Journal of Economic Perspectives—Volume 24, Number 2—Spring 2010—Pages 95–108

Geographic Variation in the Gender Differences in Test Scores

Devin G. Pope and Justin R. Sydnor

In the 1960s, the gender gap in college enrollments was 1.55 males for every female. By the 1980s, this gap had been erased. By 2003, the college gender gap was 1.30 females for every male undergraduate (Goldin, Katz, and Kuziemko, 2006). All cohorts of U.S. women born since 1960 have had higher average years of schooling than their male counterparts (Charles and Luoh, 2003). This educational convergence has even taken place in the historically male-dominated areas of science and engineering, with women earning 42.7 percent of bachelor's degrees in these fields in 1990 and 50.6 percent by 2001 (National Science Foundation, 1998, 2001).

Despite this convergence at the undergraduate level, women are still greatly underrepresented in the upper echelons of many fields, particularly in the ranks of faculty in science, math, and engineering at prestigious universities. In the science faculty at MIT, for example, 8 percent of the faculty were women in 1990, rising slightly to 12 percent by 1999 (Committee on Women Faculty at MIT, 1999). As of 2000, the proportion of tenured U.S. faculty who are women was under 5 percent for engineering and around 10 percent for economics and physical sciences (Ginther and Kahn, 2004).

This pattern of rough gender equality in averages, but differences at the extremes, is also found in standardized test scores of pre-collegiate students.

■ *Devin G. Pope is Assistant Professor of Operations and Information Management, Wharton School, University of Pennsylvania, Philadelphia, Pennsylvania. Justin R. Sydnor is Assistant Professor of Economics, Weatherhead School of Management, Case Western Reserve University, Cleveland, Ohio. Their e-mail addresses are ⟨dpope@wharton.upenn.edu⟩ and ⟨justin.sydnor@case.edu⟩.*

doi=10.1257/jep.24.2.95

Analyzing data on test scores of twelfth graders from the 1972 National Longitudinal Survey and the 1988 National Education Longitudinal Survey, Goldin, Katz, and Kuziemko (2006) documented in this journal that in 1972 boys had average math scores that were 0.25 standard deviations higher than those of girls, while girls had a slight edge of 0.035 standard deviations in average reading scores. By 1992, the girls had cut into the average math gap by 0.17 standard deviations and had added to their lead in reading. In a meta-analysis of 100 studies of math tests, Hyde, Fennema, and Lamon (1990) concluded that the average standardized difference in test scores between males and females was very small and statistically insignificant. However, the variance of test scores differs substantially by gender, and as a result, significantly more males than females score in the very high ranges on science and math tests and significantly more females score very highly on language and reading tests (Hedges and Nowell, 1995; Husain and Millimet, 2009; Hyde, Fennema, and Lamon, 2008). As one example, Hedges and Nowell (1995) review data from six national studies conducted between 1960 and 1992. Across the six math tests they examine, the ratio of males to females among students scoring in the 95th percentile of the national distribution ranges from 1.50 to 2.34 and is above 2.0 for half of the tests.

These gender gaps in high achievement on test scores have played a part in heated debates about the causes behind gender disparities in academia and other top fields. One vivid example of this debate is, of course, the controversy that erupted in the aftermath of Larry Summers's speech at the NBER Conference on Diversifying the Science and Engineering Workforce in January 2005. In discussing the underrepresentation of women in tenured positions in science and engineering at top universities, Summers (2005) suggested that one hypothesis for these patterns was the possibility of "different availability of aptitude at the high end" in math and science between men and women. These comments, which reflected Summers's reading of the evidence of pervasive gender differences in the very high ends of academic achievement as measured by test scores, sparked an intense debate about the role that innate abilities might play in gender disparities seen at the top of many fields of study.[1]

In this paper, we examine geographic variation in gender disparities on standardized test scores in the United States. We find that patterns of gender disparity at the national level hide large and statistically significant variations in gender gaps across states and census divisions. The sex differences on test scores in the most gender-equal states are less than half the size of the sex differences that are found in the most gender-unequal states. Moreover, this variation is geographically clustered. For example, using individual-level data on math, science, and reading tests given to 8th graders since 2000 through the National Assessment of Educational Progress, we compute that in the New England census division (Connecticut, New Hampshire, Massachusetts, Maine, Rhode Island, and Vermont), the ratio

[1] For a good example of the debate surrounding Summers's remarks, see the transcripts of the public debate on the topic between Harvard psychologists Elizabeth Spelke and Steven Pinker at ⟨http://www.edge.org/3rd_culture/debate05/debate05_index.html⟩.

of males to females scoring above the 95th percentile on the science and math tests are 1.46 and 1.29, respectively, while in the East South Central census division (Alabama, Kentucky, Mississippi, and Tennessee) the male–female ratios are 2.14 and 1.57.

Moreover, areas which have smaller gender disparities in stereotypically male-dominated tests of math and science *also* tend to have smaller disparities in stereotypically female-dominated tests of reading. For example, the New England census division, which has the lowest male–female ratios in the 95th percentile on math and science, also has the lowest *female–male* ratio (2.067) at the 95th percentile on the reading test. Thus, the variation across states in test score disparities is not simply a reflection of some states improving the performance of females relative to males. Rather, some states appear to be more gender-equal across all tests and adhere less to gender stereotypes in both directions.

In short, stereotypical gender norms on standardized tests vary systematically at the state level. From a policy standpoint, this finding is important because it highlights that the pervasive gender gaps in test scores seen in national-level data are not showing up to the same degree throughout the country. The existence of more gender-equal states may provide policymakers concerned with gender disparities a starting point for understanding how these disparities can be lessened.

These results also speak to the nature–nurture debate surrounding cognitive ability and test scores.[2] It seems reasonable to assume that the genetic distinction and the hormonal differences between sexes that might affect early cognitive development (that is, innate abilities) are the same regardless of the state in which a person happens to be born. If one accepts that premise, then the variation we observe in gender gaps across states can be plausibly interpreted as coming from different social forces that exist in different states. Our evidence points toward a strong role for these different social forces in creating gender differences in performance on test scores. Indeed, the most gender-equal regions have gender gaps at the 95th percentile in math and science that are roughly 50 percent lower than what is seen at the national level. Because much of the social and educational environment within the United States does not vary at the state level, our findings likely represent a lower bound on the effect of different environments on gender ratios in high-end test score performance. However, the geographic variation that we explore in this paper does not fully explain stereotypical gender performance, which leaves room for the possibility of a partial biological/genetic root to gender differences in test scores.

[2] This paper adds to the literature that addresses the question of nature vs. nurture across a wide array of economic outcomes, which is reviewed by Sacerdote (2008). This paper also adds to the small economics literature that discusses biological and environmental impacts on test scores. Specifically, Guiso, Monte, Sapienza, and Zingales (2008) find that the gender gaps in test scores (in all subjects) are higher in some countries than in others and Figlio (2008) provides evidence that girls with more feminine names—even when looking within families—are less likely to select into math and science courses than their counterparts.

National Patterns of Gender Differences: Comparable Averages, Differing Variances

National data from the National Assessment of Educational Progress (NAEP) confirm the established patterns of gender differences on tests scores. The NAEP is arguably the best source of standardized test score data for making state-level comparisons in the United States. The NAEP is a series of standardized tests administered to public school students in grades 4, 8, and 12 throughout the United States in subjects such as math, reading, and science. For the state-level examinations, which are the data we use here, schools and students within schools are randomly selected to take the tests based on a probability sampling design that takes account of characteristics such as whether the school is urban or rural, income levels, and other factors. The goal of the sampling is to ensure that the population of students in the NAEP sample is representative of all of the students in that state. More information on the sampling methodology used for the NAEP is available on the website of the National Center for Education Statistics at ⟨http://nces.ed.gov⟩. Throughout our analysis, we use the individual-level sampling weights provided in the data.

