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WOMEN IN FINANCE

RENÉE B. ADAMS

TOM KIRCHMAIER

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Women in Finance[1]

Renée B. Adams
University of New South Wales, FIRN & EGGI

Tom Kirchmaier
FMG, London School of Economics

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Abstract

Across countries, banks have less gender diverse boards than other firms. Bank board diversity is particularly low in countries with greater gender gaps in PISA math scores and lower average math scores. We find similar results using state-level NAEP math scores in the United States. The influence of math scores appears to transcend standard cultural explanations. Female directors are more likely to have an MBA in banks, especially in countries with greater gender gaps in math scores.
Our results suggest that low female participation in STEM and finance fields has important consequences for corporate leadership structures in STEM and finance industries. To ensure that the best managerial talent is in charge of firms, it may not be enough to ask or mandate firms to have more women on their board. Board diversity policies may need to be adapted to industry circumstances. They may also need to be complemented by policies that ensure more equal education outcomes for girls and boys.

Our evidence suggests that differences in educational outcomes for boys and girls may have long-lasting implications for their career development.

Keywords: Mathematics; Gender Gaps; Finance; Banks; STEM; Board; Diversity; Growth; PISA; NAEP
JEL Codes: J16; J22; G34; G38

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"In this regard, it is striking how closely the broader gender patterns in later career and occupational choices are already mirrored in the mathematics performance of 15-year-old males and females as observed by PISA." OECD (2004, p. 97)

I. Introduction

In this report, we demonstrate systematic evidence that across countries boardroom gender diversity is lower in financial firms, particularly banks, than in other firms. Since the facility for math is important in finance and our research has discovered that there are gender gap in math test scores across countries that has persisted over time, we hypothesize that real or perceived differences in math outcomes by gender may be one explanation for lack of women on the boards of financial firms. Our evidence is consistent with this hypothesis.

Gender gaps in math scores have been documented in the OECD's Program for International Student Assessment (PISA) test, the Trends in International Mathematics and Science Study (TIMSS), the National Assessment of Education Progress (NAEP), the Early Childhood Longitudinal Study Kindergarten Cohort (ECLS-K), Standard Aptitude Test (SAT) scores and the American Mathematics Competition, amongst others.[2] While some argue that mean gender gaps are narrowing over time (e.g. Else-Quest, Hyde and Linn, 2010), the gaps are remarkably persistent—especially at the right tail of the distribution (e.g. Ellison and Swanson, 2010; Wai et al., 2010).

Ellison and Swanson (2010) and Wai et al. (2010) argue, along with many others, that these persistent gender differences in math outcomes may explain why women are relatively underrepresented in STEM fields. Reuben, Sapienza and Zingales (2014) provide experimental evidence that stereotypes concerning women's ability to do math may affect their entry into science fields.

If fewer women enter STEM fields, presumably fewer women also hold corporate leadership positions in these fields. Adams and Kirchmaier (2016) provide evidence consistent with this argument. In their sample, firm-level board diversity is 1.8% lower in STEM industries than in other industries. This suggests that differences in math outcomes may affect not only women's entry into STEM fields, but also their likelihood of attaining a corporate leadership position in those fields.

Although finance is not always considered a STEM industry, Phillipon and Reshef (2012) document that, relative to the rest of the nonfarm private sector, occupations in finance score relatively high on math aptitude. Thus we posit that gender differences in math outcomes may help explain why few women hold directorship positions in the finance industry.

To provide some suggestive evidence that the relationship between gender and math is different in the finance industry, we use data on occupational skill intensity by industry and gender from Autor, Levy and Murnane (2003). We first confirm Philippon and Reshef's (2012) finding that the finance industry is

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[2] See e.g. OECD (2015), Mullis et al. (2000), U.S. Department of Education (2013), Fryer, Jr. and Levitt (2010), Wai, et al. (2010) and Ellison and Swanson (2010).

math intensive as compared to other industries. We then show that the average math intensity of women's occupations is lower than that of men's occupations, but particularly so in the finance industry.

One may argue that gender gaps in math may not be relevant in more senior positions. However, we find that the math intensity of women's occupations in finance is lower even if we restrict the sample to college educated workers. In addition, gender gaps in math skills generally do not disappear for managerial and professional occupations, but other gender gaps do. For example, the percent difference between men and women in "direction control and planning"—a measure of non-routine cognitive skills—is only 0.25% relative to the mean for these occupations, but the gender gap in math skills is still 2.6% relative to the mean.

While suggestive, the patterns in the occupational skill data do not provide direct evidence that math outcomes for women are relevant for their career advancement. To examine this more directly, we relate math scores and gender gaps in math scores to women's representation on boards of financial and non-financial firms across countries. We focus on boards because attaining data on lower levels of the corporate hierarchy is extremely difficult. Since women and men can only attain a board position if they have been in the work force long enough, the attainment of a board position represents our measure of career advancement.

To measure math outcomes across countries, we first use the PISA survey of 15 year-olds in OECD and partner countries. According to the OECD (2010), PISA is the most comprehensive and rigorous international program to assess student educational performance. The first PISA survey was carried out in 2000, followed by surveys in 2003, 2006, 2009 and 2012. We use the average national PISA math scores and the difference in average math scores between boys and girls, the 'gender gap', from the 2009 survey because it covers the most countries in our sample period.

The 2009 PISA scores are not direct measures of directors' own math outcomes as teenagers. The average age of our directors is 58, which means they were 15 in the period 1958-1967. This is exactly the period during which the International Association for the Evaluation of Educational Achievement (IEA) developed the first test to compare student performance across countries. The IEA carried out the First International Mathematics Study (FIMS) in 1964 but only 11 countries participated.[3] The number of countries (according to current definitions) did not increase substantially until the Third International Mathematics and Science Study (TIMSS) in 1995.[4, 5]

We examine the robustness of our results using Altinok, Diebolt and Demeulemeester (ADD) (2014)'s compilation of FIMS and subsequent tests between 1965 and 2010 as well as time series data on NAEP scores for the U.S.. The timing of the ADD scores might make them intuitively more appealing as

[3] Australia, Belgium, England, Finland, France, Germany (FRG), Israel, Japan, Netherlands, Scotland, Sweden, and United States.

[4] The Second International Mathematics Study (SIMS) surveyed Belgium (Flemish), Belgium (French), Canada (British Columbia and Ontario), England and Wales, Finland, France, Hong Kong, Hungary, Israel, Japan, Luxembourg, Netherlands, New Zealand, Nigeria, Scotland, Swaziland, Sweden, Thailand, and United States.

[5] Hanushek and Woessmann (2008) provide more information on the availability of cross-country test scores.

direct proxies of directors' math outcomes. However, the ADD data suffers from limited coverage prior to 1995. We believe the 2009 PISA scores are still of interest for two reasons.

First, using NAEP scores for the U.S. we confirm that gender gaps in math scores are extremely persistent (see also Fryer, Jr. and Levitt, 2010; College Board, 2011). Assuming that this is also the case outside the U.S., current math outcomes can be considered to be reasonable proxies for past math outcomes.

Second, the literature on gender gaps in math scores argues that math scores are driven in part by factors unrelated to intrinsic ability, such as stereotypes and societal factors (Nosek et al., 2009; Fryer, Jr. and Levitt, 2010) or culture (e.g. Guiso, Monte, Sapienza, Zingales, 2008; Hyde and Mertz, 2009). To the extent this is true, the 2009 PISA scores should contain information about contemporaneous stereotypes concerning women's ability to do math. These perceptions may influence both a board's decision to appoint a woman during the time of our sample as well as a woman's decision to join the board of a financial firm with the responsibility of overseeing a business dealing in often complex financial instruments. Since the release of the PISA scores is accompanied by extensive media coverage (e.g. Stack, 2007; Breaksprear, 2012; Wiseman, 2013), contemporaneous PISA scores may also reinforce beliefs concerning women's ability to do math (as e.g. Nosek et al., 2009 argue in the context of TIMSS).

Using BoardEx data across countries for the period 2001-2010, we find that more women are on bank boards in countries with above sample median PISA math scores and below median PISA math gaps. The results are similar when we use 1965 math scores from ADD. Banks also have greater board diversity in countries in which a higher percentage of girls score at Level 6—the highest level in PISA.

As Hanushek and Kimko (2000) and Hanushek and Woesserman (2008; 2012) point out, it is difficult to establish causality when examining measures of educational quality at the country level due to the limited number of available cross-sectional observations. Identification is further complicated in our context by the fact that math gender gaps are extremely persistent over time. But the mere fact that gender gaps are persistent suggests to us that reverse causality may not be a major concern. It also seems implausible to us that girls would do better on tests if they knew more women sat on the boards of banks. However, endogeneity due to omitted country level-characteristics is a concern. For example, gender gaps in math outcomes may reflect underlying cultural factors related to gender equality (e.g. Guiso, Monte, Sapienza, Zingales, 2008; Hyde and Mertz, 2009).

To address concerns about omitted variables we use three approaches. First, we include country-level variables related to gender equality in the specifications using PISA scores. In our analysis using ADD's database, we include country fixed effects. Second, we use a variation of Hanushek and Kimko's (2000) method of dealing with omitted country-level factors by restricting our sample to U.S. states (see also Adams and Kirchmaier, 2015).

The fixed effects methodology involves including dummy variables for each country in the regression. This essentially controls for time invariant unobserved heterogeneity, that is unobserved differences between countries that are constant over time which could be correlated with board diversity. Such differences could include cultural, political or demographic differences, providing these do not change within each country over the time period analysed. Failing to control for these factors leads to a biased estimate through omitting variables which are potentially related to board diversity. Time fixed effects are also included to control for factors which change across time but not across country, for example global economic conditions. The inclusion of both country and time fixed effects attempts to ensure that variables of interest in the regression do not appear significant simply because they are correlated with unobserved country or time specific factors that influence board diversity.

Hanushek and Kimko (2000) examine educational quality in the U.S. to abstract from variation in labor markets across countries. By repeating our analyses using state-level NAEP math scores, we can similarly restrict ourselves to a more homogenous institutional and cultural environment than in the cross-country sample. Although directors generally need not come from the same state as the firm on whose board they sit, banks are subject to regulatory residency requirements for their directors (Adams, 2010). In a sample of large U.S. bank holding companies (BHCs), Adams (2010) documents that 36.8 percent of nonexecutive directors work in the same city as the BHC and 61.2 percent work within 101 miles of the BHC. This suggests that state-level institutional and cultural characteristics may be particularly important for banks. Because there is some variation in NAEP scores over time, we can also include state fixed effects in our U.S.-level analysis.

Finally, we provide complementary evidence supporting the idea that educational outcomes are related to board composition. Female directors of banks are more likely to hold MBAs than female directors on average. This relationship is stronger in countries with greater gender gaps in math scores. This suggests that the external certification of financial knowledge that an MBA presumably conveys is more important in countries in which stereotypes about women’s ability to do math, and hence finance, might be greater. We demonstrate that math scores are also related to women’s representation on boards in other math-intensive sectors.

Given the important role the finance industry plays in economic growth (Levine, 2005; Beck, 2012), distortions in the allocation of talent to the management of financial firms can be costly to society. If women are relatively underrepresented on the boards of financial firms, we believe it is important to understand why. More generally, we connect two policy debates that are usually conducted separately: the debate about women’s underrepresentation in math-intensive or STEM fields and the debate about women’s underrepresentation on corporate boards. Our results suggest that low female participation in STEM and finance fields has important consequences for corporate leadership structures in STEM and finance industries.

Current board diversity policies are blanket policies that apply to all firms with (potentially) some concessions to firm size. To ensure that the best managerial talent is in charge of firms, it may not be enough to ask or mandate firms to have more women on their board. Board diversity policies may need to be adapted to industry circumstances. They may also need to be complemented by policies that ensure more equal education outcomes for girls and boys. For example, Ellison and Swanson (2010) suggest increasing the number of schools that allow for elite mathematical training could help narrow the gender gap in math outcomes. It may also be useful to consider whether the media attention focused on test scores is harmful (e.g. Jacobs and Eccles, 1985) and whether there are ways of moderating its impact.

II. Data

A. Data Sources and Measurement

International Sample. Our starting sample consists of the entire BoardEx database from 2000-2011 as of September 2011. BoardEx contains data on boards and directors of publicly traded companies in over 90 countries. BoardEx provides age, gender and some education data for board members, as well as information about their current and past board positions, including the company's name and director tenure at each position.

From this sample, we exclude investment companies and real estate companies. Directors of investment companies typically sit on boards of subsidiaries. These subsidiary directorships are reported the same as regular directorships even though they are not comparable to corporate directorships. As a result, the average director of an investment company has 10.9 directorships with a maximum of 50, while a typical bank director will have on average 1.79 directorships with a maximum of 10. We exclude real estate companies because they are often organized as investment companies.

The board level variables are aggregated up from BoardEx's individual director level data. The dataset is complete with respect to gender and non-executive director (NED) and executive director (ED) classifications. We also have suffix data that we use to code a dummy that is equal to one if a director has an MBA or a CFA degree. If suffix data is missing for a director, this dummy is set to missing.

In countries with a dual board system (Austria, Germany, Denmark, Netherlands), we classify supervisory board members as NEDs and management board members as EDs. Board size is the sum of the sizes of the supervisory and management boards. Board independence is the number of NEDs divided by board size.

Board gender diversity is the number of women on the board divided by board size. We also use a country-level measure of board gender diversity in banking, director participation (in banking), which is the fraction of unique women in the population of unique directors in banking in a country and year.

Our financial data is from CapitalIQ. We merge NAICS codes in CapitalIQ with Adams and Kirchmaier's (2016) supersector definition to classify firms into 10 industry super sectors as in Bureau of Labor Statistics (2015). Within the finance super sector, we classify banks as firms with a banking license following Ferreira et al. (2010); we use BoardEx industry classifications to define other types of financial firms.

We obtain country-level data on labor market participation, the number of full- and part-time employees, the gross national income per capita and tax, the birthrate and tax and social security contributions over income and the fraction of women in higher education from Euromonitor. Female Fulltime Economic Participation is defined as the ratio of women in full-time employment over all full time employed. Ideally, we would like to measure country level conditions affecting a director's career trajectories at the time when they are likely to matter the most, i.e. near the beginning of their careers. As the international coverage of economic indicators is poor in the 1980s, a 10-year lag is the natural limit for most of these variables.

Data on board diversity quotas for state-owned companies, and corporate governance codes that recommend increases in diversity and co-determination laws are from Table I in Adams and Kirchmaier (2015). We do not examine the effect of corporate board quotas as too few countries passed them during our sample period. In our regressions Codetermination is a time-invariant dummy if employees have the right to board representation in a country. Corporate Governance Code is a dummy variable that is defined to be one for a country with a code mentioning gender diversity in all years after it was introduced and zero otherwise. Quota for state-owned companies is a dummy variable that is defined to be one for a country with a board diversity quota for state-owned companies in all years after it was introduced and zero otherwise.

We follow Guiso et al. (2008) and use the World Economic Forum's Corporate Gender Gap Index (Hausman, Tyson and Zahidi, 2010) as a measure of gender culture. The GGI is larger in countries in which the World Economic Forum perceives women to be more equal to men. Since the coverage of the GGI varies over time, using each country's average yearly GGI score between 2006 and 2010 to prevent countries from dropping out of our sample in some years.

The Inglehart and Welzel's (2005) Traditional/Secular and Survival/Self-Expression value scores from the World Value Survey are used as measures of culture. Inglehart and Welzel (2005) argue that the Traditional/Secular value dimension reflects the contrast between societies in which religion is very important and those in which it is not. We expect more traditional countries with lower scores on the Traditional/Secular value dimension to have lower representation of women on boards. Inglehart and Welzel (2005) link the Survival/Self-Expression value dimension to the transition from industrial society to post-industrial societies which emphasize subjective well-being, self-expression and the quality of life. Because work is one way in which self-expression can occur, we predict that more women will sit on boards in countries with more self-expression values, i.e. higher scores on the Survival/Self-Expression value dimension.[6]

The 2009 PISA scores are from OECD (2010).[7] The PISA tests survey 15 year-olds regardless of the grade they are in. They are designed to test applied knowledge. Because PISA and other tests such as TIMSS have been criticized as potentially biased (e.g. Carnoy and Rothstein, 2013), we transform the PISA scores into indicator variables. Our measure of math score levels is a dummy variable that is equal to one if the country has math scores above the median in our sample. Our measure of math gender gaps is a dummy variable that is equal to one if the country has gender gaps in math scores (scores of boys-scores of girls) above the median in our sample. PISA classifies math scores into 6 different levels from most basic, routine skills (Level 1) to complex, conceptual skills (Level 6). From OECD (2010), we also obtain data on the percentage of boys and girls that score in Level 6 in each country.

