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Sex, science, and society

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ABSTRACT

We show that culture affects individuals' participation in science. Using Scopus data on 3.7 million scientists worldwide, we document that women's representation in science varies across fields and across countries, even within a field. Women's representation in both STEM and Non-STEM fields is higher in more gender-equal countries and countries with greater academic freedom. Women's representation is higher in fields with more inclusive cultures. We provide evidence for two channels through which culture affects representation: migration and productivity. For example, female scientists' location choices appear to be more sensitive to country culture than those of male scientists. Our results highlight that individuals' careers in science depend on social factors. Thus, a country's capacity to engage in scientific research — critical for innovation and economic growth — also hinges on social factors.

1. Introduction

Culture affects science. A corollary is that when society is more open towards women, science should also be more open towards women. We test this hypothesis by first documenting that women's representation across scientific fields and countries varies significantly. We then examine the role of country and field culture in explaining this variation.

Although the scientific establishment initially resisted the idea that culture affects science (see e.g. the account in Franklin, 1995), it is now widely accepted. Yet, as Fortunato et al. (2018) point out "Although SciSci [the science of science] seeks long-standing universal laws and mechanisms that apply across various fields of science, a fundamental challenge going forward is accounting for undeniable differences in culture, habits, and preferences between different fields and countries." We argue that this accounting is particularly important for understanding women's participation in science. It is well known that women's representation in science and research output lags behind men's. Yet, explanations for this phenomenon often do not account for culture.

Larry Summers famously described one popular explanation for women's relative underrepresentation in science, particularly in STEM fields, which is that there are sex differences in preferences and capabilities (Dillon, 2005; Ceci et al., 2014). But others argue that culture shapes preferences, which means that observed sex differences in preferences may be socially constructed rather than purely biological (e.g. Eagly and Wood, 1999; Halpern et al., 2007; Guiso et al., 2008; Schwartz and Rubel-Lifschitz, 2009). Culture may also be linked to women's education (Guiso et al., 2008; Breda et al., 2020b) and women's willingness to enter or remain in certain scientific fields (Leslie et al., 2015; Master et al., 2021). The extent to which women's representation in science is *intrinsic* versus cultural is, therefore, not clear.

As Fortunato et al. (2018) point out, the dimensions of culture that affect science can be both country- and field-specific. Both of these dimensions of culture may affect women's participation differently than men's. Guiso et al. (2008) and Breda et al. (2020b) connect general dimensions of societal culture, as proxied by the World Economic Forum's Gender Gap Index (GGI), to gender gaps in educational outcomes. Leslie et al. (2015) highlight the role of field-specific culture for women's representation. They show that there are fewer female Ph.D. students in fields in which beliefs about the talent necessary to succeed in the field are stronger. They argue that because women are stereotyped as not having this talent, fields with high ability beliefs are less welcoming to women.

To examine the influence of culture on women's participation in science, we construct measures of women's representation at the country-field level using data from the International Center for the Study of Research (ICSR) Lab on 3.7 million scientists in 2019 from Elsevier's Scopus. We complement this data set with individual-level data set on the top 2% of scientists in their respective fields in 2019 from Ioannidis

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et al. (2019, 2020). This data set contains information on working country and publication counts for top scientists across all major scientific fields globally, which we exploit to examine specific channels through which culture may affect women's representation.

We augment data on women's representation with proxies for country and field culture. We follow various authors (e.g. Guiso et al., 2008; Adams et al., 2021; Cuevas et al., 2025) in using country-level measures of gender equality as proxies for countries' gender culture and norms. Since we focus on women's entry into a domain for which education is a prerequisite, we focus on measures of gender equality related to women's (post-education) participation in labor markets, specifically the World Economic Forum Economic Participation and Opportunity Index, female labor force participation, and the World Bank's Women Business Law Workforce Index.

To these general measures of women's role in the labor market, we add a measure of country-level academic freedom from the FAU Erlangen-Nürnberg and V-Dem Institute. One reason some scientific fields and universities advocate for greater women's representation in their fields is because diversity is associated with an expansion of ideas, e.g. Nielsen et al. (2018). We argue new ideas, and hence diversity in science, are more likely to be valued and demanded in countries in which academic freedom is more important. We proxy for field culture using field-specific ability beliefs from Leslie et al. (2015).

To examine the role of culture, we regress women's representation by field and country in 2019 on our proxies for either country culture or field culture. We employ various strategies to try to identify the effect of culture, including lagging our measures of culture to the earliest feasible date (2006), and controlling for various additional country-level characteristics, such as Programme for International Student Assessment (PISA) math gender gaps, as they could be correlated with both women's representation in science and culture (e.g. Guiso et al., 2008). Since culture is slow-moving, we focus on cross-sectional regressions with fixed effects to address omitted variable concerns. Our regressions examining country culture include field fixed effects, and the regressions examining field culture include country fixed effects.

To instill further confidence that our results have a causal interpretation, we examine changes in women's representation in science around potentially exogenous shocks to culture.[1] President Trump's ongoing attempts to curb academic freedom make the link between politics and academic freedom particularly salient. Thus, we searched for countries that experienced discrete changes in academic freedom as a result of political events, primarily turnover, and identified six cases for which we could also obtain data on women's representation. These changes in academic freedom occurred in Brazil, China, Hungary, India, Mexico, and Saudi Arabia. The changes in academic freedom in these countries are unlikely to have been caused by women's representation in science, and are hence plausibly exogenous. Moreover, examining these cases may be informative about potential consequences of President Trump's agenda.

We find that countries with more gender-equal cultures and fields with lower ability beliefs have a greater share of female scientists and female top scientists. The positive (negative) relationship between women's representation in science and country (field) culture hold in both STEM and Non-STEM fields. Indeed, the role of culture is often stronger for Non-STEM fields. Our country-level case studies supports a causal interpretation, as shocks to academic freedom appear to be linked to changes in women's representation in science in both Non-STEM and STEM fields. We also find that in more gender-equal countries, women's representation in fields with higher ability beliefs is lower.

