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The Determinants of Wealth and Gender Inequity in Cognitive Skills in Latin America

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Abstract

Wealth and gender inequity in the accumulation of cognitive skills is measured as the association between subject competency and wealth and gender using the OECD's Programme for International Student Assessment. Wealth inequity is found to occur not through disparate household characteristics but rather through disparate school characteristics; little evidence is found of an association between wealth and competency within schools. Weak evidence is found of wealth mitigating gender differences through school characteristics. These findings suggest that wealth inequity in the accumulation of cognitive skills is almost exclusively associated with disparate school characteristics and that disparate school characteristics may play a role in accentuating gender inequity.

This paper—a product of the Education Team, Human Development Network—is part of a larger effort in the department to study the determinants of learning outcomes. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at kmacdonald1@worldbank.org.

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1. Introduction

Wealth and gender inequity in a child's ability to accumulate human capital impedes equality of opportunity. Wealth disparity in human capital's accumulation perpetuates intergenerational transmission of poverty by denying children of low-income households the ability to attain the human capital necessary for upward mobility; gender disparity perpetuates gender inequality in future education, labour market outcomes and socio-economic status.

Cognitive skills is a crucial component of human capital and determinant of wages (Murnane, R.J. et al. 1995; Juhn C. et al. 1993; Boissiere et al. 1985), but wealth and gender disparities in its accumulation still persist (Alderman et al. 1997, 1996a, b, c). World Bank (2005b) and Porta and Ramón (2007) found large disparities in school retention rates between high and low income households in Central America, and UNESCO (2002: 16) found lower school enrollment among females in low income households in Latin America. Often school attainment exhibits an opposite disparity with females attaining on average higher levels of schooling as documented among rural females in Mexico (Behrman et al. 2005), in other developing countries (Grant and Behrman 2008) as well as in Latin America in recent years (Behrman et al. 2004).

Researchers have begun examining the determinants of cognitive skills by using data on student achievement on standardized tests (see Todd and Wolpin 2003 for examples). The use of international student assessments such as the OECD's Programme for

International Student Assessment (PISA), and the International Association for the Evaluation of Educational Achievement's Trends in International Mathematics and Science Study (TIMSS) and Progress in International Reading Literacy Study (PIRLS) have played key role in cross-country and within-country studies of these determinants (for example, Hanushek and Luque 2003; Hanushek and Kimko 2000; Barro 2001; Lee and Barro 2001; Afonso and Aubyn 2006; Bedard and Ferrall 2002; Hanushek and Woessmann 2005; Alvarez, Garcia-Moreno and Patrinos 2007; Nabeshima 2003; Fertig 2003; Fertig and Schmidt 2002; Woessmann 2003; Fuchs and Woessmann 2007; World Bank 2005a, 2006; Parker et al. 2008).

The purpose of this paper is to measure, comparably across countries, the extent of wealth and gender inequity in cognitive skills among youth and to identify the general sources of these inequities. Being able to compare the extent of these inequities across countries as well as understanding their general sources will help guide policy makers intent on eliminating it.

To measure inequity, this paper borrows a concept from wage earnings literature. In this literature, gender (or racial) inequity is quantified by the size of the unexplained difference in earnings between males and females which emerges after the difference explained by observable characteristics such as educational attainment, etc, is removed (see for example Oaxaca, R. 1973; Blinder, A. 1973). In other words, the extent of gender inequity in wages equals the extent of wage dependence on gender. An analogous quantification applies to cognitive skills: the extent of wealth and gender inequity in cognitive skills equals the extent of its dependence on household wealth and gender, respectively[1]. If wealth and gender inequity did not exist, there would be no detectable dependence of cognitive skills on either wealth or gender controlling for other factors.

To estimate the relationship between cognitive skills on wealth and gender, this paper utilizes data from the OECD's Programme for International Student Achievement (PISA) for Argentina, Brazil, Chile, Colombia, Mexico, and Uruguay. This dataset provides measures of competency in mathematics, reading, and science for each student, and these will serve as measures of his or her cognitive skills in each subject area. Background information about the student, including gender and an index of household wealth, as well as background information about the student's school, compliment these measures of competency. Unlike other major international assessments such as TIMSS and PIRLS, PISA aims to assess a student's ability to solve practical problems using mathematics, reading, and science as opposed to a particular curriculum; these skills seem to fit the notion of cognitive skills relevant to the context of this paper.

The model used in this analysis to estimate the dependence of cognitive skills on wealth and gender stems from cognitive production function theory. In the proceeding model, both wealth and gender potentially impact cognitive skills indirectly through being correlated with household characteristics beneficial to cognitive achievement and by being correlated with better school characteristics; gender may also have a direct effect through natural ability. Consequently, wealth and gender inequity stems from two main

[1] This is a similar concept to the measure used by Schütz et al. (2008)

determinants: from disparity in school characteristics and from disparity in household characteristics and natural ability.

Understanding the extent to which inequity flows through these two main sources is important to education policy makers. If, for example, disparity in household characteristics or natural ability explains the entirety of wealth inequity, then its solution lies in either decreasing disparity in household characteristics which is largely outside the realm of education policy or in finding ways to mitigate the impact of household characteristics on child learning especially for the poor through school characteristics. Alternatively, if disparity in school quality explains the entirety of wealth inequity, then its solution lies in the allocation of school resources and the assignment of students to schools. Similarly for gender, if, for example, the entirety of inequity stems through household or natural ability, then policy makers will have a difficult time solving it. But if gender inequity flows through school resource disparity, then education policy makers can address the issue accordingly.

The proceeding methodology provides for an estimate of the strength of the association between cognitive skills and wealth and between cognitive skills and gender. Using a school fixed effects method, our methodology allows us to distinguish how much of that association occurs through disparity in school quality and how much occurs through disparity stemming from household characteristics or natural ability.

Applying our methodology reveals wealth is highly associated with cognitive skills in Latin America while in Canada, Finland, and South Korea it is either much lower or nonexistent. Gender inequity, alternatively, is neither higher nor lower in Latin America than compared to the same three high income countries; females perform higher in reading while males perform higher in mathematics.

In all countries, the source of inequity is found to occur entirely through the school; within schools, there is almost no association between competency and household wealth. This finding suggests that policy makers wishing to eliminate wealth inequity in the accumulation of cognitive skills need to focus on inequality of school characteristics including resources and teachers, the allocation of resources among schools, and on the assignment of students to schools.

Additionally, in some countries, wealth is found to associate negatively with the gender difference in reading and mathematics. Using a school-gender fixed effects model, it is shown that this interaction occurs through schools and not through households; the association between wealth and competency among males within schools appears no different than that among females. That wealth reduces the gender difference in competency through school characteristics suggests either a gender difference in the characteristics of schools which is mitigated at higher levels of wealth, a gender difference in the relationship between school characteristics and schools which is accentuated at higher levels of wealth, or both. The former case, a correlation between gender and school characteristics which diminishes with higher household wealth, may arise from two sources: either from a wealth-related gender difference in which schools a household chooses for their children or from all-girls schools differing in quality from all-male schools among schools attended by children from less wealthy households. The latter case, a difference in relationship between school characteristics and competency, may arise from either school of less wealthy households allocating resources differently to boys and girls or from higher quality schools being able to meet gender-specific learning needs better. Consequently, policy makers ought to focus on gender differences in the access to school characteristics, the allocation of school characteristics across genders within schools, and, if higher quality schools can mitigate gender differences, then the allocation of school characteristics across schools.

However, these findings are subject to the limitations of our analysis. First, the students included in PISA are those who are enrolled in school and who were attending when the exam was administered. A selection bias is probably present since the decision to attend secondary school is likely determined by a combination of both household income and cognitive skills (see for example, Parker et al. 2008). This may attenuate the measured association between wealth and achievement understating the importance of wealth. Second, the data is non-experimental; consequently, causality can not be identified using our analysis. The associations we find between wealth, gender, and competency can not be characterized as a causal relationship.

2. Data

The OECD's Programme for International Student Assessment assesses students between ages 15 years and 3 months to 16 years and 2 months in grades 7 or higher in both OECD and non-OECD countries. The assessment occurs every three years and began in 2000. In 2000, five Latin American countries participated; in 2006, six participated.

The primary sampling unit for the PISA survey is the school. School selection occurs within specified strata according to a proportional-to-size method. Within schools, 35 students within the age and grade targets are selected with equal probability. Sampling weights are then constructed reflecting changes in information about the school size, student non-response, and other factors (OECD 2002: 39 – 53).

PISA's assessment framework consists of questions or test *items* that are designed to measure the average competency of students from a particular country to "complete tasks relating to real life, depending on a broad understanding of key concepts, rather than limiting the assessment to the understanding of subject-specific knowledge" (OECD 2007: 20). The framework consists of three subject areas: mathematics, reading, and science.

Like other major international assessments, the purpose of PISA is to measure the average competency of students at a national level. Since its purpose is not to measure competency at the individual level, matrix-sampling booklet design is used where students are tested on different subsets of the items in the assessment framework; consequently, individual performance represents competency only on a subset of the assessment framework while the aggregate performance of students in a country represents competency on the entire assessment framework. This allows the assessment framework to be populated with a larger number of items and therefore represent a wider range of skills; if students were to be tested on the same items then the assessment framework would have to contain fewer of them and therefore be focused on a narrower set of skills. For example, the total amount of time of all items in PISA's assessment framework is 6.5 hours while each test contains a subset of items totalling two hours.

But the drawback of students being tested on different items is that a measure of performance is not immediately available. In order to produce a measure of competency, PISA, as well as other major assessments, uses item response theory to produce a synthetic measure of competency based on the collected data: responses to items, student responses to individual and family background questionnaires, and school principal responses to school characteristic questionnaires.

The item response model used by PISA is a combination of two models: a generalized Rasch model linking a student's competency and item difficulty to the probability of answering the item correctly and a population model linking a student's background characteristics to his or her competency.

