POLICY FORUM

EDUCATION

Societal inequalities amplify gender gaps in math

Egalitarian countries cultivate high-performing girls

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While gender gaps in average math performance are now close to zero in developed countries, women are still strongly underrepresented among math high performers (*1*). This gender gap contributes to the underrepresentation of women in math and science in higher education and to their subsequent worse position in the labor market (*2*, *3*). With the roles of nature and nurture (*4*–*6*) on gender performance gaps having been debated for more than a century, research in the 1990s and 2000s (*7*–*9*) suggested a cultural origin, relating gender gaps in math to measures of countries' gender inequality. However, with more recent studies (*10*–*12*) having shown that this relation is weak, today we have no clearly identified relationship between countries' socioeconomic or cultural environment and the gender gap in math. We relate below gender gaps in math to societal inequalities that are not directly related to gender. We find a strong and robust relationship and provide tests suggesting that it is causal: Countries that are generally more egalitarian, or that have institutions more conductive to equality, have a lower gender performance gap in math, suggesting that this gap is partly shaped by more general societal inequalities.

According to the Programme for International Student Assessment (PISA), there are on average only seven girls for ten boys in the top decile of the math performance distribution among the 35 countries belonging to the Organisation for Economic Co-operation and Development (OECD). Underrepresentation of girls at high levels of performance is a common feature of all OECD countries (table S1a) and has remained remarkably stable since 2000 (table S1b). Gender gaps of the same magnitude are also observed in science and reading, the latter in favor of girls (table S1). Much former research has been based on the gender stratification hypothesis, according to which gender differences in opportunities and status shape numerous socialization processes that in turn may affect performance (*7*). We elaborate on this idea, assuming that processes that transform differences in status between social groups into differences in performance depend on the degree of countries' inclusiveness; inclusive countries are likely to mitigate the impact of status differences in general. We hypothesize that women have a lower status than men in virtually all countries but that this lower status is more likely to be detrimental to girls' performance in countries that are in general less fair and inclusive; the more unequal a country, the more the status difference between boys and girls should translate into differences in performance.

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INEQUALITIES AND PERFORMANCE

We analyze data from five successive waves of PISA, an every-three-year international assessment of the knowledge and skills of 15-year-old students in mathematics, reading, and science taking place in more than 70 countries (see details on all data and analyses in the supplementary materials (SM)]. We relate gender gaps in PISA performance to measures of countries' societal inequalities that are not directly related to gender but reflect (i) general socioeconomic and cultural inequalities, including pure income inequalities, or (ii) educational inequalities, including inequalities in performance and in learning opportunities (*13*).

We focus primarily on "high performers" at levels 5 or 6 from the six PISA proficiency levels (10.7% of all students in OECD countries in math in 2015). We use as our main measure of the gender performance gap in math the ratio of girls to boys among these high performers. This is because (i) this ratio is very unfavorable to girls and has not narrowed over time and (ii) performance at high levels is related to underrepresentation of women among STEM college graduates.

Among the 35 OECD countries observed in 2015, this ratio is negatively and significantly correlated with socioeconomic and cultural inequalities such as the income Gini index (r = −0.55) (see fig. S1) or the variance in the socioeconomic and cultural background of a country's students (r = −0.66), with inequalities in school performance such as the share of students from a low socioeconomic and cultural background among high performers (r = 0.70) (see fig. S1), or with inequalities in learning opportunities at school such as the between-school variation in students' socioeconomic background (r = −0.61).

Consistent with a link between math gender gap and the way countries perpetuate or reduce initial status differences, we find a strong correlation between the gender gap in math and intergenerational earnings elasticity (r = −0.63), education mobility measured as parents-child correlations in years of schooling (r = −0.54), or the index of inequality of economic opportunity (r = −0.64), which measures income inequality due to predetermined circumstances beyond individual control (such as region of birth or parental background).

A more systematic study of those relationships using linear regression models shows that for a large variety of measures of societal inequalities, a higher level of inequality is associated with a significantly lower girls-to-boys ratio among high performers in math (see the table and table S2, column 1). About 30% of the cross-country variance in this ratio can be accounted for by a single measure of inequality, and the explained variance reaches 60% when three variables reflecting different aspects of inequalities are jointly included.

Several robustness checks show that the relation is still observed when (i) controlling for countries' gross domestic product (GDP) and extent of gender stratification (table S3); (ii) including 37 partner non-OECD countries (table S4); (iii) considering the gender gap in average performance, although the relation is weaker (table S5); (iv) using different measures of the gender gap in math among high performers (table S6); (v) using former PISA surveys or other data sources (see, e.g., table S7); and (vi) using lagged measures of income inequalities [in the 1980s and to some extent in the 1950s and 1960s (see SM)]. We also show that inequalities are associated with lower school performance of both boys and girls, with the estimated association systematically larger for girls (table S8).