To examine potential mechanisms behind our results, we exploit the individual data on top scientists. We examine two potential mechanisms through which country culture may influence women's ability to become top scientists. The first is selection through migration. It is plausible that top female scientists prefer to work in more gender-equal countries. The literature on female migration highlights the importance of culture as a "pull" factor (Naghsh-Nejad and Young, 2014; Antman, 2018; Ruyssen and Salomone, 2018; Anastasiadou et al., 2023), and there is evidence that high-skilled women migrate to more equal countries (e.g. Parey et al., 2017). It is also plausible that universities in more gender-equal countries are more willing to hire women. Consistent with these arguments, we find that female migration may be one reason why countries with more gender-equal cultures have more female top scientists.

The second mechanism we explore is research output. A substantial body of evidence argues that there is a "productivity puzzle" (e.g. Zuckerman and Cole, 1984), with female scientists publishing on average fewer papers than male scientists. This has important implications for women's advancement in science because academic promotion processes often focus on counts of publication output (e.g. Long et al., 1993). Our evidence is consistent with the idea that women's ability to produce papers depends on the culture they work in.

Leslie et al. (2015) shows that women's representation among earned doctorates in the United States varies with field-specific ability beliefs. Adams and Xu (2023) show that field-specific ability beliefs help explain women's representation in the field of finance. By showing that the influence of field-specific ability extends beyond the Ph.D. stage and appears robust across countries, we show that country-level socialization (e.g. Rossi, 1965; Schiebinger, 1987; Fryer, Jr. and Levitt, 2010) does not entirely drive women's field-level representation. Thus, our evidence supports the idea that scientific fields have cultures that transcend national boundaries. Our evidence also complements previous work linking country culture to women's educational outcomes (e.g. Cheung and Chan, 2007; Guiso et al., 2008). Since cultural norms may influence women's desire to enter, and their ability to remain in a field, our work helps rationalize the longitudinal cross-country evidence in Huang et al. (2020) showing that gender differences in academic career paths can be partly explained by different career lengths and exit rates.

We complement other work proposing explanations for the "gender equality paradox" (Breda et al., 2020b; Richardson et al., 2020), which suggests that more gender-equal countries exhibit greater sex differences in STEM educational outcomes and occupations (e.g. Charles and Bradley, 2009; Stoet and Geary, 2018). In our data, the relationship between gender equality and women's scientific representation is different across STEM and Non-STEM fields, but it is always positive. Our evidence suggests one potential explanation for the gender equality paradox. In countries with greater gender equality, women may be less willing to accept the barriers imposed by field-specific culture and may be freer to select into more welcoming fields.

Our results reinforce the importance of moving beyond preference- and evolution-based explanations for women's representation in science (e.g. Halpern et al., 2007). Such explanations often suggest that policies to change gender gaps in science can do little more than to ask women to change their preferences, or "lean-in" (see also the discussion in Cortes and Pan, 2018; Eckel et al., 2020; Ceci et al., 2023). Bertrand (2011) writes: "Sorting out the relative importance of nature versus nurture has important policy implications." But, an inability to conclusively resolve this debate should not be taken as a justification for inaction. Our results suggest that any policy that reduces barriers to women's labor force participation and academic freedom may increase women's representation in science. Similarly, policies to improve field culture should make fields with relatively few women more attractive to them (e.g. Adams and Lowry, 2022c).

Consistent with the observation in Ritz and Greaves (2024, p. 36) that "science has never been insulated from social and cultural biases", our analysis highlights that societal factors shape countries' participation in the scientific endeavour, which plays an important role in their innovation and growth trajectories (e.g. Fortunato et al., 2018; Clancy,

[1] We are grateful to an anonymous referee for suggesting this strategy.

2021b). As Powell and Snellman (2004) argue, scientific thought leadership is fundamental to knowledge economies. The full potential of scientific thought leadership is unlikely to be realized, however, if it is not diverse (e.g. Nielsen et al., 2018). The absence of scientific diversity may lead important research questions to remain unanswered (e.g. Clancy, 2021a). The same barriers that prevent women from becoming scientists and thought leaders may also constrain the development of ideas (e.g. Adams and Lowry, 2022a,b; Kozlowski et al., 2022; Yang et al., 2022; Wright, 2024).

Thus, our results suggest that innovation policy and policies to increase gender equality should go hand-in-hand.

2. Background

The conduct of science requires a culture that supports originality, independence of thought, and dissent (see, e.g., Iaccarino, 2003). While scientific fields can develop institutions, like professional associations, and norms, such as adherence to journal rankings, to promote scientific culture, science is also dependent on the culture in which it is embedded. President Trump's "war on DEI" which exploits culture wars against "wokeness" to curtail academic freedom through legal means (see, e.g., Kang, 2025) provides a real-time illustration of this dependence. Norris (2025) provides more systematic evidence that backsliding in liberal democracy threatens academic freedom. Perhaps more importantly, her evidence suggests that legal restrictions on academic freedom may also encourage scientific self-censorship and the suppression of debate, thereby weakening culture within science.

Other than through institutional constraints on academic freedom, country-level culture may influence the conduct of science directly through beliefs, or "point of view" (Phillips et al., 2014), and institutions, e.g. educational systems. Cultural beliefs, norms, and institutions may influence individuals' interests in science. Because cultural affinity may also affect hiring practices (e.g., Siniscalchi and Veronesi, 2020; Wright, 2024), culture can also influence any individual's ability to enter and succeed in science.