A simple Rasche model can be thought of as a random effects logit model that predicts the probability of an item being answered correctly as a function of which item is being tested and which student is being tested[2]. Items which increase or decrease the probability of the item being answered correctly are considered easier or harder respectively while students that increase or decrease the probability of the item be answered correctly are considered more or less competent respectively. The generalized Rasche model utilized by PISA allows for part marks on items, different competencies for reading, mathematics, and science, as well as their sub-domains, and treats student competency as a random effect.

The population model links a student's characteristics with his or her competency in order to improve the measure of competency. Combining the generalized Rasche model with the population model allows the random effect of student competency to be conditioned on background characteristics. Estimation of this combined model renders estimates for the difficulty of the items and the relationship between background characteristics and competency.

Using the functional form of their item response model, student competency can be described as a random variable distributed conditionally on students' responses to the items, the difficulty of these items, and the selected background characteristics of both the students and their schools; this distribution is the *posterior distribution*. Since the posterior distribution function contains an integral, calculating statistics which are

[2] For example, imagine estimating a logit model on a dataset containing observations for each student and item whose dependent variable is whether the item is answered correctly and whose dependent variables are binary variables for each student and for each item.

functions of competency, such as regression coefficients, requires the Monte-Carlo method. For this reason, the PISA dataset includes five random draws for each subject area from the posterior distribution; these random draws are called *plausible values* and they are used to compute a country's official "score" in PISA. For further details see OECD (2002, pp99–108).

In addition to these measures of competency, three of PISA's background variables are used: student's gender, grade level, and household wealth. Student's gender and grade level are based on responses to the respective questions in the student background questionnaire; household wealth, alternatively, is an index created by PISA and based on students' responses to questions about household possessions. To construct the index, a type of Rasche model is used where, instead of estimating the difficulty of a test item, the "expense" of a household possession is estimated. Possessions are assumed to be more expensive if they decrease the probability of a student's household owning one and cheaper if otherwise. The wealth index is the magnitude of effect of a particular student's household on the probability of owning a possession that maximizes the probability of owning the possessions actually owned by the household given the Rasche-estimated expensiveness of the possessions. This method is explained in more detail in OECD (2002: 217-49). One limitation of this index is it does not represent the monetary value of household assets directly. This may distort the comparability between two households since two households might have the same possessions used in the calculation of the index but one may be monetarily much wealthier. Consequently, our measure of wealth is not as intuitive as a monetary value. Table 1 presents the means of the variables used in our model for each country.

The final set of variables from the PISA dataset used in this analysis are re-sampling replicate weights used in the calculation of standard errors. Intra-cluster correlation violates an assumption needed for the unbiasness of the analytical method of calculating standard errors based on the variation of the sample. Re-sampling methods such as bootstrapping, Jackknifed Repeated Replication, and Balanced Repeated Replication serve as alternative means of calculating standard errors. These methods calculate sampling variance by re-sampling the same sample to mimic re-sampling of the original population. Replicate weights are alternative sample weights which represent a sub-sample based on the original sampling design. PISA provides replicate weights compatible with Fay's adjusted Balanced Repeated Replication. These weights were constructed to reflect the sampling design including any country specific modifications, as well as non-response by students or schools (OECD 2002: 89 – 98).

3. Model

This paper quantifies wealth and gender inequity in cognitive skills as the dependence of cognitive skills on wealth and gender. While the concept of dependence on gender is relatively clear, the concept of dependence on wealth needs to be relevant to the overarching problem of intergenerational transmission poverty and upward immobility. Consequently, the dependence of a child's cognitive development on wealth should not be construed as a dependence on assets *per se* but rather on being from a wealthier (or poorer) household. Wealthier households do not just have more assets, but generally they have more educated parents, more educational related resources, a higher value towards education, more information, healthier members, access to better schools, etc. Assets alone probably have little impact on the development of cognitive skills once these other factors are taken into account. Hence, the dependence on wealth which needs to be measured is really a dependence on all the observable and unobservable household and school characteristics relevant to the development of cognitive skills that are associated with being from a wealthier household. Of the various indexes in the PISA dataset, the wealth index seems to provide the best measure for this purpose. Since it is constructed from the same set of possessions in all countries (PISA: 217-49), the measure is comparable across countries. Other measures which proxy for household wealth usually include education level of the parents, but this may not be comparable across countries.

This analysis uses cognitive production function theory to develop a means to estimate the dependence of cognitive skills on wealth and gender. We adopt a basic model of cognitive skills from Todd and Wolpin (2003), but, in order to be applicable to PISA, we equate cognitive skills to *competency* in one of the subject areas and model its production.

Competency in a particular subject area, without loss of generality, for the i^{th} student in the j^{th} school, $\theta_{i,j}$, is modeled as a function of a vector of household inputs received over the entire life of the student, $\boldsymbol{h}_{i,j}$, a vector of school inputs received over the life of the student until entry into the student's current school, $\boldsymbol{s}^{P}{}_{i,j}$, a vector of inputs received over the student's time at the present school, $\boldsymbol{s}^{C}{}_{i,j}$, and the student's endowed mental capacity, $u_{i,j}$.

(1) $$\theta_{i,j} = f\left(\boldsymbol{h}_{i,j}, \boldsymbol{s}_{i,j}^{P}, \boldsymbol{s}_{i,j}^{C}, u_{i,j}\right)$$

Further, it is assumed that a student's exposure to the current school's characteristics, $\boldsymbol{s}^{C}{}_{i,j}$, is a function of the vector of school characteristics, $\boldsymbol{s}^{E}{}_{,j}$, grade level, $g_{i,j}$, and the number of years the student has attended the school, $a_{i,j}$.

(2) $$\boldsymbol{s}_{i,j}^{C} = \boldsymbol{f}_{s}\left(\boldsymbol{s}_{j}^{E}, g_{i,j}, a_{i,j}\right)$$

We allow the possibility that natural ability, $u_{i,j}$, may be influenced by the student's gender; natural ability is a function of gender, denoted by the binary variable for female, $f_{i,j}$, and an unobserved component, $e^{u}{}_{i,j}$.

(3) $$u_{i,j} = f_{u}\left(f_{i,j}, e_{i,j}^{u}\right)$$

In the PISA dataset, much of household and school components are unobserved. For example, nothing is known about a student's previous schooling or the number of years the student has attended his or her current school, or his or her early childhood experiences. As well, only cursory information about the household and current school are available. However, suppose we could observe all the necessary household and schooling variables, then, in absence of the unobserved component of natural ability and the number of years a student has attended his or her current school, competency, $\theta_{i,j}$, can be thought of as a random variable conditionally distributed on the household and schooling variables, gender, and grade level.

$$(4) \qquad \theta_{i,j} \mid \boldsymbol{h}_{i,j}, \boldsymbol{s}^P_{i,j}, \boldsymbol{s}^E_j, f_{i,j}, g_{i,j} \sim f_\theta\left(\boldsymbol{h}_{i,j}, \boldsymbol{s}^P_{i,j}, \boldsymbol{s}^E_j, f_{i,j}, g_{i,j}\right)$$

It is assumed that the conditional expected competency can be expressed as a linear function of these conditioning variables. If ξ_0, ξ_3, and ξ_4 are scalars and $\boldsymbol{\xi}_1$ is a column matrix with a number of elements equal to the sum of those in the vectors $\boldsymbol{h}_{i,j}$ and $\boldsymbol{s}^P{}_{i,j}$, and if $\boldsymbol{\xi}_2$ is a column matrix with a number of elements equal to those in vector $\boldsymbol{s}^E{}_j$, then

$$(5) \qquad E\left[\theta_{i,j} \mid \boldsymbol{h}_{i,j}, \boldsymbol{s}^P_{i,j}, \boldsymbol{s}^E_j, f_{i,j}, g_{i,j}\right] = \xi_0 + \left(\boldsymbol{h}_{i,j}, \boldsymbol{s}^P_{i,j}\right)\boldsymbol{\xi}_1 + \boldsymbol{s}^E_j \boldsymbol{\xi}_2 + \xi_3 f_{i,j} + \xi_4 g_{i,j}$$

Wealth alone does not impact competency, but rather it impacts household characteristics, previous schooling, and current school characteristics. Alternatively, we allow for the possibility that gender may have some kind of direct effect through natural ability (see Guiso, L. et al. 2008), but it may also influence competency through the same channels as wealth.

The expected value of the vector of household and previous schooling experience is assumed to be a linear function of wealth and gender. If $\boldsymbol{\alpha}_0$, $\boldsymbol{\alpha}_1$, and $\boldsymbol{\alpha}_2$ are row matrices with a number of elements equal to $\boldsymbol{\xi}_1$, then

$$\text{(6)} \qquad \mathrm{E}\left[\left(\boldsymbol{h}_{i,j}, \boldsymbol{s}_{i,j}^{P}\right) \mid w_{i,j}, g_{i,j}\right] = \boldsymbol{\alpha_0} + \boldsymbol{\alpha}_1 w_{i,j} + \boldsymbol{\alpha}_2 f_{i,j}$$

Next, we assume that current school characteristics to be a linear function of wealth, gender, and being in a rural community, $r_{i,j}$. If λ_0, λ_1, λ_2, and λ_3 are column matrices with a number of elements equal to $\boldsymbol{\xi}_2$, then

$$\text{(7)} \qquad \mathrm{E}\left[\boldsymbol{s}_{j}^{E} \mid w_{i,j}, g_{i,j}, r_{i,j}\right] = \boldsymbol{\lambda}_0 + \boldsymbol{\lambda}_1 w_{i,j} + \boldsymbol{\lambda}_2 f_{i,j} + \boldsymbol{\lambda}_3 r_{i,j}$$

The relationship between wealthier households and school characteristics stems from the ability of wealthier households to send their children to better schools. In urban areas, where school choice is possible, this ability arises from being able to afford higher school fees but also from having better information about schools, living in neighbourhoods with better schools, or being financially able and willing to send their children further away from home to a better school if necessary. In rural areas, where school choice does not exist, then wealthier households cannot send their children to better schools but likely the quality of the school reflects the average wealth of the community.