We obtain the Altinok, Diebolt and Demeulemeester (ADD) (2014) database directly from the authors. ADD standardize the results of various international education assessment programs including the IEA studies (FIMS, SIMS and TIMSS) and PISA studies to construct a panel database (with gaps) of educational quality measures from 1965-2010. While other similar databases of educational quality exist (e.g. Hanushek and Woessman, 2012 and Angrist, Patrinos, and Schlotter, 2013), the ADD database is the only database we are aware of that disaggregates math scores by gender. We use the 8th grade scores by gender from this database.

After merging Boardex to financial data, country data and math scores, we end with a sample that contains data on 53 countries. Because Boardex's coverage is poor for many countries in most years, we focus most of our analysis on a subsample of countries for which Boardex has good enough coverage that our data can be considered to be representative of the population of listed firms in those countries. We construct this data set following Adams and Kirchmaier (2015). To ensure BoardEx's coverage can be considered to be representative by restricting the full sample to those country-year observations for which BoardEx covers at least 70% of market capitalization according to CapitalIQ. We also require both CapitalIQ and BoardEx to cover at least 10 listed companies per country-year and a country to appear more than one year in the sample. The year 2000 is dropped due to its low coverage, and the year 2011 is dropped as it is incomplete. Norway and India are dropped because they are likely to be outliers when it comes to gender equality. Norway passed gender quota legislation towards the beginning of our sample period and India ranks the lowest on the GGI among the countries with good coverage in Boardex. We end with a sample of 8,353 firms in 19 countries: Australia, Austria, Belgium, Canada, Denmark, Finland,

[6] The advantage of using these scores rather than individual items from the WVS is that they account for multiple dimensions of culture. Inglehart and Welzel (2005) document that these dimensions explain over 70 percent of the cross-cultural variance of more specific value scores in the WVS. Moreover, the country-level coverage of these scores is more complete than for individual items in the WVS.

[7] Our results are also robust to using the 1995 TIMSS scores. The PISA and the TIMSS test slightly different skills. TIMSS surveys 8th graders regardless of their age. While PISA tests applied knowledge, the TIMSS focuses on aspects of the curriculum. Nevertheless, as Hanushek and Woessmann (2008) discuss, the PISA and TIMSS scores from roughly the same years are highly correlated at the country level.

France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, Switzerland, United Kingdom and the U.S.

Banks comprise 40.84% (678 banks; 4,219 bank-year observations) of financial firms in the representative sample; insurance companies comprise 12.04% (200 firms) and specialty finance and investment companies comprise 19.51% (324 firms) and 26.08% (433 firms) respectively for our sample of firms in these 19 countries. Appendix Table A.I provides details on the number of banks in each country-year in the representative sample. For the sake of brevity, we do not provide the corresponding numbers for financial firms. They are available upon request. The Appendix (Table A.II) also provides details on international math scores for this sample.

In our analyses, we use log (book assets) as a proxy for size (see e.g. Adrian and Shin, 2010).[8] Since banks tend to be much larger than non-financial firms, we also use an asset-matched subsample of our representative sample to reduce the effect of firm size on our results. Stata's propensity score command psmatch2 is used to match banks to non-financial firms. And we match on log (book assets), country and year with replacement.

U.S. sample. In Section V, we mirror our cross-country analysis as much as possible after restricting our sample to the US. We identify company headquarter locations in each year using McDonald and Yun's 1994-2010 10-K Header's data.[9] State level GDP/capita data is from the US Bureau of Economic Analysis. GDP/Capita is lagged by 15 years.

From NAEP national math test scores for 17 year olds between 1978 and 2012 are extracted and state-level math test scores for 8th graders by gender from 1990 (the first year state scores for 8th graders are reported separately by gender), 1992 and 1996. Yearly data on state-level math SAT scores by gender from 1995 (the first year state scores are reported separately by gender) until 2014 are from the College Board.

The files containing distributions of task intensities by gender for various years came from Autor, Levy and Murnane (2003). One set of files contains task intensities by industry, education and gender; the other set contains data on occupation by gender. The task intensities come from the Department of Labor's Dictionary of Occupational Titles (DOT) which characterizes each occupation in terms of a variety of ordinal task intensities coded between 1 (lowest) to 10 (highest). Autor, Levy and Murnane merge a subset of these task intensities from the 1977 and the 1991 DOT to Census data at various years between 1960 and 1998 and average them at the occupation level for all non-institutionalized, employed workers, ages 18 to 64 using full-time equivalent hours as weights. Autor, Levy and Murnane then average the task intensities at the industry level and at the industry-gender-education level using full-time

[8] Our base currency for assets as well as all other accounting variables is the US Dollar (USD). All non-USD denominated values were converted into USD at market exchange rates on the disclosure day. We do not correct assets for inflation since we use the log of assets in the regressions and year dummies capture the effects of inflation.

[9] http://www3.nd.edu/~mcdonald/10-K_Headers/10-K_Headers.html.

equivalent hours as weights. Gender differences in task intensities arise because of different distributions of women and men across occupations and industries.

Autor, Levy and Murnane's (2003) data contains mean task intensities for two routine manual skills (finger dexterity and set limits, tolerances), one non-routine manual skill (eye, hand, foot coordination) and two non-routine, cognitive skills (direction, control and planning and GED-math). Direction, control and planning is a measure of interactive, communication, and managerial skills. GED-math stands for "general educational development in math" and measures the quantitative reasoning requirements of an occupation.

To examine gender differences in task intensities in finance and among managers, we create two files out of Autor, Levy and Murnane's data. One is an industry-level data set that consists of the DOT 91 industry file appended to the DOT 77 industry file. The other is the union of six files for different time periods 1970s, 1960-1970, 1980-1990 and different DOT classifications (DOT 77 and DOT 91). Using 1990 Census industry classification codes and Autor, Levy and Murnane's consistent industry code (ind6090) between 1960 and 1990, we classify industries as belonging to 12 industry sectors: finance, agriculture, mining, manufacturing, transportation, wholesale, retail, personal services, business services, entertainment, professional services and public administration. We define finance as containing banking, credit agencies, savings and loan associations (ind6090=706); security, commodity brokerage, and investment companies (ind6090==710) and insurance (ind6090==711).

Using Census occupation classification codes for the years 1960 for the 1960-1970 data, 1970 for the 1970 date and 1980 for the 1980-1990 data, we classify occupations into 13 broad occupational categories: professionals, managers, sales, clerical workers, craftsmen, operatives, laborers, farmers, farm laborers, service workers, technicians, household service workers and unreported occupations. We code managerial and professional occupations as having occupation codes less than or equal to 290, excluding 200 and 222 in the 1960-1970 data, codes less than or equal to 245 in the 1970 data and less than or equal to 200 in the 1980-1990 data.

B. Summary Statistics

For the sake of brevity, we provide summary statistics for the representative sample only in Table I. Summary statistics for the bigger sample are available upon request. Panel A shows summary statistics for country-level variables except for the policy dummies. Panel B provides summary statistics for firm-level data. Panel C provides summary statistics for U.S. state-level data. Panel D provides summary statistics for director-level data in the matched sample. Panel E contains summary statistics for Autor, Levy and Murnane's data.

Table I - Panel B: Summary Statistics – Firm-level Data

This table summarizes the firm level variables in our dataset. Assets in column (1) is the book value of total assets (in billions of USD), for non-US firms converted into USD at market prices at the end of the reporting period. Board size (2) is the number of directors on the board for a given firm and year. Column (3) exhibits Boardroom Diversity measured as the number of women over board size, while Independence in (4) is the ratio of independent outside directors over board size. Column (5) and (6) depicts the fraction of board members that have managerial or top Management Experience in Banking, and Outside Director Experience in Banking respectively. State Ownership (7) is a dummy indicating whether the state owns any stake in the firm, and Tenure (8) indicates the average tenure of outside, or non-executive, directors in years. Data on directors is from BoardEx, ownership data from FactSet. (9) ROE is the return on equity, calculated as the fraction of net income over total common equity, and truncated at -1, (10) to (16) are indicator variables for the various types of the financial industry, (17) is an indicator variable if the firm is domiciled in the United States, (18) to (20) indicate the fraction of those in the various regions of the US.

		Obs	Mean	Std. Dev	Min	Max
Assets (USD)	(1)	51,636	12,295	97,990	0.000	3,658,609
- Banks	(1a)	4,213	79,144	297,504	0.000	3,658,609
- Non-bank financials	(1b)	3,152	42,829	163,782	0.030	3,221,972
- Non-financials	(1c)	41,803	4,039	18,441	0.000	797,769
- Matched (non-fin.)	(1d)	3,201	13,770	49,924	0.380	797,769
Boardsize	(2)	52,361	8.244	3.673	1	34
Diversity (Perc. Women)	(3)	52,361	0.074	0.101	0	1
- Banks	(3a)	4,266	0.095	0.091	0	0.600
- Non-bank financials	(3b)	3,188	0.079	0.103	0	0.667
- Non-financials	(3c)	42,385	0.073	0.104	0	1.000
- Matched (non-fin.)	(3d)	3,201	0.094	0.097	0	0.600
Independence	(4)	52,361	0.571	0.282	0	1
Tenure	(5)	51,179	6.302	4.059	0.000	43.900
ROE	(6)	48,664	0.131	0.555	-1.000	4.038
Financials	(7)	52,361	0.207	0.405	0	1
Non-bank Financials	(8)	52,361	0.127	0.333	0	1
Banks	(9)	52,361	0.081	0.272	0	1
Insurance	(10)	52,361	0.024	0.154	0	1
Life Assurance	(11)	52,361	0.003	0.056	0	1
Private Equity	(12)	52,361	0.000	0.020	0	1
Speciality Finance	(13)	52,361	0.032	0.177	0	1
USA	(14)	52,361	0.557	0.497	0	1
Southern States	(15)	29,256	0.215	0.411	0	1
West Coast	(16)	29,256	0.411	0.492	0	1
East Coast	(17)	29,256	0.198	0.398	0	1

Table I - Panel C: Summary Statistics – US State Level

This table shows the SAT math levels, stratified gap measured as the gender difference (male-female) of the lagged state level SAT score, and an interaction effect between math gap and the bank indicator variable. Math gap (relative) is the above math gap relative to the general math level in that state and year, followed by lagged and interpolated NAEP scores and gaps, State level GDP / capita, and the indicator variable for Southern, as well as for East and West Coast states.

Variable		Obs.	Mean	Std. Dev.	Min	Max
SAT Male Score	(1)	357	551.686	35.479	489	637
SAT Female Score	(2)	357	515.045	33.273	449	587
SAT Gender Math Gap	(3)	357	36.641	6.062	18	64
NAEP State Score	(4)	357	268.296	10.258	231	284
NAEP State Gap	(5)	357	2.155	2.943	-6.800	14.230
GDP / Capita (lagged)	(6)	357	27,317	9,732	17,058	87,044
Southern States	(7)	51	0.235	0.428	0	1
West Coast	(8)	51	0.333	0.476	0	1
East Coast	(9)	51	0.098	0.300	0	1

Table I - Panel D: Summary Statistics – Director-level Data

This table shows the director level data for a panel of matched firms that corresponds to Table XI. (1) MBA degree is an indicator variable if the director has a MBA degree, (2) & (3) indicate whether a director is a non-executive/outside director (NED) or executive director ED respectively, (4) indicates if a director is female, (5) if a director is independent, and (6) shows the age of a director, (7) indicates whether the firm on which board the director sits on is US based, and (8) whether it is a bank.

Variable		Obs.	Mean	Std. Dev.	Min	Max
MBA Degree	(1)	431,823	0.181	0.385	0	1
NED	(2)	431,823	0.761	0.426	0	1
ED	(3)	431,823	0.239	0.426	0	1
Female	(4)	431,823	0.082	0.274	0	1
Independence	(5)	431,823	0.579	0.494	0	1
Age	(6)	408,167	58.036	9.731	19	100
USA	(7)	431,823	0.542	0.498	0	1
Bank	(8)	431,823	0.073	0.259	0	1

Table I - Panel E: Summary Statistics – Task Intensity Data

The data from Autor, Levy and Murnane (2003) who match occupational task intensities from the 1977 and 1991 Dictionary of Occupational Titles to Census data from various years between 1960 and 1998 and average them at the occupation level for all noninstitutionalized, employed workers, ages 18 to 64 using full-time equivalent hours as weights. Autor, Levy and Murnane also average the task intensities at the industry level and at the industry-gender-education level using full-time equivalent hours as weights. Gender differences in task intensities arise because of different distributions of women and men across occupations and industries. Autor, Levy and Murnane's (2003) data contains mean task intensities for two routine manual skills (finger dexterity and set limits, tolerances), one non-routine manual skill (eye, hand, foot coordination) and two non-routine, cognitive skills (direction, control and planning and GED-math). Direction, control and planning is a measure of interactive, communication, and managerial skills. GED-math stands for "general educational development in math" and measures the quantitative reasoning requirements of an occupation. We construct two files from Autor, Levy and Murnane's (2003) data. One is an industry-level data set that consists of the DOT 91 industry file appended to the DOT 77 industry file. The other is the union of six files for different time periods 1970s, 1960-1970, 1980-1990 and different DOT classifications (DOT 77 and DOT 91). We classify industries as belonging to 12 industry sectors, finance, agriculture, mining, manufacturing, transportation, wholesale, retail, personal services, business services, entertainment, professional services and public administration using 1990 Census industry classification codes and Autor, Levy and Murnane's consistent industry code (ind6090) between 1960 and 1990. We define finance as containing banking, credit agencies, savings and loan associations (ind6090=706); security, commodity brokerage, and investment companies (ind6090==710) and insurance (ind6090==711). We classify occupations into 13 broad occupational categories, professionals, managers, sales, clerical workers, craftsmen, operatives, laborers, farmers, farm laborers, service workers, technicians, household service workers and unreported occupations, using Census occupation classification codes for the years 1960 for the 1960-1970 data, 1970 for the 1970 date and 1980 for the 1980-1990 data. We code managerial and professional occupations as having occupation codes less than or equal to 290, excluding 200 and 222 in the 1960-1970 data, codes less than or equal to 245 in the 1970 data and less than or equal to 200 in the 1980-1990 data. Summary statistics in industry-level data are for all education categories and both genders.

Variable	Obs	Mean	Std. Dev.	Min	Max
			Industry-level data		
Finger dexterity	2,550	3.831	0.500	2.585	6.433
Set Limits, Tolerances	2,550	4.744	1.757	0.314	9.685
Eye-Hand-Foot	2,550	1.201	0.678	0.032	4.472
Direction, Control and Planning	2,550	2.320	0.959	0.062	7.739
GED-math	2,550	3.510	0.845	1.021	6.914
Finance dummy	2,550	0.021	0.144	0	1
			Occupational-level data		
Direction, Control and Planning	4,408	2.299	3.390	0	10
GED-math	4,408	3.772	2.356	0	10
Manager and Professional Occupations	4,408	0.379	0.485	0	1

As the summary statistics demonstrate, banks are on average substantially larger, as measured by log(assets), than other types of firms—even the matched non-financials. Mean bank assets are 79,144 billion, mean non-bank financial assets are 42,829 billion; mean non-financial assets are 4,039 billion and mean matched non-financial assets are 13,770 billion. Across countries, average board diversity is 7.4%. It is 9.5% for banks, 7.9% for non-bank financials, 7.3% for non-financials and 9.4% for matched non-financials. Table A.III shows mean board diversity for our sample banks in each year.

Figure I – Trends in Math Scores by Gender and Math Gender Gaps

The Figures depict average scores in Mathematics by level per gender and the gender gap (male-female) over time using different math tests.

Figure I - Panel A: Altinok, Diebolt and Demeulemeester (ADD) Cross-Country Data

This panel shows the results of the Altinok, Diebolt and Demeulemeester's (2014) compilation of FIMS and subsequent tests from 1995-2012. The results are not lagged. Math score for male and females show the average secondary school math skills across 18 countries, with gap indicating the difference between male and female in secondary math skills. Min and max show the minimum and maximum math skill gap per country and year of assessment.