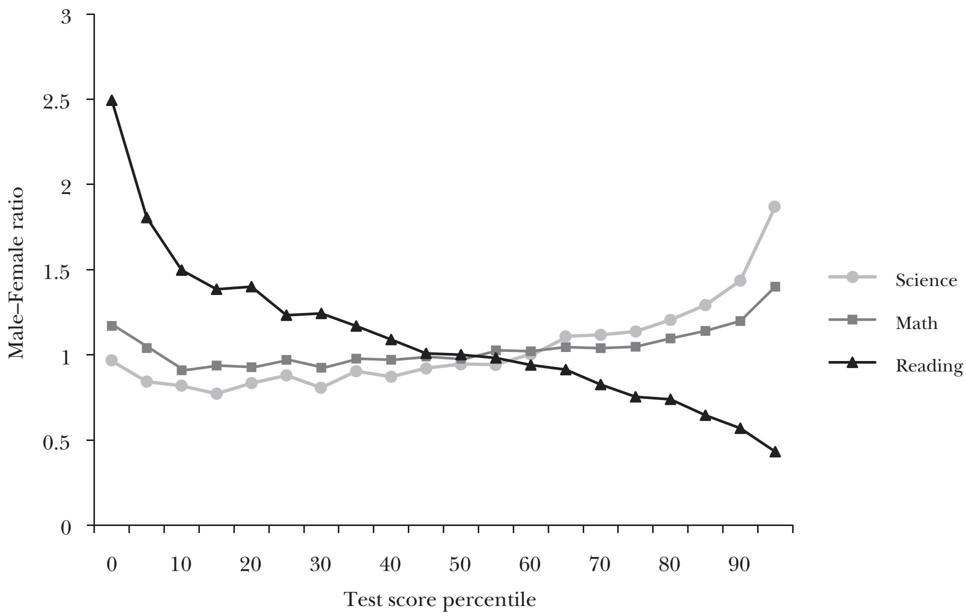
We analyze individual-level data from the state NAEP tests in science, math, and reading given to 8th graders in 2000, 2003, and 2005. We obtained test score information at the state level via restricted-access license for the math test in 2000, 2003, and 2005, the science test in 2000 and 2005, and the reading test in 2003 and 2005. (To circumvent questions regarding differences in gender disparities across races, which may correlate with geographic areas, we focus exclusively on white students. In addition, the sample size for minority students is too small to obtain inferences for non-white races in all states.) Pooling across years, there are 142,121 usable observations for the science test, 251,867 usable observations for the math test, and 190,710 usable observations for the reading test.

There are only slight differences in the mean scores. On average, male scores are 0.17 standard deviations higher than females for science, 0.06 standard deviations for math, and 0.38 standard deviations lower for reading. However, Figure 1 shows that there are substantial differences in the gender ratios of students scoring in the higher percentiles on these tests. The ratio of males to females scoring in the top 25 percent is 1.33 for science and 1.17 for math, and rises in the top 5 percent to a ratio of 1.87 for science and 1.40 for math. The disparities in favor of women on the reading test are even stronger, with a female–male ratio of 1.62 in the top 25 percent and of 2.31 in the top 5 percent.

Variation in Gender Ratios across States and Census Divisions

Our interest in this paper is to understand whether these gender ratios in high achievement on the tests are the same in each state. These comparisons are complicated somewhat by the fact that the overall distribution of test scores varies across states. That is, in some states boys score better on the tests than they do in other states, so there is a question about how to define "high achievement."

Figure 1
Male–Female Ratios in Science, Math, and Reading across the Distribution



Notes: This figure uses data from the National Assessment of Educational Progress. All white, 8^{th}-grade students who took the test between 2000 and 2005 in science, math, or reading are included in the sample. Male–Female ratios were created at each five percentile level using the sample weights provided in the data.

There are two reasons for our focus on national-level cutoffs. First, there is a national labor-market for the types of jobs where this type of high achievement may matter, especially in academia, so it seems natural to question whether there is variation across states in the gender ratios of students who perform at the same high level. The second reason we use national-level cutoffs is somewhat technical and comes from the nature of the differences in the test-score distributions across states. We are interested in understanding whether the difference between scores for boys and scores for girls varies across states, but the scores of boys themselves varies across states. The appropriate cutoff rule for comparisons across states should ensure that if the process that makes boys' scores vary across states affects girls' scores across states in the same way, then we will observe the same boy-girl difference in each state. The distribution of test scores we observe for boys in higher-score states is skewed to the right relative to that of boys in lower-score states. So it seems that the probability of scoring highly is depressed, especially at the higher end of the distribution, for boys in lower-performing states. If the probability of obtaining a given high score is reduced proportionally for girls in the low-performing states in the same way it is for boys, then a national-level cutoff rule is appropriate for our comparisons. In this case, there will be fewer students scoring above the national-level cutoff in the low-performing states, but in the absence of state variation in relative gender performance, the chances that a student who does perform at that level would be a boy would be the same in each state. Using national-level cutoffs, then, if we see the probability that a high-scoring student is a boy varying across states, we can conclude that there are state-differences in relative gender performance. Different types of distribution shifts for boys in low-performing states relative to boys in high-performing states could make state-level cutoffs more appropriate for the analysis. In particular, if the distributions of boys' scores in low-performing states showed a simple mean-shift relative to that of boys in high-performing states, rather than the skewed shift we actually observe, then a state-level cutoff would be more appropriate. The online appendix, available at ⟨http://www.e-jep.org⟩, repeats the analysis here using state-level cutoffs and shows that the empirical patterns we document in this section using national-level cutoffs broadly hold, but are somewhat weaker, with that approach.

We examine variation in gender ratios of "high achievers" at the state level and census level. The sample sizes in the NAEP are not large enough to extend the analysis to the level of counties or metropolitan statistical areas. We compute a top 25 percent and a top 5 percent cutoff value for each test subject and year based on the full national sample of test scores. At each of these two cutoff points, we calculate the ratio of the number of males to females scoring above the cutoff in each state and census region. Ideally we would conduct these tests even higher in the distribution—say the top 0.1 percent—since the debate about gender differences in ability often surrounds the very extreme levels of performance. However, there simply is not enough power in the NAEP data to study state-level variation at those extreme tails.

The prevailing stereotypes show up in all states at both the 95$^{\text{th}}$ and 75$^{\text{th}}$ percentiles, with the sole exception of Hawaii.[3] At the 95$^{\text{th}}$ percentile, the two smallest male–female ratios (that is, most gender equal) in math are 0.81 in Hawaii and 1.06 in New York; in science, the two smallest male–female ratios are 1.30 in Massachusetts and 1.43 in Washington state; in reading, the two smallest female–male ratios are 1.75 in Massachusetts and 1.88 in Rhode Island.

These ratios display considerable variation. For instance, in contrast to the low ratios at the 95$^{\text{th}}$ percentile on the math test for Hawaii and New York, the two highest ratios are roughly twice as high—1.93 for Oklahoma and 2.07 for Kentucky. On the science test, the three states of Utah, Mississippi, and New Jersey have male–female ratios above 3.0—more than twice the low-end ratios observed in Massachusetts and Washington. On the reading test, the highest female–male ratio at the 95$^{\text{th}}$ percentile occurs in Utah at a staggering 4.47, implying that 82 percent of the Utah students scoring at the top 5 percent of the reading test were female. An *F*-test can be used to test the null hypothesis that these gender ratios are the same across states.[4] For each test at both the 95$^{\text{th}}$ and 75$^{\text{th}}$ percentiles, the *F*-test

[3] The low male–female ratio in Hawaii suggests that girls outperform boys in math in Hawaii, but this result could also come from sampling noise.
[4] Similarly, a chi-squared test can be used to analyze whether the mean gender gaps are different across states. However, the *F*-test allows us to include the sampling weights provided in the NAEP data; a standard chi-squared test does not.

rejects the null hypothesis that the gender ratios are the same across states, with *p*-values below 0.05 in every case.