Combining model (5) with (6) and (7) yields,

$$\text{(8)} \qquad \mathrm{E}\left[\theta_{i,j} \mid \bullet\right] = \beta_0 + \left(\boldsymbol{\alpha}_1 \xi_1 + \boldsymbol{\lambda}_1 \boldsymbol{\xi}_2\right) w_{i,j} + \left(\boldsymbol{\alpha}_2 \xi + \boldsymbol{\lambda}_2 \boldsymbol{\xi}_2 + \xi_3\right) f_{i,j} + \beta_3 r_{i,j} + \xi_4 g_{i,j}$$

where β_0 and β_3 are simplified notation.

Wealthier households, as measured by $w_{i,j}$, associate with competency through a household effect, $\alpha_1\xi_1$, and a school characteristic effect, $\lambda_1\xi_2$. The former originates from equation (6) and represents the dependence of competency on wealth through the household and previous schooling experience; the latter originates from equation (7) and represents the dependence on wealth through the present school's characteristics.

If household inputs and previous schooling have no impact on competency, then vector ξ_1 would be zero; if wealth were not correlated with the requisite household inputs or previous schooling for competency, then vector α_1 would be zero. Thus, if either were zero, then wealth equity through the household would be achieved since being from a poor or wealthy household would provide no advantage or disadvantage. Analogously, if present school inputs had no impact on competency, then vector ξ_2 were zero; if wealth were unrelated to school inputs, then λ_1 were zero. Either being zero implies wealth equity through the school is achieved since, in the first case, there are no good or bad schools, and in the second case students from wealthy households are just as likely to end up in good schools as those from less wealthy households.

The interpretation is the same for gender: competency is dependent on gender either through the combined effect of the importance of household characteristics in competency, ξ_1, and the correlation of gender with these characteristics, α_2, as well as the combined effect of the importance of school characteristics in competency, ξ_2, and the correlation of gender with these characteristics, $\boldsymbol{\lambda}_2$. Also, gender may impact competency through differences in natural ability as measured by ξ_3.

Model (8) provides a means to estimate the total association of competency with wealth, ($\boldsymbol{\alpha_1 \xi_1} + \boldsymbol{\lambda_1 \xi_2}$) and the total dependence of competency with gender, ($\boldsymbol{\alpha_2 \xi_1} + \boldsymbol{\lambda_2 \xi_2} + \xi_3$), but it does not allow us to distinguish the household effects from the school characteristic effects.

However, a school fixed effects transformation of the variables of (5) eliminates the school characteristics from the model. If $\bar{x}_j$ represents the mean of variable x for the j^{th} school, then

(9) $$\mathrm{E}\left[\theta_{i,j} - \bar{\theta}_j \mid \bullet\right] = \left(\left(\boldsymbol{h}_{i,j}, \boldsymbol{s}_{i,j}^{P}\right) - \left(\bar{\boldsymbol{h}}_j, \bar{\boldsymbol{s}}_j^{P}\right)\right)\boldsymbol{\xi}_1 + \xi_3\left(f_{i,j} - \bar{f}_j\right) + \xi_4\left(g_{i,j} - \bar{g}_j\right)$$

Substituting in (6) yields

(10) $$\mathrm{E}\left[\theta_{i,j} - \bar{\theta}_j \mid \bullet\right] = \boldsymbol{\alpha}_1\boldsymbol{\xi}_1\left(w_{i,j} - \bar{w}_j\right) + \left(\boldsymbol{\alpha}_2\boldsymbol{\xi}_1 + \xi_3\right)\left(f_{i,j} - \bar{f}_j\right) + \xi_4\left(g_{i,j} - \bar{g}_j\right)$$

Estimating equation (10) provides an estimate of the dependence of competency on wealth through the household, $\boldsymbol{\alpha_1 \xi_1}$, and on gender through the household and natural ability, $\boldsymbol{\alpha_2 \xi_2} + \xi_3$. Estimates of wealth dependence through the school, $\boldsymbol{\lambda_1 \xi_2}$, and gender dependence through the school, $\boldsymbol{\lambda_2 \xi_2}$, can be estimated from the difference between the estimates of model (8) and (10). However, this difference may be upward biased since it would also include the dependence of wealth and gender through household characteristics or previous schooling that do not vary within schools.

By estimating model (8), we are able to create a measure of wealth and gender inequity that is comparable across countries. By estimating model (10), we are able to measure the importance in the disparity of households and of schools in the generation of this inequity. The relative importance of these sources is crucial to policy formulation. For example, if a bulk of the inequity stems through household disparity, then education planners need to examine diminishing the impact of household backgrounds such as providing meals, health services, etc. Alternatively, if the bulk of the inequity flows through disparate school quality, then education planners need to focus on how students and resources are assigned to schools within the school system.

Since evidence points to gender gaps in enrollment correlating with wealth quintile, it is worth examining whether wealth has any association with gender inequity in cognitive skills. In our model of PISA competency, there are several channels through which gender and wealth could interact. First, wealth may affect gender differences in household or previous schooling characteristics: the decision to acquire educational related resources may be influenced by the gender of their child in poorer households. Second, wealth may affect gender differences in school characteristics: among poorer households, the gender of the child may influence the quality of the school chosen. Also, lower quality schools, to which poorer households may only have access, could exhibit characteristics which deter one gender more than another; for example, a poorer school may have more of a problem with violence and bullying which may deter households from sending females more than males.

The third way wealth and gender may interact is if household characteristics have a different relationship with competency between genders. This different relationship might represent discrimination if, for example, resources within the household are allocated differently between males and females. The same applies to school characteristics. School characteristics might have a different relationship with competency due to discrimination in the allocation of resources within schools, or higher quality schools may be able to better suit gender-specific learning needs.

Model (5) can be augmented to allow for household and previous schooling characteristics as well as school characteristics to have a different relationship with competency for each gender.

$$(11) \qquad \mathrm{E}\left[\theta_{i,j} \mid \bullet\right] = \xi_0 + \left(\boldsymbol{h}_{i,j}, \boldsymbol{s}_{i,j}^P\right)\boldsymbol{\xi}_1 + \boldsymbol{s}_j^E \boldsymbol{\xi}_2 + \xi_3 f_{i,j} + \xi_4 g_{i,j} + \left(\boldsymbol{h}_{i,j}, \boldsymbol{s}_{i,j}^P\right) f_{i,j} \boldsymbol{\delta}_1 + \boldsymbol{s}_j^E f_{i,j} \boldsymbol{\delta}_2$$

The vector, $\boldsymbol{\delta}_1$, is the impact of household and previous schooling characteristics on the gender difference in competency while $\boldsymbol{\delta}_2$ is the impact of school characteristics.

Let α_3 be the marginal effect of wealth on the gender gap in the expected value of household and previous schooling characteristics in equation (6), and let λ_4 be the marginal effect of wealth on the gender gap in the expected value of school characteristics in equation (7). Substituting in these amended equations yields

$$\text{(12)} \qquad \mathrm{E}\left[\theta_{i,j} \mid \bullet\right] = \delta_0 + \left(\boldsymbol{\alpha}_1\boldsymbol{\xi}_1 + \boldsymbol{\lambda}_1\boldsymbol{\xi}_2\right)w_{i,j} + \left(\boldsymbol{\alpha}_2\boldsymbol{\xi} + \boldsymbol{\lambda}_2\boldsymbol{\xi}_2 + \xi_3 + \boldsymbol{\alpha}_2\boldsymbol{\delta}_1 + \boldsymbol{\lambda}_2\boldsymbol{\delta}_2\right)f_{i,j}$$

$$+ \beta_3 r_{i,j} + \xi_4 g_{i,j} + \left(\boldsymbol{\alpha}_3\boldsymbol{\xi}_1 + \boldsymbol{\alpha}_1\boldsymbol{\delta}_1 + \boldsymbol{\alpha}_3\boldsymbol{\delta}_1 + \boldsymbol{\lambda}_4\boldsymbol{\xi}_2 + \boldsymbol{\lambda}_1\boldsymbol{\delta}_2 + \boldsymbol{\lambda}_4\boldsymbol{\delta}_2\right)w_{i,j} f_{i,j} + \boldsymbol{\lambda}_3\boldsymbol{\delta}_2 r_{i,j} f_{i,j}$$

Wealth associates with gender differences in competency in two broad ways: through the household, $\boldsymbol{\alpha}_3\boldsymbol{\xi}_1 + \boldsymbol{\alpha}_1\boldsymbol{\delta}_1 + \boldsymbol{\alpha}_3\boldsymbol{\delta}_1$, and through school characteristics, $\boldsymbol{\lambda}_4\boldsymbol{\xi}_2 + \boldsymbol{\lambda}_1\boldsymbol{\delta}_2 + \boldsymbol{\lambda}_4\boldsymbol{\delta}_2$.

Estimation of equation (12) provides an estimate of the total association of the interaction of wealth and gender on competency. In order to distinguish how much arises through wealth related gender disparity in household characteristics or how much arises from wealth related gender disparity in school characteristics, a fixed effects transformation of the data needs to occur. However, instead of using a fixed effect for each school, two fixed effects are needed for each school, one for females and one for males. Let k index all the school-gender groups, and let $\bar{x}_k$ be the mean of variable x for the k^{th} school-gender group. Then, equation (11) can be re-expressed as

$$\text{(13)} \qquad \mathrm{E}\left[\theta_{i,k} - \bar{\theta}_k \mid \bullet\right] = \left(\left(\boldsymbol{h}_{i,k}, \boldsymbol{s}_{i,k}^{P}\right) - \left(\bar{\boldsymbol{h}}_k, \bar{\boldsymbol{s}}_k^{P}\right)\right)\boldsymbol{\xi}_1 + \xi_4\left(g_{i,k} - \bar{g}_k\right)$$

$$+ \left(\left(\boldsymbol{h}_{i,k}, \boldsymbol{s}_{i,k}^{P}\right)f_{i,k} - \overline{\left(\boldsymbol{h}_{i,k}, \boldsymbol{s}_{i,k}^{P}\right)f_{i,k}}_{\,k}\right)\boldsymbol{\delta}_1$$

Any variable that is constant within the gender group within the school will be differenced out. Substituting the gender-wealth interacted modification of equation (6) yields

$$\text{(14)} \qquad \mathrm{E}\left[\theta_{i,j} - \bar{\theta}_k \mid \bullet\right] = \boldsymbol{\alpha}_1 \xi_1 \left(w_{i,k} - \bar{w}_k\right) + \xi_4 \left(g_{i,k} - \bar{g}_k\right)$$

$$+ \left(\boldsymbol{\alpha}_3 \boldsymbol{\xi}_1 + \boldsymbol{\alpha}_1 \boldsymbol{\delta}_1 + \boldsymbol{\alpha}_3 \boldsymbol{\delta}_1\right)\left(w_{i,k}\, f_{i,k} - \left(\overline{w_{i,k}\, f_{i,k}}\right)_k\right)$$

Differencing estimates of equation (12) and (14) distinguishes how much of the interaction between wealth and gender in equity stems through the household and through the school. The estimate of its association through the household does not distinguish how much owes to a gender different relationship between competency and household characteristics, $\alpha_1\delta_1$, how much owes to wealth associating with a gender difference in household characteristics, $\alpha_3\xi_1$, or both, $\alpha_3\delta_1$. Likewise, through school characteristics, one can not distinguish how much owes to a gender difference in the relationship between competency and school characteristics, $\lambda_1\delta_2$, how much owes to wealth associating with a gender difference in school characteristics, $\lambda_4\xi_2$, or both, $\lambda_4\delta_2$. However, if wealth is associated with gender differences in competency, then knowing whether or how much of this originates through household factors or through school factors is important to policy makers in order to find a solution.