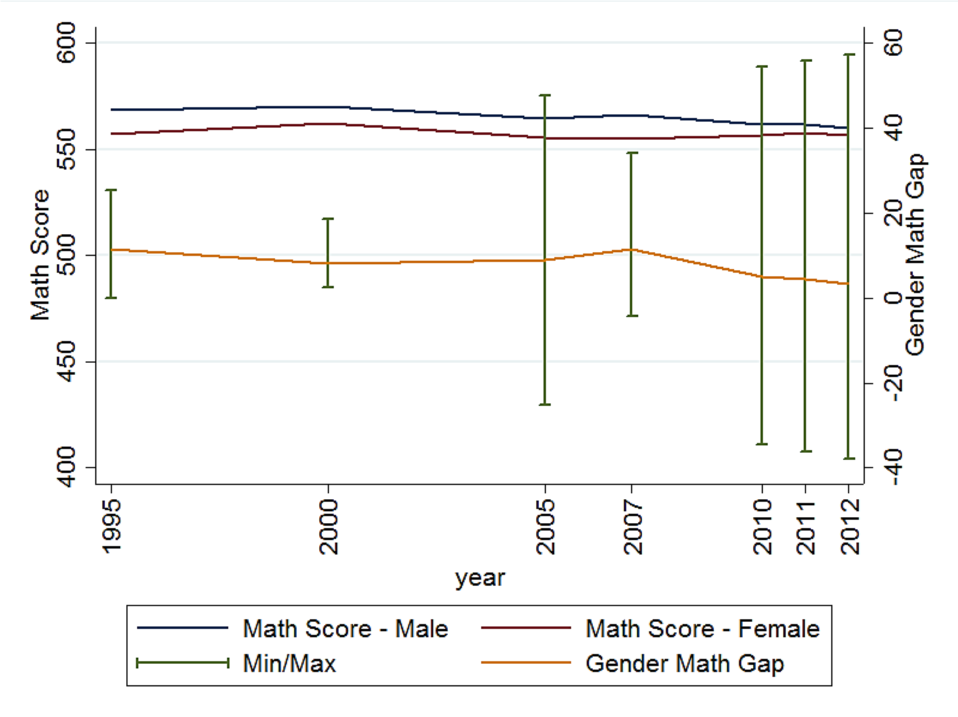


Figure I – Panel B: State-level NAEP Data

The Figure depicts the average state-level secondary math skills in Mathematics by gender, and the gender gap (calculated as male – female) over time. The results are shown as is, hence not lagged. Min and max shows the minimum and maximum gender gap per year of assessment across all U.S. states.

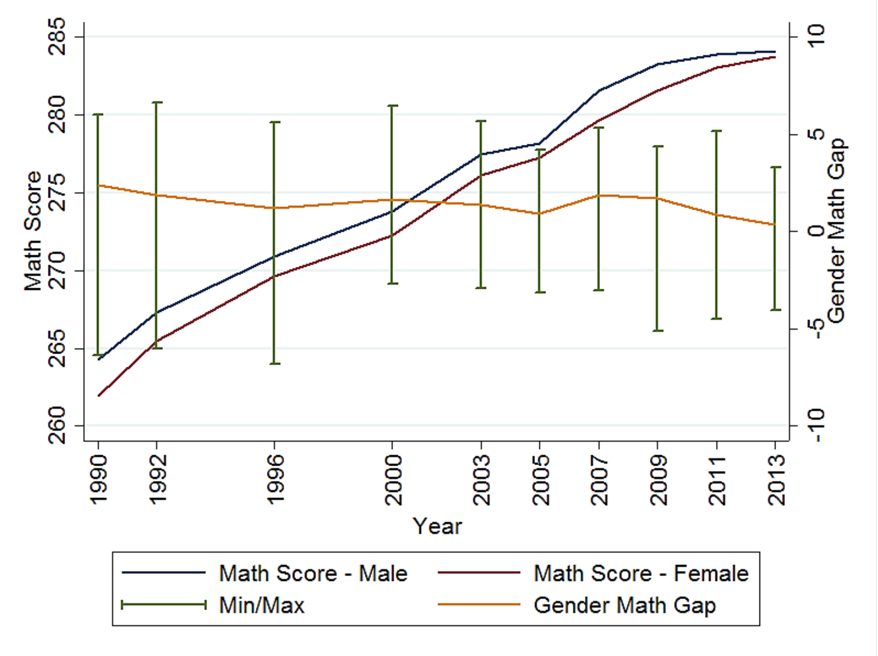


Figure I-Panel C: National NAEP Data

The Figure depicts the U.S. national average scores for long-term trend mathematics, age 17 by level and the gender gap. As it shows the national average, it is available for longer than the individual state scores.

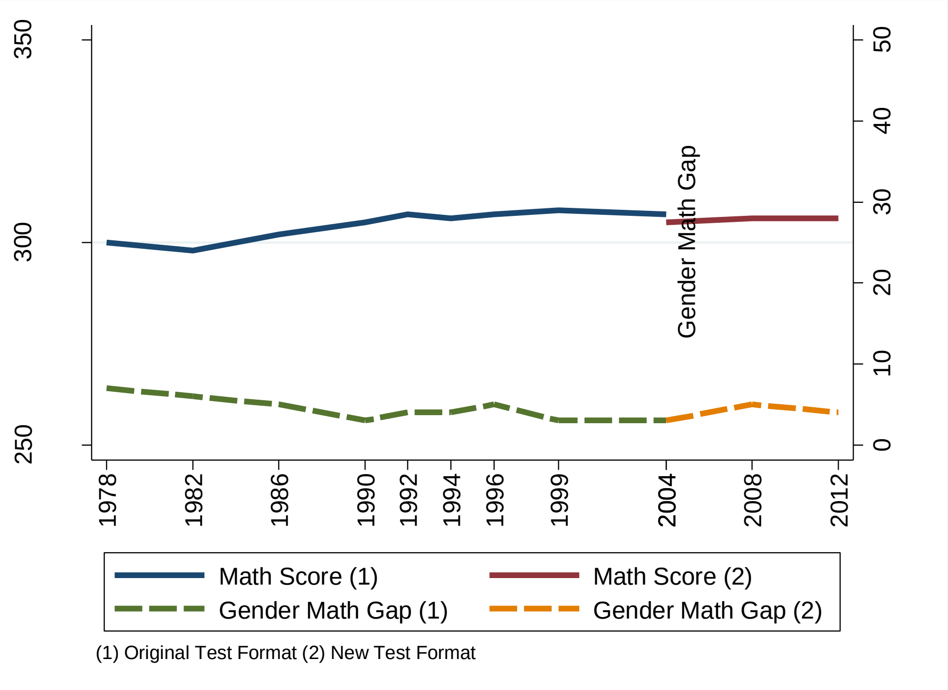
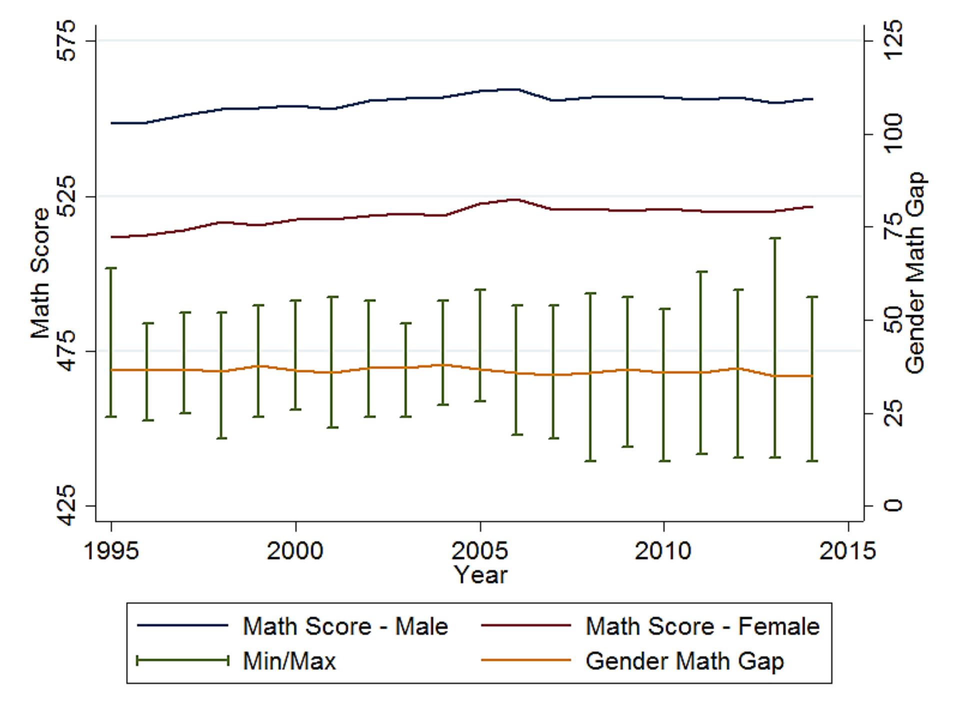


Figure I-Panel D: State-level SAT Data

The Figure depicts the average SAT scores in Mathematics by level per gender, and the gender gap in SAT scores over time. SAT scores are available per state, and for every year since 1995. The results are not lagged. Minimum and maximum indicate the extremes of the gender gap, across all 50 states.



Median math scores and gaps in our representative sample are 496.5 and 16. These are both slightly higher than in the full sample of PISA countries. If we exclude China and the UAE from the full sample because scores are only calculated for Hong Kong, Macau, Shanghai and Taipei for China and Dubai for the UAE, there are 59 countries with PISA scores in 2009. The median scores and gaps are 483 and 9 in this sample. The fact that the median gap is higher in our representative sample suggests that the correlation between levels and gaps is not very high. In the full sample it is 0.246; in our sample it is -0.092.

We summarize our math data graphically to illustrate the persistence of math gender gaps in our sample countries. Panel A of Figure I shows linearly interpolated math scores by gender (left axis) and the gender gap (right axis) for 8th grade ADD math scores for the countries in our representative sample from 1995 to 2012. We restrict the data to this time period to eliminate the effect of entry into the sample. Prior to 1995 the average number of countries in our representative sample with available math scores is 4.5. In 1995, 16 countries in our representative sample have math scores. By 2000, they all do. To give a sense of the distribution of the gender gaps, we plot a line connecting the minimum and maximum country-level gender gaps for each year test scores are available. Panel A shows that the scores and the gender gap are quite flat over time, especially in the early part of the sample. While the magnitude of the mean gender gaps is not large, the dispersion of gaps is wide. Furthermore, the dispersion is not narrowing over time. The dispersion is similar even if we focus on the 90th and 10th percentiles instead of the minimum and maximum (results available upon request).

Panel B shows linearly-interpolated mean U.S. state-level 8th grade NAEP scores by gender and the gender gap from 1990 to 2012. As in panel A, we plot a line connecting the minimum and maximum state-level gender gap for each year test scores are available. Although math scores are rising over time, the male and female trend lines are almost parallel and the gender gap is fairly stable.

To provide a longer term perspective, we use national NAEP scores from 1978-2012 which are only available for 17 year olds. Panel C shows that the gender gap is also stable in the linearly-interpolated time series of scores.

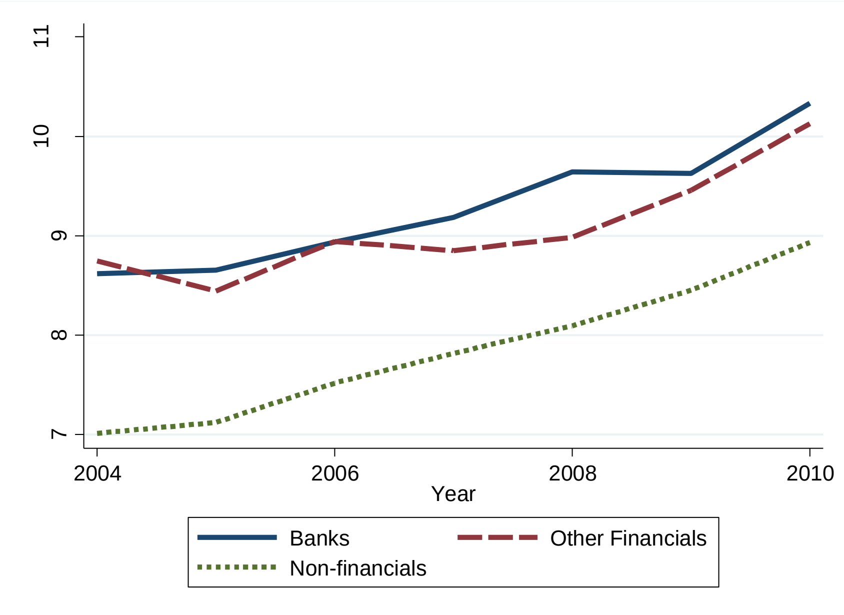
While the math gaps appear stable in Panels A-C, they may not appear large. However, small math gaps may be symptomatic of bigger gender gaps that manifest themselves over time. Fryer, Jr. and Levitt (2010) document, for example, that math gaps between boys and girls do not exist when they enter school, yet they grow bigger as the students get older. We show some evidence consistent with this argument in Panel D where we plot gender gaps in yearly state-level SAT scores over time. As with ADD and NAEP scores, the gender gaps are stable, but they are also larger. This is even more striking since students self-select to take the SAT.

III. Board diversity in Finance

In Figure II, we illustrate general trends in board gender diversity in banks, non-bank financials and non-financial firms in the representative sample over time. To reduce the impact of entry and exit from the sample, we restrict ourselves to firms with at least 6 years of data. The figure does not suggest that women are underrepresented on the boards of financials. If anything the opposite seems to be true: board diversity appears higher in both banking and non-bank finance as compared to non-financial firms. Furthermore, diversity is increasing in financial firms, just as it is in non-financial firms.

Figure II: Gender Diversity over Time

For the countries in our sample, and a stable sample of firms for which we have at least 6 years of data, this Figure shows the average diversity rates of women on boards of banks, other financial firms, and non-financial firms over time. *Diversity* is measured as the number of women on a board over board size. The sample consists of the entire population of firms, as described in detail in Adams and Kirchmaier (2012), which is the complete BoardEx dataset in 2011, but curtailed to those country-year observations for which BoardEx covers a representative sample of firms (>70% of market capitalization). For the identification of banks, we follow the classification in Ferreira et al. (2010); other financial firms are classified as such if they are identified in BoardEx as financials, in SIC classification 6, and not otherwise identified as banks. Non-financial firms are all other, excluding real estate and investment companies.



However, the raw data is misleading. Adams and Kirchmaier (2015) argue that women are much more likely to sit on the boards of large firms. Banks, in particular, are on average larger than other types of firms, so it is important to control for firm size. For example, the average percent banks in a country is 8.2% in our sample, but the average percent equity they hold is 23.49%. In contrast, the average percent non-bank financials is 7.39% but they hold only 9.18% equity on average.

In Table II we illustrate that adjusting for size matters for understanding women's representation on boards in different types of firms. We regress board diversity on dummies for various types of financial firms and various factors that previous literature associates with greater board diversity (e.g. Adams and Kirchmaier, 2015; Terjesen, Couto and Francisco, 2015), such as board independence and board size, the log of assets and Female Fulltime Economic Participation and the existence of governance codes or quotas targeting board diversity. We also include average board tenure in the regressions as boards with lower turnover might have fewer women.