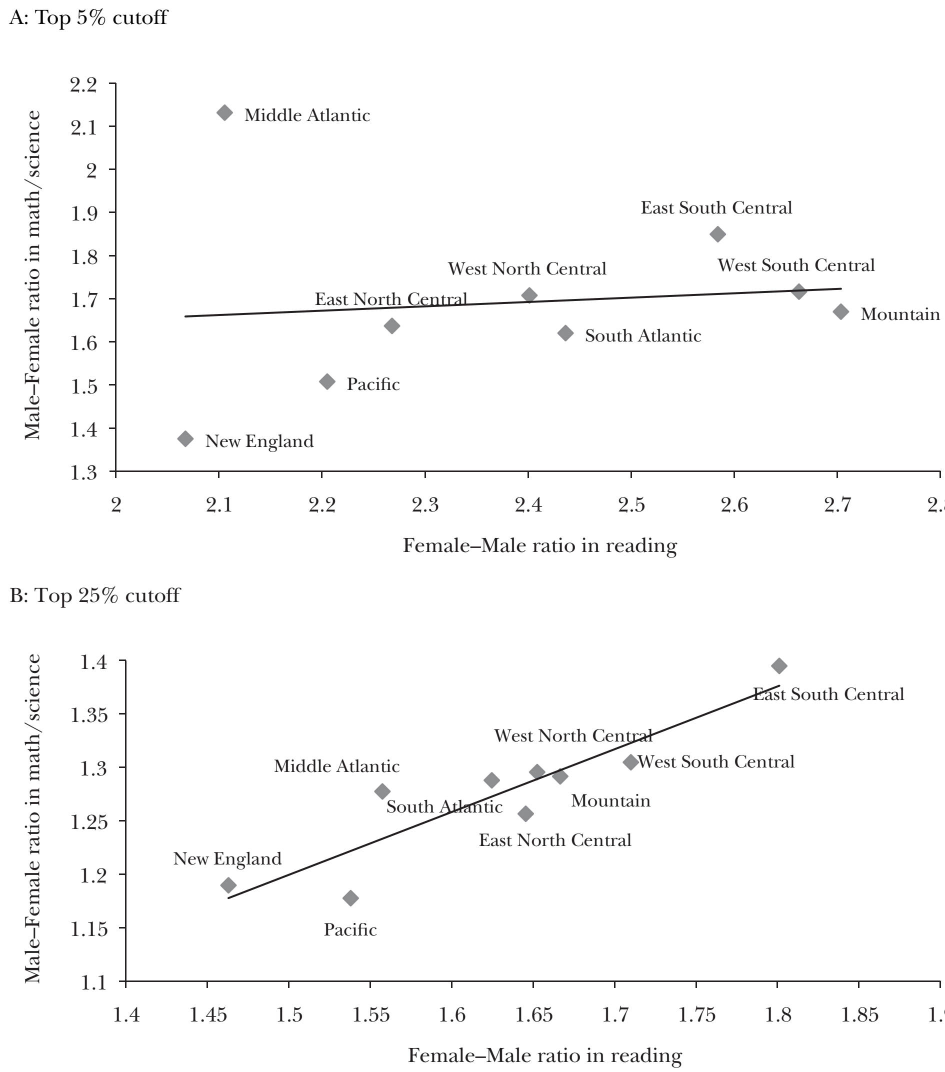
An intriguing pattern emerges when we examine the gender gaps across the three tests in each state: there is correlation between the gender gaps within a state. For instance, states like Utah and Oklahoma have high male–female ratios at the 95th percentile of both the math and science tests: in terms of gender equity, Utah ranks 45th out of all the states on the math and 48th on the science, while Oklahoma ranks 49th on the math and 46th on the science. Initially, one might suspect, then, that these states have environments that favor boys over girls. Yet looking at the reading tests, we see that in these same states girls *outperform* boys on the reading tests by an unusually large margin. Utah has the highest *female–male* ratio at the 95th percentile on the reading test, and Oklahoma has the 8th highest. Looking across all states, there is a strong correlation between 1) the average of the male–female ratios on science and on math and 2) the female–male ratio on reading, at both the 95th and 75th percentiles of the distribution (with *p*-values below 0.01 at both levels). This pattern suggests that certain areas adhere more or less strongly to the prevailing gender stereotypes in test performance rather than simply favoring one sex over the other. Figure 2 illustrates this pattern graphically using the average ratios by census division.

Grouping states by census division makes sense because it turns out that states with high levels of stereotypical gender differences in test scores also appear to be clustered geographically. To examine this geographic clustering, we create a state-level "stereotype adherence index" by averaging a state's male–female ratio in math and science with the state's female–male ratio in reading using the top-5-percent cutoff. Figure 3 presents a map of the United States shaded to represent the level of the stereotype adherence index for each state. For purposes of shading, we categorize states based on their stereotype adherence index as more than .65 standard deviations above the mean; from the mean up to .65 standard deviations above the mean; from the mean to .65 standard deviations below the mean; or more than .65 standard deviations below the mean. The states with a very high stereotype adherence index—those with large gender disparities—are predominately found in the South and Mountain West, while the states with a very low stereotype adherence index are mostly found in the West, Southwest, and Northeast. This figure also provides a simple table showing the level of the index for each state. Utah shows the highest level of the index at 3.1, implying that across the tests, the stereotypically dominant gender is overrepresented in the top 5 percent by a bit over three times. The lowest index is found in Massachusetts at 1.4.

These census geographic divisions provide a useful a priori grouping for discussing the amount of influence different environments appear to have on gender gaps in test scores. There is a significant amount of variation in the stereotype adherence index across census divisions; an *F*-test of equality of the index across divisions rejects with *p*-values below 0.01.[5] One, admittedly imperfect, way to quantify how

[5] This also holds true for a stereotype adherence index defined for the top 25 percent of students, rather than the top 5 percent.

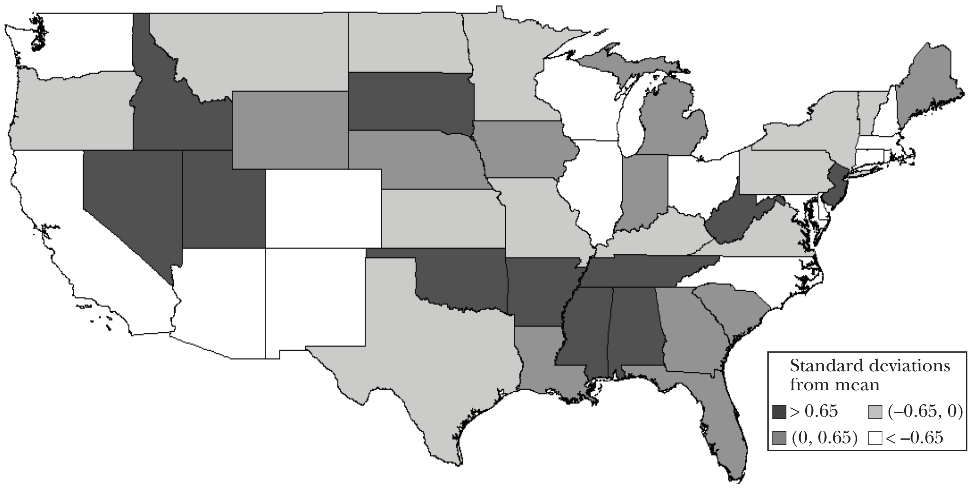
Figure 2
The Gender Gap in Math and Science and the Gap in Reading by Census Division