Overall, equations (8) and (12) provide two different models of how the conditional expectation of competency relates to wealth, gender, grade level and rural location. But this model can not be estimated because student competency is unobserved. The only observable data available are the students' responses to a background questionnaire, their principals' responses to a school questionnaire, and the students' responses to test items. However, PISA's item response model specifies competency as a random variable conditionally distributed on student responses to items, vector $\boldsymbol{m}_{i,j}$, and their personal and school background information, $\boldsymbol{x}_{i,j}$. Consequently, if we condition our models on this data and if h_θ denotes conditional probability density function then,

$$(15) \qquad \mathrm{E}\left[\theta_{i,j} \mid w_{i,j}, f_{i,j}, g_{i,j}, r_{i,j}, \boldsymbol{m}_{i,j}, \boldsymbol{x}_{i,j}\right] = \int_\theta \mathrm{E}\left[\theta_{i,j} \mid w_{i,j}, f_{i,j}, g_{i,j}, r_{i,j}\right] h_\theta\left(\theta_{i,j} \mid \boldsymbol{m}_{i,j}, \boldsymbol{x}_{i,j}\right) d\theta_{i,j}$$

is a complete specification of our models which does not rely on an observable measure of competency.

However, no analytical solution exists to this model, its parameters can only be estimated in conjunction with the Monte-Carlo method; PISA provides five random draws from h_θ for each student called plausible values in order to accomplish this. In particular, sample weighted ordinary least squares can be used to estimate the parameters of the model for each plausible value while Balanced Repeated Replication is used to estimate the parameters' standard errors. The estimates from each plausible value are then combined to form the estimates of the parameters for the model; this methodology is coherent with PISA's item response model.

The purpose of our method is not to estimate the causal effect of wealth or gender on competency but rather their association. PISA only measures the competency of students who are enrolled in school and not those who drop out or were never enrolled. It is likely that students with lower cognitive achievement are more likely to drop out than those with higher cognitive achievement and that this likelihood decreases as wealth increases. If this is true, students of less wealthy households included in the sample are above average for that level of wealth; the estimated association between wealth and competency for the population of 15 year olds may be higher than that found in our analysis.

Additionally, by including grade level and whether the school is in a rural location, the association of wealth through these channels is ignored. For example, less wealthy students may be forced to start at a later year than wealthier students; consequently the impact on achievement of wealth through this is not captured. Also, households in rural areas have a lower average level of wealth than those in non-rural areas; controlling for rural eliminates the role of wealth between urban and rural areas in competency. Excluding grade and rural area in our model would, therefore, increase the association of competency with wealth.

4. Wealth Inequity

This section applies the preceding model to estimate the extent of wealth inequity in six Latin American countries, Argentina, Brazil, Chile, Colombia, Mexico, and Uruguay, as well as in three high income comparator countries, Canada, Finland, and the Republic of Korea.

To understand the dispersion of both wealth and cognitive achievement in these countries, Figure 1 characterizes wealth and reading competency inequality in these countries. For each country, the vertical dashed line denoting PISA wealth and the vertical solid line denoting PISA reading competency start at the country's 10% quantile level and terminate at the country's 90% quantile level of wealth and reading competency respectively. The country mean levels of wealth and reading are denoted by the squares.

Argentina displays the largest inequality in reading competency with 317 points separating the top and bottom 10%; this is followed by Uruguay with a difference of 311 points. The difference between the top and bottom 10% of the PISA wealth index for these countries is 2.2 and 2.4, respectively. In general, the six Latin American countries show larger dispersions in both reading competency and in the wealth index than the three high income countries. But Mexico stands out as the country most able to mitigate wealth inequality in Latin America: it exhibits the widest difference in wealth between the top and bottom 10%, 2.9 points, but exhibits at the same time the narrowest difference in competency between the top and bottom 10% at 245 points.

In order to understand the relationship between wealth and competency, Figure 2 displays the differences in PISA reading competency between the top and bottom quartiles of the wealth index. The heights of the grey columns denote the sizes of differences in reading competency between the poorest 25% and richest 25% in terms of PISA wealth. Each column begins at the mean level of reading competency for the poorest 25% and terminates at the mean level for the richest 25%.

While Argentina and Uruguay display the largest level of inequality in reading competency in the previous figure, Brazil displays the largest difference between rich and poor with a spread of 102 points. Uruguay actually displays the smallest difference with a spread of 74. Compared to the high income countries, Latin American countries display much wider differences between rich and poor. Finland exhibits a negative difference in competency; the poorest quartile performs slightly better than the wealthiest.

However, neither of the preceding figures captures the importance of wealth differences in the determination of competency which is required to understand wealth inequity in the accumulation of cognitive skills. Nor do they help us distinguish whether this inequity stems through disparity in households or disparity in school characteristics.

Equation (5) in the preceding section presents the assumed functional form of the relationship between reading competency and these inputs; equation (8) establishes this relationship in terms of household wealth, gender, grade level, and the school being in a rural location. The estimates of this model for reading competency are presented in Table 2. This table lists three of the estimated coefficients from nine regressions: one for each country. The dependent variable in each is the student’s unobserved competency in PISA reading, and the covariates are his or her household’s wealth index, a binary variable for being female, binary variables for each grade excluding grade 10, and a binary variable for whether the school is located in a rural area. These coefficients and their standard errors were estimated using the Monte-Carlo method described in the previous section and detailed in OECD (2002).

Wealth associates strongest with reading competency in Chile where a unit change, or approximately one standard deviation, in a student's household's wealth index corresponds to a 30 point increase in competency. From Figure 1, the difference between the top and bottom 10% of wealth is 2.4 points which translates to a 71.2 point difference between the top and bottom 10% or approximately 0.7 of a standard deviation in PISA. This is approximately equivalent to a grade of schooling in Chile.

Uruguay and Mexico exhibit the lowest association of wealth with competency: 17.4 and 14.9 points respectively and nearly half that of Chile. This means that a student in Uruguay and Mexico from a poorer household will only have half the disadvantage than that of a student in a poorer household in Chile. In the high income countries, the association with wealth is much smaller, and in Finland, that it is zero or negative can not be statistically ruled out.

Being female has a positive association with reading competency, but this will be discussed in more detail in the proceeding section.

In order to isolate the association of wealth to competency stemming solely from differences in household characteristics and not school characteristics, the association of wealth and competency within schools can be measured using a fixed effects transformation of the data. This is equation (10) in our model.

However, estimating model (10) relies on the fixed effect of each school not acting as a proxy variable for individual household wealth. This would occur if there were little overlap in wealth between schools or little variation in wealth within schools.

Table 3 describes how much of the variation in reading competency occurs within school and how much occurs between schools. The standard deviation within schools and between schools for each country, as well as the standard deviation in total for each country, are presented. Table 4 presents the within and between school standard deviation in the PISA household wealth index.

For reading competency, within school measures of variation are generally higher than between school variations. This suggests that household or individual factors are more important at explaining variations in learning outcomes than school differences. This difference is more pronounced in the high income comparator countries. However, that a bulk of the variation occurs within schools is typical of most other countries, including OECD countries where within school variation is approximately twice that of between school variation; or equivalently, within school standard deviation is approximately 1.4 times higher than between school standard deviation.

For the wealth index, within school variation is also higher than between school variation. This suggests that schools in Latin America are not divided into wealth-homogeneous groups of students, but rather that there are students of wide socio-economic backgrounds within schools.

Figure 3 characterizes how much overlap in wealth exists between schools for one country, Argentina. In this figure, each vertical bar represents the difference in the PISA wealth index between the 10% quantile and the 90% quantile for each school in Argentina. The schools are sorted from lowest average wealth to highest average wealth. As can be seen, most schools have a lot of overlap in wealth. The only lack of overlap is between the 3 or 4 wealthiest schools and the 5 or 6 poorest schools. Consequently, school fixed effects will not eliminate the variation in household wealth.

Table 5 presents estimates of the school fixed effects model, equation (10). The estimates for the coefficients of wealth and being female are presented and denoted “within” since they represent the association between wealth and female and competency within schools. The difference between these within estimates and the total estimates presented in Table 5 are listed in the last two rows. These are denoted “between” since they represent the association of wealth between schools. The standard errors for both the fixed effects and the regular models were estimates simultaneously using Balanced Repeated Replication allowing for estimates of the sampling covariance between the fixed effects and regular coefficients need in calculating the standard errors of the between estimates.