Similarly, field-specific scientific institutions and norms influence both the conduct of science and individuals' ability to enter and succeed in science. In her book on epistemic cultures, Cetina (1999) uses two scientific fields, high-energy physics and molecular biology, to argue that science has diverse cultures. Fourcade et al. (2015) conduct a similar analysis for the social sciences, with a focus on highlighting the hierarchical nature of economics. Wright (2024) argues that the power asymmetries that characterize economics have important consequences for the production of economic knowledge.

Both societal and field-specific cultures may play a particularly important role in influencing women's ability to participate and succeed in science. Restrictions on academic freedom that target fields in which women are overrepresented, e.g., gender studies (Mendes et al., 2020), directly affect women's participation. Societal culture and norms around gender roles also influence women's education (e.g., Guiso et al., 2008; Breda et al., 2020b) and can shape sex differences in preferences (e.g., Eagly and Wood, 1999; Guiso et al., 2008; Schwartz and Rubel-Lifschitz, 2009) that may affect both women's willingness to enter science and men's willingness to hire women. These societal factors may also affect women's ability to be considered to be productive, and hence remain, in science (e.g., Schiebinger, 1987).

Gender role expectations may influence women's participation in science at all stages of their careers. Adams and Lowry (2022b) show, for example, that even among members of the most prestigious academic finance association, the American Finance Association, female finance academics in 2020 still carry out most child-care duties. Moreover, the availability of on campus child care significantly affects the job satisfaction of female, but not male, academics. Cultural norms around child care may be one reason why female scientists publish on average fewer papers than men (e.g., Long, 1990), have shorter careers and are less represented at the top of the scientific hierarchy (e.g., Mulders et al., 2024).

The literature on epistemic injustice (e.g., Fricker, 1999; Catala, 2015) highlights that societal inequality and power imbalances may also be associated with other less visible constraints on women's participation in science. Fricker (1999)'s concept of "testimonial injustice" describes situations in which women's knowledge is discredited because they are women. The lack of credibility accorded women's knowledge may be one explanation for the gender imbalance in citation patterns in publications (e.g., Koffi, 2021; Lerman et al., 2022) and patents (e.g., Bikard et al., 2025).

Societal attitudes and field-level culture may also influence women's participation and ability to succeed in specific scientific fields (e.g., Leslie et al., 2015; Master et al., 2021; Berland et al., 2023). The literature on women's representation in STEM fields emphasizes the relevance of many dimensions of culture, including structural inequality and norms (e.g., Straza and Scan, 2024). Berland et al. (2023) provides an example of how the hierarchical culture of economics affects women's participation in the field. This discussion highlights that there are many supply- and demand-side channels through which societal and field-level culture may affect women's participation in science. However, to date, there is no systematic evidence of a link between culture and women's representation in science.

Despite substantial evidence of a strong link between societal beliefs about gender roles and general female labor force outcomes (Boserup, 1970; Fernández, 2007; Fernández and Fogli, 2009; Alesina et al., 2013), there is no consistent mapping between the major cross-national cultural frameworks by Schwartz (1999) and Hofstede (2001) and beliefs about women's roles.[2] Thus, we follow various authors (e.g., Guiso et al., 2008; Adams et al., 2021; Cuevas et al., 2025) in using country-level measures of gender equality related to women's participation in the workforce as proxies for countries' gender culture and norms.

The measures of country culture we examine here, together with a measure of academic freedom, encapsulate some of the norms and institutions that affect women's ability to participate in science, such as beliefs about education, societal gender roles, social norms with respect to child care, and the tolerance of different points of view. The field-level measure of culture we examine, "expectations of brilliance" from Leslie et al. (2015), is a proxy for power imbalances in the field that is related to Fricker's (1999) concept of testimonial injustice, as it suggests the extent to which those who are not considered "brilliant" may not be accorded credibility (see also Siniscalchi and Veronesi, 2020).

Ongoing events in the U.S. highlight that shocks to academic freedom are often connected with "brain drain" (e.g., Cohen, 2025). This motivates our analysis of migration as a mechanism through which culture affects women's representation in science.

Zhao et al. (2023) propose that international migration could help narrow the gender gap in academia. Using bibliometric data from Scopus, they demonstrate that female scientists are increasingly mobile but that they move to a narrower set of destinations than men. The literature on high-skilled women's migration is as yet underdeveloped (Dodson, 2021). However, there is evidence that countries with low levels of discrimination are relatively more attractive to female migrants in general (e.g., Fleury, 2016). This suggests the culture of the working country may be a "pull factor" for female scientists in our individual-level data. While the top scientists we analyze may have more opportunities to migrate than other scientists, Zhao et al. (2023) suggest that international migration is an important career advancement strategy for all scientists. We provide suggestive evidence

[2] For example, Kaasa (2021) describes that Hofstede's masculinity-femininity dimension may be better associated with achievement orientation than gender egalitarianism. She also describes the absence of a link between a single Schwartz cultural dimension and gender egalitarianism.

consistent with their argument in a robustness check using a sample of data that is not restricted to top scientists from Bohannon and Doran (2017).

Finally, we examine whether culture is related to individual scientists' publication counts, as they are the focus of a vast literature on the "productivity puzzle" (e.g., Zuckerman and Cole, 1984). However, the theoretical link between culture and women's research output is not necessarily clear. In countries where it is easier for women to work, e.g., because access to child care is better, female scientists may be able to write more papers. On the other hand, in countries where women face more barriers, women may need write more papers to establish themselves as top scientists (e.g., Warren, 2019). A full analysis of the role of culture would require data on scientists throughout their careers. Nevertheless, the cross-sectional link between research output of top scientists and culture in our data is potentially informative, as the effects of culture are likely to operate in the same direction for scientists below the top.