Notes: This figure illustrates the relationship between the female–male ratio in reading (on the x-axis) and the average of male–female ratios in math and in science (on the y-axis) by U.S. states. Panel A computes ratios by looking at students scoring in the top 5 percent while panel B focuses on students scoring in the top 25 percent, using national-level cutoffs in each case.

much of the national-level gender gap can be explained by environmental forces is simply to compare it to the gender gap in the most gender-equal region of the country. The stereotype adherence index is 1.86 at the national level, but drops to 1.61 in the most gender-equal census division, New England. If we define the gender gap as the degree to which this index deviates from 1, then we can say that at least 29 percent (that is, ((0.86–0.61)/0.86) of the national-level gender gap can be

Figure 3
Geographic Representation of the Stereotype Adherence Index (SAI)



Stereotype Adherence Index, by State

Utah	3.1	South Dakota	2.2	Iowa	2.0	Kansas	1.9	Maryland	1.8
Oklahoma	2.6	South Carolina	2.2	Michigan	2.0	Kentucky	1.9	Arizona	1.8
Idaho	2.6	Wyoming	2.2	Missouri	2.0	Virginia	1.8	Ohio	1.7
West Virginia	2.6	Nevada	2.2	Montana	2.0	North Dakota	1.8	Delaware	1.7
Mississippi	2.5	Maine	2.2	Oregon	2.0	Connecticut	1.8	California	1.7
Nebraska	2.4	Alaska	2.1	New York	2.0	New Hampshire	1.8	Colorado	1.6
New Jersey	2.4	Indiana	2.1	Texas	2.0	Illinois	1.8	Rhode Island	1.6
Tennessee	2.3	Louisiana	2.1	Vermont	2.0	Hawaii	1.8	North Carolina	1.6
Alabama	2.3	Florida	2.1	Pennsylvania	1.9	Wisconsin	1.8	New Mexico	1.6
Arkansas	2.3	Georgia	2.0	Minnesota	1.9	Washington	1.8	Massachusetts	1.4

Notes: The map presents the stereotype adherence index (the average of the male–female ratios in math and science and the female–male ratio in reading) for the top 5 percent of students. States are ordered by this index and then broken into four categories. Each shade of color represents a different grouping with the darker shades indicating a larger amount of stereotypical gender differences. The individual stereotype adherence index scores for each state are provided in table format at the bottom.

explained by environmental forces). We say at least 29 percent, because it could be that the gap in New England is partially or wholly explained by environmental forces, but our approach cannot identify those environmental forces.

One potential concern with these results is that there is some small underlying variation in the ratio of boys to girls at the state level who are in the public schools sampled by the NAEP tests. Perhaps this variation is driven by differential rates of public school attendance by gender; for example, if parents from certain states are more likely to send their girls to private schools than parents from other states. Or perhaps it is driven by underlying sex-ratio differences at the state level. Whatever the underlying reason, we can address this issue by replicating the analysis above, but netting out the relevant gender ratio for all test takers in the state. So for example, if a state has a male–female ratio of 1.75 on the math test at the 95th percentile and a male–female ratio of 1.02 overall among math-test takers, the state's net male–female ratio would be 1.72. The results above hold throughout, and are actually strengthened in many cases, when we account for the underlying variation in state gender ratios.

Correlates with Stereotypical Gender Disparities

Although it is difficult to establish causal mechanisms for these state-level variations—especially given the potential relevance of hard-to-measure characteristics like culture and gender attitudes—it seems natural to investigate the state-level characteristics that correlate with stereotypical test score gender disparities. Understanding these correlations may help focus policymakers on the areas with greatest gender disparities and will hopefully provide directions for future research on gender differences in the upper tails of test scores.

There is a negative correlation between a state's stereotype adherence index and its median income level. The coefficient estimate from a simple linear regression of a state's stereotype adherence index on its median income implies that a $10,000 increase in a state's median income decreases the state's stereotype adherence index by 0.19 (as shown in Table 1, column 1), which is significant at the 5 percent level. To put this effect in perspective, consider that a change of $10,000 represented around a 20-spot change in the state-income ranking in the 2000 Census, while a change of 0.19 in the stereotype adherence index is approximately equivalent to a change of seven spots in the ranking of the index. The correlation between the fraction of adults with high-school educations and the stereotype adherence index is also negative, as shown in the second and third columns of Table 1, but is not statistically significant at conventional levels.

We also investigate more direct measures of cultural attitudes and gender stereotypes at the state level using a question from the General Social Survey (GSS). The GSS does not ask questions directly related to gender stereotypes on standardized test scores. However, there is one question on gender attitudes/issues that has been asked consistently between 1972 and 2006 and that has a reasonably large number of responses in most states: "Is it much better for everyone involved if the man is the achiever outside the home and the woman takes care of the home and family?" Pooling across all years of data and limiting to the 37 states where at least 100 survey respondents answered the question, 41.5 percent of respondents answered "yes" to this question. Figure 4A shows the correlations between the percent of respondents who answer "yes" to this question on the survey question and the stereotype adherence index for each census division. There is a very strong correlation; areas where people are more likely to answer that it is better if women take care of the home have higher levels of the stereotype adherence index.[6] (This

[6] To find out whether differential sampling in the GSS data affects these results, we also regressed the individual responses to this question on the individual-level demographic variables included in the GSS: age, gender, race, self-reported income, and education. We then averaged the residuals from this regression at the state-level in order to generate state-level measures of cultural attitudes that

Table 1
Correlates with Stereotypical Gender Differences at the State Level

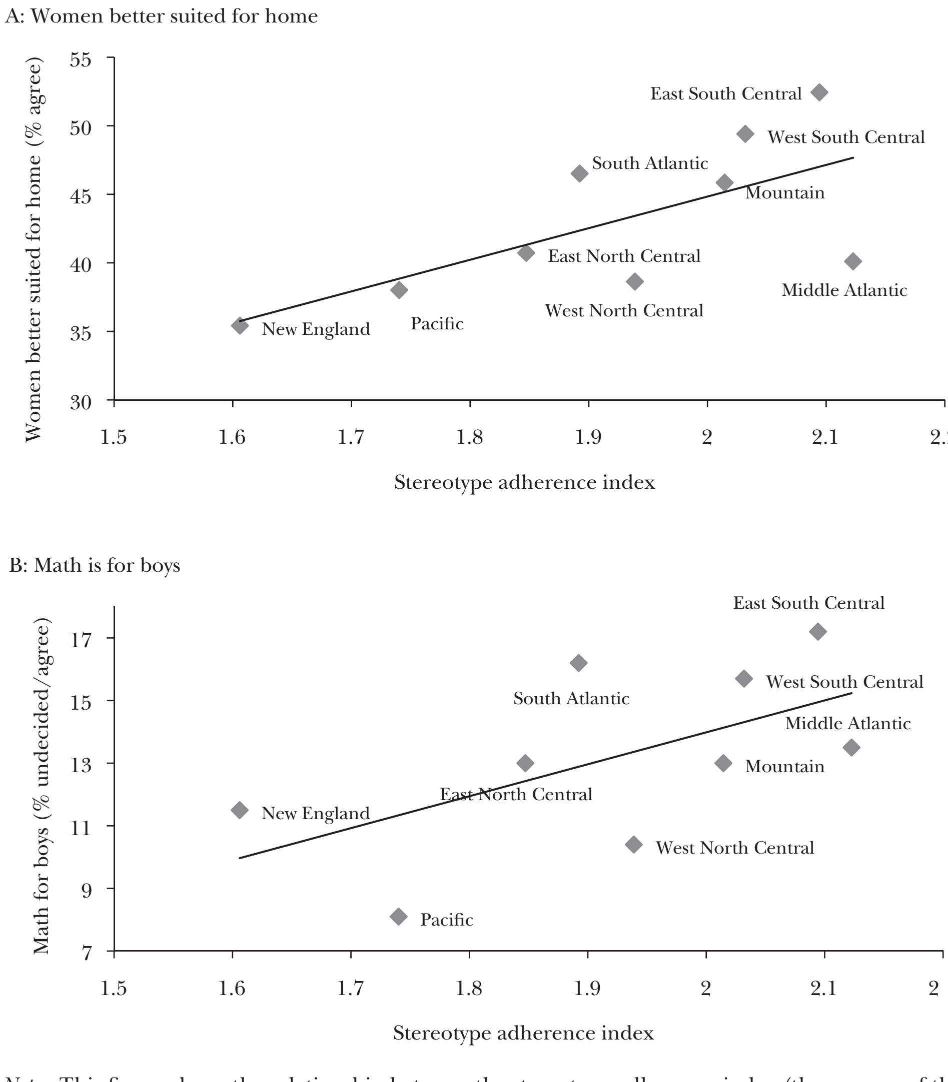
	Dependent variable: Stereotype Adherence Index				
	(1)	(2)	(3)	(4)	(5)
2000 Census variables					
Median household income ($1,000s)	–0.019 (.009)**				
Fraction with high school (HS) degree		–1.822 (1.417)			
Fraction of females with HS degree			–1.875 (1.434)		
Survey Questions					
Women better suited for home (agree)				0.024 (.006)***	
Math is for boys (undecided or agree)					0.050 (.018)***
R^2	0.144	0.062	0.065	0.401	0.111
Observations	37	37	37	37	35