As presented in Table 5, the association between wealth and competency within schools is small compared to that between schools. For example, in Chile, the association between wealth and achievement is nearly zero at 0.18 while between schools it is 29.71. In other words, a unit change in the wealth index, approximately equivalent to one standard deviation, associates with a 30 point increase in achievement due to better school characteristics. Similarly, this association within schools in Uruguay is essentially zero as well. Of the Latin American countries, the highest proportion of the overall association between wealth and achievement presented in Table 2 that occurs within schools is in Argentina; here, a quarter of the overall association stems from the within school relationship between wealth and achievement. Wealth associates with competency primarily through school characteristics.

In order for schools to be associated with competency, there must be variation in their quality, or, more precisely, in their characteristics conducive to learning. Consequently, wealth associates with higher quality schools, and it is through this association that wealth inequity perpetuates. Eliminating this wealth inequity then hinges on either changing the characteristics of schools to equalize their quality or by decoupling the link between wealth and these characteristics. Table 6 provides a similar picture by presenting the results of a regression of the estimates of the school fixed effects and the school averages of the same student background characteristics. Wealth is strongly associated with these fixed effects and in some countries gender as well.

This analysis can be replicated for private and public schools as well. Table 7 presents the estimates for private schools. This table only presents the coefficients for wealth and female estimates from the regular model (total) and from the fixed effects model (within) and their differences (between). Generally the strength of wealth's association between schools appears higher than in the previous estimates where public and private schools were both included. This is intuitive since presumably the cost of attending a private school is positively related to its quality.

Table 8 provides the same estimates for public schools. In public schools, the association between wealth and competency appears smaller, but it is still present. This suggests that while public schools are typically free, there still exists wealth related barriers in accessing higher quality public schools. This may stem from hidden fees or costs or a neighbourhood effect combined with a cost of sending students to schools outside the neighbourhood. This may also reflect information differences among rich and poor households, or other factors such as children from poorer households preferring to attend schools with peers of similar backgrounds.

Overall, we find that wealth is an important associate with competency and that this competency stems through wealth related disparate school characteristics. Policy makers, consequently, need to focus on issues such as access and inequality of school characteristics in order to eliminate wealth inequity in the acquisition of cognitive skills.

5. Gender Inequity

This section applies the model to estimate the extent of gender inequity in the six Latin American countries and three high income comparator countries. To understand the extent and direction of gender differences in competency, Figure 4 describes average differences in reading and mathematics. The height of the column denotes the size of the difference between females and males. Females tend to have better scores in reading and lower scores in mathematics. Previously, in Figure 2 it was shown that the high income comparator countries had much smaller differences in competency between the richest and poorest wealth quartiles. But according to this figure, there seems to be no difference between the Latin American countries and the high income countries. This suggests that the problem or magnitude of gender differences in competency is not unique to Latin America.

In the previous section, Table 2 presents wealth differences and gender differences in reading. As can be seen, the difference is largest in Finland and second largest in Argentina. Colombia has the smallest gender difference in reading.

As modelled in equation (8), gender differences can emerge from three sources: the household, natural ability, and the school. School fixed effects eliminates gender differences which stem through school characteristics, but retains the portion of the difference that stems through households and natural ability; we can not distinguish the role of the household from that of natural ability since we not know whether any students come from the same household.

Table 5 decomposes the gender difference into a within portion explained by both household characteristics and natural ability and into a between portion explained by school characteristics. As shown, most of the gender difference is a within school phenomena; with the exception of Mexico and Argentina, that the size of the gender gap emerging from disparate school characteristics is zero or negative can not be statistically rejected.

Table 9 presents the same results for mathematics competency. While a bulk of the gender difference in mathematics occurs within schools, Mexico and Argentina exhibit a statistically significant difference between schools. This estimate is positive for both reading and math, and this suggests that females have access to better school characteristics or that females, or it may be that females benefiting more from school characteristics than males.

To account for the ability of household and school characteristics to have a different relationship with competency across genders, equation (11) presents a different model where household characteristics and school characteristics can have a different association for females and males. Since wealth is a determinant of household and school characteristics, it is along this avenue that wealth and gender interact. But there may also be wealth and gender interaction in the determinants of household and school characteristics. For example, if there is a gender gap in household characteristics or in school characteristics as suggested in the previous table for Argentina and Mexico, then this difference may be affected by the wealth of the household.

Table 10 presents estimates of the wealth-gender interaction model of equation (12) for reading competency. In no Latin American country is there a statistically significant interaction between wealth and gender differences in reading competency.

By using fixed effects for gender-school combinations, the interaction can be decomposed into a portion stemming from within schools and a portion stemming from between schools as captured by model (13); Table 11 presents the estimates of model (14). In two countries, Brazil and Uruguay, wealth has a weak statistically significant and negative interaction with the gender difference in reading between schools; this suggests that wealth is positively associated with school characteristics that diminish gender differences in reading competency.

Table 12 presents the same estimates for mathematics. Generally, wealth does not have statistically significant association with gender except in Argentina, one of the countries where a between school gender difference emerged. For Argentina, the interaction is positive meaning that an increase in wealth associates with a decrease in the gender difference in mathematics between schools.

This, in addition to the evidence from Brazil and Uruguay in reading, suggests the possibility of wealth associating with the school characteristics needed to reduce gender differences. In no other case can this possibility be statistically rejected.

6. Conclusion

This paper finds evidence that household wealth is strongly related to a student's competency in PISA for the Latin American countries compared to the three high income comparator countries. However, within schools, this relationship almost vanishes. That wealth is important to competency only because it is positively associated with the school characteristics needed for better learning is consistent with these findings.

Gender is also strongly associated with differences in competency in PISA, although the differences in Latin America are neither larger nor smaller than the differences in the three high income comparator countries. In some cases, wealth is negatively associated with the gender difference in competency, and this association occurs through school characteristics. That wealth is positively associated with the school characteristics needed to reduce gender differences in learning is consistent with these findings.

The association between PISA competency, which serves as a measure of cognitive skills, and household wealth represents wealth inequity in the accumulation of human capital since it indicates that students from poorer households are less able to accumulate cognitive skills than students from wealthier households. The presence of this inequity contributes to intergenerational transmission of poverty. For analogous reasons, gender differences in PISA competency represent gender inequity in the accumulation of human capital.

The results of this analysis suggest that if there were no association between household wealth and school characteristics or if there were no variation in school characteristics, then a student's ability to accumulate cognitive skills would not be hindered by being from a poorer household and gender differences in this accumulation may be reduced. Consequently, further research is needed on the costs and benefits of alternative ways to assign students to schools and on identifying school characteristics related to improving cognitive skills among students and reducing gender gaps in order to help policy makers to reduce variation in school quality.

