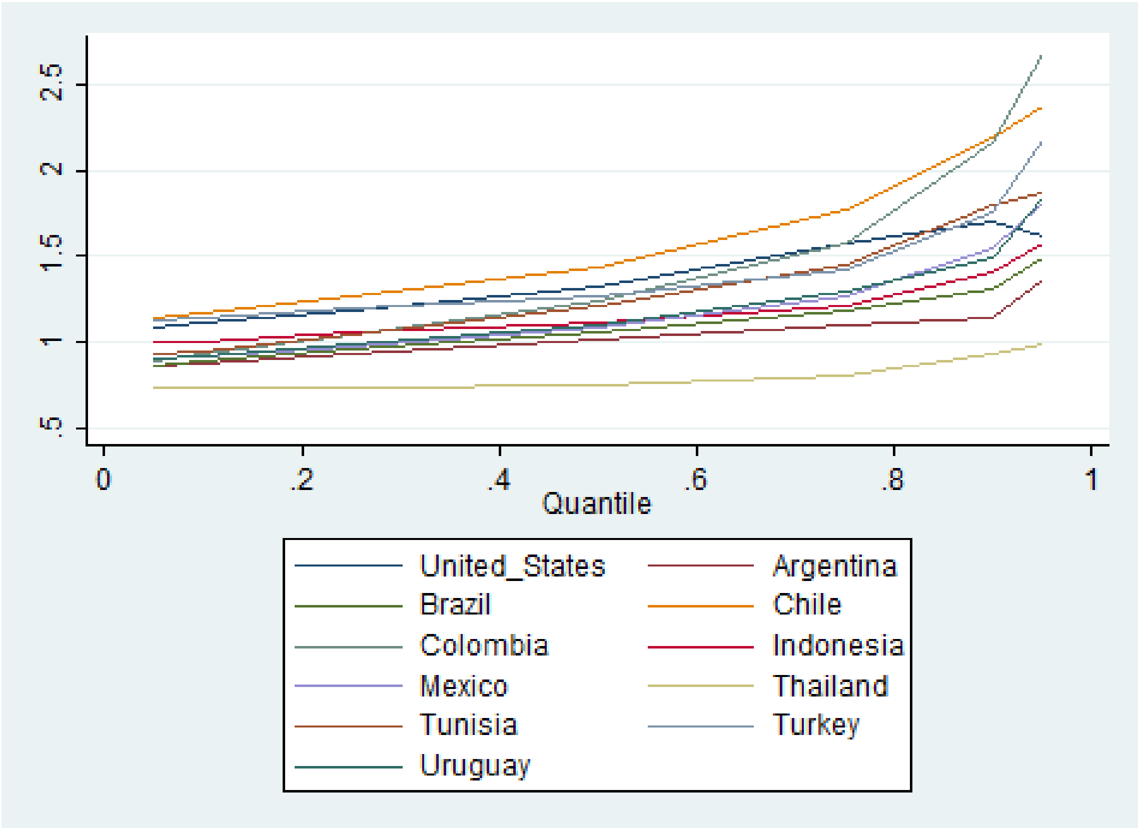

Figure 1: Gender Gap Size By Quantile

Table 1: Quantile Regressions of Math Scores Using Pooled PISA Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quantile	50	50	75	75	90	90	95	95
Male	0.292***	0.256***	0.320***	0.290***	0.343***	0.313***	0.349***	0.324***
	(0.00500)	(0.00457)	(0.00579)	(0.00512)	(0.00793)	(0.00665)	(0.00997)	(0.00823)
Age	-0.157***	-0.0923***	-0.149***	-0.0543***	-0.133***	-0.0509***	-0.122***	-0.0370**
	(0.00910)	(0.00831)	(0.0105)	(0.00929)	(0.0144)	(0.0121)	(0.0182)	(0.0149)
Year 2009	-0.0216***	-0.0599***	-0.0265***	-0.0636***	-0.0382***	-0.0781***	-0.0294***	-0.0650***
	(0.00508)	(0.00565)	(0.00588)	(0.00633)	(0.00806)	(0.00822)	(0.0101)	(0.0102)
Grade 8 or Below	-0.592***	-0.500***	-0.651***	-0.521***	-0.775***	-0.561***	-0.860***	-0.578***
	(0.00916)	(0.00839)	(0.0106)	(0.00939)	(0.0145)	(0.0122)	(0.0183)	(0.0151)
Grade 10	0.708***	0.561***	0.759***	0.552***	0.747***	0.531***	0.697***	0.503***
	(0.00624)	(0.00577)	(0.00723)	(0.00646)	(0.00990)	(0.00839)	(0.0125)	(0.0104)
Grade 11 or Above	0.892***	0.689***	0.953***	0.702***	0.953***	0.690***	0.899***	0.657***
	(0.0118)	(0.0108)	(0.0137)	(0.0121)	(0.0187)	(0.0158)	(0.0236)	(0.0195)
Mother Educated at ISCED Level 1		-0.00235		-0.00380		-0.0269**		-0.0442***
		(0.00723)		(0.00809)		(0.0105)		(0.0130)
Mother Educated at ISCED Level 2		0.0507***		0.0646***		0.0518***		0.0605***
		(0.00725)		(0.00811)		(0.0105)		(0.0130)
Mother Educated at ISCED Level 3		0.150***		0.173***		0.187***		0.185***
		(0.00791)		(0.00885)		(0.0115)		(0.0142)
Mother Educated at ISCED Level 4		0.0987***		0.123***		0.131***		0.150***
		(0.00936)		(0.0105)		(0.0136)		(0.0168)
Mother Educated at ISCED Level 5		0.0216***		0.0483***		0.0383***		0.0439***
		(0.00738)		(0.00826)		(0.0107)		(0.0133)
Mother Educated at ISCED Level 6		0.0981***		0.145***		0.156***		0.168***
		(0.00882)		(0.00987)		(0.0128)		(0.0159)
Mother Has Upper Blue Collar Job		0.0891***		0.101***		0.133***		0.133***
		(0.00967)		(0.0108)		(0.0141)		(0.0174)
Mother Has Upper White Collar Job		0.275***		0.270***		0.285***		0.283***
		(0.00699)		(0.00782)		(0.0102)		(0.0126)
Mother Has Lower White Collar Job		0.139***		0.146***		0.137***		0.130***
		(0.00657)		(0.00735)		(0.00956)		(0.0118)
Father Has Upper Blue Collar Job		0.0156***		-0.00192		0.00415		0.00460
		(0.00600)		(0.00672)		(0.00873)		(0.0108)
Father Has Upper White Collar Job		0.246***		0.254***		0.265***		0.263***
		(0.00654)		(0.00732)		(0.00951)		(0.0118)
Father Has Lower White Collar Job		0.0966***		0.0926***		0.0864***		0.0804***
		(0.00753)		(0.00843)		(0.0110)		(0.0135)
Mother Is Immigrant		-0.255***		-0.205***		-0.149***		-0.101***
		(0.0141)		(0.0158)		(0.0205)		(0.0254)
Wealth Index		0.110***		0.111***		0.111***		0.112***
		(0.00254)		(0.00284)		(0.00369)		(0.00457)
Childs Household Has 11 to 25 Books		0.0589***		0.0632***		0.0634***		0.0796***
		(0.00587)		(0.00657)		(0.00854)		(0.0106)
Childs Household Has 26 to 100 Books		0.243***		0.271***		0.300***		0.312***
		(0.00644)		(0.00721)		(0.00937)		(0.0116)
Childs Household Has 101 to 200 Books		0.337***		0.406***		0.463***		0.510***
		(0.00958)		(0.0107)		(0.0139)		(0.0172)
Childs Household Has 201 to 500 Books		0.518***		0.594***		0.648***		0.655***
		(0.0130)		(0.0145)		(0.0189)		(0.0233)
Childs Household Has More Than 500 Books		0.400***		0.501***		0.595***		0.631***
		(0.0169)		(0.0189)		(0.0245)		(0.0303)
Constant	1.938***	0.802***	2.356***	0.670***	2.668***	1.069***	2.858***	1.107***
	(0.142)	(0.130)	(0.165)	(0.146)	(0.226)	(0.189)	(0.284)	(0.234)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	199,268	199,268	199,268	199,268	199,268	199,268	199,268	199,268

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: Cross-Country Regression of PISA Math Gender Gap

	Dependent Variable: Gender Gap at Mean in PISA Math Scores							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.0708*** (0.0076)	0.0944*** (0.032)	0.0799 (0.093)	-2.482*** (0.84)	-0.240** (0.12)	0.888*** (0.24)	0.120*** (0.032)	0.152 (0.16)
GDP Per Capita		-0.000216 (0.00037)	-0.000255 (0.00049)	-0.000364 (0.00051)	-0.00224*** (0.00042)	0.00102** (0.00048)	-0.000642 (0.00039)	-0.000034 (0.00061)
Cellular Subscriptions		-0.0184 (0.021)	-0.0193 (0.024)	-0.0341** (0.016)	0.00127 (0.014)	-0.00930 (0.023)	0.0437 (0.028)	0.0422** (0.015)
Reading Gender Gap							0.573*** (0.14)	0.512*** (0.12)
Male Literacy Rate						-0.0118*** (0.0032)		-0.00321** (0.0012)
Female Literacy Rate						0.00346** (0.0014)		0.00241 (0.0018)
WVS: University more important for a boy					0.0405 (0.040)			0.0546** (0.021)
WVS: Men have more right to scarce jobs					0.112*** (0.038)			0.0981*** (0.023)
WVS: Men make better political leaders					0.0633* (0.035)			-0.000349 (0.024)
WVS: Being housewife as fulfilling as paid work					-0.0662** (0.032)			0.00315 (0.018)
Gender Gap Index			0.0236 (0.15)					-0.449** (0.17)
GGI: Economic Participation and Opportunity				-0.183* (0.095)				
GGI: Educational Attainment				1.328*** (0.45)				
GGI: Health and Survival				1.432* (0.75)				
GGI: Political Empowerment				0.0347 (0.059)				
Observations	62	62	56	56	42	33	62	27
R-squared	0.00	0.03	0.03	0.28	0.62	0.54	0.40	0.94

Robust standard errors in parentheses (weighted by population)
* significant at 10%; ** significant at 5%; *** significant at 1%
Cellular subscriptions are in per person terms for 2009 (World Bank data);
GDP per capita is for 2009 in thousands of US dollars (World Bank data);
WVS questions are on three- or four-point scale, with higher answers indicating stronger disagreement with the statement given;
GGI and subindices are higher for more gender equality.