Science, of course, can also affect culture. Giorcelli et al. (2022) document that after Charles Darwin published "On the Origin of Species", the concept of evolution became associated not only with biology but also with broader public discourse, reflecting a wider cultural transformation. Specific scientific and technological breakthroughs, like the creation of the internet and the rise of artificial intelligence, can also have a fundamental impact on culture. Fourcade et al. (2015) also point out the important role economics has in shaping policy, which may influence institutional aspects of culture. However, the literature on culture often emphasizes how slow-moving it is (e.g., Alesina et al., 2013), and the effects of science on culture are not systematically documented. Indeed, Giorcelli et al. (2022) claim to provide the first large-sample quantitative analysis of the effect of science on culture.

Women's representation in science may lead to more diversity in topics and greater innovation (e.g., Zheng et al., 2022), which could influence field-level culture. It could also affect society by influencing stereotypes (see, e.g. Miller et al., 2015) and the career choices of girls (e.g., Breda et al., 2020a). However, it is not yet clear that increases in women's representation in science leads to improved field- or country-level culture along the dimensions we examine here.

Rossiter (1997) highlights that women's experiences in a field change as women's representation increases, in part because women might form committees to address difficulties they experience with recognition and advancement. However, it is not clear how effective these committees are at changing field-level culture. In economics, such a committee, the Committee for the Status of Women in the Economics Profession (CSWEP), exists since 1973, but gender imbalances in economics are remarkably persistent (e.g., Berland et al., 2023). More generally, Bagues et al. (2017) do not find that women's representation on scientific promotion committees affects women's promotions. It is also unclear whether role-modeling effects operate on the extensive margin — leading girls and women to enter the workforce or science who otherwise would not — or whether these effects operate on the intensive margin.

Much more research remains to be done on the consequences of women's increased participation in science. Of course, the absence of literature on this topic does not justify dismissing the effect of science on culture as a source of endogeneity in our analysis. We describe the steps we take to address its potential role in our analysis in Section 4.

3. Data

3.1. Data sources

We use four data sets in our analysis: (1) a country–field-level data set containing measures of women's representation in science in 2019 that we construct from Scopus data, (2) a country-field-year-level data set containing measures of women's representation in science that we construct from Scopus data for the years 2008 to 2022 for six selected countries and their four nearest-neighbor matched countries by region and numbers of scientists, (3) an individual-level data set of top scientists in 2019 compiled from Scopus data by Ioannidis et al. (2019, 2020), and (4) an individual-level data set of scientists in ORCID between 2013 and 2016 compiled by Bohannon and Doran (2017).

We use the first two data sets to analyze the relationship between culture and women's representation. We use the second two data sets to examine channels for cultural transmission. Data sets (1), (3), and (4) contain GDP and the relevant country and field culture proxies that we describe below.

To construct measures of women's representation in the country-field-level data, we obtain data on approximately 3.7 million scientists indexed in Scopus as of 2019 from ICSR Lab, a division of Elsevier. We choose 2019 as the year of analysis to match the year of the data from Ioannidis et al. (2019, 2020). A key feature of this data set is that it classifies scientists' gender. Following Ioannidis et al. (2019, 2020), we include scientists who have authored at least five publications — defined as articles, reviews, or conference papers — in Scopus. When aggregating the individual data to the country-field level, we avoid double-counting scientists by assigning them to the field in which they have the highest number of publications.[3]

Scopus uses Science-Metrix to classify publication research areas into 20 fields. According to this classification, economics is part of the field of business. But Leslie et al. (2015) do not provide field-specific ability beliefs for any business-related discipline except economics. Thus, we create an additional field by using Science-Metrix sub-field classifications to separate economics and finance from business.

We follow the same procedure to construct the country-field-year-level data for the six countries in our case study for the period from 2008 to 2022. The end year of 2022 is determined by the availability of our Scopus data. We chose a start year of 2008 to have enough data prior to the first shock (2012) to observe pre-event trends.

Since ICSR does not allow us to download data at the individual level, we obtain individual-level data from Ioannidis et al. (2019, 2020). Ioannidis et al. (2019, 2020) provide two top scientist data sets, one that classifies top scientists based on citations in a single calendar year, 2019, and one that uses citations from 1996 to 2019. We focus on the data set using citations in 2019 because it contains more female scientists and scientists at more comparable stages in their careers. The data set contains individual names, institutional affiliations, countries of the institutions, academic field, years of first publication, and citation metrics for the top 2% of scientists with at least five publications indexed by Scopus. The data set does not contain gender or nationality. We use scientists' names to classify their gender using Genderize.io.[4] As in Adams and Xu (2023), we drop about 34,000 scientists for whom the certainty of the assigned gender is lower than 90%. To infer nationality, we rely on scientists' names using Nationalize.io.

We define a dummy variable top scientist to have migrated if their nationality (origin country) differs from the country of their institutional affiliation (working country). Since this measure does not rely on location data, it is unclear how accurate it is. Moreover, using names to estimate demographic information introduces measurement error (e.g., Lockhart et al., 2023). Thus, we use ORCID data from Bohannon and Doran (2017) to examine the robustness of our migration analysis. ORCID is a non-profit organization that provides researchers with unique identification codes. ORCID data are self-reported, which means they should be fairly accurate. However, registration in ORCID is voluntary, which means it is not as representative as the Scopus data. Nevertheless, many universities ask their faculty to register in ORCID. Providing an ORCID ID is also a requirement for grant submission for

[3] We use the field classification of a publication rather than the field classification of a journal to define the research area.

[4] Since names are considered to be gendered, we use the term "gender" instead of "sex" when discussing our data and results.

some funders, e.g., the UK Research Council. Thus, this data set may have reasonable coverage of active scientists.

Bohannon and Doran (2017) collect ORCID data for 2013 to 2016. Their data set contains scientists' unique ORCID identifiers, their PhD status, their PhD conferment year, the location of their first job,[5] and the countries where they worked in 2016. The data set does not contain scientists' fields, gender, or names. To classify gender, we use scientists' unique identifiers to collect their names from the ORCID website and apply Genderize.io to the names. We drop scientists for whom the certainty of the assigned gender is lower than 90% and those without PhD degrees. In this sample, we code a scientist as having migrated if the countries of their first jobs (origin country) differ from the countries where they worked in 2016. We assign scientists to cohorts based on the years they obtained their PhD degrees.