Notes: This table illustrates the relationship between the stereotype adherence index (the average of the male–female ratios in math and science and the female–male ratio in reading, for the top 5 percent of students) and state characteristics including attitudes on women's issues. The "women better suited for home" question was taken from the General Social Survey and the "math is for boys" question is taken from the National Assessment of Educational Progress. (See text for details.)
***, **, and * indicates statistical significance at the 1, 5, and 10 percent levels respectively.

pattern also holds if we redefine our stereotype adherence index using ratios for the top 25 percent of students, rather than the top 5 percent.) Column 4 in Table 1 provides the coefficient estimates for this correlation by showing results from the simple linear regression of this measure on the state-level stereotype adherence index. The estimated effect suggests that a one standard deviation (8.6 percent) decrease in the percent of people in the state who say that women are better suited for the home is associated with a change in the stereotype adherence index of 0.21.[7] This is approximately the same size effect as column 1 in Table 1 suggests comes from a $10,000 increase in a state's median income level. Looking at the R^2, this simple measure of gender attitudes accounts for approximately 40 percent of the variation in the state-level stereotype adherence index. Interestingly, this measure of gender attitudes has a much higher R^2 value than a state's median household income (R^2 of 14 percent in column 1).

are independent of the demographic characteristics of the survey respondents. The results from this procedure were very similar to the raw units shown in Figure 4A.
[7] 8.6 (one standard deviation in percent) multiplied by the coefficient (.024) is 0.21.

Figure 4
Attitudes on Gender Issues and Stereotype Index



Notes: This figure shows the relationship between the stereotype adherence index (the average of the male–female ratios in math and science and the female–male ratio in reading, for the top 5 percent of students) and attitudes on women's issues. Panel A graphs the stereotype adherence index against responses to a General Social Survey question asking whether women are better suited to stay at home. Panel B graphs the stereotype adherence index against 8th-grader responses to the query "Is math for boys?" from the National Assessment of Educational Progress).

This question from the GSS provides information about the cultural attitudes of adults, but it is also interesting to think about the gender role attitudes of children taking tests and how those attitudes might correlate with stereotypical test score performance. We were able to find one piece of evidence on children's gender attitudes. An earlier wave of the NAEP given in 1990 and 1992 asked students to say how much they agreed or disagreed with the statement “math is for boys.” We gathered the responses to this question for students who took the math test in 1990 and 1992 and found the percent of students who were undecided or agreed with the question in each state. Figure 4B shows that there is a strong correlation between the answers to this question and the stereotype adherence index across census divisions.

Discussion and Conclusion

States and regions through the country demonstrate some common gender patterns in test scores. Males and females have roughly equivalent average scores. However, males are disproportionately represented at the top of test scores in math and science while females are disproportionately represented at the top of reading test scores. Across states and regions, there is substantial variation in these high-end gender ratios, and this variation tends to be geographically clustered. States with highly unequal ratios in favor of boys on math and science tests also tend to have highly unequal ratios in favor of girls on reading tests. This finding suggests that gender inequality in high performance on test scores more likely stems from stereotyping and states concentrating their educational efforts by gender than from broadly better treatment of one sex over the other. The findings in this paper also raise the possibility that a substantial share of observed differences in gender ratios in high-end test scores in the United States are a matter of environments rather than differences in innate abilities between the genders: nurture rather than nature.

Our analysis has several limitations that point to directions for future research. Data limitations make it difficult for us to analyze variation in gender ratios for students scoring in the very highest percentiles, like the 99th percentile or higher. Because this range of extreme talent is especially relevant for discussions of gender representation in very competitive fields such as scientific academia, it will be important to extend this analysis to higher percentiles of test scores as more data become available. Also, while we argue that our results indicate the importance of environmental factors in contributing to the test score gap, we have not identified in a precise way the cultural or environmental differences that may be driving the results we find. Possible candidates include differences in resource allocation, home or classroom instruction, opportunities in the workforce, or the psychological effect of stereotypes. Future research should seek to examine more deeply the specific forces that influence stereotypical gender disparities in test scores.

■ *We thank Betsey Stevenson, Uri Simonsohn, and seminar participants at Case Western Reserve University, the University of Pennsylvania, and Stanford University for helpful comments and suggestions.*

References

Charles, Kerwin Kofi, and Ming-Ching Luoh. 2003. "Gender Differences in Completed Schooling." *The Review of Economics and Statistics*, 85(3): 559–77.

Committee on Women Faculty at MIT. 1999. "A Study on the Status of Women Faculty in Sciences at MIT." http://web.mit.edu/fnl/women/women.html.

Figlio, David. 2008. "Why Barbie Says 'Math is Hard.'" Unpublished paper.

Ginther, Donna K., and Shulamit Kahn. 2004. "Women in Economics: Moving Up or Falling Off the Academic Career Ladder?" *Journal of Economic Perspectives*, 18(3): 193–214.

Goldin, Claudia, Lawrence F. Katz, and Ilyana Kuziemko. 2006. "The Homecoming of American College Women: The Reversal of the College Gender Gap." *Journal of Economic Perspectives*, 20(4): 133–56.

Guiso, Luigi, Ferdinando Monte, Paola Sapienza, and Luigi Zingales. 2008. "Culture, Math, and Gender." *Science*, 320(5880): 1164–65.

Hedges, Larry V., and Amy Nowell. 1995. "Sex Differences in Mental Test Scores, Variability, and Numbers of High-Scoring Individuals." *Science*, 269(5220): 41–45.

Husain, Muna, and Daniel L. Millimet. 2009. "The Mythical 'Boy Crisis'?" *Economics of Education Review*, 28(1) 38–48.

Hyde, Janet S., Elizabeth Fennema, and Susan J. Lamon. 1990. "Gender Differences in Mathematics Performance: A Meta-Analysis." *Psychological Bulletin*, 107(2): 139–55.

Hyde, Janet S., Sara M. Lindberg, Marcia C. Linn, Amy B. Ellis, and Caroline C. Williams. 2008. "Gender Similarities Characterize Math Performance." *Science*, 321(5888): 494–95.