Table 3: Quantile Regressions Including Sibling Data Using Pooled PISA Data

	(1)	(2)	(3)	(4)
Quantile	50	75	90	95
Male	0.237***	0.246***	0.305***	0.329***
	(0.0118)	(0.0133)	(0.0178)	(0.0219)
(Number brothers > 0) X (Number sisters > 0)	0.209***	0.183***	0.169***	0.167***
	(0.0113)	(0.0127)	(0.0170)	(0.0209)
(Number brothers > 0) X (Number sisters = 0)	0.228***	0.208***	0.218***	0.219***
	(0.0119)	(0.0133)	(0.0179)	(0.0220)
(Number brothers = 0) X (Number sisters > 0)	0.296***	0.267***	0.248***	0.248***
	(0.0128)	(0.0144)	(0.0193)	(0.0238)
Male X (Number brothers > 0) X (Number sisters > 0)	0.0367**	0.0491***	0.0177	0.0213
	(0.0160)	(0.0180)	(0.0242)	(0.0297)
Male X (Number brothers = 0) X (Number sisters > 0)	0.0639***	0.0784***	0.0339	-0.00777
	(0.0186)	(0.0210)	(0.0281)	(0.0346)
Male X (Number brothers > 0) X (Number sisters = 0)	0.0706***	0.100***	0.0165	-0.00662
	(0.0170)	(0.0191)	(0.0256)	(0.0316)
Age	-0.106***	-0.0814***	-0.0829***	-0.0984***
	(0.0113)	(0.0127)	(0.0170)	(0.0209)
Grade 8 or Below	-0.445***	-0.445***	-0.480***	-0.499***
	(0.0113)	(0.0127)	(0.0170)	(0.0209)
Grade 10	0.561***	0.567***	0.549***	0.514***
	(0.00767)	(0.00864)	(0.0116)	(0.0143)
Grade 11 or Above	0.845***	0.855***	0.836***	0.790***
	(0.0164)	(0.0185)	(0.0247)	(0.0305)
Mother Educated at ISCED Level 1	0.0331***	0.0286**	0.00989	0.00496
	(0.0103)	(0.0116)	(0.0156)	(0.0192)
Mother Educated at ISCED Level 2	0.0994***	0.108***	0.108***	0.114***
	(0.0105)	(0.0118)	(0.0158)	(0.0195)
Mother Educated at ISCED Level 3	0.203***	0.226***	0.249***	0.259***
	(0.0109)	(0.0123)	(0.0165)	(0.0203)
Mother Educated at ISCED Level 4	-0.0283	-0.0192	-0.0414	-0.0270
	(0.0218)	(0.0246)	(0.0329)	(0.0405)
Mother Educated at ISCED Level 5	0.0472***	0.0627***	0.0399***	0.0374**
	(0.00917)	(0.0103)	(0.0138)	(0.0170)
Mother Educated at ISCED Level 6	-0.105***	-0.0718***	-0.0328	-0.00969
	(0.0145)	(0.0163)	(0.0218)	(0.0269)
Mother Has Upper Blue Collar Job	0.102***	0.106***	0.127***	0.136***
	(0.0129)	(0.0146)	(0.0195)	(0.0240)
Mother Has Upper White Collar Job	0.256***	0.260***	0.281***	0.282***
	(0.00982)	(0.0111)	(0.0148)	(0.0182)
Mother Has Lower White Collar Job	0.125***	0.133***	0.118***	0.110***
	(0.00891)	(0.0100)	(0.0135)	(0.0166)
Father Has Upper Blue Collar Job	0.0249***	8.58e-05	-0.000199	-0.00615
	(0.00797)	(0.00897)	(0.0120)	(0.0148)
Father Has Upper White Collar Job	0.248***	0.256***	0.277***	0.280***
	(0.00873)	(0.00983)	(0.0132)	(0.0162)
Father Has Lower White Collar Job	0.0782***	0.0618***	0.0675***	0.0578***
	(0.0101)	(0.0114)	(0.0152)	(0.0188)
Mother Is Immigrant	-0.263***	-0.226***	-0.142***	-0.0827**
	(0.0197)	(0.0222)	(0.0298)	(0.0366)
Wealth Index	0.106***	0.109***	0.118***	0.117***
	(0.00348)	(0.00392)	(0.00526)	(0.00648)
Childs Household Has 11 to 25 Books	0.0545***	0.0576***	0.0645***	0.0804***
	(0.00781)	(0.00880)	(0.0118)	(0.0145)
Childs Household Has 26 to 100 Books	0.214***	0.236***	0.249***	0.277***
	(0.00863)	(0.00972)	(0.0130)	(0.0160)
Childs Household Has 101 to 200 Books	0.304***	0.372***	0.419***	0.454***
	(0.0129)	(0.0146)	(0.0195)	(0.0240)
Childs Household Has 201 to 500 Books	0.473***	0.551***	0.609***	0.626***
	(0.0176)	(0.0199)	(0.0266)	(0.0328)
Childs Household Has More Than 500 Books	0.329***	0.457***	0.559***	0.550***
	(0.0228)	(0.0256)	(0.0344)	(0.0423)
Constant	0.732***	0.830***	1.317***	1.849***
	(0.177)	(0.200)	(0.267)	(0.329)
Country Dummies	Yes	Yes	Yes	Yes
Observations	108,542	108,542	108,542	108,542

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Main Regression Specification Using SIMCE Results

	Standardized 4th grade SIMCE			Standardized 8th grade SIMCE		
Dummy for Male	0.0826***	0.0874***	0.0927***	0.196***	0.205***	0.211***
	(0.00164)	(0.00162)	(0.00162)	(0.00305)	(0.00267)	(0.00267)
Log Birth Weight		0.243***	0.238***		0.245***	0.244***
		(0.00488)	(0.00482)		(0.00801)	(0.00795)
Full term Birth		0.00185	-0.000208		-0.000399	-0.00222
		(0.00205)	(0.00203)		(0.00329)	(0.00326)
Mother's Age at Birth		0.00218***	0.00193***		0.00138***	0.00121***
		(0.000132)	(0.000131)		(0.000218)	(0.000217)
Unmarried Mother		-0.0405***	-0.0360***		-0.0218***	-0.0175***
		(0.00170)	(0.00168)		(0.00277)	(0.00275)
Mother attended High School		0.228***	0.209***		0.161***	0.144***
		(0.00208)	(0.00206)		(0.00330)	(0.00328)
Mother attended Colege		0.422***	0.397***		0.346***	0.322***
		(0.00332)	(0.00330)		(0.00562)	(0.00559)
Mother Employed		0.0797***	0.0736***		0.0601***	0.0556***
		(0.00200)	(0.00199)		(0.00337)	(0.00335)
Additional controls		School FE	Class FE		School FE	Class FE
Observations	1,444,735	1,225,761	1,225,761	422,319	418,017	418,017
R-squared	0.003	0.255	0.345	0.010	0.353	0.400

* significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in brackets
All specifications have year of test fixed effects

Table 5: Linear Regression of Top Scores from SIMCE Data

	Standardized 4th grade SIMCE								
	Probability of being in the top 10%			Probability of being in the top 5%			Probability of being in the top 1%		
Dummy for Male	0.0251***	0.0246***	0.0253***	0.0156***	0.0150***	0.0155***	0.00591***	0.00567***	0.00588***
	(0.000520)	(0.000548)	(0.000563)	(0.000394)	(0.000422)	(0.000433)	(0.000226)	(0.000246)	(0.000253)
Controls		School FE	Class FE		School FE	Class FE		School FE	Class FE
Male/Female	1.27	1.26	1.27	1.35	1.33	1.35	1.86	1.67	1.86
Observations	1,444,735	1,225,761	1,225,761	1,444,735	1,225,761	1,225,761	1,444,735	1,225,761	1,225,761
R-squared	0.002	0.119	0.173	0.001	0.082	0.133	0.001	0.038	0.085
	Standardized 8th grade SIMCE								
	Probability of being in the top 10%			Probability of being in the top 5%			Probability of being in the top 1%		
Dummy for Male	0.0353***	0.0337***	0.0339***	0.0221***	0.0208***	0.0209***	0.00896***	0.00812***	0.00786***
	(0.000961)	(0.000879)	(0.000887)	(0.000730)	(0.000680)	(0.000684)	(0.000430)	(0.000414)	(0.000414)
Controls		School FE	Class FE		School FE	Class FE			
Male/Female	1.42	1.40	1.41	1.56	1.50	1.50	2.64	2.33	2.33
Observations	422,319	418,017	418,017	422,319	418,017	418,017	422,319	418,017	418,017
R-squared	0.003	0.230	0.265	0.002	0.175	0.210	0.001	0.089	0.122

* significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in brackets
All specifications have year of test fixed effects and controls for log birth weight, gestational age, mother's education, age, marital and employment status.