3.2. Classifying STEM fields and measuring culture

To analyze differences across STEM and non-STEM fields, we assign fields to STEM and non-STEM fields in each data set except the ORCID data.

There is no universal definition of STEM fields (Manly et al., 2018). We use a strict definition of STEM and classify fields according to the acronym, i.e., we consider STEM fields to be fields that relate specifically to science, technology, or engineering and that are math-intensive. Thus, we classify the following fields as STEM fields: biology, biomedical research, chemistry, earth & environmental sciences, economics & finance, enabling & strategic technologies, engineering, information & communication, mathematics & statistics, and physics & astronomy.

Non-STEM fields include agriculture fisheries & forestry, built environment & design, business (excluding economics and finance), clinical medicine, communication & textual studies, historical studies, philosophy & theology, psychology & cognitive sciences, public health & health services, social science, and visual & performing arts. In Table OA4, we show that our results are robust to alternative definitions of STEM that either separate STEM fields by their math intensity, or that allocate agriculture, fisheries & forestry and psychology & cognitive sciences to STEM as per the definition used by the U.S. Department of Homeland Security's Immigration and Customs Enforcement Service.[6]

We use four measures of country-level culture that we incorporate into the data sets indicated in Section 4: the Economic Participation and Opportunity index (WEF EPO)—a subindex of the World Economic Forum's Gender Gap Index, labor force participation (LFP), the Women Business Law workforce index (WBL Workforce), and the Academic Freedom Index (AFI). The WEF EPO index, constructed by the World Economic Forum, tracks the gender wage gap and labor force participation, as well as the representation of women among legislators, professionals, and managers. LFP is women's labor force participation divided by men's labor force participation, as in Falk and Hermle (2018), both sourced from the World Bank.

The WBL Workforce index is a subindex of the World Bank's Women Business Law index (World Bank, 2023). It focuses on legislation that is relevant for women's decisions to enter and remain in the workforce. The Academic Freedom Index is from FAU Erlangen-Nürnberg and the V-Dem Institute. It captures essential aspects universally relevant to academic freedom (Kinzelbach et al., 2023), such as the freedom to research and teach, academic exchange, institutional autonomy, campus integrity, and academic and cultural expression.

We use field-specific ability belief scores from Leslie et al. (2015) to measure culture within a scientific field in our country-field-level data set and our individual data set from Ioannidis et al. (2019, 2020). These scores reflect individuals' beliefs regarding the importance of innate talent in their respective fields. Specifically, Leslie et al. (2015) pose the following questions to faculty, postdoctoral fellows, and graduate students across various academic disciplines:*(1) Being a top scholar of [discipline] requires a special aptitude that just cannot be taught; (2) If you want to succeed in [discipline], hard work alone just will not cut it; you need to have an innate gift or talent; (3) With the right amount of effort and dedication, anyone can become a top scholar in [discipline]; (4) When it comes to [discipline], the most important factors for success are motivation and sustained effort; raw ability is secondary.* Fields in which respondents give more weight to questions (1) and (2) tend to have higher field-specific ability belief scores.[7]

We collect country-level math scores in 2006 from PISA. We define the math gap as the difference between the average PISA scores of boys and girls. In robustness checks, we also use field-level Graduate Record Examination (GRE) math data from Ginther and Kahn (2015).

We use the logarithm of GDP per capita for 2006 to measure economic development. GDP data are from the Maddison Project Database.[8]

3.3. Summary statistics

Our final country-field-level data set contains data on women's representation in 21 fields across about 170 countries. Our individual-level data set contains data on over 125,000 scientists across 21 fields and about 80 countries.[9] The ORCID data set includes approximately 18,000 migrated scientists across about 150 countries.[10]

Table 1 shows descriptive statistics for our country-field-level data (Panel A), the individual-level data (Panel B), and the ORCID data (Panel C). All variable definitions are in Table A.1. The correlation matrix is in Online Appendix Table OA1. On average, 33% of scientists and 15% of top scientists are women. On average, a country has 1634 scientists in a field, of which 168 are classified as top scientists. In the individual-level data, the average number of publications a top scientist published between 1960 and 2019 is 181; the average career span is 29 years. Additionally, 53% of top scientists and 24% of scientists in ORCID are classified as migrants. Because of the difficulty in inferring origin countries from names, we are able to classify migration status for only 27,150 top scientists.

Fig. 1 shows variation in women's representation in science by country. In Portugal, Romania, and Argentina, women's representation in science is close to 50%. In Korea, Saudi Arabia, and Japan, women's representation is close to 15%. Fig. 2 shows that women's representation also varies by field. In public health & health services and psychology & cognitive sciences, more than 50% of scientists are women; in physics & astronomy, engineering, and information & communication technologies, fewer than 20% of scientists are women.

[5] A scientist's first job may predate 2013, as ORCID records capture career histories prior to that year.

[6] https://www.ice.gov/sites/default/files/documents/stem-list.pdf

[7] Ginther and Kahn (2015) argue that field-specific ability beliefs do not account for the gender gap in PhD attainment after controlling for mathematics and verbal GRE scores. But Cimpian and Leslie (2015) argue that the analysis in Ginther and Kahn (2015) suffers from multicollinearity problems.

[8] Our results are robust if we use GDP per capita from the World Bank.

[9] The fact that roughly 50% of countries have no top scientists explains the difference in the number of observations in the country-field-level data we compile from Scopus and the individual-level data.

[10] The exact numbers of scientists, countries, and fields in each regression varies depending on the availability of our culture proxies. Throughout the paper, we use all available data to show that our results are not driven by small changes in sample composition, which is a concern Fryer, Jr. and Levitt (2010) raise in the context of cross-country regressions of gender equality and math gaps.