National Science Foundation Division of Science Resources Statistics. 1998, 2001. *Science and Engineering Degrees, by Race/Ethnicity: 1990–1998* and *Science and Engineering Degrees, by Race/Ethnicity: 1992–2001.* Both available at http://128.150.4.107/statistics/degreerecipients.

Sacerdote, Bruce. 2008. "Nature and Nurture Effects on Children's Outcomes: What Have We Learned from Studies of Twins and Adoptees?" Working paper forthcoming in the *Handbook of Social Economics.*

Summers, Lawrence H. 2005. "Remarks at NBER Conference on Diversifying the Science and Engineering Workforce." June 14. http://www.president.harvard.edu/speeches/summers_2005/nber.php.

This article has been cited by:

1. Maria Laura Di Tommaso, Dalit Contini, Dalila De Rosa, Francesca Ferrara, Daniela Piazzalunga, Ornella Robutti. 2024. Tackling the gender gap in mathematics with active learning methodologies. *Economics of Education Review* **100**, 102538. [Crossref]
2. Can Tang, Liqiu Zhao. 2024. Gender Social Norms and Gender Gap in Math: Evidence and Mechanisms. *Applied Economics* **56**:17, 2039-2057. [Crossref]
3. Stefanie J. Huber, Hannah Paule-Paludkiewicz. 2024. Gender norms and the gender gap in higher education. *Labour Economics* **87**, 102491. [Crossref]
4. Ahmad Shah Mobariz, Shishir Shakya. 2024. Cultural influences on gender gap in test scores: findings from Afghanistan's university entrance examination. *Applied Economics Letters* 1-4. [Crossref]
5. Julian Messina, Anna Sanz-de-Galdeano, Anastasia Terskaya. 2024. Birds of a Feather Earn Together. Gender and Peer Effects at the Workplace. *SSRN Electronic Journal* **115**. . [Crossref]
6. Simon Calmar Andersen, Henrik Hansen, Lóa Björk Jóelsdottir, Helena Skyt Nielsen. 2024. The male shortcut to math achievement. *SSRN Electronic Journal* **79**. . [Crossref]
7. David Autor, David Figlio, Krzysztof Karbownik, Jeffrey Roth, Melanie Wasserman. 2023. Males at the Tails: How Socioeconomic Status Shapes the Gender Gap. *The Economic Journal* **133**:656, 3136-3152. [Crossref]
8. Helena Holmlund, Helmut Rainer, Patrick Reich. 2023. All geared towards success? Cultural origins of gender gaps in student achievement. *Journal of Economic Behavior & Organization* **209**, 222-242. [Crossref]
9. Jennifer Ashlock, Miodrag Stojnic, Zeynep Tufekci. 2023. Connecting Spaces: Gender, Video Games and Computing in the Early Teens. *Sociological Perspectives* **66**:2, 201-225. [Crossref]
10. Fernando Saltiel. 2023. Multi-Dimensional Skills and Gender Differences in STEM Majors. *The Economic Journal* **133**:651, 1217-1247. [Crossref]
11. Natalie Bau, Raquel Fernández. Culture and the family 1-48. [Crossref]
12. Kathryn Markovitz. 2023. What Causes the Math Gender Gap Across Cultures?: The Critical Role of Gender Equality Index Choice. *SSRN Electronic Journal* **2**. . [Crossref]
13. Julián Messina, Anna Sanz-de-Galdeano, Anastasia Terskaya. 2023. Birds of a Feather Earn Together. Gender and Peer Effects at the Workplace. *SSRN Electronic Journal* **115**. . [Crossref]
14. Upasak Das, Karan Singhal. 2023. Solving it correctly: Prevalence and persistence of gender gap in basic mathematics in rural India. *International Journal of Educational Development* **96**, 102703. [Crossref]
15. Georg Graetz, Arizo Karimi. 2022. Gender gap variation across assessment types: Explanations and implications. *Economics of Education Review* **91**, 102313. [Crossref]
16. Alicia Adserà, Aditi Bhowmick. 2022. English Proficiency, Gender and the Occupations of Childhood Immigrants in the US. *Journal of Labor Research* **43**:3-4, 321-344. [Crossref]
17. Clelia Cascella, Julian Scott Williams, Maria Pampaka. 2022. Gender differences in mathematics outcomes at different levels of locality to inform policy and practice. *European Educational Research Journal* **21**:5, 705-731. [Crossref]
18. Lina Aldén, Emma Neuman. 2022. Culture and the gender gap in choice of major: An analysis using sibling comparisons. *Journal of Economic Behavior & Organization* **201**, 346-373. [Crossref]
19. Noelia Rivera-Garrido. 2022. Can education reduce traditional gender role attitudes?. *Economics of Education Review* **89**, 102261. [Crossref]
20. Jennifer Ashlock, Miodrag Stojnic, Zeynep Tufekci. 2022. Gender Differences in Academic Efficacy across STEM Fields. *Sociological Perspectives* **65**:3, 555-579. [Crossref]

21. Silvia Mendolia, Agne Suziedelyte, Anna Zhu. 2022. Have girls been left behind during the COVID-19 pandemic? Gender differences in pandemic effects on children's mental wellbeing. *Economics Letters* **214**, 110458. [Crossref]
22. Nuria Rodríguez-Planas, Anna Sanz-de-Galdeano, Anastasia Terskaya. 2022. Gender norms in high school: Impacts on risky behaviors from adolescence to adulthood. *Journal of Economic Behavior & Organization* **196**, 429-456. [Crossref]
23. Lina Anaya, Frank Stafford, Gema Zamarro. 2022. Gender gaps in math performance, perceived mathematical ability and college STEM education: the role of parental occupation. *Education Economics* **30**:2, 113-128. [Crossref]
24. Lin Bian. Gender Stereotypes and Education 255-275. [Crossref]
25. Rufaro Chibanda, Pitso Tsibolane, Thando Nkohla-Ramunenyiwa. Gendered Inequality on Digital Labour Platforms in the Global South: Towards a Freedom-Based Inclusion 55-68. [Crossref]
26. Yijin Shi. The Consequences of Higher Education: Gender Dilemmas in Contemporary American Female Employment 1104-1112. [Crossref]
27. Yan Song. 2021. Noncognitive skills and gender gap in test scores. *Applied Economics* **53**:29, 3423-3437. [Crossref]
28. Maryam Dilmaghani. 2021. The gender gap in competitive chess across countries: Commanding queens in command economies. *Journal of Comparative Economics* **49**:2, 425-441. [Crossref]
29. Xuan Jiang. 2021. Women in STEM: Ability, preference, and value. *Labour Economics* **70**, 101991. [Crossref]
30. Gaia Dossi, David Figlio, Paola Giuliano, Paola Sapienza. 2021. The Family Origin of the Math Gender Gap Is a White Affluent Phenomenon. *AEA Papers and Proceedings* **111**, 179-183. [Abstract] [View PDF article] [PDF with links]
31. Julie Buhl-Wiggers, Sam Jones, Rebecca Thornton. 2021. Boys lagging behind: Unpacking gender differences in academic achievement across East Africa. *International Journal of Educational Development* **83**, 102382. [Crossref]
32. Gaia Dossi, David Figlio, Paola Giuliano, Paola Sapienza. 2021. Born in the family: Preferences for boys and the gender gap in math. *Journal of Economic Behavior & Organization* **183**, 175-188. [Crossref]
33. Fengpei Wu, Xiang Su, Young Seok Ock, Zhiying Wang. 2021. Personal Credit Risk Evaluation Model of P2P Online Lending Based on AHP. *Symmetry* **13**:1, 83. [Crossref]
34. Paola Giuliano. 2020. Gender and culture. *Oxford Review of Economic Policy* **36**:4, 944-961. [Crossref]
35. Alicia Garcia Holgado, Carina S. Gonzalez-Gonzalez, Francisco Jose Garcia-Penalvo. Gender gap perceptions of computing students: a case study in two Spanish universities 1-4. [Crossref]
36. Brindusa Anghel, Núria Rodríguez-Planas, Anna Sanz-de-Galdeano. 2020. Is the math gender gap associated with gender equality? Only in low-income countries. *Economics of Education Review* **79**, 102064. [Crossref]
37. Shelly Lundberg. 2020. Educational gender gaps. *Southern Economic Journal* **87**:2, 416-439. [Crossref]
38. Z. Eylem Gevrek, Deniz Gevrek, Christian Neumeier. 2020. Explaining the gender gaps in mathematics achievement and attitudes: The role of societal gender equality. *Economics of Education Review* **76**, 101978. [Crossref]
39. Marianne Bertrand. 2020. Gender in the Twenty-First Century. *AEA Papers and Proceedings* **110**, 1-24. [Abstract] [View PDF article] [PDF with links]
40. Paola Profeta. Gender Equality and Public Policy **40**, . [Crossref]