Table 6: Regressions on Twins Sample

	Standardized 4th grade SIMCE				
	Mean	Probability of being in the top percentile			
		25	10	5	1
Dummy for Male	0.148***	0.0643***	0.0485***	0.0305***	0.00774**
	(0.0167)	(0.00893)	(0.00698)	(0.00568)	(0.00349)
Constant	-0.137***	0.202***	0.0741***	0.0388***	0.0129***
	(0.00870)	(0.00466)	(0.00364)	(0.00296)	(0.00182)
Male to female ratio		1.26	1.67	1.99	2.08
Observations	22,074	22,074	22,074	22,074	22,074
Number of Twin Groups	12,461	12,461	12,461	12,461	12,461
	Standardized 8th grade SIMCE				
	Mean	Probability of being in the top percentile			
		25	10	5	1
Dummy for Male	0.269***	0.115***	0.0728***	0.0405***	0.0113*
	(0.0327)	(0.0173)	(0.0136)	(0.0110)	(0.00674)
Constant	-0.187***	0.187***	0.0668***	0.0379***	0.0120***
	(0.0166)	(0.00881)	(0.00693)	(0.00561)	(0.00342)
Male to female ratio		1.57	1.90	1.94	3.44
Observations	6,293	6,293	6,293	6,293	6,293
Number of Twin Groups	3,834	3,834	3,834	3,834	3,834

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Parental Investments and SIMCE Scores from 2002

	OLS: Standardized 4th grade SIMCE Score		
Male	0.0912***	0.0952***	0.0977***
	(0.00449)	(0.00417)	(0.00415)
Investments in Math	0.177***	0.116***	0.110***
	(0.00494)	(0.00434)	(0.00430)
Investments in Reading	0.101***	0.0139***	0.0135***
	(0.00511)	(0.00452)	(0.00449)
Controls		School FE	Classroom FE
Observations	184,144	182,189	182,189
R-squared	0.015	0.301	0.339

* significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in brackets
All specifications control for log birth weight, gestational age, mother's age, education, marital and employment status. Investments in each subject are derived from parent surveys where parents respond a question of "How often do you pose Math problems to your child" or "How often do you read to your child". 1 indicates frequent investment and 0 indicates infrequent investment.

Table 8: Teacher Gender and Math Scores

	OLS: Standardized 4th grade SIMCE Score		
Dummy for Male	0.0914***	0.0914***	0.0896***
	(0.00209)	(0.00209)	(0.00226)
Math teacher Male		-0.0635***	-0.0703***
		(0.00571)	(0.00648)
Male X Math teacher Male			0.0127**
			(0.00602)
Observations	797,102	797,102	797,102
R-squared	0.256	0.257	0.257

* significant at 10%; ** significant at 5%; *** significant at 1%
Standard errors clustered at the classroom level in brackets.
Other controls include class size, fraction male in class, school fixed effects. All regressions also include log birth weight, gestational age, mother's age, education, marital and employment status. Teacher gender information not available for 2009 and 2010.

Table 9: SIMCE Scores Regressed on Class Size and Composition

	4th grade SIMCE scores			
		——Full Sample——		Excluding single-sex schools
Male X Class Size	0.00109***		0.000930***	0.000989***
	(0.000121)		(0.000122)	(0.000121)
Male	0.0514***	0.0869***	0.0545***	0.0622***
	(0.00427)	(0.00891)	(0.00998)	(0.0101)
Class Size	-0.000729***		-0.000676***	-0.000717***
	(0.000180)		(0.000180)	(0.000188)
Male X Fraction Male		0.0103	0.0133	-0.00549
		(0.0168)	(0.0168)	(0.0172)
Fraction Male		-0.109***	-0.103***	-0.127***
		(0.0137)	(0.0138)	(0.0167)
Observations	1,225,761	1,225,761	1,225,761	1,125,046
R-squared	0.255	0.255	0.255	0.245
	8th grade SIMCE scores			
		——Full Sample——		Excluding single-sex schools
Male X Class Size	0.000983***		0.000561	0.000495
	(0.000335)		(0.000519)	(0.000524)
Male	0.175***	0.246***	0.213***	0.203***
	(0.0105)	(0.0119)	(0.0247)	(0.0257)
Class Size	0.00728***		0.0108***	0.0109***
	(0.000570)		(0.00102)	(0.00108)
Male X Fraction Male		-0.0641***	-0.0394	-0.0153
		(0.0222)	(0.0328)	(0.0357)
Fraction Male		-0.0821***	-0.0428***	-0.0391**
		(0.00905)	(0.0149)	(0.0177)
Observations	418,017	418,017	181,029	162,548
R-squared	0.354	0.354	0.393	0.366

Standard errors clustered at the classroom level in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%
Controls include Birth Weight, Gestational Age, Mother's Age and Education, Mother Employment status, and School FE

Table 10: Gender and Perceptions about Math Ability

Responses are in agreement with the statements	In general I am quite good at Math	I like math classes in my school	Math is harder for me than for the rest of my peers	
Dummy for Male	0.104***	0.0272***	-0.0168***	
	(0.00164)	(0.00163)	(0.00136)	
Simce math score	0.164***	0.0184***	-0.132***	
	(0.000907)	(0.000940)	(0.000766)	
Observations	364,337	389,653	387,355	
R-squared	0.152	0.086	0.114	
Mean of dependent variable	0.477	0.443	0.223	
Responses are in agreement with the statements	**I learn math quickly and easily**	**I am not good at Math**	**I like to study Math**	**I get good grades in Math without studying**
Dummy for Male	0.116***	-0.0139***	0.0454***	0.0885***
	(0.00163)	(0.00124)	(0.00169)	(0.00154)
Simce math score	0.134***	-0.0951***	0.0619***	0.119***
	(0.000916)	(0.000715)	(0.000960)	(0.000901)
Observations	386,128	383,740	372,307	368,427
R-squared	0.106	0.086	0.079	0.104
Mean of dependent variable	0.448	0.168	0.459	0.301

Robust standard errors in parentheses, clustered at the classroom level.
*** p<0.01, ** p<0.05, * p<0.1
Notes: controls are year of SIMCE test, full term birth, mother's education, marital status and age. School fixed effects in all regressions.