We conclude that the relationship between the math gender performance gap and societal inequality is larger and more robust than other relationships already documented with more obvious country characteristics such as gender stratification or economic development.

To back up this point, we run "horse races" and also apply three standard machine-learning techniques for model selection to compare the explanatory power of measures of gender inequality and of countries' development to our measures of non-gender-related inequalities (see SM). For instance, the effect of the Gender Gap Index (GGI) or of the Female Labor Force Participation on the gender gap in math becomes statistically nonsignificant as soon as a measure of (non-gender-related) societal inequalities is introduced as a competing explanatory variable in regression models (table S9).

Societal inequalities are also associated with lower girls-to-boys ratios in science (increasing the gender gap, as in math) and higher boys-to-girls ratio in reading (reducing the gender gap) (tables S2, S4, S5, and S8). Consistent with our hypothesis, inequalities are detrimental to the performance of girls relative to boys in the three topics math, reading, and science.

UNDERSTANDING ORIGINS

To suggest causality and better understand the origin of the relationship between non-gender-related inequality measures and gender performance gaps, we offer three different strategies: (i) individual-level regressions, (ii) panel analysis, and (iii) instrumental variables.

We first check that our results are not driven by cross-country differences in observable students' characteristics. We replicate our analysis using the full PISA student-level data, which contains information on students' grade repetition, parents' education, and households' economic and cultural resources. Conditional on these controls and their interaction with students' gender, girls still have a lower probability relative to boys to score above the high-performance cutoff in more unequal countries (see the table, column 2, and table S10). This shows, in particular, that our main results are not driven by differential effects of parents' education on their daughters' and sons' math performance or by differential allocation of household resources across children's gender.

To explore whether unobserved country characteristics are driving the results, we control for countries' time-constant unobserved heterogeneity using country fixed-effects models. Variations over time in our main inequality indicators are almost all significantly related to variations over time in the girls-to-boys ratio in math, showing that countries that reduce relatively more (or increase relatively less) socioeconomic inequalities also reduce relatively more the gender performance gap in math (see the table, column 3, table S11, and fig. S2).

To assess further a possible causal link, we exploit institutional differences between countries' labor markets as instruments for their extent of income inequality. We argue that institutional features such as bargaining coverage, union density, or the value of the minimum wage are not likely to have a direct link with the gender performance gap at school, such that any impact they may have on the math gap would likely be through their impact on social inequalities. To obtain estimates less likely to reflect reverse causality or omitted variables biases, we retrieve variations in the Gini index that are solely explained by those institutional variables. These "instrumented" inequalities, solely driven by institutional factors, affect the gender gap in math to the same extent as noninstrumented inequalities (table S12).

We also study whether institutional features of education systems affect gender performance gaps by considering measures of inequalities in learning opportunities across schools or across students' socioeconomic background, measures of vertical stratification at school, such as the extent of grade repetition, and measures of the quality of education. All those measures, known to affect socioeconomic inequalities at school (*14*, *15*), directly relate to gender performance gaps across countries (tables S2 and S4 to S7).

It is striking that general indicators of inequalities can explain so well the patterns of gender differences in math, science, and reading performance across countries (whereas other indicators directly related to gender stratification have limited explanatory power). In more egalitarian countries, differences in initial status seem less likely to translate into differences in performance, and girls are more represented among high performers as are, for example, students from a low socioeconomic and cultural background. This suggests that the gender gap in math is a form of social inequality like many others.

This is consistent with our results that gender performance gaps at school are linked to countries' institutions that more generally reduce social and economic inequalities. As a consequence, gender equality may not only be a matter of gender norms and stereotypes. General policies in favor of more inclusive, less vertically stratified, and more standardized education systems may also have a positive impact on girls' performance.

Inequalities and gender gaps among high performers in math

Estimates in column 1 are obtained from separate simple linear country-level regression models on 35 OECD countries in PISA 2015. The dependent variable is the ratio of the numbers of girls and boys among high math performers. Column 2 provides similar estimates based on individual-level regressions with several control variables and adjusted standard errors (see SM). Column 3 is a country fixed-effect version of column 1 based on PISA 2003, 2006, 2009, 2012, and 2015.

EXPLANATORY VARIABLE	COUNTRY-LEVEL REGRESSIONS	INDIVIDUAL-LEVEL LOGISTIC MODELS	COUNTRY FIXED-EFFECT MODELS (2003-2015)
Income inequalities (GINI index)	0.067**	–0.094**	–0.094**
Inequalities in socioeconomic and cultural background	–0.081**	–0.169**	–0.043*
Socioeconomic inequalities in performance	–0.085**	–0.157**	–0.027*
Inequalities in learning opportunities	–0.075**	–0.154**	–0.075

*** P < 0.01, * P < 0.05. See SM for methodological details, the exact definition of inequality variables, sample sizes, standard errors, and R-squares.*

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SUPPLEMENTARY MATERIALS

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