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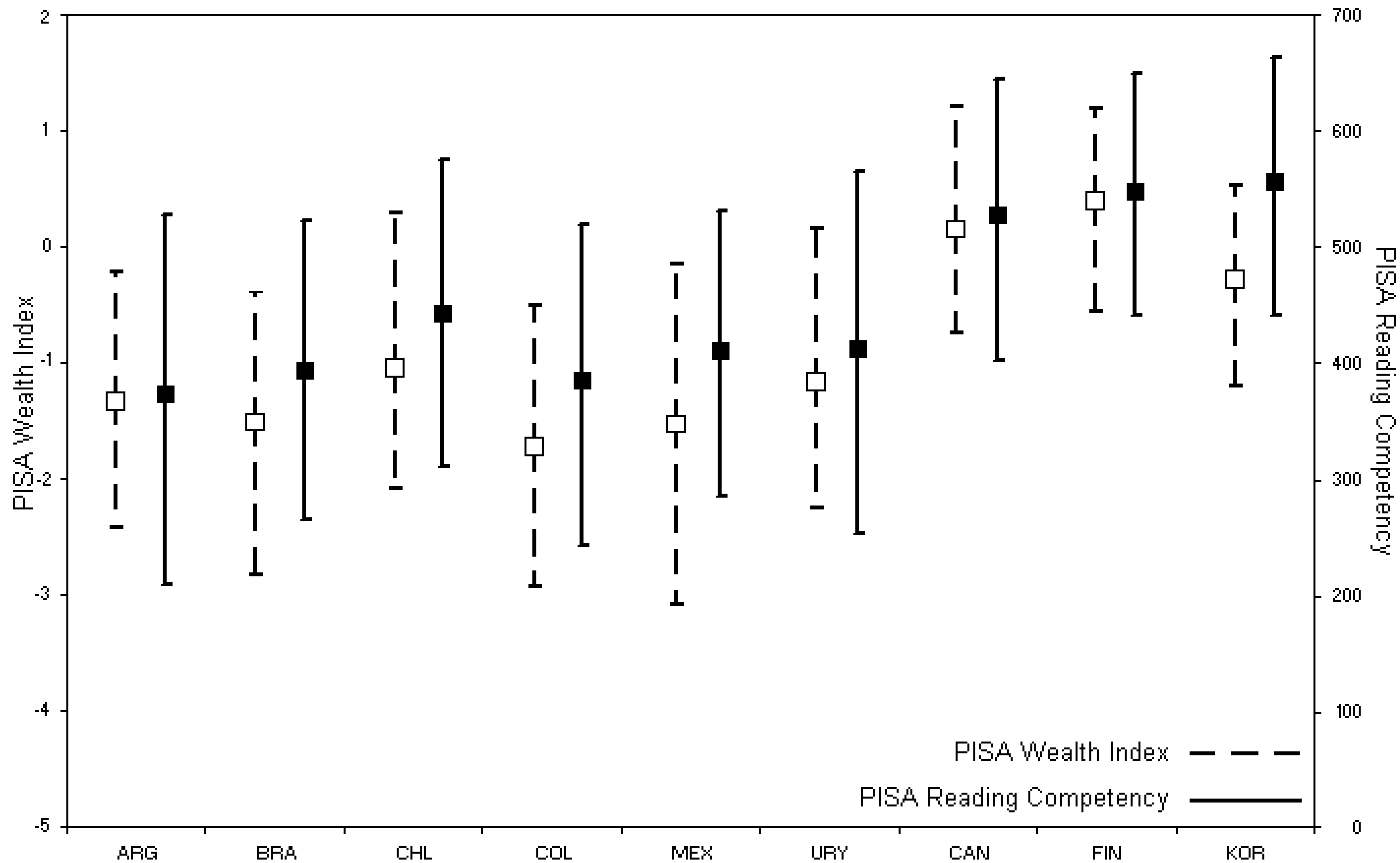
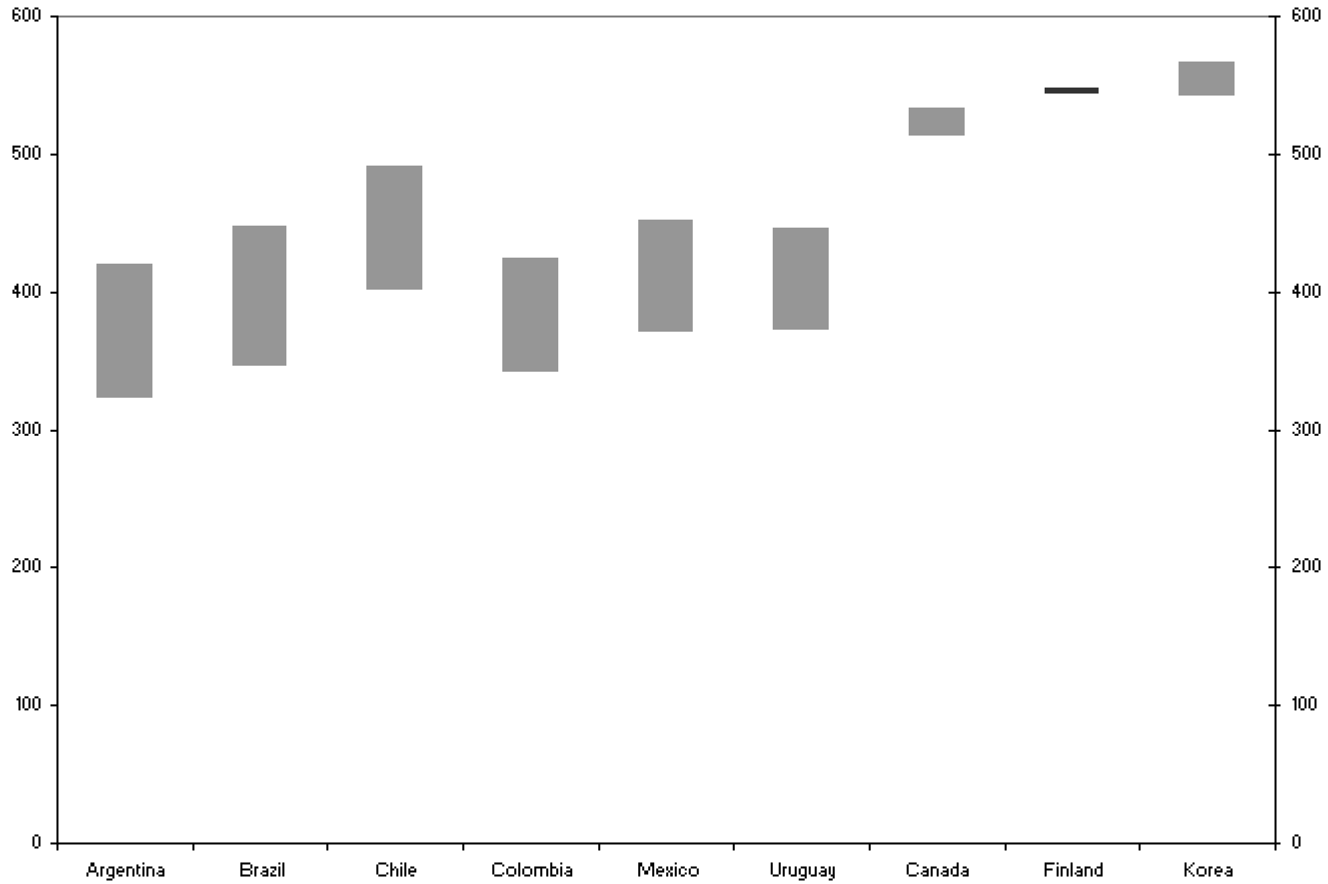
Figure 1: Reading Competency and Wealth Distributions – Differences between Top and Bottom 10%



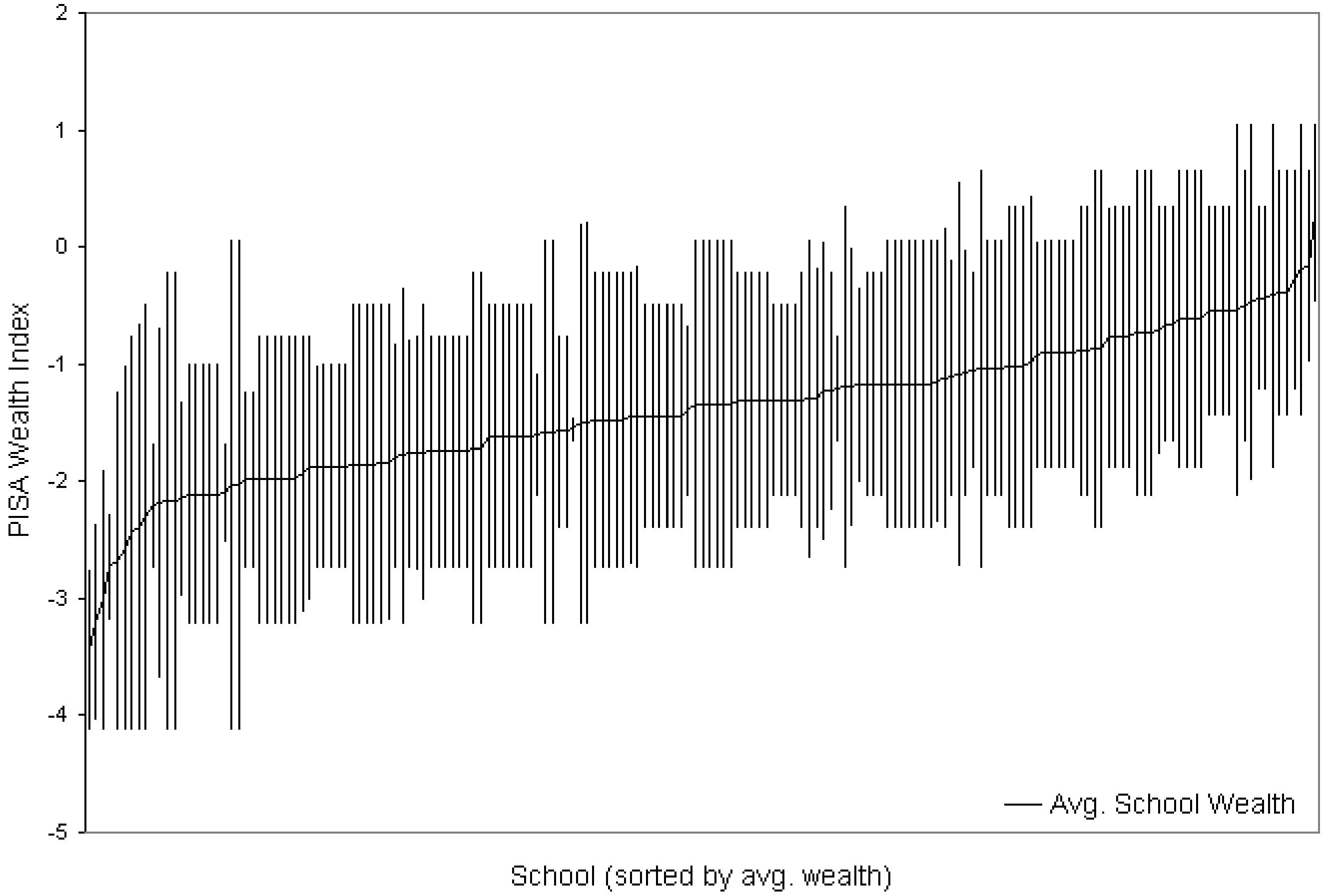
Data: PISA 2006. Vertical lines denote the size of difference between the top and bottom 10% of the PISA Wealth Index and Reading Competency; each line begins at the 10% quantile and terminates at the 90%.

Figure 2: Differences in Mean Reading Competency between Top and Bottom PISA Wealth Quartile



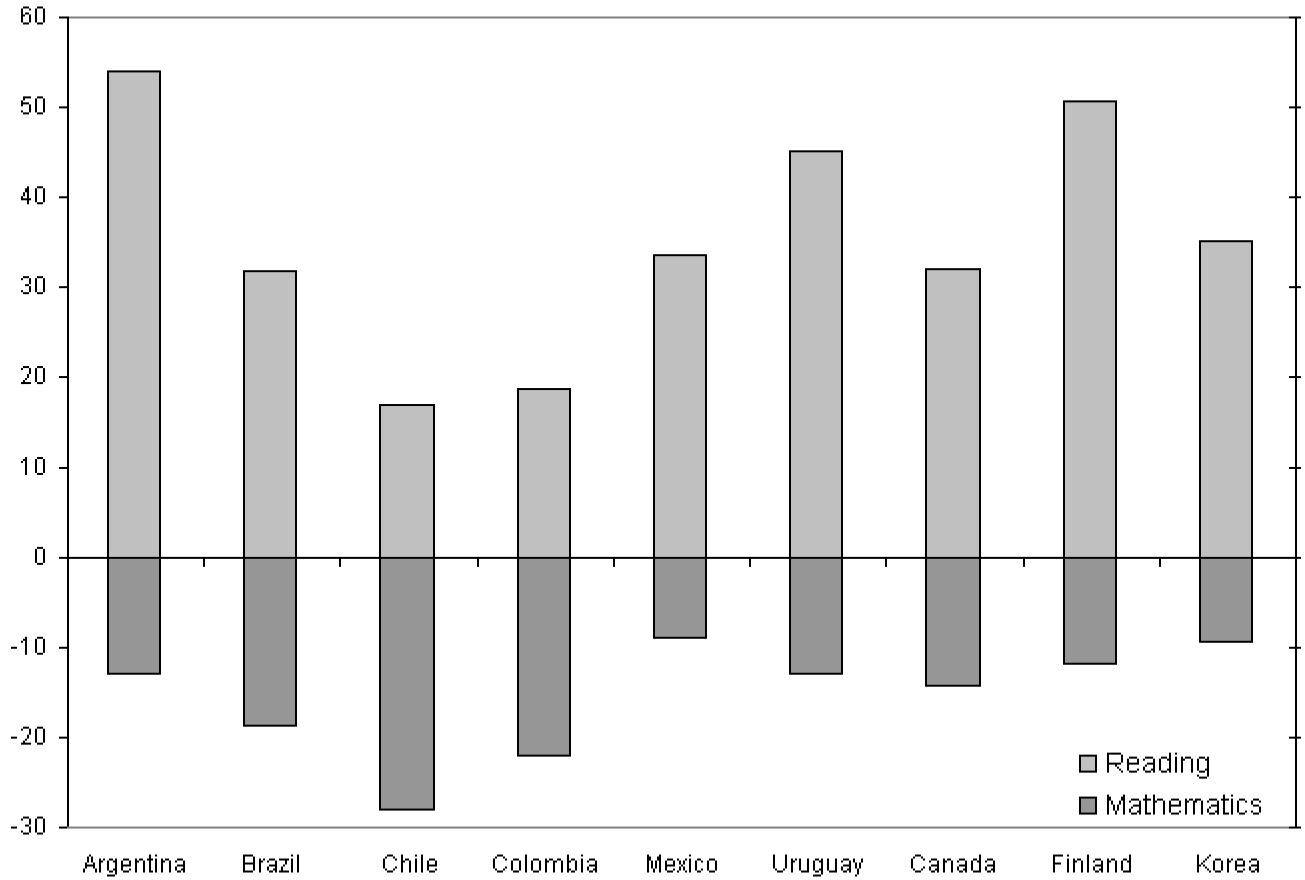
Data: PISA 2006. Columns show the difference between average PISA reading competency for the top and bottom PISA wealth index quartile. Columns being at the bottom wealth quartile's average achievement and terminate at top quartiles level of achievement. Finland the difference is negative.