A Appendix

Table A.1: PISA Descriptive Statistics by Year and Country: Argentina-Colombia

	Argentina		Brazil		Chile		Colombia	
	2006	2009	2006	2009	2006	2009	2006	2009
Male	0.4566	0.4573	0.4581	0.4522	0.5408	0.5063	0.4562	0.4685
	(0.4982)	(0.4982)	(0.4983)	(0.4977)	(0.4984)	(0.5)	(0.4981)	(0.499)
(Number brothers $>$ 0) X (Number sisters $>$ 0)		0.3871		0.2676		0.2815		0.2434
		(0.4871)		(0.4427)		(0.4498)		(0.4292)
(Number brothers $>$ 0) X (Number sisters $=$ 0)		0.248		0.2842		0.2784		0.2594
		(0.4319)		(0.451)		(0.4482)		(0.4384)
(Number brothers $=$ 0) X (Number sisters $>$ 0)		0.1891		0.1544		0.2104		0.1896
		(0.3917)		(0.3613)		(0.4077)		(0.392)
(Number brothers $=$ 0) X (Number sisters $=$ 0)		0.1757		0.2938		0.2297		0.3075
		(0.3806)		(0.4555)		(0.4207)		(0.4615)
Age	15.69	15.7	15.78	15.87	15.82	15.79	15.85	15.84
	(0.2789)	(0.2829)	(0.2876)	(0.281)	(0.2812)	(0.2821)	(0.2862)	(0.2798)
Grade 8 or Below	0.1224	0.1558	0.4058	0.2435	0.0285	0.0333	0.1679	0.1396
	(0.3278)	(0.3627)	(0.4911)	(0.4292)	(0.1663)	(0.1795)	(0.3738)	(0.3466)
Grade 9	0.1574	0.1975	0.4087	0.3981	0.1898	0.1963	0.222	0.2086
	(0.3642)	(0.3982)	(0.4916)	(0.4895)	(0.3921)	(0.3973)	(0.4156)	(0.4063)
Grade 10	0.6681	0.5905	0.1775	0.328	0.7193	0.7171	0.4015	0.4474
	(0.4709)	(0.4918)	(0.3821)	(0.4695)	(0.4494)	(0.4505)	(0.4903)	(0.4973)
Grade 11 or Above	0.0408	0.0448	0.008	0.0304	0.0625	0.0533	0.2086	0.2044
	(0.1978)	(0.2069)	(0.0889)	(0.1716)	(0.2421)	(0.2246)	(0.4063)	(0.4033)
Mother Educated at ISCED Level 0	0.1189	0.0788	0.1732	0.1052	0.0833	0.0529	0.1516	0.1367
	(0.3237)	(0.2694)	(0.3785)	(0.3068)	(0.2764)	(0.2239)	(0.3587)	(0.3436)
Mother Educated at ISCED Level 1	0.2086	0.1768	0.175	0.2216	0.0476	0.0504	0.1829	0.1692
	(0.4063)	(0.3815)	(0.38)	(0.4153)	(0.2129)	(0.2189)	(0.3866)	(0.3749)
Mother Educated at ISCED Level 2	0.1106	0.1052	0.2003	0.1951	0.2028	0.2071	0.136	0.1774
	(0.3137)	(0.3068)	(0.4003)	(0.3963)	(0.4021)	(0.4053)	(0.3428)	(0.382)
Mother Educated at ISCED Level 3	0	0	0	0.0277	0.0976	0	0	0
	(0)	(0)	(0)	(0.164)	(0.2969)	(0)	(0)	(0)
Mother Educated at ISCED Level 4	0.1883	0.173	0.131	0.2055	0.2591	0.4034	0.1251	0.1565
	(0.391)	(0.3783)	(0.3375)	(0.4041)	(0.4382)	(0.4906)	(0.3308)	(0.3634)
Mother Educated at ISCED Level 5	0.1327	0.164	0.0543	0.043	0.0787	0.1055	0.1536	0.185
	(0.3393)	(0.3703)	(0.2267)	(0.2029)	(0.2693)	(0.3072)	(0.3606)	(0.3883)
Mother Educated at ISCED Level 6	0.1798	0.2321	0.2205	0.1771	0.1546	0.1316	0.1811	0.1602
	(0.384)	(0.4222)	(0.4146)	(0.3817)	(0.3616)	(0.3381)	(0.3852)	(0.3668)
Mother Has Lower Blue Collar Job	0.0922	0.1422	0.2484	0.2508	0.3742	0.188	0.182	0.2193
	(0.2893)	(0.3493)	(0.4321)	(0.4335)	(0.484)	(0.3908)	(0.3859)	(0.4138)
Mother Has Upper Blue Collar Job	0.032	0.0184	0.04	0.0832	0.0361	0.0411	0.0601	0.061
	(0.1761)	(0.1345)	(0.196)	(0.2761)	(0.1866)	(0.1985)	(0.2376)	(0.2393)
Mother Has Upper White Collar Job	0.2459	0.2715	0.2882	0.2361	0.1657	0.1877	0.2146	0.2173
	(0.4307)	(0.4448)	(0.453)	(0.4247)	(0.3718)	(0.3905)	(0.4106)	(0.4124)
Mother Has Lower White Collar Job	0.1839	0.1546	0.16	0.1597	0.198	0.2805	0.1536	0.1434
	(0.3875)	(0.3615)	(0.3666)	(0.3664)	(0.3985)	(0.4493)	(0.3606)	(0.3505)
Father Has Lower Blue Collar Job	0.1399	0.2302	0.3827	0.1668	0.254	0.2433	0.2508	0.2449
	(0.3469)	(0.421)	(0.4861)	(0.3728)	(0.4353)	(0.4291)	(0.4335)	(0.4301)
Father Has Upper Blue Collar Job	0.2616	0.203	0.1015	0.3332	0.2366	0.2321	0.2416	0.2564
	(0.4395)	(0.4023)	(0.3019)	(0.4714)	(0.425)	(0.4222)	(0.4281)	(0.4367)
Father Has Upper White Collar Job	0.2593	0.2748	0.3029	0.2393	0.2285	0.2464	0.2872	0.2543
	(0.4383)	(0.4465)	(0.4595)	(0.4267)	(0.4199)	(0.431)	(0.4525)	(0.4355)
Father Has Lower White Collar Job	0.2159	0.159	0.0633	0.1202	0.159	0.1545	0.0907	0.0764
	(0.4115)	(0.3657)	(0.2434)	(0.3252)	(0.3657)	(0.3615)	(0.2872)	(0.2656)
Mother Is Immigrant	0.0523	0.058	0.0432	0.0115	0.0111	0.0115	0.0074	0.0077
	(0.2227)	(0.2338)	(0.2034)	(0.1065)	(0.1047)	(0.1065)	(0.0855)	(0.0874)
Wealth Index	-1.309	-0.9536	-1.523	-1.344	-0.9987	-0.6254	-1.67	-1.284
	(0.8972)	(0.8919)	(0.9489)	(0.8679)	(0.952)	(0.9768)	(1.054)	(1.078)
Child's Household Has 0 to 10 Books	0.2936	0.2652	0.3521	0.362	0.2102	0.1942	0.312	0.2977
	(0.4555)	(0.4415)	(0.4777)	(0.4806)	(0.4075)	(0.3956)	(0.4633)	(0.4573)
Child's Household Has 11 to 25 Books	0.2768	0.256	0.3045	0.3128	0.2828	0.2653	0.2845	0.3046
	(0.4475)	(0.4365)	(0.4602)	(0.4636)	(0.4504)	(0.4415)	(0.4512)	(0.4603)
Child's Household Has 26 to 100 Books	0.2512	0.2591	0.2132	0.2151	0.3088	0.3235	0.2582	0.2707
	(0.4338)	(0.4382)	(0.4096)	(0.4109)	(0.462)	(0.4679)	(0.4377)	(0.4443)
Child's Household Has 101 to 200 Books	0.0885	0.0987	0.0598	0.0553	0.0996	0.1152	0.0717	0.074
	(0.2841)	(0.2982)	(0.2372)	(0.2286)	(0.2994)	(0.3193)	(0.258)	(0.2618)
Child's Household Has 201 to 500 Books	0.044	0.0507	0.0263	0.0206	0.0466	0.0529	0.0326	0.0234
	(0.2052)	(0.2194)	(0.1599)	(0.1419)	(0.2109)	(0.2239)	(0.1776)	(0.151)
Child's Household Has More Than 500 Books	0.023	0.0287	0.0144	0.0143	0.0214	0.0252	0.0109	0.0077
	(0.1501)	(0.167)	(0.1192)	(0.1186)	(0.1447)	(0.1568)	(0.104)	(0.0874)