41. Hideo Akabayashi, Kayo Nozaki, Shiho Yukawa, Wangyang Li. 2020. Gender differences in educational outcomes and the effect of family background: A comparative perspective from East Asia. *Chinese Journal of Sociology* **6**:2, 315-335. [Crossref]
42. Joseph R. Cimpian. 2020. Why Focusing on Test Metrics May Impede Gender Equity: Policy Insights. *Policy Insights from the Behavioral and Brain Sciences* **7**:1, 64-71. [Crossref]
43. Steven W. Hemelt, Matthew A. Lenard. 2020. Math acceleration in elementary school: Access and effects on student outcomes. *Economics of Education Review* **74**, 101921. [Crossref]
44. Graziella Bertocchi, Monica Bozzano. Gender Gaps in Education 1-31. [Crossref]
45. Chandan Jain. 2019. Analysing Changes in Gender Difference in Learning in Rural India over Time. *Journal of Quantitative Economics* **17**:4, 913-935. [Crossref]
46. Suzanne Duryea, Luísa Baptista de Freitas, Luana Marques-Garcia Ozemela, Breno Sampaio, Gustavo R. Sampaio, Giuseppe Trevisan. 2019. Universities and Intergenerational Social Mobility in Brazil: Examining Patterns by Race and Gender. *Journal of Economics, Race, and Policy* **2**:4, 240-256. [Crossref]
47. Sean F. Reardon, Erin M. Fahle, Demetra Kalogrides, Anne Podolsky, Rosalía C. Zárate. 2019. Gender Achievement Gaps in U.S. School Districts. *American Educational Research Journal* **56**:6, 2474-2508. [Crossref]
48. Judith M. Delaney, Paul J. Devereux. 2019. Understanding gender differences in STEM: Evidence from college applications#. *Economics of Education Review* **72**, 219-238. [Crossref]
49. Analia Schlosser, Zvika Neeman, Yigal Attali. 2019. Differential Performance in High Versus Low Stakes Tests: Evidence from the Gre Test*. *The Economic Journal* **129**:623, 2916-2948. [Crossref]
50. Eiji Yamamura. 2019. Gender wage gap and its effect on test scores of immigrant students. *Journal of Economic Studies* **46**:4, 872-887. [Crossref]
51. Mor Zahavi, Iris BenDavid-Hadar, Joseph Klein. 2019. Education and competencies within Belt and Road countries. *International Journal of Educational Management* **ahead-of-print**:ahead-of-print. . [Crossref]
52. Christophe J Nordman, Leopold R Sarr, Smriti Sharma. 2019. Skills, personality traits, and gender wage gaps: evidence from Bangladesh. *Oxford Economic Papers* **71**:3, 687-708. [Crossref]
53. Alex Bell, Raj Chetty, Xavier Jaravel, Neviana Petkova, John Van Reenen. 2019. Who Becomes an Inventor in America? The Importance of Exposure to Innovation*. *The Quarterly Journal of Economics* **134**:2, 647-713. [Crossref]
54. Brindusa Anghel, Nuria Rodriguez-Planas, Anna Sanz-de-Galdeano. 2019. Culture, Gender, and Math: A Revisitation. *SSRN Electronic Journal* **24**. . [Crossref]
55. Graziella Bertocchi, Monica Bozzano. 2019. Gender Gaps in Education. *SSRN Electronic Journal* **69**. . [Crossref]
56. Farzana Munir, Rudolf Winter-Ebmer. 2018. Decomposing international gender test score differences. *Journal for Labour Market Research* **52**:1. . [Crossref]
57. Meijuan Li, Yongmei Zhang, Hongyun Liu, Yi Hao. 2018. Gender differences in mathematics achievement in Beijing: A meta-analysis. *British Journal of Educational Psychology* **88**:4, 566-583. [Crossref]
58. Juan Sebastián Muñoz. 2018. The economics behind the math gender gap: Colombian evidence on the role of sample selection. *Journal of Development Economics* **135**, 368-391. [Crossref]
59. Victor Lavy, Edith Sand. 2018. On the origins of gender gaps in human capital: Short- and long-term consequences of teachers' biases. *Journal of Public Economics* **167**, 263-279. [Crossref]

60. Sumit Agarwal, Richard Green, Eric Rosenblatt, Vincent W. Yao, Jian Zhang. 2018. Gender difference and intra-household economic power in mortgage signing order. *Journal of Financial Intermediation* **36**, 86-100. [Crossref]

61. Quentin Lippmann, Claudia Senik. 2018. Math, girls and socialism. *Journal of Comparative Economics* **46**:3, 874-888. [Crossref]

62. Moshe Justman, Susan J. Méndez. 2018. Gendered choices of STEM subjects for matriculation are not driven by prior differences in mathematical achievement. *Economics of Education Review* **64**, 282-297. [Crossref]

63. Hanan Innabi, Hamzeh Dodeen. 2018. Gender differences in mathematics achievement in Jordan: A differential item functioning analysis of the 2015 TIMSS. *School Science and Mathematics* **118**:3-4, 127-137. [Crossref]

64. Núria Rodríguez-Planas, Natalia Nollenberger. 2018. Let the girls learn! It is not only about math … it's about gender social norms. *Economics of Education Review* **62**, 230-253. [Crossref]

65. Angela Urick. Secondary Data Analysis in the Field of Educational Leadership and Policy Studies 143-171. [Crossref]

66. Donna K. Ginther, Shulamit Kahn, Jessica McCloskey. Gender and Academics 5116-5133. [Crossref]

67. Glenn David Ellison, Ashley Swanson. 2018. Dynamics of the Gender Gap in High Math Achievement. *SSRN Electronic Journal* **30**. . [Crossref]

68. Javier D. Donna, Greg Veramendi. 2018. Gender Differences within the Firm: Evidence from Two Million Travelers. *SSRN Electronic Journal* **116**. . [Crossref]

69. Anne Gielen, Esmee Zwiers. 2018. Biology and the Gender Gap in Educational Performance: The Role of Prenatal Testosterone in Test Scores. *SSRN Electronic Journal* **25**. . [Crossref]

70. Zahide Eylem Gevrek, Christian Neumeier, Deniz Gevrek. 2018. Explaining the Gender Test Score Gap in Mathematics: The Role of Gender Inequality. *SSRN Electronic Journal* **66**. . [Crossref]

71. Deborah A. Cobb-Clark, Julie Moschion. 2017. Gender gaps in early educational achievement. *Journal of Population Economics* **30**:4, 1093-1134. [Crossref]