Figure 3: Difference Between Top and Bottom 10% of Wealth by School in Argentina



Data: PISA 2006. Columns show the difference between the top and bottom 10% of the PISA Wealth Index by school in Argentina. Schools are sorted by average wealth.

Figure 4: Gender Differences in Math and Reading



Data: PISA 2006. Size of columns denote the difference between females and males; positive indicates females perform higher.

Table 1: Variable Means by Country

	Argentina	Brazil	Chile	Colombia	Mexico	Uruguay	Canada	Finland	Korea
Reading Competency	374	393	442	385	410	413	527	547	556
Math Competency	381	370	411	370	406	427	527	548	547
Wealth	-1.33	-1.51	-1.05	-1.72	-1.52	-1.16	0.16	0.40	-0.28
Female	0.53	0.54	0.46	0.54	0.52	0.51	0.50	0.50	0.49
Grade 7	0.04	0.12	0.01	0.06	0.02	0.07	0.00	0.00	0.00
Grade 8	0.10	0.22	0.03	0.12	0.08	0.10	0.02	0.12	0.00
Grade 9	0.17	0.48	0.19	0.22	0.34	0.17	0.13	0.88	0.02
Grade 10	0.65	0.18	0.71	0.38	0.49	0.59	0.84	0.00	0.97
Grade 11	0.03	0.01	0.06	0.21	0.05	0.07	0.01	0.00	0.01
Grade 12	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00
Grade 13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Rural	0.07	0.07	0.02	0.06	0.17	0.07	0.07	0.15	0.03

Data: PISA 2006

Table 2: Reading Competency Wealth and Gender Inequity Model Estimates

	Argentina	Brazil	Chile	Colombia	Mexico	Uruguay	Canada	Finland	Korea
Wealth	27.45***	26.22***	29.89***	20.68***	17.44***	14.87***	9.04***	-1.3	13.19***
	(3.09)	(2.42)	(2.75)	(2.86)	(2.16)	(2.68)	(1.86)	(1.66)	(2.85)
Female	39.13***	24.71***	16.15***	9.86**	27.31***	31.52***	30.29***	48.86***	34.47***
	(5.06)	(2.68)	(4.79)	(4.44)	(2.56)	(5.23)	(2.27)	(2.77)	(5.6)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	427.75***	474.78***	484.73***	441.96***	456.29***	453.73***	522.95***	545.52***	545.31***
	(7.39)	(6.72)	(6.09)	(6.1)	(3.74)	(6.13)	(2.92)	(20.78)	(4.43)
R-Square	0.35	0.33	0.24	0.25	0.28	0.31	0.10	0.13	0.08
Observations	4214	9063	4952	4430	29804	4768	21260	4708	5172

Data: PISA 2006. Statistics calculated using the Monte-Carlo method with five plausible values for reading; standard errors were calculated using BRR(0.5), see OECD (2005) for more information. Statistical significance at the 1%, 5%, and 10% levels denoted by ***, **, * respectively.

Table 3: Between and Within School Standard Deviation in PISA Reading Competency

	Argentina	Brazil	Chile	Colombia	Mexico	Uruguay	Canada	Finland	Korea
Between Schools	88.2	76.4	69.9	63.2	69.0	83.8	50.4	29.2	57.5
Within Schools	91.1	73.6	78.4	89.9	68.9	92.5	84.3	77.3	68.7
Total	124.2	102.5	103.2	107.8	95.7	121.2	96.3	81.2	88.3

Data: PISA 2006. Statistics calculated using the Monte-Carlo method with five plausible values for reading.

Table 4: Between and Within School Standard Deviation in PISA Household Wealth

	Argentina	Brazil	Chile	Colombia	Mexico	Uruguay	Canada	Finland	Korea
Between Schools	0.56	0.65	0.65	0.66	0.80	0.55	0.31	0.21	0.30
Within Schools	0.75	0.72	0.72	0.82	0.83	0.80	0.64	0.72	0.73
Total	0.92	0.94	0.95	1.03	1.13	0.94	0.70	0.73	0.77

Data: PISA 2006

Table 5: Reading Competency Wealth and Gender Inequity Model - School Fixed Effects Estimates

	Argentina	Brazil	Chile	Colombia	Mexico	Uruguay	Canada	Finland	Korea
Wealth (within)	6.74*	1.95	0.18	4.19	2.44**	-0.08	2.7*	-2.31	-3.28*
	(3.42)	(1.33)	(1.63)	(2.7)	(1.13)	(2.24)	(1.44)	(1.58)	(1.72)
Female (within)	28.55***	22.4***	21.42***	5.77	21.26***	27.24***	28.14***	48.62***	32.76***
	(4.32)	(2.54)	(3.58)	(4.58)	(1.81)	(4)	(1.99)	(2.72)	(3.97)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4214	9063	4952	4430	29804	4768	21260	4708	5172
Wealth (between)	20.71***	24.26***	29.71***	16.49***	15.00***	14.94***	6.34***	1.01	16.47***
	(3.12)	(2.54)	(2.92)	(2.17)	(2.03)	(2.41)	(1.49)	(0.83)	(2.51)
Female (between)	10.58***	2.31	-5.28	4.09	6.05**	4.28	2.16	0.24	1.71
	(2.78)	(1.82)	(4.08)	(2.85)	(2.31)	(3.43)	(1.33)	(0.86)	(5.77)

Data: PISA 2006. Statistics calculated using the Monte-Carlo method with five plausible values for reading; standard errors were calculated using BRR(0.5), see OECD (2005) for more information. Between estimates are the differences between the corresponding coefficients of the fixed effects transformed model and regular model in Table 2. Sampling covariances estimated using BRR(0.5). Statistical significance at the 1%, 5%, and 10% levels denoted by ***, **, * respectively. For total wealth and female association see Table 2.

Table 6: Reading Fixed Effects Estimates Regression

	ARG	BRA	CHL	COL	MEX	URY
Wealth	48.35***	36.71***	51.87***	30.53***	28.61***	48.15***
	(10.31)	(5.84)	(11.59)	(7.69)	(1.76)	(7.03)
Female	77.14**	53.43*	-32.32	5.15	40.9***	8.71
	(28.39)	(23.42)	(25.61)	(26.14)	(10.74)	(20.45)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	20.88	50.36**	78.49***	28.43	27.36***	30.45*
	(19.65)	(20.28)	(22.32)	(25.09)	(9.02)	(15.68)

Source: PISA 2006; Dependent variable are the estimates of the school fixed effects for each plausible value from Table 4. Statistical significance at the 1%, 5%, and 10% levels denoted by ***, **, * respectively.

Table 7: Reading Competency Wealth and Gender Inequity Model - Private School Estimates

	Argentina	Brazil	Chile	Colombia	Mexico	Uruguay	Canada	Finland	Korea
Wealth (within)	10.64 (8.4)	1.96 (3.92)	-0.18 (2.06)	0 (5.07)	0.87 (3.78)	-7.07 (4.77)	-3.12 (5.44)	11.36 (7.96)	-2.38 (1.97)
Wealth (between)	15.62** (5.99)	21.38*** (5)	29.7*** (3.6)	20.48** (9.29)	17.88*** (3.53)	18.96*** (5.91)	5.21 (4.39)	9.37** (4.26)	17.42*** (4.37)
Wealth (total)	26.27*** (5.92)	23.33*** (5.07)	29.53*** (3.36)	20.48** (9.09)	18.75*** (4.63)	11.89* (6.92)	2.08 (7.2)	20.72** (8.19)	15.04*** (4.38)
Female (within)	29.97*** (6.94)	16.16*** (5.29)	21.18*** (4.06)	10.47 (12.2)	22.88*** (5.38)	22.56*** (7.82)	25.03*** (6.35)	74.51*** (8.56)	31.38*** (5.61)
Female (between)	12.16** (5.01)	-2.67 (2.68)	-2.26 (4.84)	5.27 (9.44)	6.61 (7.71)	0.03 (3.24)	-5.74 (5)	-5.22 (6.8)	-3.89 (9.09)
Female (total)	42.13*** (8.54)	13.49** (5.27)	18.92*** (6.37)	15.73 (10.84)	29.5*** (7.89)	22.59*** (8.12)	19.3*** (6.82)	69.29*** (9.12)	27.49*** (8.9)
Observations	1348	1441	2480	816	3536	1000	1573	149	2446

Data: PISA 2006. Statistics calculated using the Monte-Carlo method with five plausible values for reading; standard errors were calculated using BRR(0.5), see OECD (2005) for more information. Statistical significance at the 1%, 5%, and 10% levels denoted by ***, **, * respectively.