Table II: Gender Diversity

This table shows the results of pooled cross-sectional OLS regressions of gender diversity on firm and country characteristics for 9035 firms spanning 19 countries. *Diversity* is measured as the number of women on a board divided by the number of board members per firm-year observation. *Financials* is a dummy indicating a firm in the financial sector, non-bank financials a dummy identifying financials firms that are not banks. Correspondingly, *Banks* is a dummy variable identifying banks as outlined in Figure I above. *Assets* is the book value of total assets (in billions of USD), for non-US firms converted into USD at market prices at the end of the reporting period. *Boardsize* is the number of directors on the board. *Tenure* indicates the average tenure of outside, or non-executive, directors in years. *Independence* is the ratio of independent outside directors over board size. *Female Fulltime Economic Participation* is full-time female employment over full-time employment, and lagged by 10 years. *GNI per Capita* denotes the gross national income per capita in USD in constant 2011 prices and exchange rates, and is lagged by 10 years. *Corporate Governance Code* is a dummy variable indicating whether diversity has been explicitly mentioned in the Corporate Governance code for that year and country. *Quota for State-owned Companies* is a dummy variables identifying whether for a given year and country a formal board quota was in place for state-owned companies. For an extensive discussion of the latter two variables see Adams and Kirchmaier (2012). Regression (1)-(3) excludes county fixed effects, (4)-(6) includes them. Robust standard errors are clustered on firm level, with corresponding t-statistics shown in brackets. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Diversity		Diversity		Diversity		Diversity	
Banks	-0.007**	-0.007**	-0.004	-0.004	-0.006*	-0.006*	-0.004	-0.003
	[-2.06]	[-2.07]	[-1.39]	[-1.41]	[-1.80]	[-1.81]	[-1.03]	[-1.00]
Non-bank Financials	0.007		0.002		-0.001		-0.001	
	[0.52]		[0.11]		[-0.15]		[-0.34]	
Insurance		-0.001		-0.001		-0.002		0.001
		[-0.18]		[-0.18]		[-0.34]		[0.11]
Life Assurance		0.007		0.001		0.021		0.025
		[0.50]		[0.06]		[0.59]		[0.74]
Private Equity		0.023***		-0.008		0.001		-0.002
		[3.06]		[-0.91]		[0.03]		[-0.12]
Speciality Finance		-0.004		-0.008*		-0.000		-0.003
		[-0.97]		[-1.79]		[-0.01]		[-0.59]
Assets (log)	0.005***	0.005***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	[11.22]	[11.28]	[12.50]	[12.63]	[10.40]	[10.40]	[10.62]	[10.59]
Tenure	-0.001**	-0.001**	-0.001**	-0.001**	-0.001	-0.001	-0.000	-0.000
	[-2.47]	[-2.49]	[-2.33]	[-2.38]	[-1.46]	[-1.45]	[-1.06]	[-1.07]
Boardsize (log)	0.023***	0.023***	0.028***	0.028***	0.024***	0.024***	0.030***	0.030***
	[7.68]	[7.64]	[9.09]	[9.04]	[6.33]	[6.33]	[7.74]	[7.73]
Independence	0.016***	0.016***	0.014***	0.014***	0.012**	0.012**	0.016***	0.016***
	[3.94]	[3.86]	[3.46]	[3.32]	[2.36]	[2.36]	[3.01]	[3.01]
Female Fulltime Economic Participation	0.286***	0.286***	0.162*	0.161*	0.270***	0.270***	-0.152	-0.152
	[12.30]	[12.29]	[1.66]	[1.65]	[9.47]	[9.47]	[-1.24]	[-1.23]
GNI / Capita (lagged)	-0.517***	-0.513***	-0.902	-0.885	-0.131	-0.130	2.301***	2.296***
	[-4.21]	[-4.19]	[-1.59]	[-1.56]	[-0.92]	[-0.91]	[3.49]	[3.49]
CG Code	0.070***	0.070***	0.045***	0.045***	0.040***	0.040***	0.012***	0.012***
	[9.86]	[9.85]	[8.67]	[8.67]	[8.75]	[8.75]	[5.29]	[5.29]
Quota for State-owned Companies	0.020**	0.020**	0.038**	0.037**	0.028***	0.028***	0.063**	0.063**
	[2.29]	[2.30]	[2.58]	[2.52]	[2.90]	[2.90]	[2.36]	[2.36]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
Number of countries	53	53	53	53	19	19	19	19
Observations	57,720	57,720	57,720	57,720	47,048	47,048	47,048	47,048
Adj. R-sq	0.080	0.081	0.103	0.103	0.090	0.090	0.115	0.115

We examine two specifications. The first specification contains a bank and a non-bank financial dummy. The second specification breaks the non-bank financial dummy into dummies for insurance, life assurance, private equity and specialty finance. We estimate these specifications with and without country fixed effects. In columns 1-4 we use our full sample of 53 countries. In columns 5-8, we use our representative sample. All regressions include year effects and standard errors are clustered at the firm level.

In contrast to Figure I, the results from Table II suggest that diversity is lower in financial firms, but primarily in banks. Only one non-bank financial dummy, the private equity dummy, is statistically significant and it is significant in only one specification. The coefficients on the bank dummy are always negative and statistically significant at greater than the 10% level in all specifications without country fixed effects. In the specifications with country fixed effects (columns 3, 4, 7 and 8), the coefficients are no longer statistically significant. As our sample contains many small firms that might not have much variation in board diversity over time, we replicate our results in our size matched subsample in Table III. Because the results in Table II suggest that board gender diversity is particularly low for banks, we focus on banks in Table III and the rest of the paper.

Table III: Gender Diversity – Matched Sample

This table shows the results of pooled cross-sectional OLS regressions of gender diversity on board on firm and country characteristics for a matched sample of banks, and non-financial firms. The non-financial firms are matched to banks on book value of assets, with replacement. *Diversity* is measured as the number of women on a board divided by the number of board members per firm-year observation. *Banks* is a dummy variable identifying banks as outlined in Figure I. *Assets* is the book value of total assets (in billions of USD), for non-US firms converted into USD at market prices at the end of the reporting period. *Board size* is the number of directors on the board. *Tenure* indicates the average tenure of outside, or non-executive, directors in years. *Independence* is the ratio of independent outside directors over board size. *Female Fulltime Economic Participation* is full-time female employment over full-time employment, and lagged by 10 years. *GNI per Capita* denotes the gross national income per capita in USD in constant 2011 prices and exchange rates, and is lagged by 10 years. *Corporate Governance Code* is a dummy indicating whether gender balance was explicitly stated in the governance code for that year and country. For an extensive discussion of this variable see Adams and Kirchmaier (2012). *Quota for State-owned Companies* is a dummy variables identifying whether for a given year and country a formal board quota was in place for state-owned companies. Regression (1)-(2) excludes county fixed effects, (3)-(4) includes them. Robust standard errors are clustered on firm level, with corresponding t-statistics shown in brackets. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels respectively.

	(1)	(2)	(3)	(4)
	Diversity		Diversity	
Banks	-0.007*	-0.009**	-0.008**	-0.009**
	[-1.72]	[-2.07]	[-2.04]	[-2.13]
Assets (log)	0.011***	0.008***	0.008***	0.008***
	[6.71]	[6.33]	[6.25]	[6.33]
Tenure	-0.001***	-0.001***	-0.001**	-0.001***
	[-2.83]	[-2.66]	[-2.56]	[-2.65]
Boardsize (log)	0.035***	0.041***	0.038***	0.041***
	[4.48]	[5.10]	[4.81]	[5.20]
Independence	0.067***	0.073***	0.085***	0.072***
	[5.07]	[5.97]	[6.75]	[5.93]
Female Fulltime Economic	0.498***	-0.091	0.320**	-0.113
Participation (lagged)	[5.69]	[-0.25]	[2.03]	[-0.32]
GNI / Capita (lagged)	1.090**	1.608	-0.160	0.852
	[2.24]	[0.56]	[-0.21]	[0.30]
Corporate Governance Code	0.043***	0.007	0.005	0.006
	[3.58]	[1.18]	[0.87]	[1.00]
Quota for State-owned	0.058***	0.017	0.042*	-0.059
Companies	[3.05]	[0.42]	[1.71]	[-0.68]
Codetermination			-0.002	
			[-0.10]	
GGI			0.761***	
			[2.76]	
Fraction of Women in Higher			0.153	-0.207
Education (lagged)			[0.99]	[-1.42]
Birth Rate (lagged)			-0.000	-0.004
			[-0.08]	[-0.84]
Tax & Social Security (lagged)			-0.000	-0.002
			[-0.59]	[-0.97]
Traditional vs. Secular Values			0.021	
			[1.55]	
Survival vs. Self-expression			0.027	
Values			[1.17]	
Year FE	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes
Observations	7,226	7,226	7,216	7,216
Adj. R-sq	0.114	0.151	0.143	0.151

In column 1 of Table III we regress board diversity on the bank dummy and the same controls as in Table II in the size-matched subsample. In column 2, country fixed effects are included. All regressions include year dummies and standard errors are clustered at the firm level.

The results suggest that board diversity is lower in banks as compared to size matched non-financial firms. This result is both statistically significant (at greater than the 10% level) and economically significant. For example, the specification with country fixed effects in column 2 suggests that board diversity is 0.9% lower in banks. This represents an 11.84% difference relative to the sample mean of 7.6% and is roughly one standard deviation in diversity.

In columns 3 and 4, we add additional controls to the specifications in columns 1 and 2 to ensure our results are not driven by omitted variables related to gender culture. Following Adams and Kirchmaier (2015) who examine country-level factors related to women's representation in the director pool, we add codetermination, the GGI index, 10-year lagged fraction of women in higher education, birth rate and tax and social security, as well as traditional vs. secular values and survival vs. self-expression values to both specifications. Because the values, the codetermination dummy and GGI are time-invariant, they drop out of the specification with country fixed effects in column 4.

The coefficient on GGI is positive and statistically significant in column 3, consistent with the idea that women are more likely to achieve board positions in countries with stronger gender culture. But gender culture does not appear to be driving the negative coefficient on the bank dummy. In fact, the opposite seems to be true. The coefficient on the bank dummy is more negative and more statistically significant than in column 1. The results in column 4 are also consistent with those in the previous columns. Under the assumption that the inclusion of our control variables and country and year effects are sufficient to address omitted variable problems, the coefficient on the bank dummy is identified in Table III and we can conclude that board gender diversity is lower in the banking industry than in other types of firms of similar size.

IV. **Math Skill Intensity in Finance**

To motivate our interest in the relationship between math outcomes and bank board diversity that we analyze in Section V, we examine patterns in occupational skill intensity by industry and gender and by occupation and gender using Autor, Levy and Murnane's (2003) data. We first follow Philippon and Reshef (2012) and confirm that the finance industry is math intensive as compared to other industries. In Panel A of Table A.IV we regress finger dexterity, set limits, tolerances, eye, hand, foot coordination and direction, control and planning and GED-math on a dummy that is one if the industry is classified as belonging to finance, year dummies and dot dummies. We cluster standard errors at the industry sector level. Panel A is for task means of individuals at all education levels. Panel B is for college educated individuals.

Table A.IV suggests that the finance industry is generally characterized by greater non-routine cognitive task intensity as measured by direction, control and planning and math intensity. Finance also exhibits greater routine manual task intensity as measured by finger dexterity. For college-educated workers, finance occupations have lower routine and non-routine manual task intensities along every dimension but continue to exhibit greater non-routine cognitive task intensities than other industries. Relative to the task intensity means for college-educated workers, finance is 7% more math-intensive and 2.64% more direction, control and planning intensive than all other industries together.

Table IV: Task Intensities for Women in Finance and Other Industries

The table shows regressions of 5 measures of task intensity across industries on a finance sector dummy.

Panel A: Men and Women in finance and other industries at all education levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Finger Dexterity		Set Limits, Tolerances		Eye-Hand-Foot		Direction, Control, Planning		GED-Math	
Female	0.864***	0.850***	0.929***	0.868***	-0.749***	-0.761***	-1.223***	-1.192***	-0.516***	-0.503***
	[14.99]	[15.21]	[3.45]	[3.41]	[-6.49]	[-6.39]	[-17.07]	[-16.66]	[-3.36]	[-3.13]
Finance	0.018	-0.309***	-0.417	-1.830**	-0.804***	-1.085***	1.251***	1.973***	1.210***	1.518***
	[0.23]	[-3.53]	[-0.80]	[-3.02]	[-9.82]	[-9.08]	[6.00]	[9.08]	[5.38]	[8.24]
Female*Finance		0.653***		2.825***		0.562***		-1.445***		-0.617***
		[11.69]		[11.09]		[4.72]		[-20.19]		[-3.84]
Constant	3.714***	3.721***	5.038***	5.068***	1.393***	1.399***	2.221***	2.205***	3.552***	3.545***
	[44.95]	[46.04]	[8.62]	[8.78]	[13.89]	[13.93]	[10.29]	[10.45]	[15.62]	[15.77]
Observations	5,014	5,014	5,014	5,014	5,014	5,014	5,014	5,014	5,014	5,014
Adj. R-sq	0.395	0.399	0.101	0.112	0.298	0.302	0.326	0.333	0.118	0.120

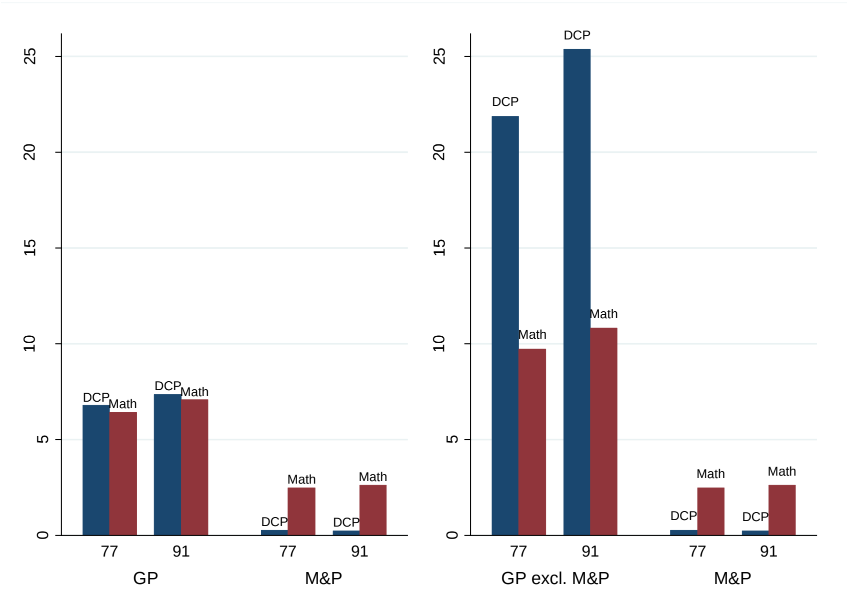
Panel B: College-educated men and women in finance and other industries

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
VARIABLES	Finger Dexterity		Set Limits, Tolerances		Eye-Hand-Foot		Direction, Control, Planning		GED-Math	
Female	0.663***	0.656***	1.233***	1.194***	-0.393***	-0.398***	-1.928***	-1.929***	-0.717***	-0.715***
	[11.17]	[10.61]	[7.23]	[6.84]	[-6.07]	[-6.00]	[-9.78]	[-9.58]	[-7.47]	[-7.22]
Finance	-0.139***	-0.302***	-0.295	-1.184***	-0.478***	-0.605***	0.244	0.224	0.333**	0.395**
	[-3.27]	[-5.43]	[-0.83]	[-3.40]	[-5.69]	[-5.53]	[1.56]	[0.93]	[2.75]	[2.50]
Female*Finance		0.328***		1.779***		0.256***		0.041		-0.123
		[5.30]		[10.19]		[3.85]		[0.20]		[-1.24]
Constant	3.703***	3.707***	4.074***	4.093***	0.832***	0.834***	4.364***	4.364***	5.101***	5.100***
	[52.98]	[53.77]	[9.53]	[9.73]	[11.50]	[11.41]	[31.37]	[30.98]	[43.66]	[43.23]
Observations	4,876	4,876	4,876	4,876	4,876	4,876	4,876	4,876	4,876	4,876
Adj. R-sq	0.222	0.222	0.117	0.121	0.122	0.123	0.308	0.308	0.124	0.124

In Table IV, we examine the task intensity of women's occupations in finance. We use the industry task intensity data by gender and add a female dummy and the interaction between the finance and the female dummies to the regressions in Table A.IV. The results from Panel A suggest that women tend to be in occupations with greater manual task intensity and less GED-math and direction, control and planning intensity, but particularly so in the finance industry. When we restrict the sample to college educated individuals, we find that the coefficient on the interaction between female and finance becomes positive for direction, control and planning but remains negative for GED-math. This suggests that even in more senior positions gender differences in math may play a role in finance.

Figure III: Non-routine Cognitive Skills for General Population and Managerial and Professional Occupations

The figure shows the % difference in task intensity for Direction, Control and Planning (DCP) and GED-math (Math) for men and women relative to the mean in the general population (GP) and managerial and professional occupations (M&P). The Occupational task intensity Data are from Autor, Levy, Murnane (2003). See Table I, Panel E for more details. We classify occupations into 13 broad occupational categories, professionals, managers, sales, clerical workers, craftsmen, operatives, laborers, farmers, farm laborers, service workers, technicians, household service workers and unreported occupations, using Census occupation classification codes for the years 1960 for the 1960-1970 data, 1970 for the 1970 date and 1980 for the 1980-1990 data. We code managerial and professional occupations as having occupation codes less than or equal to 290, excluding 200 and 222 in the 1960-1970 data, codes less than or equal to 245 in the 1970 data and less than or equal to 200 in the 1980-1990 data.



To provide additional evidence that gender differences in math may play a role even at senior positions, we use the occupation-level data and compare the percent difference ((men-women)/mean) in the two cognitive task intensities for managerial and professional occupations and all other occupations. The left panel of Figure IV shows the percent differences in direction, control and planning and GED-math for all occupations and managerial and professional occupations for both the DOT 77 and the DOT 91. The right panel compares all occupations except managerial and professional occupations to managerial and professional occupations.

What is most striking in the figure is that non-managerial gender differences in direction, control and planning are large (more than 20%), but nearly vanish for managerial occupations. In contrast, math gender differences do not vanish even for managerial and professional occupations. For managers and professionals, the percent difference between men and women in direction control and planning is only 0.25% relative to the mean, but the gender gap in math skills is still 2.6% relative to the mean.