Table A.2: PISA Descriptive Statistics by Year and Country: Indonesia-Tunisia

	Indonesia		Mexico		Thailand		Tunisia	
	2006	2009	2006	2009	2006	2009	2006	2009
Male	0.4969	0.4934	0.4581	0.4761	0.4212	0.4307	0.472	0.4761
	(0.5)	(0.5)	(0.4982)	(0.4994)	(0.4938)	(0.4952)	(0.4993)	(0.4995)
(Number brothers $>$ 0) X (Number sisters $>$ 0)		0.2897		0.3568		0.1605		0.5134
		(0.4537)		(0.4791)		(0.3671)		(0.4999)
(Number brothers $>$ 0) X (Number sisters $=$ 0)		0.1752		0.2256		0.217		0.1935
		(0.3802)		(0.418)		(0.4123)		(0.3951)
(Number brothers $=$ 0) X (Number sisters $>$ 0)		0.147		0.1705		0.2032		0.0977
		(0.3541)		(0.3761)		(0.4024)		(0.2969)
(Number brothers $=$ 0) X (Number sisters $=$ 0)		0.388		0.2471		0.4193		0.1954
		(0.4874)		(0.4313)		(0.4935)		(0.3965)
Age	15.76	15.76	15.72	15.72	15.68	15.7	15.88	15.88
	(0.2867)	(0.2862)	(0.2783)	(0.2784)	(0.2875)	(0.2906)	(0.2823)	(0.2776)
Grade 8 or Below	0.1136	0.072	0.0567	0.0561	0.0118	0.0071	0.2858	0.2129
	(0.3173)	(0.2586)	(0.2312)	(0.2302)	(0.1079)	(0.0838)	(0.4518)	(0.4094)
Grade 9	0.474	0.4509	0.1488	0.2175	0.3169	0.2448	0.2235	0.2662
	(0.4993)	(0.4976)	(0.3558)	(0.4126)	(0.4653)	(0.43)	(0.4166)	(0.442)
Grade 10	0.3657	0.4278	0.6712	0.7188	0.6386	0.7173	0.4455	0.4696
	(0.4817)	(0.4948)	(0.4698)	(0.4496)	(0.4805)	(0.4504)	(0.4971)	(0.4991)
Grade 11 or Above	0.0467	0.0493	0.1066	0.0066	0.0328	0.0308	0.0453	0.0513
	(0.211)	(0.2164)	(0.3087)	(0.0807)	(0.1781)	(0.1729)	(0.2079)	(0.2206)
Mother Educated at ISCED Level 0	0.1035	0.116	0.1195	0.125	0.0754	0.0694	0.1037	0.2737
	(0.3046)	(0.3203)	(0.3243)	(0.3307)	(0.2641)	(0.2541)	(0.3049)	(0.4459)
Mother Educated at ISCED Level 1	0.2606	0.3144	0.1922	0.2018	0.4144	0.457	0.2543	0.2226
	(0.439)	(0.4643)	(0.394)	(0.4014)	(0.4927)	(0.4982)	(0.4355)	(0.416)
Mother Educated at ISCED Level 2	0.1822	0.1939	0.2238	0.2668	0.1378	0.1099	0.1569	0.1447
	(0.386)	(0.3954)	(0.4168)	(0.4423)	(0.3447)	(0.3128)	(0.3637)	(0.3518)
Mother Educated at ISCED Level 3	0.0508	0.0327	0.0198	0.0205	0.0363	0.0275	0.0175	0.0327
	(0.2196)	(0.1779)	(0.1394)	(0.1417)	(0.1871)	(0.1635)	(0.131)	(0.1779)
Mother Educated at ISCED Level 4	0.239	0.22	0.0872	0.1055	0.1743	0.1648	0.2476	0.1717
	(0.4265)	(0.4143)	(0.2821)	(0.3073)	(0.3794)	(0.371)	(0.4317)	(0.3772)
Mother Educated at ISCED Level 5	0.0482	0.0448	0.1109	0.1015	0	0	0.0599	0.0486
	(0.2142)	(0.2068)	(0.314)	(0.302)	(0)	(0)	(0.2374)	(0.2151)
Mother Educated at ISCED Level 6	0.1047	0.0664	0.2091	0.1591	0.1408	0.1578	0.1474	0.0486
	(0.3062)	(0.249)	(0.4067)	(0.3658)	(0.3479)	(0.3645)	(0.3546)	(0.2151)
Mother Has Lower Blue Collar Job	0.0922	0.1258	0.1398	0.1579	0.1508	0.1687	0.0899	0.1041
	(0.2894)	(0.3316)	(0.3468)	(0.3647)	(0.3579)	(0.3745)	(0.286)	(0.3055)
Mother Has Upper Blue Collar Job	0.124	0.1421	0.0416	0.0383	0.2917	0.2667	0.042	0.046
	(0.3296)	(0.3492)	(0.1996)	(0.1919)	(0.4546)	(0.4423)	(0.2007)	(0.2095)
Mother Has Upper White Collar Job	0.1078	0.1131	0.187	0.1857	0.2285	0.2071	0.1114	0.1007
	(0.3102)	(0.3168)	(0.3899)	(0.3889)	(0.4199)	(0.4052)	(0.3147)	(0.301)
Mother Has Lower White Collar Job	0.1097	0.0898	0.2031	0.1881	0.1672	0.1274	0.0407	0.0444
	(0.3125)	(0.2859)	(0.4023)	(0.3908)	(0.3731)	(0.3334)	(0.1977)	(0.206)
Father Has Lower Blue Collar Job	0.2546	0.2662	0.2702	0.2987	0.23	0.2199	0.3888	0.3891
	(0.4357)	(0.442)	(0.444)	(0.4577)	(0.4208)	(0.4142)	(0.4875)	(0.4876)
Father Has Upper Blue Collar Job	0.2935	0.3248	0.235	0.2184	0.3004	0.2736	0.1711	0.1845
	(0.4554)	(0.4683)	(0.424)	(0.4131)	(0.4585)	(0.4458)	(0.3767)	(0.3879)
Father Has Upper White Collar Job	0.1797	0.1579	0.2725	0.2644	0.2566	0.2469	0.2707	0.2303
	(0.3839)	(0.3647)	(0.4452)	(0.441)	(0.4368)	(0.4312)	(0.4444)	(0.421)
Father Has Lower White Collar Job	0.1512	0.1369	0.1414	0.1289	0.1056	0.0831	0.1067	0.1417
	(0.3583)	(0.3438)	(0.3484)	(0.3351)	(0.3074)	(0.276)	(0.3087)	(0.3488)
Mother Is Immigrant	0.0039	0.0031	0.0225	0.0209	0.0061	1.60E-04	0.0192	0.0133
	(0.0619)	(0.0557)	(0.1484)	(0.1432)	(0.0781)	(0.0127)	(0.1372)	(0.1147)
Wealth Index	-2.614	-1.775	-1.373	-1.561	-1.418	-1.172	-1.882	-1.669
	(1.257)	(1.242)	(1.076)	(1.139)	(1.08)	(0.9934)	(1.163)	(1.105)
Child's Household Has 0 to 10 Books	0.203	0.2305	0.3535	0.3692	0.235	0.1979	0.3631	0.3758
	(0.4022)	(0.4212)	(0.4781)	(0.4826)	(0.424)	(0.3985)	(0.481)	(0.4844)
Child's Household Has 11 to 25 Books	0.3861	0.3701	0.289	0.2911	0.3191	0.3052	0.2959	0.3391
	(0.4869)	(0.4829)	(0.4533)	(0.4543)	(0.4662)	(0.4605)	(0.4565)	(0.4734)
Child's Household Has 26 to 100 Books	0.2718	0.2625	0.2248	0.2107	0.2842	0.3046	0.203	0.1804
	(0.4449)	(0.44)	(0.4175)	(0.4078)	(0.4511)	(0.4603)	(0.4023)	(0.3846)
Child's Household Has 101 to 200 Books	0.0641	0.0592	0.0664	0.061	0.0888	0.0988	0.0468	0.0357
	(0.245)	(0.236)	(0.249)	(0.2393)	(0.2845)	(0.2984)	(0.2112)	(0.1856)
Child's Household Has 201 to 500 Books	0.0201	0.0259	0.0302	0.0281	0.042	0.0535	0.0181	0.0174
	(0.1403)	(0.1588)	(0.1711)	(0.1651)	(0.2006)	(0.225)	(0.1333)	(0.1306)
Child's Household Has More Than 500 Books	0.0167	0.0218	0.0138	0.0139	0.0182	0.0288	0.0149	0.0149
	(0.1282)	(0.1461)	(0.1165)	(0.1169)	(0.1339)	(0.1671)	(0.121)	(0.1213)

Table A.3: PISA Descriptive Statistics by Year and Country: Turkey-Uruguay

	Turkey		United States		Uruguay	
	2006	2009	2006	2009	2006	2009
Male	0.5366	0.5106	0.5061	0.5135	0.4695	0.4717
	(0.4987)	(0.4999)	(0.5)	(0.4999)	(0.4991)	(0.4992)
(Number brothers $>$ 0) X (Number sisters $>$ 0)		0.297		0.2649		0.2647
		(0.457)		(0.4413)		(0.4412)
(Number brothers $>$ 0) X (Number sisters $=$ 0)		0.2456		0.2717		0.2706
		(0.4305)		(0.4449)		(0.4443)
(Number brothers $=$ 0) X (Number sisters $>$ 0)		0.211		0.236		0.214
		(0.408)		(0.4247)		(0.4102)
(Number brothers $=$ 0) X (Number sisters $=$ 0)		0.2464		0.2274		0.2506
		(0.431)		(0.4192)		(0.4334)
Age	15.9	15.82	15.82	15.79	15.87	15.86
	(0.2875)	(0.2806)	(0.2952)	(0.2964)	(0.2853)	(0.2774)
Grade 8 or Below	0.0235	0.0274	0.0057	7.60E-04	0.1414	0.1731
	(0.1514)	(0.1633)	(0.0753)	(0.0276)	(0.3484)	(0.3783)
Grade 9	0.4061	0.2518	0.1098	0.108	0.1575	0.2182
	(0.4912)	(0.4341)	(0.3126)	(0.3104)	(0.3643)	(0.4131)
Grade 10	0.5405	0.6791	0.7161	0.6916	0.6222	0.5625
	(0.4984)	(0.4669)	(0.4509)	(0.4619)	(0.4849)	(0.4961)
Grade 11 or Above	0.0299	0.0416	0.1681	0.1997	0.0789	0.0462
	(0.1705)	(0.1998)	(0.374)	(0.3998)	(0.2697)	(0.2099)
Mother Educated at ISCED Level 0	0.0552	0.1311	0.0248	0.0174	0.0773	0.0522
	(0.2285)	(0.3375)	(0.1554)	(0.1307)	(0.2671)	(0.2225)
Mother Educated at ISCED Level 1	0.346	0.4742	0.0214	0.0266	0.1819	0.2646
	(0.4757)	(0.4994)	(0.1447)	(0.1608)	(0.3858)	(0.4411)
Mother Educated at ISCED Level 2	0.2036	0.1667	0.0736	0.0663	0.1769	0.2704
	(0.4027)	(0.3728)	(0.2612)	(0.2488)	(0.3816)	(0.4442)
Mother Educated at ISCED Level 3	0.0089	0.006	0	0	0.0134	0.0151
	(0.0939)	(0.0773)	(0)	(0)	(0.1151)	(0.122)
Mother Educated at ISCED Level 4	0.2293	0.1147	0.4058	0.4097	0.0899	0.1427
	(0.4204)	(0.3187)	(0.4911)	(0.4918)	(0.2861)	(0.3498)
Mother Educated at ISCED Level 5	0.048	0.016	0.1285	0.1525	0.2565	0.0995
	(0.2137)	(0.1255)	(0.3347)	(0.3595)	(0.4367)	(0.2994)
Mother Educated at ISCED Level 6	0.0979	0.0512	0.2816	0.3046	0.1383	0.1131
	(0.2973)	(0.2205)	(0.4498)	(0.4603)	(0.3452)	(0.3168)
Mother Has Lower Blue Collar Job	0.018	0.0268	0.0611	0.0688	0.1965	0.2056
	(0.133)	(0.1616)	(0.2396)	(0.2531)	(0.3974)	(0.4042)
Mother Has Upper Blue Collar Job	0.0374	0.0254	0.0219	0.0302	0.049	0.0571
	(0.1898)	(0.1574)	(0.1464)	(0.1711)	(0.2158)	(0.232)
Mother Has Upper White Collar Job	0.0645	0.0689	0.4507	0.4714	0.2668	0.2473
	(0.2458)	(0.2532)	(0.4976)	(0.4992)	(0.4423)	(0.4315)
Mother Has Lower White Collar Job	0.0362	0.0476	0.2834	0.279	0.255	0.2357
	(0.1869)	(0.213)	(0.4507)	(0.4485)	(0.4359)	(0.4245)
Father Has Lower Blue Collar Job	0.1297	0.1753	0.1704	0.1599	0.2186	0.2364
	(0.336)	(0.3803)	(0.376)	(0.3666)	(0.4134)	(0.4249)
Father Has Upper Blue Collar Job	0.3191	0.2548	0.1673	0.2024	0.2271	0.2434
	(0.4662)	(0.4358)	(0.3733)	(0.4018)	(0.419)	(0.4292)
Father Has Upper White Collar Job	0.3112	0.3088	0.3782	0.3732	0.2852	0.2303
	(0.463)	(0.4621)	(0.485)	(0.4837)	(0.4515)	(0.4211)
Father Has Lower White Collar Job	0.1453	0.1313	0.0781	0.0948	0.1442	0.1675
	(0.3524)	(0.3378)	(0.2683)	(0.2929)	(0.3514)	(0.3735)
Mother Is Immigrant	0.015	0.0142	0.1864	0.2253	0.0223	0.021
	(0.1215)	(0.1184)	(0.3895)	(0.4178)	(0.1477)	(0.1433)
Wealth Index	-1.497	-1.02	0.151	0.4138	-1.084	-0.6823
	(1.005)	(1.247)	(0.7984)	(0.8911)	(0.9591)	(0.9141)
Child's Household Has 0 to 10 Books	0.2252	0.2342	0.1586	0.1989	0.2191	0.2928
	(0.4178)	(0.4235)	(0.3654)	(0.3992)	(0.4136)	(0.4551)
Child's Household Has 11 to 25 Books	0.2709	0.2496	0.154	0.1752	0.2439	0.2431
	(0.4445)	(0.4328)	(0.361)	(0.3802)	(0.4294)	(0.429)
Child's Household Has 26 to 100 Books	0.3029	0.2972	0.286	0.2777	0.2817	0.2481
	(0.4596)	(0.4571)	(0.452)	(0.4479)	(0.4499)	(0.432)
Child's Household Has 101 to 200 Books	0.101	0.1151	0.18	0.1628	0.1269	0.0977
	(0.3013)	(0.3192)	(0.3842)	(0.3692)	(0.3329)	(0.2969)
Child's Household Has 201 to 500 Books	0.0587	0.0588	0.1301	0.1116	0.063	0.053
	(0.235)	(0.2354)	(0.3364)	(0.3149)	(0.243)	(0.2241)
Child's Household Has More Than 500 Books	0.0304	0.0312	0.0761	0.0592	0.0327	0.0302
	(0.1716)	(0.1739)	(0.2652)	(0.2361)	(0.1777)	(0.1712)