Table 8: Reading Competency Wealth and Gender Inequity Model - Public School Estimates

	Argentina	Brazil	Chile	Colombia	Mexico	Uruguay	Canada	Finland	Korea
Wealth (within)	5*	1.91	0.66	5.04	2.65**	0.88	3.08**	-2.71	-4.01
	(2.69)	(1.5)	(2.71)	(3.05)	(1.23)	(2.37)	(1.49)	(1.64)	(2.6)
Wealth (between)	10.94***	13.75***	20.02***	11.14***	10.39***	5.3***	5.37***	0.6	15.87***
	(2.65)	(2.09)	(4.15)	(1.9)	(1.76)	(1.68)	(1.34)	(0.87)	(2.91)
Wealth (total)	15.95***	15.66***	20.69***	16.18***	13.04***	6.18**	8.45***	-2.1	11.86***
	(3.49)	(2.25)	(4.32)	(3.21)	(1.92)	(2.54)	(1.61)	(1.72)	(3.6)
Female (within)	27.79***	2.62	21.75***	5.08	21.01***	4.89	28.41***	48.03***	6.8
	(5.23)	(2.18)	(5.44)	(4.67)	(1.91)	(3.9)	(2.12)	(2.74)	(7.97)
Female (between)	5.21	23.44***	-11.46*	3.38	4.19***	28.19***	2.76**	0.49	33.34***
	(3.34)	(2.92)	(6.76)	(2.63)	(1.55)	(4.99)	(1.29)	(0.84)	(5.34)
Female (total)	33***	26.07***	10.29	8.47*	25.2***	33.08***	31.17***	48.52***	40.14***
	(5.89)	(3.14)	(7.02)	(4.47)	(2.27)	(6.15)	(2.36)	(2.75)	(8.38)
Obseravtions	2866	7622	2112	3538	26268	3724	19687	4559	2726

Data: PISA 2006. Statistics calculated using the Monte-Carlo method with five plausible values for reading; standard errors were calculated using BRR(0.5), see OECD (2005) for more information. Statistical significance at the 1%, 5%, and 10% levels denoted by ***, **, * respectively.

Table 9: Mathematics Competency Wealth and Gender Inequity Model Estimates

	Argentina	Brazil	Chile	Colombia	Mexico	Uruguay	Canada	Finland	Korea
Wealth (within)	5.62*	5.01***	0.72	1.25	1.53	6.58**	3.73**	5.09***	6.48***
	(2.63)	(1.37)	(1.45)	(2.08)	(1)	(2.37)	(1.63)	(1.53)	(1.7)
Wealth (between)	22.39***	26.25***	28.85***	17.15***	13.3***	11.99***	2.09*	0.49	18.57***
	(2.8)	(2.36)	(2.72)	(2.52)	(1.55)	(1.74)	(1.2)	(0.73)	(2.97)
Wealth (total)	28.01***	31.26***	29.58***	18.4***	14.83***	18.56***	5.82***	5.59***	25.04***
	(3)	(2.4)	(2.47)	(2.6)	(1.71)	(2.33)	(1.78)	(1.65)	(3.11)
Female (within)	-30.67***	-23.84***	-24.16***	-32.48***	-19.37***	-26.65***	-18.08***	-12.62***	-12.55***
	(3.33)	(2.31)	(2.77)	(2.79)	(1.59)	(2.86)	(1.84)	(2.56)	(4.28)
Female (between)	6.62**	0.51	-4.45	2.9	4.33*	1.93	2.03*	-0.05	3.21
	(2.52)	(1.54)	(3.52)	(2.49)	(2.42)	(2.45)	(1.1)	(0.81)	(5.99)
Female (total)	-24.06***	-23.33***	-28.61***	-29.58***	-15.04***	-24.72***	-16.04***	-12.68***	-9.34
	(4.21)	(2.45)	(3.97)	(3.55)	(2.66)	(3.8)	(1.94)	(2.56)	(5.76)
Obseravtions	2866	7622	2112	3538	26268	3724	19687	4559	2726

Data: PISA 2006. Statistics calculated using the Monte-Carlo method with five plausible values for reading; standard errors were calculated using BRR(0.5), see OECD (2005) for more information. Statistical significance at the 1%, 5%, and 10% levels denoted by ***, **, * respectively.

Table 10: Reading Competency Interacted Wealth and Gender Inequity Model Estimates

	Argentina	Brazil	Chile	Colombia	Mexico	Uruguay	Canada	Finland	Korea
Wealth	25.27***	27.54***	29.72***	20.17***	16***	14.54***	8.69***	-2.99	9.07***
	(4.29)	(3.22)	(3.42)	(3.55)	(2.28)	(3.65)	(2.54)	(2.73)	(3.22)
Female	43.28***	20.72***	15.91**	12.26	28.27***	33.44***	29.3***	46.61***	36.26***
	(8.42)	(5.38)	(7.46)	(7.56)	(4.57)	(7.4)	(2.53)	(3.25)	(5.86)
Wealth x Female	4.07	-2.47	0.39	1.01	2.64	0.49	0.73	3.41	8.53**
	(4.69)	(3.04)	(3.88)	(4.13)	(2.4)	(3.9)	(3.1)	(3.86)	(3.9)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	425.71***	476.88***	484.91***	440.69***	455.7***	452.78***	523.44***	548.73***	544.5***
	(8.22)	(7.28)	(6.69)	(6.51)	(3.93)	(6.83)	(2.97)	(21.9)	(4.58)
R-Square	0.35139103	0.32910526	0.2427202	0.25322613	0.28266451	0.31440589	0.0974847	0.1290131	0.0804327
Observations	2866	7622	2112	3538	26268	3724	19687	4559	2726

Data: PISA 2006. Statistics calculated using the Monte-Carlo method with five plausible values for reading; standard errors were calculated using BRR(0.5), see OECD (2005) for more information. Statistical significance at the 1%, 5%, and 10% levels denoted by ***, **, * respectively.

Table 11: Reading Competency Interacted Wealth and Gender Inequity Model Estimates - Fixed Effects Model

	Argentina	Brazil	Chile	Colombia	Mexico	Uruguay	Canada	Finland	Korea
Wealth (within)	8.06 (4.68)	0.34 (2.05)	-0.23 (2.93)	3.23 (3.71)	2.6 (1.69)	-2.21 (3.77)	2.22 (2.27)	-3.78 (2.69)	-6.71*** (2.32)
Wealth x Female (within)	-0.52 (6.18)	3.14 (3.37)	0.63 (4.56)	1.17 (4.61)	-0.06 (2.53)	7.32 (5.18)	1.46 (3.11)	3.29 (3.86)	7.76** (3.1)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2866	7622	2112	3538	26268	3724	19687	4559	2726
Wealth (between)	17.2*** (4.05)	27.2*** (3.36)	29.95*** (3.87)	16.93*** (2.81)	13.39*** (2.22)	16.75*** (3.53)	6.47*** (2.11)	0.79 (1.34)	15.78*** (2.66)
Wealth x Female (between)	4.58 (4.16)	-5.62* (3.26)	-0.25 (4.63)	-0.16 (4.01)	2.7 (2.41)	-6.83* (3.54)	-0.73 (2.27)	0.11 (1.68)	0.77 (3.22)

Data: PISA 2006. Statistics calculated using the Monte-Carlo method with five plausible values for reading; standard errors were calculated using BRR(0.5), see OECD (2005) for more information. Between estimates are the differences between the corresponding coefficients of the fixed effects transformed model and regular model in Table 10. Sampling covariances estimated using BRR(0.5). Statistical significance at the 1%, 5%, and 10% levels denoted by ***, **, * respectively.

Table 12: Mathematics Competency Interacted Wealth and Gender Inequity Model Estimates

	Argentina	Brazil	Chile	Colombia	Mexico	Uruguay	Canada	Finland	Korea
Wealth (within)	4.92	3.99*	0.17	0.36	1	4.61	0.32	3.77	3.03
	(3.35)	(2.22)	(1.77)	(3.08)	(1.64)	(3)	(2.74)	(2.72)	(2.15)
Wealth (between)	17.12***	27.16***	28.6***	17.08***	12.07***	13.69***	2.67*	-0.04	18.88***
	(3.43)	(3.15)	(3.05)	(3.03)	(1.79)	(2.43)	(1.5)	(1.11)	(3.49)
Wealth (total)	22.03***	31.15***	28.76***	17.44***	13.07***	18.3***	5.67**	3.73	21.91***
	(3.93)	(2.79)	(3.05)	(3.3)	(2.04)	(3.1)	(2.39)	(2.67)	(3.86)
Wealth x Female (within)	2.88	3	0.78	1.57	1.38	2.78	1.8	2.86	7.32**
	(3.89)	(3.03)	(2.56)	(3.72)	(2.02)	(3.47)	(2.7)	(4.16)	(3.19)
Wealth x Female (between)	8.31**	-2.78	0.92	0.25	1.88	-2.29	-1.47	0.82	-0.83
	(3.46)	(3.13)	(3.04)	(2.94)	(2.05)	(2.43)	(1.96)	(1.62)	(3.39)
Wealth x Female (total)	11.19***	0.22	1.7	1.83	3.26	0.49	0.32	3.68	6.49
	(3.8)	(2.35)	(3.25)	(3.71)	(2.18)	(2.95)	(2.74)	(4.18)	(3.93)
Observations	2866	7622	2112	3538	26268	3724	19687	4559	2726

Data: PISA 2006. Statistics calculated using the Monte-Carlo method with five plausible values for reading; standard errors were calculated using BRR(0.5), see OECD (2005) for more information. Statistical significance at the 1%, 5%, and 10% levels denoted by ***, **, * respectively.