We believe the patterns in the occupational skill data suggest that math outcomes for women are relevant for their career advancement. To examine this more directly, we relate math scores to board diversity in banking in the next section.

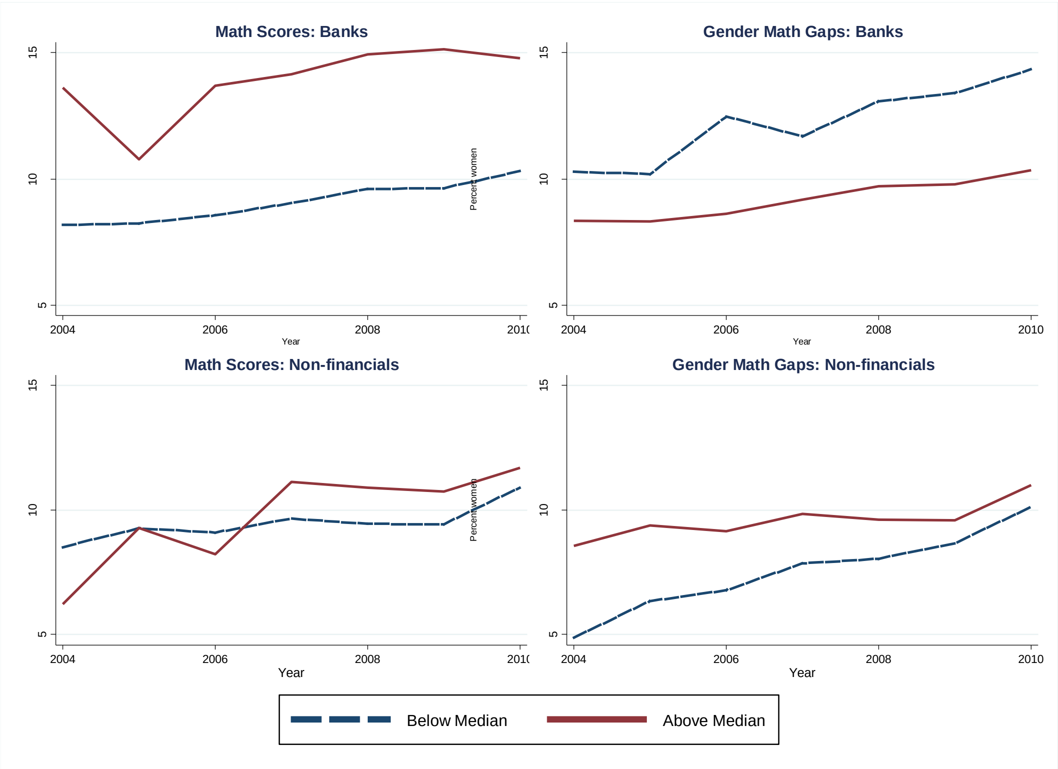
V. Math Scores and Board Diversity in Banking

Graphical Evidence. Figure V provides suggestive evidence that there is a correlation between math outcomes and bank board diversity. We plot mean board diversity for banks (top panels) and non-financial firms (bottom panels) stratified by above and below median math scores (left panels) and above and below median math gaps (right panels). The graphs in Panel A are for our representative sample. The graphs show that mean bank board diversity is higher in countries with above median math scores and lower in countries with above median math gaps. If math outcomes simply proxy for (gender) culture, we would expect to see the same pattern for non-financial firms. But mean board diversity in non-financial firms is higher, not lower, in countries with above median math gaps and there is no clear difference in mean board diversity in non-financial firms between countries with above and below median math scores.

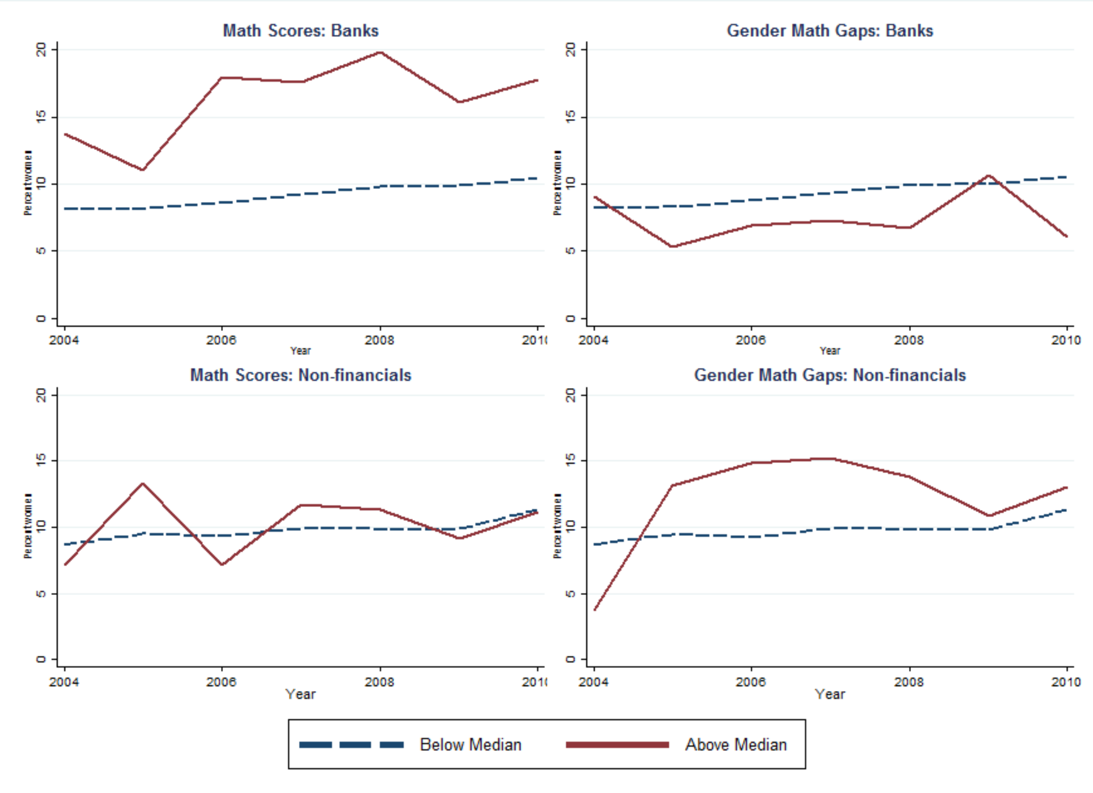
Figure IV: Math Scores, Math Gender Gap and Boardroom Diversity for Banks and Non-Financial Companies over Time

The below figures depicts the Gender Boardroom Diversity for all banks, and a matched sample of non-financial companies over time, stratified by being above or below the median math score, and gender math gap, respectively. Gender participation rates cover both executive and non-executive director positions. *Math Score* is a dummy variable indicating whether the average math score for a particular country was above the median math score of all countries in our sample. Correspondingly, *Math Gap* indicates whether the gap between the math scores for men and women was larger than the median gap for all countries. For a detailed description see Tables I above. Norway and India is excluded. Panel A is based on a matched sample of firms, Panel B depicts the results based on the ADD math scores from 1965 for Australia, Finland, France, Netherlands, and the U.S, but excludes Belgium. The NAEP data in Panel C is lagged by 14 years.

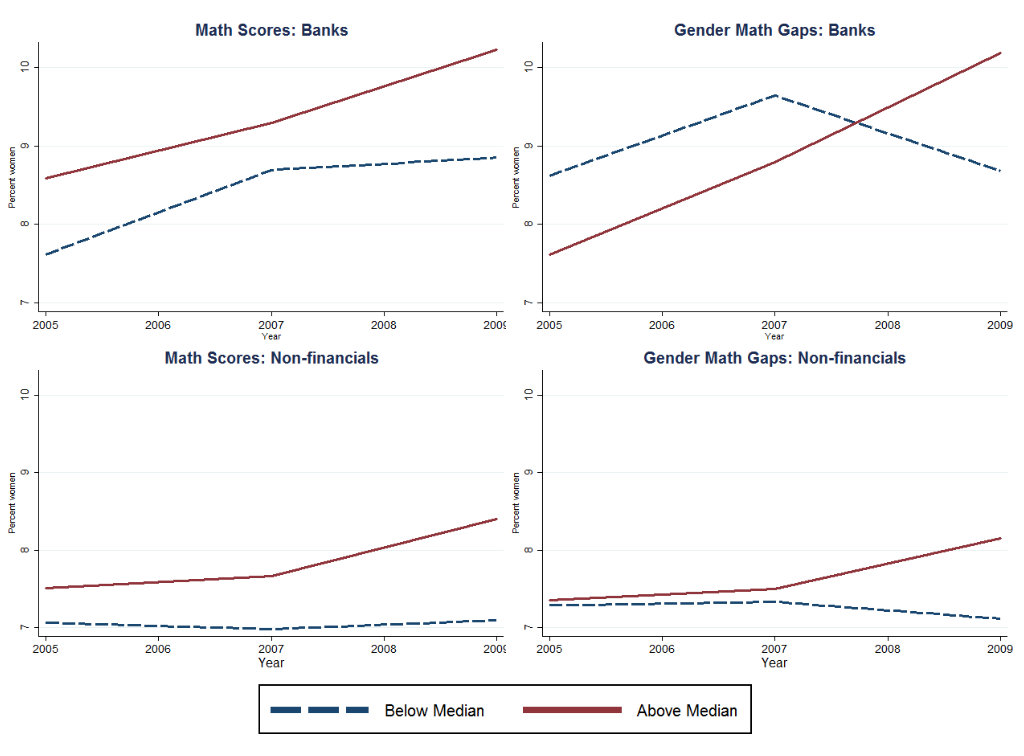
Panel A: Matched Sample



Panel B: ADD Data in 1965



Panel C: NAEP Data



In Panel B we illustrate that a similar pattern holds as in Panel A if we use the earliest available math scores from 1965 in ADD. Math scores are available for Australia, Belgium, Finland, France, Israel, the Netherlands and the US. We drop Israel because it is not included in the countries in Panel A. We drop Belgium because historically the differences in educational systems between Flemish and French Belgium were so large that the SIMS and TIMSS collected data for Flemish Belgium separately. Thus the scores for Belgium are not directly comparable to those in Panel A.

We show mean board diversity for the remaining five countries stratified by banks and non-financial firms and above and below median 1965 math scores and gaps. The graphs are remarkably similar to the graphs in Panel A. Banks have greater board diversity in countries with above median 1965 math scores and below median 1965 math gaps. Math scores do not appear related to board diversity in non-financial firms but diversity is higher when math gaps are higher. Since the 1965 math scores are unlikely to be affected by reverse causality, the graphs in Panel B are suggestive of a causal link between math outcomes and bank board diversity.

In Panel C, we show mean board diversity for the U.S. only stratified by banks and non-financial firms and above and below median headquarter state-level NAEP math scores and gaps. In contrast to the country-level evidence, both banks and non-financials have greater board diversity in states with higher math scores. But consistent with the country-level evidence, bank board diversity is higher in states with lower gaps, except in the crisis period, and non-financial board diversity is lower in states with lower gaps. Since cultural variation across U.S. states is likely to be much smaller than in the cross-country data, the patterns in Panel C suggest that the relationship between math outcomes and bank board diversity is unlikely to be driven by culture. We examine this relationship in more detail in a regression framework next.

Macro Evidence. We first examine whether math scores help explain diversity in the bank director pool at the country level. The bank director pool in a given year consists of all unique individuals who are directors of banks. Examining the fraction of the bank director pool that is female is useful because it enables us to abstract from gender differences in propensities to hold more than one directorship. We examine firm-level board diversity and math outcomes later.

An obvious concern in analyzing the relationship between math outcomes and board diversity is that math scores simply reflect other aspects of culture related to gender attitudes (e.g. Guiso, Monte, Sapienza, Zingales, 2008; Else-Quest, Hyde and Linn, 2010). However, it is not clear that negative attitudes towards women necessarily translate into poor math outcomes for women. Instead, there may be a math-specific component to gender attitudes. We attempt to isolate this component by including the same country-level factors as in Table III.

We call the fraction of the bank director pool that is female "Female Director Participation in Banks" because it mirrors labour force participation measures in that it counts each individual only once. In column 1 of Table V, we regress Female Director Participation in Banks on all controls in Table III except for values. In columns 2, 3 and 4 we add the 2009 PISA math scores and math gaps separately and together. In columns 5-8, we replicate columns 1-4 after including values. All regressions include year effects and standard errors are clustered at the country level.

Table V: Female Director Participation in Banks – Country Level

This table shows the results of pooled cross-sectional OLS regressions of Female Director Participation in Banks in the boardroom on country and policy characteristics for 19 countries. *Female Director Participation in Banks* is calculated as the number of unique women in banking, over all unique directors in baking in a given country and year. *Math Score* is a dummy variable indicating whether the average math score for a particular country was above the median math score of all countries in the sample. Correspondingly, *Math Gap* indicates whether the gap between the math scores for men and women was larger than the median gap for all countries. Both values are taken from the 2009 'PISA' study. *Female Fulltime Economic Participation* is full-time female employment over full-time employment per year and country, and lagged by 10 years. These, as well as all following variables, are described in detail in Adams and Kirchmaier (2012). *Codetermination* which is a dummy variable whether or not a country has codetermination, *GNI per Capita* denotes the gross national income per capita in USD in constant 2011 prices and exchange rates, and is lagged by 10 years. *Gender Wage Gap* is the average gender pay gap score of the World Economic Forum for the years 2006 to 2010, for the years available. The *birth rate* gives the number of births per 1000 inhabitants, and is lagged by 10 years. *Tax & Social Security* measures the percentage of tax and social security as percentage of gross income; it is again lagged by 10 years. *Traditional vs. secular* and *survival vs. self-expression* measure cultural dimensions and are based on Inglehart and Welzel (2005). *Corporate Governance Code* is a dummy indicating whether gender balance was explicitly stated in the governance code for that year and country. *Quota for State-owned Companies* is a dummy variables identifying whether for a given year and country a formal board quota was in place for state-owned companies. Robust standard errors are clustered on country level, with corresponding t-statistics shown in brackets. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Female Director Participation in Banks							
Math Score Above Median		0.030		0.047***		0.037*		0.050***
		[1.38]		[3.73]		[1.89]		[5.58]
Math Gap Above Median			-0.050**	-0.064***			-0.047***	-0.056***
			[-2.77]	[-5.59]			[-3.40]	[-5.90]
Female Fulltime Economic	0.411	0.487*	0.586**	0.753***	0.065	0.211	0.300	0.544***
Participation (lagged)	[1.67]	[2.03]	[2.65]	[4.73]	[0.36]	[1.25]	[1.68]	[4.41]
Codetermination	-0.009	-0.018	-0.005	-0.018	0.024	0.018	0.015	0.005
	[-0.50]	[-0.76]	[-0.43]	[-1.31]	[0.88]	[0.98]	[0.60]	[0.36]
GNI / Capita (lagged)	1.269	0.355	0.657	-0.962	-0.763	-1.088	-1.201	-1.728**
	[1.23]	[0.33]	[0.66]	[-1.25]	[-0.40]	[-0.70]	[-0.98]	[-2.25]
GGI	1.720***	1.794***	1.412***	1.449***	0.910**	1.182***	0.759**	1.099***
	[8.09]	[6.08]	[6.83]	[6.63]	[2.28]	[3.16]	[2.25]	[4.88]
Fraction of Women in Higher Education (lagged)	0.427	0.365	0.013	-0.198	0.437	0.403	0.023	-0.105
	[1.45]	[1.43]	[0.04]	[-0.78]	[1.64]	[1.69]	[0.11]	[-0.48]
Birth Rate (lagged)	-0.006	-0.006	-0.004	-0.003	-0.009	-0.015**	-0.003	-0.009***
	[-1.38]	[-1.47]	[-0.89]	[-1.44]	[-1.32]	[-2.28]	[-0.59]	[-3.14]
Tax & Social Security (lagged)	0.001	0.001	0.001	0.001*	-0.002	-0.001	-0.001	0.000
	[0.68]	[0.87]	[1.03]	[1.96]	[-1.31]	[-1.14]	[-0.72]	[0.55]
Corporate Governance Code	-0.028*	-0.025*	-0.014	-0.005	-0.021	-0.020	-0.008	-0.004
	[-1.77]	[-2.07]	[-1.04]	[-0.39]	[-1.65]	[-1.75]	[-0.58]	[-0.33]
Quota for State-owned Companies	-0.030*	-0.035	-0.002	-0.003	-0.014	-0.023	0.008	0.001
	[-1.85]	[-1.68]	[-0.14]	[-0.17]	[-0.68]	[-0.97]	[0.47]	[0.05]
Traditional vs. Secular Values					0.014	-0.007	0.022**	-0.005
					[0.93]	[-0.36]	[2.93]	[-0.76]
Survival vs. Self-expression Values					0.083*	0.083***	0.059	0.054***
					[1.84]	[3.15]	[1.43]	[3.13]
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126	126	126	126	126	126	126	126
Adj. R-sq	0.725	0.748	0.793	0.850	0.768	0.792	0.821	0.866

The coefficient on math score is positive in both columns 2 and 4 and statistically significant in column 4. The coefficient on math gap is negative and statistically significant at greater than the 5% level in columns 3 and 4. The statistical significance on the coefficients on both scores and gaps increase when we control for values, although the magnitudes decrease somewhat. Relative to the mean, the coefficient on math gap in column 7 suggests that Female Director Participation in Banks is 41.59% lower in countries with above median math gaps.