Table 1
Descriptive statistics

Panel A: Country-Field-Level Data								
	N	Mean	SD	Min	p25	Median	p75	Max
% Female	2293	0.33	0.16	0.03	0.2	0.31	0.44	1
% Top female	800	0.15	0.14	0	0.06	0.12	0.21	0.75
Number of scientists	2293	1,633.62	8,681.3	5	27	135	723	243,948
Number of top scientists	800	167.88	763.35	5	10	29	94.5	18,249
WEF EPO	2031	0.6	0.11	0.24	0.53	0.62	0.68	0.81
LFP	2598	0.68	0.2	0.16	0.57	0.74	0.81	1.04
WBL Workforce	2593	0.66	0.33	0	0.5	0.75	1	1
AFI	2550	0.69	0.28	0.01	0.51	0.81	0.93	0.98
Ability belief	2025	4.06	0.32	3.55	3.79	4.11	4.29	5.11
Ability belief (male)	2025	4.16	0.3	3.72	3.92	4.16	4.35	5.07
Ability belief (female)	2025	3.86	0.38	3.35	3.63	3.76	4.1	5.23
STEM	2777	0.51	0.5	0	0	1	1	1
Math gap	1619	0.07	0.09	−0.14	0.01	0.09	0.13	0.28
log(GDP)	2523	9.35	1.11	6.56	8.72	9.45	10.3	11.41

Panel B: Individual-Level Data (Top 2% Scientists)								
	N	Mean	SD	Min	p25	Median	p75	Max
Female	127,585	0.17	0.37	0	0	0	0	1
Number of papers	127,585	180.62	159.03	2	79	137	229	3050
Career span	127,396	29.13	12.01	0	20	28	38	70
Cohort	127,566	1985.48	13.25	<1940	1980	1990	2000	2010
Migrated	27,150	0.53	0.50	0	0	1	1	1

Panel C: ORCID Data								
	N	Mean	SD	Min	p25	Median	p75	Max
Female	75,174	0.36	0.48	0	0	0	1	1
PhD cohort	75,174	2004	8.97	1950	2000	2010	2010	2010
Migrated	75,174	0.24	0.43	0	0	0	0	1

This table reports the summary statistics for our data. We construct measures of women's representation in a country and field using data from ICSR. Individual-level data on the top 2% ranked scientists is from Ioannidis et al. (2019, 2020). ORCID data are from Bohannon and Doran (2017). The country culture measures are from the World Economic Forum, the World Bank, and the FAU Erlangen-Nurnberg and V-Dem Institute. Field culture measures are from Leslie et al. (2015). Panel A presents the summary statistics for country-field level variables. Panels B and C present summary statistics for individual-level variables in the individual-level data and ORCID data. *% Female* is the percentage of women among all scientists in an academic field in a country. *% Top female* is the percentage of women among top scientists in an academic field in a country. *WEF EPO* is the WEF Economic Participation and Opportunity index. *LFP* is the women's labor force participation divided by men's labor force participation. *WBL Workforce* is the Women Business Law workforce index. *AFI* is the Academic Freedom Index. *Math gap* refers to the difference between the average scores of boys and the average scores of girls on PISA math tests. *log(GDP)* is the logarithm of GDP per capita. *Ability belief* is the field-specific ability belief score from the survey conducted by Leslie et al. (2015). *Ability belief (male)* is the field-specific ability belief score of male respondents, while *Ability belief (female)* is the field-specific ability belief score of female respondents, both from the same survey. *STEM* is an indicator equal to one if the field is biology, biomedical research, chemistry, earth & environmental sciences, economics & finance, enabling & strategic technologies, engineering, information & communication, mathematics & statistics, or physics & astronomy. *Number of papers* is the cumulative number of papers published by a scientist between 1960 and 2019. *Career span* is the difference between the year of a scientist's first publication and the year of their last publication in the sample. *Cohort* is the decade in which a scientist published their first paper. The first cohort includes those scientists whose first publications appeared before 1940. *Migrated* is an indicator equal to one if a scientist's origin country differs from the working country in 2019 in the individual-level data, and if a scientist's country of first job differs from the working country in 2016 in the ORCID data. PhD cohort refers to the decade in which a scientist was awarded their PhD degree. Table A.1 provides the definitions for all variables.

4. Empirical strategy

4.1. Culture and women's representation in the cross-section

Because our measure of field culture is time-invariant, and country culture changes slowly over time, our analysis focuses on cross-sectional data. This limits the methods we can employ to address potential endogeneity problems. To complement these methods, we introduce a time-series dimension with the case study which we describe in Section 4.2.

To examine the relationship between culture and women's participation in science, we regress women's representation by field and country on our proxies for either country culture or field culture. To address potential reverse causality concerns, we lag both country and field culture measures relative to women's representation by the greatest number of years possible. We measure women's representation in 2019. We measure country culture in the first year we have data on all measures: 2006.[11] Field culture is from Leslie et al. (2015), which means the data are from 2015 or earlier. While lagging data is not a perfect solution to address reverse causality problems given the slow moving nature of culture, conceptually it is difficult to argue that women's representation in science in 2019 is predictive of e.g., academic freedom in 2006 or ability beliefs prior to 2015, especially given the shorter career lengths of women in science (Huang et al., 2020).

We also include various control variables and fixed effects to address endogeneity concerns related to omitted variables. In the regressions examining the role of country culture, we estimate the following regression model in our country-field data:

$$\%\text{Female}_{if2019} = \alpha + \beta\,\text{Country culture}_{i2006} + \lambda\,\log(\text{GDP}_{i2006}) + \phi_f + \epsilon_{ij} \quad (1)$$

where i indexes the country where scientists work and f indexes the scientific field.