72. Francine D. Blau, Lawrence M. Kahn. 2017. The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature* **55**:3, 789-865. [Abstract] [View PDF article] [PDF with links]

73. Ozkan Eren. 2017. Differential Peer Effects, Student Achievement, and Student Absenteeism: Evidence From a Large-Scale Randomized Experiment. *Demography* **54**:2, 745-773. [Crossref]

74. Piotr S. Bobkowski, Sarah B. Cavanah, Patrick R. Miller. 2017. Who Are the "Journalism Kids"? Academic Predictors of Journalism Participation in Secondary Schools. *Journalism & Mass Communication Educator* **72**:1, 68-82. [Crossref]

75. Seo-Young Cho. 2017. Explaining Gender Differences in Confidence and Overconfidence in Math. *SSRN Electronic Journal* **106**. . [Crossref]

76. Natalia Nollenberger, Nuria Rodriguez-Planas. 2017. Let the Girls Learn! It is Not Only About MathãÂ¢Ã¢ÂÂ¬ÃÂ¦ it's About Gender Social Norms. *SSRN Electronic Journal* **15**. . [Crossref]

77. Renee B. Adams, Brad M. Barber, Terrance Odean. 2017. The Math Gender Gap and Women's Career Outcomes. *SSRN Electronic Journal* **2**. . [Crossref]

78. Katja Görlitz, Christina Gravert. 2016. The effects of the high school curriculum on school dropout. *Applied Economics* **48**:54, 5314-5328. [Crossref]

79. Pedro Bordalo, Katherine Coffman, Nicola Gennaioli, Andrei Shleifer. 2016. Stereotypes*. *The Quarterly Journal of Economics* **131**:4, 1753-1794. [Crossref]

80. Joseph R. Cimpian, Sarah T. Lubienski, Jennifer D. Timmer, Martha B. Makowski, Emily K. Miller. 2016. Have Gender Gaps in Math Closed? Achievement, Teacher Perceptions, and Learning Behaviors Across Two ECLS-K Cohorts. *AERA Open* **2**:4, 233285841667361. [Crossref]
81. Naomi Friedman-Sokuler, Moshe Justman. 2016. Gender streaming and prior achievement in high school science and mathematics. *Economics of Education Review* **53**, 230-253. [Crossref]
82. Ingvild Almås, Alexander W. Cappelen, Kjell G. Salvanes, Erik Ø. Sørensen, Bertil Tungodden. 2016. Willingness to Compete: Family Matters. *Management Science* **62**:8, 2149-2162. [Crossref]
83. Glenn Ellison, Ashley Swanson. 2016. Do Schools Matter for High Math Achievement? Evidence from the American Mathematics Competitions. *American Economic Review* **106**:6, 1244-1277. [Abstract] [View PDF article] [PDF with links]
84. Juanna Schrøter Joensen, Helena Skyt Nielsen. 2016. Mathematics and Gender: Heterogeneity in Causes and Consequences. *The Economic Journal* **126**:593, 1129-1163. [Crossref]
85. Natalia Nollenberger, Núria Rodríguez-Planas, Almudena Sevilla. 2016. The Math Gender Gap: The Role of Culture. *American Economic Review* **106**:5, 257-261. [Abstract] [View PDF article] [PDF with links]
86. Francesca Borgonovi. 2016. Video gaming and gender differences in digital and printed reading performance among 15-year-olds students in 26 countries. *Journal of Adolescence* **48**:1, 45-61. [Crossref]
87. Eiji Yamamura. 2016. Gender Wage Gap and Its Effect on Test Scores of Immigrant Students. *SSRN Electronic Journal* **46**. . [Crossref]
88. Moshe Justman, Susan J. Mendez. 2016. Gendered Selection of STEM Subjects for Matriculation. *SSRN Electronic Journal* **11**. . [Crossref]
89. Donna K. Ginther, Shulamit Kahn, Jessica McCloskey. Gender and Academics 1-18. [Crossref]
90. Оксана Баскаева. 2015. Самосбывающееся пророчество как результат ожиданий учителя. *Психологические исследования* **8**:43. . [Crossref]
91. David Newton, Mikhail Simutin. 2015. Of Age, Sex, and Money: Insights from Corporate Officer Compensation on the Wage Inequality Between Genders. *Management Science* **61**:10, 2355-2375. [Crossref]
92. Alexander Koch, Julia Nafziger, Helena Skyt Nielsen. 2015. Behavioral economics of education. *Journal of Economic Behavior & Organization* **115**, 3-17. [Crossref]
93. Andy Dickerson, Steven McIntosh, Christine Valente. 2015. Do the maths: An analysis of the gender gap in mathematics in Africa. *Economics of Education Review* **46**, 1-22. [Crossref]
94. Kehinde F. Ajayi, Marric Buessing. 2015. Gender Parity and Schooling Choices. *The Journal of Development Studies* **51**:5, 503-522. [Crossref]
95. Sumit Agarwal, Richard K. Green, Eric Rosenblatt, Vincent W. Yao, Jian Zhang. 2015. Who Bears the Pen? Relative Income and Gender Gap in Mortgage Signing Order. *SSRN Electronic Journal* **94**. . [Crossref]
96. Deborah A. Cobb-Clark, Julie Moschion. 2015. Gender Gaps in Early Educational Achievement. *SSRN Electronic Journal* **61**. . [Crossref]
97. Stephen J. Ceci, Donna K. Ginther, Shulamit Kahn, Wendy M. Williams. 2014. Women in Academic Science. *Psychological Science in the Public Interest* **15**:3, 75-141. [Crossref]
98. Brian Neelon, Alan E. Gelfand, Marie Lynn Miranda. 2014. A Multivariate Spatial Mixture Model for Areal Data: Examining Regional Differences in Standardized Test Scores. *Journal of the Royal Statistical Society Series C: Applied Statistics* **63**:5, 737-761. [Crossref]

99. Thomas Breda. 2014. 5. Pourquoi y a-t-il si peu de femmes en science ?. *Regards croisés sur l'économie* **n° 15**:2, 99-116. [Crossref]

100. David Newton, Mikhail Simutin. 2014. Of Age, Sex, and Money: Insights from Corporate Officer Compensation on the Wage Inequality between Genders. *SSRN Electronic Journal* **67**. . [Crossref]

101. Alexander K. Koch, Julia Nafziger, Helena Skyt Nielsen. 2014. Behavioral Economics of Education. *SSRN Electronic Journal* **40**. . [Crossref]

102. Benjamin Artz, David M. Welsch. 2014. The Effect of Peer and Professor Gender on College Student Performance. *Southern Economic Journal* **80**:3, 816-838. [Crossref]

103. Aedín Doris, Donal O'Neill, Olive Sweetman. 2013. Gender, single-sex schooling and maths achievement. *Economics of Education Review* **35**, 104-119. [Crossref]

104. Juanna Schrrter Joensen, Helena Skyt Nielsen. 2013. Math and Gender: Is Math a Route to a High-Powered Career?. *SSRN Electronic Journal* **30**. . [Crossref]

105. Muriel Niederle, Carmit Segal, Lise Vesterlund. 2013. How Costly Is Diversity? Affirmative Action in Light of Gender Differences in Competitiveness. *Management Science* **59**:1, 1-16. [Crossref]

106. Thomas E. Wei. 2012. Sticks, Stones, Words, and Broken Bones. *Educational Evaluation and Policy Analysis* **34**:4, 465-488. [Crossref]

107. Muriel Niederle, Lise Vesterlund. 2011. Gender and Competition. *Annual Review of Economics* **3**:1, 601-630. [Crossref]

108. Jayanti Owens, Douglas S. Massey. 2011. Stereotype threat and college academic performance: A latent variables approach. *Social Science Research* **40**:1, 150-166. [Crossref]