The results do not seem to be driven by the correlation between PISA scores and culture. GGI and survival vs. self-expression values are both positive and statistically significant in almost all regressions. Adding values to the regression in column 1 (reported in column 5) reduces the coefficient on GGI by 47.1% which suggests there is a high correlation between GGI and values. But adding math gap to column 1 (reported in column 3) leads to only a 17.91% reduction in the coefficient on GGI. This suggests math gap contains information pertinent to explaining board diversity in banking that is not fully captured by GGI.

Firm-level Evidence. In Table VI, we analyze the relationship between PISA math scores and math gaps and bank board diversity using firm-level data. We regress firm-level board diversity on the 2009 PISA math scores and math gaps, a bank dummy and the interaction between math scores and the bank dummy and the interaction between math gap and the bank dummy. To distinguish the effect of math from the effect of culture, we also include the interaction between GGI and the bank dummy.

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Table VI: Math Scores and Boardroom Diversity - Firm Level Analysis

This table shows the results of pooled cross-sectional OLS regressions of gender diversity on firm and country characteristics for the entire sample of 8,353 firms in 19 countries (model 1-4). The matched sample consists of 2,459 firms in 19 countries (model 5-8). The results of the unrestricted sample covering 10,651 firms in 53 and 45 countries respectively are in column 9-12. For the unrestricted sample we only have WEF data for 39 countries, but in total we have 54 countries hence we leave the WEF variable out in this case. *Math Score* is a dummy variable indicating whether the average math score for a particular country was above the median math score of all countries in our sample. Correspondingly, *Math Gap* indicates whether the gap between the math scores for men and women was larger than the median gap for all countries. In addition, both values are also interacted with a bank dummy and labelled as *Math Score x Banks* and *Math Gap x Banks.* All other variables are as in Table I. Robust standard errors are clustered on firm level, with corresponding t-statistics shown in brackets. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Diversity		Diversity		Diversity		Diversity		Diversity		Diversity	
Math Score Above Median	0.001	0.001	-0.004	-0.004	0.031***	0.022*	0.028*	0.019	-0.004	-0.006**	-0.004	-0.005
	[0.23]	[0.33]	[-0.88]	[-0.80]	[2.99]	[1.89]	[1.89]	[1.16]	[-1.54]	[-2.11]	[-0.89]	[-1.14]
Maths Gap Above Median	- 0.011***	- 0.009***	- 0.011***	-0.009**	- 0.035***	-0.005	- 0.035***	-0.005	- 0.011***	- 0.012***	-0.003	-0.003
	[-3.29]	[-2.65]	[-2.77]	[-2.31]	[-3.24]	[-0.39]	[-2.82]	[-0.33]	[-4.30]	[-4.60]	[-1.22]	[-1.09]
Maths Score Above Median * Banks		0.010		0.012		0.016		0.016		0.035***		0.029**
		[0.77]		[0.87]		[0.90]		[0.93]		[2.86]		[2.34]
Maths Gap Above Median * Banks		-0.022*		-0.017		- 0.045***		- 0.044***		0.012		-0.004
		[-1.75]		[-1.35]		[-2.62]		[-2.69]		[1.16]		[-0.40]
Banks	- 0.418***	-0.389**	- 0.492***	- 0.453***	-0.466**	-0.440*	-0.484**	-0.458**	-0.007**	-0.020**	-0.005	-0.004
	[-2.60]	[-2.20]	[-3.13]	[-2.60]	[-2.21]	[-1.85]	[-2.38]	[-2.04]	[-2.13]	[-2.01]	[-1.55]	[-0.46]
Other Financial Companies	-0.002	-0.001	-0.001	-0.001					0.009	0.009	0.003	0.004
	[-0.38]	[-0.33]	[-0.24]	[-0.20]					[0.61]	[0.63]	[0.23]	[0.28]
Assets (log)	0.006***	0.006***	0.006***	0.006***	0.008***	0.007***	0.008***	0.007***	0.005***	0.005***	0.005***	0.005***
	[10.80]	[10.46]	[10.29]	[10.04]	[5.98]	[5.51]	[5.75]	[5.31]	[10.71]	[10.60]	[11.42]	[11.19]
ROE	0.004***	0.004***	0.004***	0.004***	0.004	0.004	0.004	0.004	0.002***	0.002***	0.002***	0.002***
	[3.64]	[3.58]	[3.84]	[3.79]	[1.03]	[0.90]	[1.05]	[0.92]	[5.06]	[5.13]	[4.95]	[5.03]
Tenure	-0.000	-0.000	-0.000	-0.000	-0.001**	-0.001**	-0.001**	-0.001**	- 0.001***	- 0.001***	-0.001**	-0.001**
	[-1.05]	[-0.99]	[-0.90]	[-0.87]	[-2.42]	[-2.39]	[-2.35]	[-2.30]	[-2.64]	[-2.59]	[-2.37]	[-2.31]
Boardsize (log)	0.024***	0.025***	0.029***	0.029***	0.039***	0.041***	0.041***	0.043***	0.023***	0.024***	0.028***	0.028***
	[6.14]	[6.21]	[7.10]	[7.16]	[5.21]	[5.46]	[5.25]	[5.48]	[7.78]	[7.87]	[8.94]	[9.00]
Independence	0.019***	0.020***	0.019***	0.020***	0.080***	0.082***	0.079***	0.082***	0.013***	0.013***	0.020***	0.020***
	[3.62]	[3.80]	[3.57]	[3.66]	[7.15]	[7.50]	[6.33]	[6.57]	[3.38]	[3.46]	[4.79]	[4.93]

Female Fulltime Economic	0.333***	0.337***	0.418***	0.416***	0.583***	0.563***	0.549***	0.554***	0.253***	0.252***	0.272***	0.273***
Participation (lagged)	[11.14]	[11.24]	[7.47]	[7.43]	[7.93]	[7.49]	[3.41]	[3.37]	[11.03]	[10.89]	[7.18]	[7.19]
GGI	0.631***	0.644***	0.397***	0.411***	0.566**	0.568***	0.358	0.399				
	[9.35]	[9.56]	[3.87]	[4.04]	[2.53]	[2.65]	[1.12]	[1.10]				
GGI * Banks	0.577**	0.563**	0.680***	0.646**	0.639**	0.659*	0.662**	0.682**				
	[2.56]	[2.18]	[3.10]	[2.55]	[2.17]	[1.89]	[2.34]	[2.08]				
Corporate Governance	0.021***	0.021***	0.011***	0.011***	0.010	0.011	0.013**	0.012**	0.066***	0.066***	0.051***	0.051***
Code	[5.96]	[5.91]	[4.35]	[4.33]	[1.56]	[1.56]	[2.13]	[2.00]	[9.99]	[9.87]	[9.12]	[9.10]
Codetermination			-0.017**	-0.016**			-0.001	-0.004			-0.006	-0.006
			[-2.40]	[-2.30]			[-0.06]	[-0.21]			[-1.51]	[-1.43]
GNI / Capita (lagged)			0.172	0.168			-0.427	-0.361			- 0.614***	- 0.616***
			[0.75]	[0.73]			[-0.55]	[-0.48]			[-3.46]	[-3.46]
Fraction of Women in			0.008	0.013			-0.121	-0.129			0.025	0.029
Higher Education (lagged)			[0.16]	[0.26]			[-0.76]	[-0.80]			[0.64]	[0.72]
Birth Rate (lagged)			0.003**	0.003**			0.004	0.004			0.008***	0.008***
			[2.15]	[2.15]			[1.00]	[0.99]			[12.01]	[11.86]
Tax & Social Security			0.002***	0.002***			0.000	0.000			-0.000	-0.000
(lagged)			[4.78]	[4.71]			[0.40]	[0.58]			[-0.17]	[-0.18]
Quota for State-owned			0.008	0.007			0.029	0.030			0.015	0.014
Companies			[0.83]	[0.72]			[1.27]	[1.30]			[1.56]	[1.48]
Traditional vs. Secular			0.017***	0.017***			0.007	0.007			0.027***	0.027***
Values			[3.94]	[3.86]			[0.52]	[0.51]			[9.37]	[9.31]
Survival vs. Self-expression			-0.004	-0.003			0.011	0.006			0.014***	0.014***
Values			[-0.42]	[-0.34]			[0.50]	[0.28]			[4.05]	[3.96]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Matched Sample	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No
Number Countries	19	19	19	19	19	19	19	19	53	53	45	45
Observations	44,370	44,370	44,254	44,254	7,066	7,066	7,056	7,056	57,720	57,720	56,078	56,078
Adj. R-sq	0.109	0.110	0.117	0.117	0.150	0.155	0.153	0.157	0.081	0.082	0.098	0.099

Because performance could be correlated with a taste for discrimination (e.g. Becker, 1971), we control for return on equity (ROE) as a proxy for performance in addition to the country-level control variables we include in Table VI and the firm-level control variables from Table III. Columns 1-4 report results for the representative sample. Columns 5-8 report results for the matched sample. Results in columns 9-12 are for the full sample of 53 countries although we lose some country data when we include all country-level controls in columns 11 and 12. Since GGI is only available for 39 countries, we leave it out of the specifications in columns 9-12. We leave the indicator variable for Other Financial Companies out of the matched sample specifications as this sample excludes non-bank financial firms. For each sample we report two short specifications without and with the bank interaction terms and two long specifications that include all country-level controls.

Across all columns the coefficient on math gap is negative and it is statistically significant in all but 4 columns. The coefficient on math score is less consistent as it changes signs across specifications. It is negative and statistically significant in column 6, but positive and statistically significant in columns 5, 6 and 7. It is insignificant in the other columns. This suggests that there is no clear relationship between math outcomes and firm-level diversity for the typical firm in the sample—which includes both financial and non-financial firms.

However, the coefficients on the interaction terms between math outcomes and the bank dummy suggest that math outcomes matter for banks. The interaction terms between math scores and the bank dummy are positive and statistically significant at greater than the 5% level in columns 10 and 11. Even though the coefficients on the interaction terms between GGI and the bank dummy are statistically significant and positive in columns 1-8, the interaction terms between math gap and the bank dummy are negative and statistically significant in column 2 and in the matched sample in columns 6 and 8. The matched sample results suggest that countries with greater math gaps banks have fewer women on boards than similar sized firms.

Alternative measures of math scores. While math gaps are persistent, they do not seem large. In fact, Hyde, Lindberg, Linn, Ellis, and Williams (2008) and Hyde and Mertz (2009) argue that math gaps have almost disappeared. Thus it may appear puzzling that we find any relation at all between math outcomes and board diversity. One reason may be that countries with above median math scores or below median math gaps also have more girls in the group of high-achieving students where math gender gaps are typically larger (e.g. Ellison and Swanson, 2010). Gaps at higher levels may be particularly important for finance.

Table VII: Math Scores and Boardroom Diversity - Level 6 PISA Math Scores

This table shows the results of OLS regressions of gender diversity on firm and country characteristics for the entire sample of 8,353 firms in 19 countries. *Level 6* indicates the fraction of pupils that achieve the top level (level 6) in the PISA math test, level 6 gap shows the difference in fraction between men and women. All other variables are as in Table I, and Table VI above. Robust standard errors are clustered on firm level, with corresponding t-statistics shown in brackets. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels respectively.

	(1)	(2)	(3)	(4)
VARIABLES	Diversity		Diversity	
Level 6 Fraction	0.007***	0.005**	0.007**	0.006*
	[3.04]	[2.28]	[2.11]	[1.69]
Level 6 Gap	-0.013***	-0.010**	-0.017***	-0.014**
	[-2.92]	[-2.27]	[-2.59]	[-2.24]
Level 6 Fraction * Banks		0.050***		0.047***
		[4.78]		[4.52]
Level 6 Gap * Banks		-0.082***		-0.078***
		[-4.36]		[-4.15]
Banks	-0.393**	0.115	-0.472***	0.015
	[-2.45]	[0.71]	[-3.02]	[0.09]
Non-bank Finance	-0.002	-0.002	-0.001	-0.001
	[-0.49]	[-0.50]	[-0.25]	[-0.24]
Assets (log)	0.007***	0.007***	0.006***	0.006***
	[10.78]	[10.67]	[10.31]	[10.21]
ROE	0.004***	0.004***	0.004***	0.004***
	[3.68]	[3.67]	[3.84]	[3.81]
Tenure	-0.000	-0.000	-0.000	-0.000
	[-1.13]	[-1.14]	[-0.93]	[-0.95]
Boardsize (log)	0.025***	0.026***	0.029***	0.030***
	[6.35]	[6.50]	[7.08]	[7.18]
Independence	0.018***	0.018***	0.019***	0.019***
	[3.33]	[3.37]	[3.57]	[3.59]
Female Fulltime Economic	0.288***	0.290***	0.415***	0.417***
Participation (lagged)	[9.35]	[9.45]	[7.84]	[7.87]
GGI	0.564***	0.581***	0.319***	0.353***
	[7.77]	[8.03]	[3.12]	[3.48]
GGI * Banks	0.541**	-0.151	0.652***	-0.013
	[2.41]	[-0.66]	[2.99]	[-0.05]
Corporate Governance Code	0.021***	0.021***	0.009***	0.009***
	[5.88]	[6.05]	[3.34]	[3.32]
Codetermination			-0.017**	-0.016**
			[-2.57]	[-2.52]
GNI / Capita (lagged)			0.242	0.312
			[0.87]	[1.12]
Fraction of Women in Higher Education			-0.038	-0.034
(lagged)			[-0.73]	[-0.66]
Birth Rate (lagged)			0.001	0.001
			[0.99]	[0.78]
Tax & Social Security (lagged)			0.002***	0.002***
			[5.47]	[5.61]
Quota for State-owned Companies			0.004	0.001
			[0.41]	[0.13]
Traditional vs. Secular Values			0.003	0.003
			[1.62]	[1.55]
Survival vs. Self-expression Values			0.015***	0.014***
			[5.29]	[5.17]
Year FE	Yes	Yes	Yes	Yes
Observations	44,370	44,370	44,254	44,254
Adj. R-sq	0.109	0.110	0.117	0.118

Consistent with this argument, we find that the correlation between the percentage of girls at Level 6 in mathematics is significantly (at the 1% level) positively correlated with the above median math score dummy (a correlation of 0.21). The correlation between the Level 6 gap (the difference between the percentage of boys at Level 6 and the percentage of girls at Level 6) is 0.25 and also significant at the 1% level. To explore whether performing at the highest level is particularly important for finance, we add the percentage of girls in 2009 Level 6 PISA scores and the Level 6 gap along with their interactions with the bank dummy to the specifications in columns 1 and 3 of Table VI. Both the coefficients on the fraction of girls in Level 6 and their interactions with the bank dummy are positive and statistically significant across all columns in Table VII. Both the coefficients on the Level 6 gap and their interactions with the bank dummy are negative and statistically significant in Table VII. Thus, bank board gender diversity appears to be higher in countries in which more girls perform at the highest level in math and their representation at this level is similar to the representation of boys.

Fixed-effect models. A concern with the cross-country results is that there could be omitted country-level variables related to both math outcomes and board diversity that are driving the results, particularly for banks. However, identification using country effects is difficult because tests happen infrequently and scores are persistent. A common method of dealing with limitations of educational quality data across countries is interpolation and extrapolation (e.g. Barro and Lee, 2013). We build on this literature and construct a time series of interpolated math scores and gaps using ADD data. We assign 1995 scores and gaps to the year 2000, 2000 scores and gaps to the year 2005 and 2005 scores and gaps to the year 2010. We interpolate the scores linearly between those three years. To increase time series variation, we do not transform the scores to above and below median math scores as in previous regressions.