The field fixed effects, ϕ_f, account for unobserved field-specific factors that may be correlated with country-level factors, such as conditions leading to the establishment of certain fields (e.g., Sweetser and Petry, 1981) and women's representation. We include $\log(\text{GDP}_{i2006})$

[11] The earliest available years for the WEF EPO, LFP, WBL Workforce and AFI proxies are 2006, 1990, 1970 and 1900, respectively. Our findings remain robust when using culture proxies from their first available years except for the Academic Freedom Index which has poor coverage in 1900.

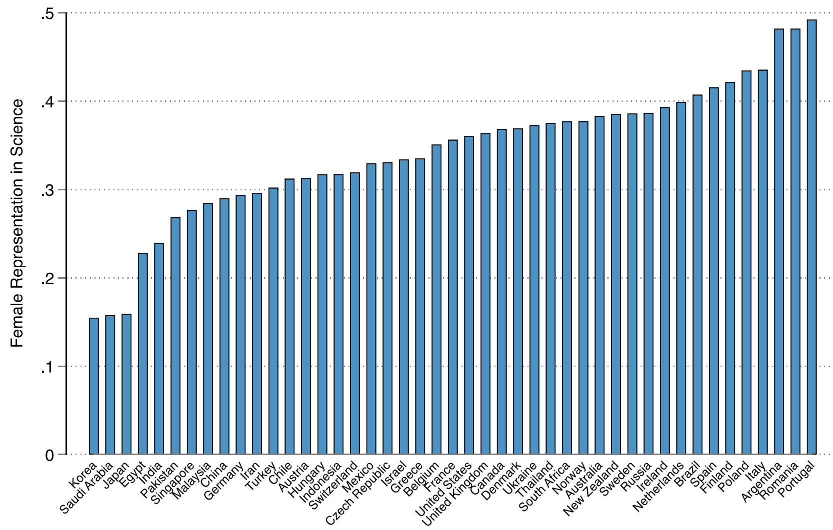

Fig. 1. Women's representation in science by country.
This figure displays the percentage of women among scientists with at least 5 publications by country. We restrict the sample to countries with more than 10,000 scientists for brevity.

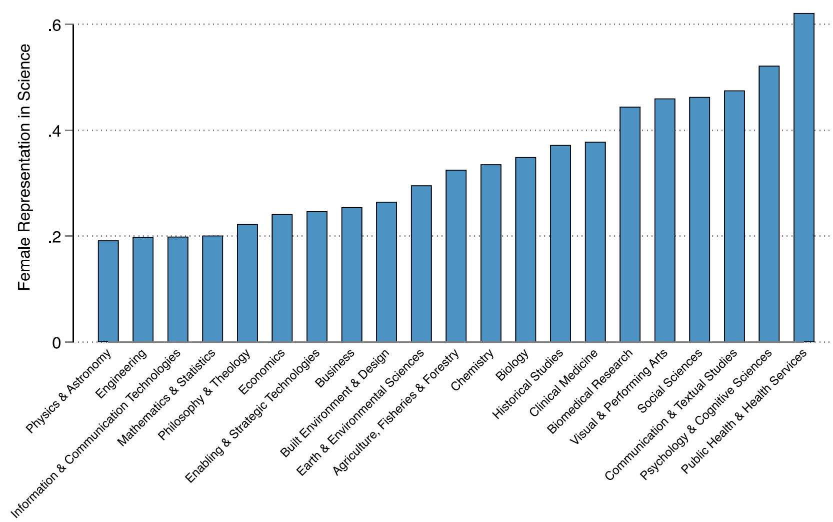

Fig. 2. Women's representation in science by field.
This figure displays the percentage of women among scientists with at least 5 publications by scientific field.

to account for differences in economic development. We also examine the sensitivity of our results to the inclusion of the math gender gaps in PISA, as they could be correlated with both women's representation in science and culture (e.g., Guiso et al., 2008; Fryer, Jr. and Levitt, 2010). We cluster standard errors at the country level to address within-group correlation.

To examine the role of field culture, we estimate the following regression model in our country-field data:

$$\%\text{Female}_{if2019} = \alpha + \beta\,\text{Field culture}_{f2015} + \delta_i + \epsilon_{ij} \tag{2}$$

where i indexes the country where scientists work, and f indexes the scientific field.

In this specification, we include country fixed effects, δ_i to account for country-specific factors such as economic and national research infrastructure that may be linked to differential investment in specific fields (e.g., May, 1997; King, 2004). We cluster standard errors at the country level.

4.2. Case study: Shocks to academic freedom and women's representation

To increase confidence that our analysis identifies a causal effect of culture on women's representation, we examine changes in women's representation around plausibly exogenous shocks to culture. It is challenging to identify shocks to culture, especially field-level culture, but the analyses in Norris (2025) and Kinzelbach et al. (2023) suggest that we can exploit political turnover to isolate shocks to at least one of our dimensions of culture: academic freedom. Since political turnover is unlikely to be caused by women's representation in science, these shocks are plausibly exogenous.

Kinzelbach et al. (2023) flags China, India, and Mexico as countries with significant recent declines in academic freedom that are associated with political turnover. Further examination of countries with changes in academic freedom in Kinzelbach et al. (2023) and Norris (2025) suggests Afghanistan, Brazil, Hungary, Saudi Arabia, and the U.S. as additional examples.

Academic freedom declined significantly in Afghanistan once the Taliban regained control in 2021. Under Jair Bolsonaro, who took office in 2018, the Brazilian government implemented budget cuts to public universities and discouraged research in areas such as sexual diversity, gender equality, and racism. As a result, the number of scientists seeking academic assistance abroad, many of them requesting indefinite exile, rose significantly (Mendes et al., 2020). Academic freedom in China declined under Xi Jinping (from 2012) when the Communist Party tightened control over research, academic exchange, and public speech (Kinzelbach et al., 2023).