Table A.4: Survival Rates to Grade 5 and Secondary Enrollment Rates by Sex

	Survival Rate to Grade 5		Net Secondary Enrollment Rate	
Country	Female	Male	Female	Male
Argentina	98	95	84	75
Brazil	NA	NA	85	78
Chile	97	96	87	84
Colombia	88 (Avg.)	88 (Avg.)	75	68
Indonesia	89	83	68	69
Mexico	95	93	74	71
Thailand	NA	NA	77	68
Tunisia	96	96	76	67
Turkey	94	94	70	77
United States	94 (Avg.)	94 (Avg.)	89	88
Uruguay	96	93	71	64

NA: Data not available

Avg: Average across both sexes. Data not available by sex.

Data: UNESCO (2010)

Table A.5: Descriptive Statistics for Chilean Administrative Data

	Observations	Mean	Standard Deviation
Birth Weight (in Grams)	1687269	3357.58	512.08
Fraction Fullterm Births (38-40 Weeks Gestation)	1687269	0.804	0.396
Fraction of Mothers Married	1481512	0.41	
Mother's Education: Primary School	1679693	0.27	
Mother's Education: High School	1679693	0.58	
Mother's Education: College	1679693	0.14	
Fraction of Mothers Employed	1686582	0.25	
Fraction Twins Both Male	25619	0.34	
Fraction Twins of Mixed Sex	25619	0.24	
Fraction Twins Both Female	25619	0.42	
Fraction of Students Male in Sample	1687269	0.502	0.50
Class size in 4th grade	1675350	31.82	13.88
Fraction Male in 4th Grade	1675350	0.51	0.18
Class size in 8th grade	784973	34.33	16.3
Fraction Male in 8th Grade	784973	0.50	0.18

Table A.6: Linear Regression of Top Scores for Pooled PISA Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Above Quantile	50	50	75	75	90	90	95	95
Male	0.115***	0.104***	0.0969***	0.0863***	0.0576***	0.0509***	0.0358***	0.0318***
	(0.00210)	(0.00202)	(0.00187)	(0.00177)	(0.00133)	(0.00127)	(0.000973)	(0.000944)
Age	-0.0644***	-0.0397***	-0.0336***	-0.0100***	-0.0110***	0.00344	-0.00175	0.00692***
	(0.00383)	(0.00366)	(0.00341)	(0.00322)	(0.00242)	(0.00231)	(0.00177)	(0.00171)
Year 2009	-0.00926***	-0.0247***	-0.00543***	-0.0154***	-0.00222*	-0.00751***	-0.000904	-0.00314***
	(0.00214)	(0.00249)	(0.00190)	(0.00219)	(0.00135)	(0.00157)	(0.000989)	(0.00117)
Grade 8 or Below	-0.242***	-0.198***	-0.138***	-0.0985***	-0.0567***	-0.0338***	-0.0275***	-0.0142***
	(0.00386)	(0.00370)	(0.00343)	(0.00325)	(0.00243)	(0.00233)	(0.00178)	(0.00173)
Grade 10	0.298***	0.241***	0.208***	0.154***	0.0981***	0.0650***	0.0513***	0.0313***
	(0.00263)	(0.00254)	(0.00234)	(0.00224)	(0.00166)	(0.00160)	(0.00122)	(0.00119)
Grade 11 or Above	0.364***	0.288***	0.275***	0.201***	0.137***	0.0910***	0.0784***	0.0505***
	(0.00497)	(0.00478)	(0.00442)	(0.00420)	(0.00313)	(0.00301)	(0.00230)	(0.00224)
Mother Educated at ISCED Level 1		-0.00566*		-0.0152***		-0.00874***		-0.00542***
		(0.00319)		(0.00280)		(0.00201)		(0.00149)
Mother Educated at ISCED Level 2		0.0196***		0.00231		-0.00418**		-0.00407***
		(0.00320)		(0.00281)		(0.00201)		(0.00150)
Mother Educated at ISCED Level 3		0.0614***		0.0519***		0.0276***		0.0138***
		(0.00349)		(0.00307)		(0.00220)		(0.00163)
Mother Educated at ISCED Level 4		0.0524***		0.0319***		0.0112***		0.00315
		(0.00413)		(0.00363)		(0.00260)		(0.00193)
Mother Educated at ISCED Level 5		0.00746**		0.0156***		0.0188***		0.0137***
		(0.00325)		(0.00286)		(0.00205)		(0.00152)
Mother Educated at ISCED Level 6		0.0297***		0.0575***		0.0442***		0.0302***
		(0.00389)		(0.00342)		(0.00245)		(0.00182)
Mother Has Upper Blue Collar Job		0.0492***		0.0334***		0.0151***		0.00365*
		(0.00426)		(0.00375)		(0.00268)		(0.00200)
Mother Has Upper White Collar Job		0.108***		0.103***		0.0648***		0.0414***
		(0.00308)		(0.00271)		(0.00194)		(0.00144)
Mother Has Lower White Collar Job		0.0615***		0.0481***		0.0231***		0.00917***
		(0.00290)		(0.00255)		(0.00183)		(0.00136)
Father Has Upper Blue Collar Job		0.00261		0.00118		0.00117		0.00110
		(0.00265)		(0.00233)		(0.00167)		(0.00124)
Father Has Upper White Collar Job		0.0951***		0.0962***		0.0586***		0.0354***
		(0.00288)		(0.00254)		(0.00182)		(0.00135)
Father Has Lower White Collar Job		0.0429***		0.0298***		0.0102***		0.00468***
		(0.00332)		(0.00292)		(0.00209)		(0.00155)
Mother Is Immigrant		-0.0755***		-0.0220***		0.00313		0.00789***
		(0.00623)		(0.00548)		(0.00392)		(0.00292)
Wealth Index		0.0428***		0.0372***		0.0223***		0.0128***
		(0.00112)		(0.000984)		(0.000705)		(0.000524)
Childs Household Has 11 to 25 Books		0.0280***		0.0143***		0.00228		-0.000523
		(0.00259)		(0.00228)		(0.00163)		(0.00121)
Childs Household Has 26 to 100 Books		0.108***		0.0850***		0.0416***		0.0216***
		(0.00284)		(0.00250)		(0.00179)		(0.00133)
Childs Household Has 101 to 200 Books		0.134***		0.129***		0.0840***		0.0514***
		(0.00422)		(0.00371)		(0.00266)		(0.00198)
Childs Household Has 201 to 500 Books		0.183***		0.199***		0.139***		0.0966***
		(0.00571)		(0.00503)		(0.00360)		(0.00268)
Childs Household Has More Than 500 Books		0.123***		0.153***		0.125***		0.0828***
		(0.00743)		(0.00653)		(0.00468)		(0.00348)
Constant	1.293***	0.841***	0.612***	0.181***	0.187***	-0.0743**	0.0297	-0.128***
	(0.0600)	(0.0574)	(0.0534)	(0.0505)	(0.0378)	(0.0362)	(0.0277)	(0.0269)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	199,268	199,268	199,268	199,268	199,268	199,268	199,268	199,268
R-squared	0.131	0.209	0.082	0.184	0.040	0.127	0.023	0.087
Ratio Male to Female	1.127	1.101	1.327	1.267	1.625	1.508	1.912	1.739