Table VIII: Math Scores and Boardroom Diversity - Country Fixed-Effect Models using ADD

This table shows the results of OLS regressions of gender diversity on firm and country characteristics for all banks in 18 countries, excluding Luxembourg. ADD level indicates the interpolated levels of ADD scores, lagged by 5 years, gap indicates the respective gender gap in secondary math skills. All other variables are as in Table I. Robust standard errors are clustered on firm level, with corresponding t-statistics shown in brackets. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Diversity			Diversity	
ADD Level	-0.000		-0.001	0.000		-0.001
	[-0.36]		[-0.91]	[0.58]		[-0.57]
ADD Gap		-0.002	-0.003*		-0.002**	-0.003*
		[-1.60]	[-1.94]		[-2.04]	[-1.77]
Assets (log)	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	[3.54]	[3.42]	[3.53]	[3.30]	[3.29]	[3.29]
ROE	0.015	0.016*	0.016*	0.015	0.015	0.015
	[1.64]	[1.67]	[1.67]	[1.53]	[1.54]	[1.55]
Tenure	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	[-2.61]	[-2.60]	[-2.62]	[-2.74]	[-2.74]	[-2.74]
Boardsize (log)	0.029***	0.029***	0.030***	0.033***	0.033***	0.033***
	[2.80]	[2.81]	[2.84]	[3.12]	[3.12]	[3.12]
Independence	0.064***	0.066***	0.064***	0.053***	0.053***	0.053***
	[3.19]	[3.30]	[3.19]	[2.67]	[2.68]	[2.68]
Female Fulltime Economic	0.266	0.237	0.168	-0.275	-0.550	-0.547
Participation (lagged)	[1.38]	[1.26]	[0.86]	[-0.44]	[-0.94]	[-0.96]
Codetermination	-0.000	0.022	0.032			
	[-0.01]	[0.84]	[1.07]			
GNI / Capita (lagged)	-0.442	0.536	0.557	5.520*	4.372	3.575
	[-0.39]	[0.44]	[0.47]	[1.81]	[1.51]	[1.27]
GGI	0.789***	0.697**	0.730**			
	[2.61]	[2.29]	[2.45]			
Fraction of Women in Higher	0.272	0.421**	0.310	-0.023	-0.171	-0.217
Education (lagged)	[1.23]	[2.06]	[1.44]	[-0.14]	[-1.15]	[-1.49]
Birth Rate (lagged)	-0.005	-0.009	-0.008	0.012	0.005	0.007
	[-0.94]	[-1.37]	[-1.28]	[1.37]	[0.48]	[0.62]
Tax & Social Security (lagged)	-0.002*	-0.002*	-0.002	0.004	0.001	-0.000
	[-1.67]	[-1.89]	[-1.47]	[1.01]	[0.27]	[-0.01]
Corporate Governance Code	0.003	0.006	0.003	0.000	0.000	0.000
	[0.42]	[0.74]	[0.48]	[0.07]	[0.04]	[0.05]
Quota for State-owned	0.024	0.029	0.023	0.135	0.008	0.035
Companies	[0.82]	[1.06]	[0.80]	[1.13]	[0.11]	[0.39]
Traditional vs. Secular Values	0.033**	0.022	0.019			
	[1.99]	[1.22]	[1.02]			
Survival vs. Self-expression	0.060	0.050*	0.065*			
Values	[1.63]	[1.82]	[1.73]			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Observations	3,907	3,907	3,907	3,907	3,907	3,907
Adj. R-sq	0.161	0.162	0.163	0.177	0.178	0.178

To minimize collinearities between the country dummies and the bank dummies and interaction terms, we restrict our representative sample to banks and report regressions of board diversity on interpolated ADD math score levels and gaps and our full set of control variables including year effects in columns 1-3 of Table VIII. In columns 4-6, we also include country fixed effects. The coefficient on ADD math scores is not statistically significant, consistent with the observation from Figure I that there is less variation in ADD math scores over time than in ADD gaps. However, the coefficient on ADD gap is negative and significant at the 10% level in column 3. This is consistent with the pattern of significance we find if we restrict our sample in Table VI to banks, i.e. the coefficients on math scores are generally not statistically significant in the sample of banks while the coefficients on math gaps are negative and significant at greater than the 5% level (results not reported for the sake of brevity). When we add country effects, the ADD gap remains negative and becomes significant at the 5% level in columns 5 and 6. This suggests that the relationship between math outcomes and board diversity is not driven by omitted country-level variables.

Another way of examining whether omitted country-level variables explain the results is to restrict the sample to one country. We follow Hanushek and Kimko (2000) and restrict our sample to U.S. banks. The evidence in Adams (2010) suggests that bank directors are particularly likely to be influenced by state-level institutional and cultural characteristics. Thus we use state-level NAEP scores by gender to calculate math gaps. As we did for ADD scores, we construct continuous scores and gaps so that we can include state fixed effects in our regressions. We use 1990 NAEP scores for 2004 data, 1992 NAEP scores for 2006 data and 1996 NAEP scores for 2010 data. We extrapolate scores for 2001-2003 and interpolate scores between 2004, 2006 and 2010.

Table IX: US State-Level Fixed Effect Models using NAEP

This table shows the results of OLS regressions of gender diversity on firm and state level characteristics for all banks in 50 states. NAEP state scores level indicates the interpolated levels of NAEP scores, lagged by 14 years; gap indicates the respective gender gap in secondary math skills on state level. All other variables are as in Table I. Model 1-3 excludes, model 4-6 includes state fixed-effects. Robust standard errors are clustered on firm level, with corresponding t-statistics shown in brackets. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Diversity			Diversity	
NAEP State Score	0.002**		0.002**	0.002**		0.002**
	[2.57]		[2.57]	[2.13]		[2.12]
NAEP State Gap		0.000	-0.000		0.001	0.001
		[0.11]	[-0.19]		[0.78]	[0.79]
Assets (log)	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**
	[2.31]	[2.28]	[2.31]	[2.20]	[2.18]	[2.20]
ROE	0.015	0.016	0.015	0.008	0.008	0.008
	[1.53]	[1.60]	[1.52]	[0.93]	[0.92]	[0.93]
Tenure	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	[-2.32]	[-2.28]	[-2.33]	[-2.29]	[-2.30]	[-2.28]
Boardsize (log)	0.051***	0.050***	0.051***	0.045***	0.045***	0.045***
	[4.64]	[4.44]	[4.63]	[4.18]	[4.21]	[4.18]
Independence	0.057**	0.054**	0.057**	0.049*	0.048*	0.049*
	[2.25]	[2.12]	[2.25]	[1.96]	[1.93]	[1.95]
GDP / Capita (log)	0.040	0.040	0.040	-0.055	-0.027	-0.041
	[1.52]	[1.47]	[1.46]	[-0.89]	[-0.42]	[-0.64]
Southern States	0.002	-0.014	0.002			
	[0.21]	[-1.60]	[0.18]			
East Coast	-0.002	-0.005	-0.002			
	[-0.29]	[-0.63]	[-0.26]			
West Coast	0.011	0.001	0.010			
	[0.90]	[0.05]	[0.79]			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes	Yes
Observations	3,234	3,234	3,234	3,234	3,234	3,234
Adj. R-sq	0.096	0.091	0.096	0.180	0.179	0.180

In Table IX we regress bank board diversity on the NAEP scores and gaps. We include the same firm-level controls as before. Instead of country-level controls, we include state-level log(GDP/capita). We include year dummies and dummies for southern, east coast and west coast Census Regions as controls for culture. Columns 1-3 present results without state fixed effects; columns 4-6 include them. Consistent with the lack of variation in NAEP gaps in Figure I, the coefficient on gaps is not significant. However, the coefficients on the scores are positive and significant across all columns. Since cultural variation is lower across U.S. states than across countries, these results suggest that the special relationship between math outcomes and bank board diversity is not driven by other measures of gender culture.

VI. Complementary Evidence

Selection. If gender gaps in math scores are correlated with stereotypes about women's ability to understand finance, we would expect to find evidence of selection. Women who end up on bank boards should be different from women who are not on bank boards (see e.g. Adams and Ragunathan, 2016) and this pattern should be stronger in countries with greater gender gaps. In our context, a key characteristic along which we might expect selection to occur is through education related to finance, in particular CFA and MBA degrees. We might expect women to have to signal more strongly that they understand finance in countries in which math gaps are greater. Alternatively, boards might hold women to a higher standard in countries in which math gaps are greater.

Table X: Global Determinants of MBA or CFA Titles - by Director Type

This table shows the results of a director level marginal probit regressions of an indicator variable of having a MBA degree on a vector of country, firm and director level characteristics for our full sample, and a banks only sample. All variables as in Table I and VI. Robust standard errors are clustered on director level, with corresponding t-statistics shown in brackets. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			MBA or CFA			
VARIABLES		NED			ED	
Female Director	-0.053***	-0.054***	-0.058**	-0.025*	-0.025*	-0.126*
	[-6.35]	[-6.42]	[-2.28]	[-1.76]	[-1.74]	[-1.87]
Banks	-0.397***	-0.143***		0.029	0.047	
	[-4.96]	[-27.61]		[0.07]	[0.11]	
Banks * Female Director	0.067***	0.073***		-0.036	-0.034	
	[3.25]	[3.57]		[-0.84]	[-0.80]	
Age	-0.005***	-0.005***	-0.004***	-0.003***	-0.003***	-0.004***
	[-22.30]	[-22.41]	[-10.56]	[-8.63]	[-8.44]	[-4.00]
Maths Score Above Median			-0.022			0.046
			[-1.38]			[0.76]
Maths Score Above Median * Female			0.003			0.157
			[0.09]			[1.20]
Maths Gap Above Median			0.010			0.003
			[0.64]			[0.07]
Maths Gap Above Median * Female			0.103**			0.159
			[2.33]			[1.15]
Assets (log)	0.014***	0.015***	0.022***	0.011***	0.011***	0.027***
	[12.12]	[12.59]	[10.88]	[7.36]	[7.18]	[4.82]
ROE	0.004**	0.004*	0.012	0.007**	0.006*	-0.016
	[2.02]	[1.90]	[1.47]	[2.11]	[1.88]	[-0.62]
Tenure	-0.003***	-0.003***	-0.002***	-0.001	-0.001	0.001
	[-6.27]	[-6.71]	[-2.69]	[-1.19]	[-1.20]	[0.39]
Boardsize (log)	-0.006	-0.007	-0.046***	-0.000	0.004	0.005
	[-0.84]	[-1.01]	[-4.11]	[-0.00]	[0.44]	[0.16]
Independence	0.120***	0.109***	0.108***	0.161***	0.152***	0.079
	[11.50]	[10.44]	[4.29]	[10.55]	[9.79]	[1.29]
Codetermination	0.044***		0.035	0.021		0.007
	[3.14]		[1.49]	[1.20]		[0.13]
GNI / Capita	2.915***	-1.632	-1.290	2.091***	2.400	-2.631
(lagged)	[4.43]	[-1.13]	[-1.25]	[2.91]	[1.39]	[-1.06]
GGI	0.520**		-0.012	0.856***		-0.356
	[2.24]		[-0.04]	[2.93]		[-0.44]
GGI * Female	1.612***			-0.111		
	[4.28]			[-0.22]		
Fraction of Women in	0.093	0.198*	-0.148	0.166	0.014	0.100
Higher Education (lgd)	[0.83]	[1.95]	[-0.76]	[1.28]	[0.10]	[0.24]
Birth Rate (lagged)	-0.009***	0.008**	-0.003	-0.008*	0.005	0.003
	[-2.71]	[2.06]	[-0.45]	[-1.67]	[0.94]	[0.14]
Tax & Social Security	-0.001	0.003*	-0.003**	-0.001	0.001	-0.007***
(lagged)	[-0.72]	[1.78]	[-2.56]	[-1.52]	[0.29]	[-2.63]
Corporate Governance	0.005	-0.001	0.005	0.007	0.001	0.038
Code	[0.95]	[-0.21]	[0.50]	[0.81]	[0.10]	[1.34]
Quota for State-owned	-0.035	-0.023	-0.037*	0.060**	0.871***	0.153*
Companies	[-1.62]	[-0.54]	[-1.69]	[2.03]	[23.78]	[1.87]
Traditional vs. Secular	-0.042***		0.002	-0.032**		-0.047

Values	[-3.80]		[0.11]	[-2.30]		[-0.93]
Survival vs. Self-expression Values	0.062***		0.103***	-0.014		0.121
	[3.64]		[4.02]	[-0.64]		[1.62]
USA	0.108***			0.067***		
	[8.87]			[4.01]		
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	No	Yes	No
Banks only	No	No	Yes	No	No	Yes
Observations	290,868	290,868	36,951	89,124	89,124	7,782

In Table X we analyze factors related to the likelihood a director has a CFA or MBA degree in the director-level data of our representative sample. In columns 1-3, we focus on non-executive directors. In columns 4-6, we focus on executive directors. In columns 1 and 2, we report coefficients of marginal probit regressions of a dummy indicating a director has a CFA or MBA degree on a female dummy, a bank dummy and the interaction between the female and the bank dummy. We include year effects and the same country- and firm-level controls as in Table VI, except that tenure is now director-level tenure instead of the board-level average. We cluster the standard errors at the director level. Presumably younger directors and directors in the U.S. are more likely to have a CFA or MBA, so we also include director age and a U.S. dummy as controls. In column 2, we include country effects so the U.S. dummy drops out.

The coefficient on the female dummy is negative and significant at the 1% level which suggests female directors are less likely to have a CFA or MBA degree on average. The coefficient on the bank dummy is also negative and significant at the 1% level which suggests bank directors are less likely to have a CFA or MBA degree on average. But the coefficient on the interaction between the female director dummy and the bank dummy is positive and significant at the 1% level which suggests that female directors are relatively more likely to have an CFA or MBA degree in banks.

In column 3 we restrict our sample to banks and include our 2009 PISA math score and the math gap measures along with their interactions with the female dummy. We cannot include country effects here. The interaction term with math scores is insignificant but the interaction with math gaps is positive and significant at the 5% level suggesting that female directors are relatively more likely to have a CFA or MBA in countries in which there are greater gender gaps in math scores.

The interactions with gender are insignificant for executive directors in columns 4-6. Since executive directors work for banks, presumably they do not need to signal their understanding of finance. Thus the evidence in Table VIII is consistent with the selection occurring on a dimension that is related to math scores: finance education through a CFA or MBA.

Math Scores and Women on Boards in Other Sectors. In our analysis we compare finance to all other sectors (in Tables IV and A.IV) and banks to all other firms. But other sectors are also math-intensive. If math outcomes are associated with girls' career paths, we should expect math outcomes to be related to women's representation on the boards of firms in those sectors as well. In fact, including non-financial firms in math-intensive sectors in our earlier analysis may have biased us against finding that math scores help explain board diversity in banks.

We examine the relationship between math scores and board diversity by sector in Table XI. We replicate columns 7 and 8 of Table V for the 10 NAICs supersectors in our representative sample following Adams and Kirchmaier (2016). The dependent variable for each supersector is director participation for that supersector in a given country and year, i.e. the number of unique female directors of firms in that supersector in a given country-year divided by the number of unique directors of firms in that supersector in that country-year. Since not all countries have firms in all sectors, the number of observations varies from 46 for Other Services to 149 for the Manufacturing, Information and Financial Activities supersectors.

Adams and Kirchmaier classify Mining and Logging, Manufacturing, Information, Financial Activities and Professional and Business Services as math-intensive sectors (STEM&F sectors). The coefficient on math gap is negative and significant for three of these sectors: Manufacturing, Information and Financial Activities. For these sectors, the coefficient on math score is positive but not significant. The coefficient on math gap is insignificant in Mining and Logging and Professional and Business Services. Among the non-STEM sectors, the coefficient on math gaps are negative and significant for Education and Health Services and Trade, Transportation and Utilities.

The results from Table XI are not entirely conclusive. One reason may be that some sectors simply have too few female directors to be able to analyze. For example, director participation in Mining and Logging is on average only 3.6% as compared to 11.3% for banks and 10% for Financial Activities. Another reason may be that the supersectors are too broadly defined. For example, the Professional and Business Services supersector contains the three sectors Professional, Scientific, and Technical Services (NAICS 54), Management of Companies and Enterprises (NAICS 55) and Administrative and Support and Waste Management and Remediation Services (NAICS 56). It is possible that math outcomes matter for the more math-intensive sectors within this supersector, but that the aggregation across sectors masks this relationship. Further research is necessary to identify whether math outcomes are related to women's representation on boards in less homogenous supersectors than Financial Activities. Nevertheless, the pattern of results in Table XI is suggestive that they are.