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.7: Linear Regression of Top Scores for Pooled PISA Data, Full Sample of PISA Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Above Quantile	50	50	75	75	90	90	95	95
Male	0.0713***	0.0765***	0.0741***	0.0768***	0.0491***	0.0500***	0.0316***	0.0320***
	(0.00104)	(0.000984)	(0.000912)	(0.000868)	(0.000639)	(0.000620)	(0.000467)	(0.000459)
Age	-0.0585***	-0.0354***	-0.0283***	-0.00952***	-0.00906***	0.00113	-0.00244***	0.00334***
	(0.00189)	(0.00178)	(0.00166)	(0.00157)	(0.00116)	(0.00112)	(0.000850)	(0.000832)
Year 2009	-0.000448	-0.0307***	0.000182	-0.0172***	0.000399	-0.00644***	0.000352	-0.00277***
	(0.00107)	(0.00136)	(0.000941)	(0.00120)	(0.000660)	(0.000857)	(0.000482)	(0.000634)
Grade 8 or Below	-0.270***	-0.208***	-0.149***	-0.101***	-0.0601***	-0.0348***	-0.0284***	-0.0143***
	(0.00229)	(0.00218)	(0.00202)	(0.00192)	(0.00141)	(0.00137)	(0.00103)	(0.00101)
Grade 10	0.270***	0.214***	0.192***	0.146***	0.0948***	0.0698***	0.0526***	0.0384***
	(0.00144)	(0.00137)	(0.00127)	(0.00121)	(0.000888)	(0.000866)	(0.000649)	(0.000640)
Grade 11 or Above	0.383***	0.298***	0.305***	0.234***	0.171***	0.132***	0.104***	0.0816***
	(0.00324)	(0.00307)	(0.00284)	(0.00271)	(0.00199)	(0.00193)	(0.00146)	(0.00143)
Mother Educated at ISCED Level 1		-0.00582***		-0.0165***		-0.0119***		-0.00709***
		(0.00218)		(0.00192)		(0.00137)		(0.00102)
Mother Educated at ISCED Level 2		0.0147***		0.00338**		0.000182		-8.54e-05
		(0.00176)		(0.00156)		(0.00111)		(0.000822)
Mother Educated at ISCED Level 3		0.0640***		0.0435***		0.0202***		0.0104***
		(0.00160)		(0.00141)		(0.00101)		(0.000747)
Mother Educated at ISCED Level 4		0.0172***		0.00688***		-0.000979		-0.00117*
		(0.00142)		(0.00126)		(0.000897)		(0.000664)
Mother Educated at ISCED Level 5		0.0190***		0.0242***		0.0161***		0.0108***
		(0.00137)		(0.00120)		(0.000861)		(0.000637)
Mother Educated at ISCED Level 6		0.0336***		0.0580***		0.0434***		0.0283***
		(0.00181)		(0.00160)		(0.00114)		(0.000845)
Mother Has Upper Blue Collar Job		0.0436***		0.0263***		0.0110***		0.00371***
		(0.00226)		(0.00199)		(0.00143)		(0.00105)
Mother Has Upper White Collar Job		0.131***		0.103***		0.0555***		0.0315***
		(0.00139)		(0.00122)		(0.000874)		(0.000647)
Mother Has Lower White Collar Job		0.0708***		0.0434***		0.0190***		0.00924***
		(0.00135)		(0.00119)		(0.000847)		(0.000627)
Father Has Upper Blue Collar Job		0.0211***		0.0108***		0.00400***		0.00194***
		(0.00136)		(0.00120)		(0.000858)		(0.000634)
Father Has Upper White Collar Job		0.126***		0.103***		0.0553***		0.0316***
		(0.00136)		(0.00120)		(0.000855)		(0.000633)
Father Has Lower White Collar Job		0.0534***		0.0345***		0.0130***		0.00561***
		(0.00171)		(0.00151)		(0.00108)		(0.000799)
Mother Is Immigrant		0.00585***		0.0174***		0.0157***		0.0111***
		(0.00160)		(0.00141)		(0.00101)		(0.000747)
Wealth Index		0.00243***		0.00151***		0.00141***		0.000566**
		(0.000591)		(0.000521)		(0.000372)		(0.000275)
Childs Household Has 11 to 25 Books		0.0556***		0.0283***		0.00988***		0.00431***
		(0.00162)		(0.00143)		(0.00102)		(0.000754)
Childs Household Has 26 to 100 Books		0.162***		0.100***		0.0432***		0.0214***
		(0.00156)		(0.00138)		(0.000986)		(0.000729)
Childs Household Has 101 to 200 Books		0.239***		0.168***		0.0804***		0.0422***
		(0.00185)		(0.00163)		(0.00117)		(0.000863)
Childs Household Has 201 to 500 Books		0.321***		0.259***		0.139***		0.0794***
		(0.00206)		(0.00182)		(0.00130)		(0.000960)
Childs Household Has More Than 500 Books		0.293***		0.258***		0.158***		0.0957***
		(0.00241)		(0.00213)		(0.00152)		(0.00112)
Constant	1.254***	0.736***	0.562***	0.159***	0.170***	-0.0408**	0.0453***	-0.0736***
	(0.0305)	(0.0289)	(0.0268)	(0.0255)	(0.0188)	(0.0182)	(0.0137)	(0.0135)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	862,283	862,283	862,283	862,283	862,283	862,283	862,283	862,283
R-squared	0.078	0.180	0.052	0.149	0.028	0.096	0.018	0.062
Above Quantile	50	50	75	75	90	90	95	95
Ratio Male to Female	1.125	1.137	1.315	1.330	1.610	1.625	1.878	1.893

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.8: Cross-Country Regression of PISA Reading Gender Gap

	Dependent Variable: Gender Gap at Mean in PISA Reading Scores							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.138***	-0.0442**	-0.197**	-0.801	0.0529	0.236	-0.107***	-0.0456
	(0.011)	(0.022)	(0.093)	(0.97)	(0.14)	(0.24)	(0.027)	(0.28)
GDP Per Capita		0.000743*	0.000364	0.000364	-0.000667	-0.000180	0.000887**	0.0000199
		(0.00044)	(0.00042)	(0.00045)	(0.00053)	(0.00058)	(0.00041)	(0.00092)
Cellular Subscriptions		-0.108***	-0.123***	-0.130***	-0.104***	-0.0997***	-0.0962***	-0.101***
		(0.021)	(0.023)	(0.025)	(0.019)	(0.027)	(0.026)	(0.027)
Math Gender Gap							0.668***	1.198***
							(0.11)	(0.22)
Male Literacy Rate						-0.00587**		0.00227
						(0.0028)		(0.0021)
Female Literacy Rate						0.00307*		-0.00259
						(0.0016)		(0.0029)
WVS: University more important for a boy					-0.0504			-0.107**
					(0.044)			(0.045)
WVS: Men have more right to scarce jobs					0.0393			-0.0974*
					(0.052)			(0.049)
WVS: Men make better political leaders					0.0822**			0.0184
					(0.040)			(0.049)
WVS: Being housewife as fulfilling as paid work					-0.0947***			-0.0304
					(0.024)			(0.031)
Gender Gap Index			0.253					0.666**
			(0.15)					(0.28)
GGI: Economic Participation and Opportunity				-0.0157				
				(0.11)				
GGI: Educational Attainment				0.977**				
				(0.45)				
GGI: Health and Survival				-0.176				
				(1.08)				
GGI: Political Empowerment				0.0243				
				(0.052)				
Observations	62	62	56	56	42	33	62	27
R-squared	0.00	0.37	0.40	0.44	0.65	0.48	0.61	0.90

Robust standard errors in parentheses (weighted by population)
* significant at 10%; ** significant at 5%; *** significant at 1%
Cellular subscriptions are in per person terms for 2009 (World Bank data);
GDP per capita is for 2009 in thousands of US dollars (World Bank data);
WVS questions are on three- or four-point scale, with higher answers indicating stronger disagreement with the statement given;
GGI and subindices are higher for more gender equality.