VII. Conclusion

When it comes to the representation of women on boards, we document that the finance industry is special. Because it is relatively human capital intensive, we argue that educational differences between men and women may influence diversity in the industry. Since math is particularly important for finance, we examine this hypothesis using various measures of math scores.

In countries with greater gender gaps in math scores and lower average math scores, we find that banks have lower boardroom diversity. The influence of math scores appears to transcend standard cultural explanations. Although special, the finance industry is not unique. Math scores also appear important for understanding boardroom diversity in STEM and other sectors.

More generally, when we connected two policy debates that are usually conducted separately: the debate about women's underrepresentation in math-intensive or STEM fields and the debate about women's underrepresentation on corporate boards. Our results suggest that low female participation in STEM and finance fields has important consequences for corporate leadership structures in STEM and finance industries.

To ensure that the best managerial talent is in charge of firms, it may not be enough to ask or mandate firms to have more women on their board. Board diversity policies may need to be adapted to industry circumstances. They may also need to be complemented by policies that ensure more equal education outcomes for girls and boys. For example, Ellison and Swanson (2010) suggest increasing the number of schools that allow for elite mathematical training could help narrow the gender gap in math outcomes. Our evidence suggests that differences in educational outcomes for boys and girls may have long-lasting implications for their career development.

Appendix

Table A.I: Sample Composition for Banks

This table shows the number of banks, and other financial companies, per country and year in our representative sample. The sample construction is described in Table Ia.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Australia				8	8	8	7	7	7	7
Austria							6	6	6	6
Belgium	3		3		3		3	4	4	4
Bermuda								1	1	
Canada						8	9	9	9	10
Denmark			2	2	3	3	3	3	3	3
Finland			1	1	1	1	2	2	2	2
France	3	3	3	3	4	4	4	4	4	4
Germany	6	7	7	8	10	10	10	10	10	10
Greece				6	6	7	8	8	8	8
India								13	13	13
Ireland	3	3	3	3	3	3	3	3	2	2
Italy	13		14	15	16	17	19	18	17	17
Netherlands	3	3	3	3	5	5	4	3	3	3
Norway			1	1	1	1	1	1	1	1
Portugal			1	1	2	2	3	3	3	2
Spain	5	5	5	5	5	7	7	7	7	6
Sweden	5	5	5	5	5	5	5	5	5	5
Switzerland	3	3	3	4	6	6	8	8	8	8
UK	5	5	5	5	6	8	8	8	8	8
United States				404	453	477	535	533	511	486
Total	49	34	56	474	537	572	645	656	632	605

Table A.II: Math Scores by Country

This table shows the mean PISA math score per country for 2009, as well as the gender gap as the math score for men minus that for women. Above Median is an indicator variable whether the math score is above median, level 6 shows the percentage of pupils achieving to top attainment level in math, followed by the difference in fraction of male minus female students, hence the level 6 gap. ADD level and gap shows the average lagged readings per country.

	Maths Score	Math Gap	Above Median	Level 6	Level 6 Gap	ADD Level	ADD Gap
Australia	514	10	1	4.5	1.8	540.4	7.4
Austria	496	19	0	3.0	2.5	563.2	15.0
Belgium	515	22	1	5.8	3.8	567.3	2.5
Canada	527	12	1	4.4	2.2	564.1	1.2
Denmark	503	16	1	2.5	1.2	548.5	17.3
Finland	541	3	1	4.9	2	559.5	5.1
France	497	16	1	3.3	2.4	565.9	8.1
Germany	513	16	1	4.6	2.8	541.5	9.2
Greece	466	14	0	0.8	0.7	512.2	13.0
Ireland	487	8	0	0.9	0.7	552.3	13.9
Italy	483	15	0	1.6	1.6	516.9	9.4
Luxembourg	489	19	0	2.3	2.3	511.0	12.2
Netherlands	526	17	1	4.4	3	575.8	11.1
Norway	498	5		1.8	0.6	518.4	4.7
Portugal	487	12	0	1.9	1.4	499.2	18.9
Spain	483	19	0	1.3	1	524.9	15.8
Sweden	494	-2	0	2.5	0.6	562.6	3.3
Switzerland	534	20	1	7.8	4.6	573.9	8.0
United Kingdom	492	20	0	1.8	1.4	574.4	3.5
United States	487	20	0	1.9	1.3	541.0	7.4
Mean	501.6	14.1		3.1	1.9	545.6	9.4
Median	496.5	16.0		2.5	1.7	550.4	8.6

Table A.III: Gender Diversity in the Boardroom of Banks

This table shows the gender diversity of banks across countries and years in our representative sample. Gender diversity is s the number of female directors over board size. Board size is the sum of supervisory and management board sizes in countries with dual boards. The sample is as described in Table Ia.

Country	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Australia				0.137	0.141	0.180	0.176	0.198	0.176	0.178
Austria							0.102	0.107	0.099	0.095
Belgium	0.111		0.102		0.130		0.118	0.125	0.149	0.188
Bermuda								0.000	0.000	
Canada						0.220	0.218	0.206	0.236	0.207
Denmark			0.198	0.213	0.153	0.131	0.136	0.158	0.153	0.147
Finland			0.125	0.125	0.125	0.125	0.213	0.299	0.313	0.313
France	0.019	0.020	0.054	0.057	0.047	0.051	0.069	0.112	0.134	0.183
Germany	0.105	0.094	0.133	0.165	0.151	0.119	0.111	0.116	0.099	0.085
Greece				0.036	0.035	0.070	0.089	0.098	0.116	0.135
India								0.071	0.064	0.073
Ireland	0.049	0.075	0.099	0.090	0.091	0.095	0.112	0.144	0.146	0.183
Italy	0.005		0.007	0.007	0.010	0.019	0.022	0.032	0.028	0.032
Netherlands	0.105	0.117	0.100	0.090	0.057	0.069	0.073	0.067	0.070	0.061
Norway			0.313	0.318	0.400	0.429	0.412	0.375	0.417	0.417
Portugal			0.000	0.000	0.026	0.024	0.016	0.014	0.013	0.019
Spain	0.031	0.066	0.083	0.082	0.081	0.066	0.086	0.067	0.078	0.082
Sweden	0.179	0.224	0.324	0.343	0.340	0.324	0.282	0.311	0.284	0.294
Switzerland	0.038	0.017	0.030	0.073	0.051	0.059	0.082	0.088	0.099	0.098
United Kingdom	0.067	0.076	0.109	0.116	0.112	0.079	0.068	0.076	0.056	0.084
United States				0.081	0.082	0.086	0.091	0.097	0.098	0.105

Table A.IV: Task Intensity in Finance

The table shows regressions of 5 measures of task intensity across industries on a finance sector dummy. The data is the union of the DOT 91 industry file and the DOT 77 industry file from Autor, Levy and Murnane (2003) who match occupational task intensities from the 1977 and 1991 Dictionary of Occupational Titles to Census data from various years between 1960 and 1998 and average them at the occupation level for all non-institutionalized, employed workers, ages 18 to 64 using full-time equivalent hours as weights. Autor, Levy and Murnane average the task intensities at the industry level and at the industry-gender-education level using full-time equivalent hours as weights. Autor, Levy and Murnane's (2003) data contains mean task intensities for two routine manual skills (finger dexterity and set limits, tolerances), one non-routine manual skill (eye, hand, foot coordination) and two non-routine, cognitive skills (direction, control and planning and GED-math). Direction, control and planning is a measure of interactive, communication, and managerial skills. GED-math stands for "general educational development in math" and measures the quantitative reasoning requirements of an occupation. We classify industries as belonging to 12 industry sectors, finance, agriculture, mining, manufacturing, transportation, wholesale, retail, personal services, business services, entertainment, professional services and public administration using 1990 Census industry classification codes and Autor, Levy and Murnane's consistent industry code (ind6090) between 1960 and 1990. We define finance as containing banking, credit agencies, savings and loan associations (ind6090=706); security, commodity brokerage, and investment companies (ind6090==710) and insurance (ind6090==711). Regressions include year dummies and dot dummies. Standard errors are corrected for clustering at the sector level. Panel A is for task intensity means for all education levels and both genders; panel B is for college education and both genders.

	Panel A: Task intensity means for all education levels and both genders				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Finger Dexterity	Set Limits, Tolerances	Eye-Hand-Foot	Direction, Control, Planning	Math Aptitude
Finance	0.202**	-0.232	-1.022***	1.078***	1.194***
	[2.31]	[-0.40]	[-9.00]	[5.63]	[6.11]
Constant	3.828***	4.990***	1.297***	1.932***	3.402***
	[43.26]	[8.67]	[11.85]	[8.81]	[14.45]
Type of Skill	Routine	Routine	Non-Routine	Non-Routine	Non-Routine
Function	Manual	Cognitive	Manual	Cognitive	Cognitive
Observations	2,514	2,514	2,514	2,514	2,514
Adj. R-sq	0.009	0.015	0.050	0.065	0.042
	Panel B: Task intensity means for college education and both genders				
	(6)	(7)	(8)	(9)	(10)
VARIABLES	Finger Dexterity	Set Limits, Tolerances	Eye-Hand-Foot	Direction, Control, Planning	Math Aptitude
Finance	-0.195***	-0.733*	-0.573***	0.127	0.354**
	[-3.94]	[-2.18]	[-5.70]	[0.51]	[2.26]
Constant	3.615***	4.078***	0.870***	4.413***	5.180***
	[71.79]	[10.02]	[10.94]	[22.75]	[34.47]
Observations	2,502	2,502	2,502	2,502	2,502
Adj. R-sq	0.008	0.019	0.024	0.027	0.031

References

Adams, Renée B. "Governance at Banking Institutions," Chapter 23 in *Corporate Governance*, R. Anderson and H.K. Baker (eds.), Wiley & Sons, 2010, Hoboken, New Jersey, pp. 451-468.

Adams, Renée B. and Tom Kirchmaier (2015) "Barriers to Boardrooms", ECGI - Finance Working Paper No. 347/2013. Available electronically.

Adams, Renée B. and Tom Kirchmaier (2016) "Women on Boards in Finance and STEM Industries," *American Economic Review: Papers & Proceedings* 2016, 106(5) 277–281

Adams, Renée B. and Vanitha Ragunathan (2016) "Lehman Sisters," Working paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2380036.

Adrian, T., and H. S. Shin (2010) "Liquidity and Leverage" *Journal of Financial Intermediation* 19, 418-437.

Altinok, Nadir & Claude Diebolt & Jean-Luc Demeulemeester (2014) "A new international database on education quality: 1965--2010," *Applied Economics*, vol. 46(11), pages 1212-1247, April.

Angrist, Noam, Harry Anthony Patrinos, and Martin Schlotter (2013) "An Expansion of a Global Data Set on Educational Quality: A Focus on Achievement in Developing Countries," World Bank Policy Research Working Paper 6536.

Autor, D. H., F. Levy, and R. J. Murnane (2003), "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 118(4), 1279-1333.

Becker, Gary S. (1971) *The Economics of Discrimination*, Chicago: The University of Chicago Press.

Barro, Robert and Jong-Wha Lee, 2013, "A New Data Set of Educational Attainment in the World, 1950-2010." Journal of Development Economics, vol 104, pp.184-198.

Beck, Thorsten (2012) "Finance and Growth: Lessons from the literature and the recent crisis," Prepared for the LSE Growth Commission.

Breakspear, S. (2012), "The Policy Impact of PISA: An Exploration of the Normative Effects of International Benchmarking in School System Performance", OECD Education Working Papers, No. 71, OECD Publishing. http://dx.doi.org/10.1787/5k9fdfqffr28-en

Carnoy, Martin and Richard Rothstein, "What do international tests really show about U.S. student performance?" EPI, January 28, 2013. Available electronically.

College Board (2011) "SAT Trends: Background on the SAT Takers in the Class of 2011," https://research.collegeboard.org/programs/sat/data/archived/cb-seniors-2011/tables

Else-Quest, Nicole M., Janet Shibley Hyde and Marcia C. Linn, (2010) “Cross-National Patterns of Gender Differences in Mathematics: A Meta-Analysis” *Psychological Bulletin*, Vol. 136, No. 1, 103–127.

Ellison, Glenn and Ashley Swanson (2010) "The Gender Gap in Secondary School Mathematics at High Achievement Levels: Evidence from the American Mathematics Competitions," *Journal of Economic Perspectives*, vol. 24(2), pages 109-28.

Ferreira, Daniel, Tom Kirchmaier and Daniel Metzger (2010) “Boards of Banks”, EGGI Finance Working Paper No 289/2010. Available electronically.

Fryer, Jr., Roland G. and Steven D. Levitt (2010) “An Empirical Analysis of the Gender Gap in Mathematics” *American Economic Journal: Applied Economics* 2 (April 2010): 210–240

Guiso, Luigi, Ferdinando Monte, Paola Sapienza, Luigi Zingales (2008) “Culture, Gender, and Math” *Science* 30 May 2008: Vol. 320, Issue 5880, pp. 1164-1165 DOI: 10.1126/science.1154094

Hanushek, Erik A. and Dennis D. Kimko (2000) “Schooling, Labor-Force Quality, and the Growth of Nations,” *American Economic Review*, 90:5, 1184-1208.

Hanushek, Erik and Ludger Woessman (2008) “The Role of Cognitive Skills in Economic Development,” *Journal of Economic Literature*, 46:3, 607–668. Available electronically.

Hanushek, Erik A. and Ludger Woessman (2012) “Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation” *J Econ Growth* (2012) 17:267–321

Hausmann, Ricardo, Laura D. Tyson, Saadia Zahidi (2010) “The Global Gender Gap Report”, World Economic Forum, Geneva Switzerland. Available electronically.

Hyde, Janet S. and Janet E. Mertz (2009) “Gender, culture, and mathematics performance,” *PNAS*, vol. 106(22), 8801–8807

Hyde, Janet S., Sara M. Lindberg, Marcia C. Linn, Amy B. Ellis, Caroline C. Williams (2008) “Gender Similarities Characterize Math Performance” Science 320, 494.

Inglehart, Ronald and Christian Welzel, (2005) *Modernization, Cultural Change and Democracy*, New York: Cambridge University Press.

Jacobs, Janis E., and Jacquelynne S. Eccles (1985) “Gender Difference in Math Ability: The Impact of Media Reports on Parents.” *Educational Researcher*, 14(3): 20–25.

Levine, Ross (2005) “Finance and Growth: Theory and Evidence” in Philippe Aghion & Steven Durlauf (ed.), 2005. *Handbook of Economic Growth*, Elsevier, edition 1, volume 1, number 1.

Mullis, Ina V.S., Michael O. Martin, Edward G. Fierros, Amie L. Goldberg, Steven E. Stemler (2000) "Gender Differences in Achievement, IEA's Third International Mathematics and Science Study", International Study Center, Lynch School of Education, Boston College.

Nosek et al. (2009) "National differences in gender-science stereotypes predict national sex differences in science and math achievement," PNAS, vol. 106(26) 10593–10597

OECD (2004) "Learning for Tomorrow's World-First Results from PISA 2003". Available electronically.

OECD (2010), "PISA 2009 Results: What Students Know and Can Do – Student Performance in Reading, Mathematics and Science (Volume I)". Available electronically.

OECD (2015), The ABC of Gender Equality in Education: Aptitude, Behaviour, Confidence, PISA, OECD Publishing. http://dx.doi.org/10.1787/9789264229945-en

Philippon, Thomas and Ariel Reshef (2012) "Wages and Human Capital in the U.S. Finance Industry: 1909–2006", *Quarterly Journal of Economics*, 127(4), 1551-1609.

Reuben, Ernesto, Paola Sapienza, and Luigi Zingales (2014) "How stereotypes impair women's careers in science", *PNAS*, vol. 111 no. 12, 4403–4408, doi: 10.1073/pnas.1314788111

Stack, Michelle (2007) "Representing School Success and Failure: media coverage of international tests" *Policy Futures in Education*, Volume 5(1), 100-110

Terjesen, Siri, Eduardo Barbosa Couto, Paulo Morais Francisco (2015) "Does the presence of independent and female directors impact firm performance? A multi-country study of board diversity," forthcoming *Journal of Management and Governance*.

U.S. Department of Education, 2013, "NAEP 2012 Trends in Academic Progress," NCES 2013–456.

Wai, Jonathan, Megan Cacchio, Martha Putallaz, and Matthew C. Makel (2010) "Sex differences in the right tail of cognitive abilities: A 30 year examination." *Intelligence* 38, 412–423.

Wiseman, A. W. (2013). Policy Responses to PISA in Comparative Perspective. In H.-D. Meyer & A. Benavot (Eds.), *PISA, Power, and Policy*. Oxford: Symposium Books.