Table A.9: Guiso Replication Using 2006 Data; Dependent Variable: Average Female Minus Male Gap in PISA Math Score

	(1)	(2)	(3)	(4)
Gender Gap Index	334.0	-103.9	-194.5*	-104.5
	(287.2)	(282.9)	(111.6)	(288.5)
Log per capita GDP	-58.96***	-29.60*	16.00**	-29.77*
	(14.88)	(14.85)	(7.116)	(15.16)
Constant	370.1**	377.0**	-12.93	378.8**
	(153.3)	(167.6)	(72.19)	(170.9)
Excluded Countries	Limited to Guiso set	None	Indonesia, Romania	Israel, Slovenia
Observations	35	48	46	46
R-squared	0.367	0.131	0.114	0.133

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.10: Guiso Replication Using 2009 Data; Dependent Variable: Average Female Minus Male Gap in PISA Math Score

	(1)	(2)	(3)	(4)
Gender Gap Index	144.9*	104.0	80.47	101.1
	(85.38)	(72.23)	(69.07)	(70.96)
Log per capita GDP	-20.44***	-16.77***	-10.42**	-16.61***
	(4.414)	(3.721)	(4.432)	(3.658)
Constant	77.21*	68.13*	19.98	68.69*
	(42.96)	(39.59)	(42.53)	(38.87)
Excluded Countries	Limited to Guiso set	None	Indonesia, Romania	Israel, Slovenia
Observations	35	59	57	57
R-squared	0.448	0.295	0.094	0.307

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.11: Guiso Replication Using 2006 and 2009 Data; Dependent Variable: Average Female Minus Male Gap in PISA Math Score

	(1)	(2)	(3)	(4)	(5)
Gender Gap Index	14.26	691.8	-31.40	-469.1**	-60.05
	(138.0)	(520.5)	(406.5)	(199.6)	(408.7)
Log per capita GDP	-22.18***	139.4***	159.6***	-62.49**	159.4***
	(7.171)	(40.37)	(40.13)	(26.85)	(40.28)
Year 2009	-43.65***	-97.75***	-81.54***	-13.27	-80.72***
	(9.690)	(13.62)	(12.47)	(8.801)	(12.55)
Constant	226.6***	-1,764***	-1,461***	932.6***	-1,440***
	(77.46)	(453.0)	(442.0)	(305.1)	(443.8)
Country Fixed Effects	No	Yes	Yes	Yes	Yes
Excluded Countries	None	Limited to Guiso set	None	Indonesia, Romania	Israel, Slovenia
Observations	107	70	107	103	103
R-squared	0.278	0.855	0.813	0.838	0.818

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.12: Linear Regressions Including Sibling Data Using Pooled PISA Data

	(1)	(2)	(3)	(4)
Above Quantile	50	75	90	95
Male	0.0893***	0.0619***	0.0326***	0.0207***
	(0.00518)	(0.00457)	(0.00329)	(0.00245)
(Number brothers $>$ 0) X (Number sisters $>$ 0)	0.0815***	0.0339***	0.00832***	0.00470**
	(0.00495)	(0.00437)	(0.00314)	(0.00234)
(Number brothers $>$ 0) X (Number sisters = 0)	0.0996***	0.0462***	0.0106***	0.00300
	(0.00521)	(0.00460)	(0.00330)	(0.00246)
(Number brothers = 0) X (Number sisters $>$ 0)	0.127***	0.0674***	0.0219***	0.00637**
	(0.00564)	(0.00497)	(0.00357)	(0.00266)
Male X (Number brothers $>$ 0) X (Number sisters $>$ 0)	0.0273***	0.0299***	0.0187***	0.00881***
	(0.00704)	(0.00621)	(0.00446)	(0.00332)
Male X (Number brothers = 0) X (Number sisters $>$ 0)	0.0238***	0.0472***	0.0346***	0.0289***
	(0.00819)	(0.00722)	(0.00519)	(0.00387)
Male X (Number brothers $>$ 0) X (Number sisters = 0)	0.0235***	0.0518***	0.0390***	0.0212***
	(0.00747)	(0.00659)	(0.00474)	(0.00353)
Age	-0.0522***	-0.0251***	-0.00465	0.00211
	(0.00495)	(0.00437)	(0.00314)	(0.00234)
Grade 8 or Below	-0.168***	-0.0744***	-0.0234***	-0.0101***
	(0.00495)	(0.00437)	(0.00314)	(0.00234)
Grade 10	0.248***	0.161***	0.0675***	0.0311***
	(0.00337)	(0.00298)	(0.00214)	(0.00159)
Grade 11 or Above	0.366***	0.276***	0.125***	0.0702***
	(0.00721)	(0.00636)	(0.00457)	(0.00340)
Mother Educated at ISCED Level 1	0.0138***	-0.00440	-0.00738**	-0.00507**
	(0.00453)	(0.00400)	(0.00287)	(0.00214)
Mother Educated at ISCED Level 2	0.0436***	0.0139***	-0.00415	-0.00532**
	(0.00460)	(0.00406)	(0.00292)	(0.00217)
Mother Educated at ISCED Level 3	0.0915***	0.0666***	0.0278***	0.0112***
	(0.00480)	(0.00423)	(0.00304)	(0.00226)
Mother Educated at ISCED Level 4	4.57e-05	-0.0206**	-0.0178***	-0.0111**
	(0.00959)	(0.00846)	(0.00608)	(0.00453)
Mother Educated at ISCED Level 5	0.00803**	0.0274***	0.0307***	0.0215***
	(0.00403)	(0.00356)	(0.00256)	(0.00190)
Mother Educated at ISCED Level 6	-0.0534***	-0.0154***	0.00961**	0.0143***
	(0.00636)	(0.00561)	(0.00403)	(0.00300)
Mother Has Upper Blue Collar Job	0.0529***	0.0388***	0.0154***	0.00203
	(0.00568)	(0.00501)	(0.00360)	(0.00268)
Mother Has Upper White Collar Job	0.101***	0.0953***	0.0592***	0.0367***
	(0.00432)	(0.00381)	(0.00274)	(0.00204)
Mother Has Lower White Collar Job	0.0570***	0.0380***	0.0173***	0.00455**
	(0.00392)	(0.00346)	(0.00248)	(0.00185)
Father Has Upper Blue Collar Job	0.00174	0.000787	0.000336	-0.000297
	(0.00350)	(0.00309)	(0.00222)	(0.00165)
Father Has Upper White Collar Job	0.0913***	0.0995***	0.0646***	0.0420***
	(0.00384)	(0.00339)	(0.00243)	(0.00181)
Father Has Lower White Collar Job	0.0342***	0.0238***	0.00634**	0.00231
	(0.00444)	(0.00391)	(0.00281)	(0.00209)
Mother Is Immigrant	-0.0744***	-0.0198***	0.00108	0.00634
	(0.00867)	(0.00765)	(0.00550)	(0.00409)
Wealth Index	0.0410***	0.0368***	0.0231***	0.0139***
	(0.00153)	(0.00135)	(0.000971)	(0.000723)
Childs Household Has 11 to 25 Books	0.0237***	0.0115***	0.00231	-0.000518
	(0.00343)	(0.00303)	(0.00218)	(0.00162)
Childs Household Has 26 to 100 Books	0.0940***	0.0727***	0.0367***	0.0196***
	(0.00379)	(0.00335)	(0.00241)	(0.00179)
Childs Household Has 101 to 200 Books	0.115***	0.122***	0.0851***	0.0530***
	(0.00569)	(0.00502)	(0.00361)	(0.00269)
Childs Household Has 201 to 500 Books	0.162***	0.182***	0.134***	0.0992***
	(0.00776)	(0.00684)	(0.00492)	(0.00366)
Childs Household Has More Than 500 Books	0.0935***	0.134***	0.115***	0.0766***
	(0.0100)	(0.00883)	(0.00635)	(0.00473)
Constant	0.921***	0.350***	0.0269	-0.0634*
	(0.0779)	(0.0687)	(0.0494)	(0.0368)
Country Dummies	Yes	Yes	Yes	Yes
Observations	108,542	108,542	108,542	108,542
R-squared	0.231	0.201	0.140	0.098
Ratio Male to Female	1.069	1.146	1.241	1.361

Standard errors in parentheses
*** p$<$0.01, ** p$<$0.05, * p$<$0.1

Table A.13: General Attitudes toward Classes and Gender

Responses are in agreement with the statements	I am as capable of learning as the rest of my peers	Generally understand very little of what happens in class	Have trouble concentrating in class	I do certain tasks even though I find them difficult	My notebooks are usually incomplete	I like to study for tests	It is important for me to get good grades	I take good notes in class
Male	-0.0191***	-0.0168***	0.000815	0.116***	-0.0139***	0.0454***	0.0885***	0.0610***
	(0.00108)	(0.00136)	(0.00129)	(0.00163)	(0.00124)	(0.00169)	(0.00154)	(0.00160)
Simce math score	0.0398***	-0.132***	-0.0887***	0.134***	-0.0951***	0.0619***	0.119***	0.0582***
	(0.000609)	(0.000766)	(0.000740)	(0.000916)	(0.000715)	(0.000960)	(0.000901)	(0.000931)
Log Birth Weight	-0.00315	-0.0233***	-0.00641	0.0506***	-0.0236***	0.0241***	0.0385***	0.0321***
	(0.00334)	(0.00420)	(0.00397)	(0.00487)	(0.00386)	(0.00507)	(0.00456)	(0.00480)
Constant	0.977***	0.470***	0.260***	-0.0471	0.449***	0.0826**	-0.0121	0.0355
	(0.0273)	(0.0349)	(0.0330)	(0.0401)	(0.0322)	(0.0415)	(0.0376)	(0.0395)
Observations	391,258	387,355	385,156	386,128	383,740	372,307	368,427	371,059
R-squared	0.067	0.114	0.111	0.106	0.086	0.079	0.104	0.081
Mean of dependent variable	0.878	0.200	0.303	0.700	0.150	0.433	0.951	0.467

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: controls are year of SIMCE test, full term birth, mother's education, marital status and age. School fixed effects in all regressions.