In Hungary, Viktor Orbán's government enacted legal reforms that effectively expelled the Central European University from Budapest in 2017; it also imposed restrictions on studies of gender and migration (Wilson, 2018). While the decline in academic freedom in Hungary is not directly associated with political turnover, we include it because it is an example of an attack on academic freedom that happened in the European Union.

In India, academic freedom began to decline around the time Narendra Modi became prime minister in 2014 (Kinzelbach et al., 2023). Since 2018, the López Obrador government in Mexico weakened university autonomy through imposing austerity measures and prioritizing research on "national problems". Attacks on students, particularly women, further eroded academic freedom (Kinzelbach et al., 2023). Upon obtaining formal power, Crown Prince Mohammed bin Salman of Saudi Arabia introduced the Saudi Vision 2030 project in 2016 to diversify the economy, empower citizens, especially women, and improve its global status. In contrast to the other countries we consider, academic freedom in Saudi Arabia improved as a result. Norris (2025) highlights the decline in academic freedom in the U.S. following the reelection of President Trump in 2024.

Since the Scopus data that we use to construct women's representation end in 2022, we do not have sufficient data to analyze the cases of Afghanistan or the U.S. Thus, we are left with six countries that experienced changes in academic freedom due to events associated with political turnover or direct attacks on academic freedom. Since the number of events is relatively small, we illustrate the trends in the Academic Freedom Index and women's representation around these events graphically, rather than through a regression analysis.

In principle, the shocks we examine could lend themselves to a difference-in-difference analysis. But we focus on a pre/post comparison for two reasons. First, as we argue, culture may affect scientists' migration behavior. Thus, a shock to culture in one country could affect the gender composition of scientists in another country. This spillover effect makes it difficult to isolate an untreated control group. Second, the effect of culture on women's representation is multi-faceted. Since different dimensions of culture could be changing at different points in time in different countries, it is difficult to isolate countries with parallel trends. To illustrate these complexities, we provide a comparison of trends in these six countries to trends in four nearest-neighbor matched countries by region and numbers of scientists.

4.3. Mechanisms for cultural transmission

We analyze scientists' migration choices as a function of working country culture and gender using the individual-level data set. To conduct this analysis, we create a bilateral source and destination country-specific data set (e.g., Krieger et al., 2020) by restricting the sample to scientists for whom the working country is different than their origin country. We then pair each scientist in this restricted data set with all countries in the sample. Our dependent variable is a dummy variable, *Working country*, which is equal to 1 if a scientist works in, and hence migrated to, a given country, and 0 otherwise. We predict migration choices by estimating a linear probability model as follows:

$$\begin{aligned}\text{Working country}_{ijfc2019} = {} & \alpha + \lambda\,\text{Female}_{ijfc} + \beta_1\,\text{Culture}_{j2006} + \beta_2\left(\text{Culture}_{i2006} \times \text{Female}_{ijfc}\right)\\ & + \gamma_1\,\log(\text{GDP}_{i2006}) + \gamma_2\left(\log(\text{GDP}_{i2006}) \times \text{Female}_{ijfc}\right)\\ & + \phi_f + \gamma_j + \kappa_c + \epsilon_{ijfc}\end{aligned} \tag{3}$$

Here i indexes the working (destination) country, j indexes the origin country, f indexes the field, and c indexes the cohort. Field fixed effects, ϕ_f, control for field specific culture. Origin country fixed effects, γ_j, allow for comparisons of migration patterns among scientists from the same country. Since migration policies vary over time, cohort fixed effects, κ_c, allow for comparisons of migration choices among scientists of similar ages. Standard errors are clustered at the origin country level.

Using names to identify country of origin in the individual-level data may introduce several types of measurement error. First, the nationality may be incorrect. Second, we may incorrectly classify descendants of immigrants as immigrants. Third, we may not identify immigrants if they assimilate, which may be particularly problematic when inferring women's migration paths. While names can provide an accurate picture of aggregate migration (e.g., Piazza et al., 1987), it is not clear how useful they are in predicting individual migration. For this reason, we re-estimate our migration regressions in ORCID data in which location data and migratory paths should be accurate. Indeed, the data were assembled for the purpose of estimating scientists' migration patterns. Since these data do not contain field classifications, these specifications omit the field fixed effects. Using the ORCID data also has the benefit that it is not restricted to the top 2% of scientists. Thus, this analysis is useful for examining whether the migration results in the individual-level data generalize.

In our analysis of research output, we use *Number of papers*, a count variable, as our dependent variable. Thus, following Cohn et al. (2022), we use Poisson regressions to predict output. The benefit of Poisson regressions in our context is that they can accommodate the incorporation of high-dimensional fixed effects necessary to address endogeneity concerns.[12] As a robustness check, we also examine ordinary least squares models with *log(Number of papers)* as the dependent variable which we show in the Online Appendix. To analyze the relationship between country or field culture and research output, we estimate the following specifications:

$$\begin{aligned}\text{Number of papers}_{ifc2019} = {} & \alpha + \beta_1\,\text{Female}_{ifc} + \beta_2\left(\text{Female}_{ifc} \times \text{Culture}_{i2006\text{ or } f2015}\right)\\ & + \beta_3\,\text{CareerSpan}_{ifc2019} + \beta_4\left(\text{Female}_{ifc} \times \text{Career Span}_{ifc2019}\right)\\ & + \beta_5\,\log(\text{GDP}_{i2006}) + \beta_6\left(\text{Female}_{ifc} \times \log(\text{GDP}_{i2006})\right)\\ & + \delta_i + \phi_f + \kappa_c + \epsilon_{ifc}\end{aligned} \tag{4}$$

Where i indexes the country where a scientist works, f indexes the field, and c indexes the cohort. Here *Culture* is either working country culture, indexed by $i2006$, or field culture, indexed by $f2015$.

We include field fixed effects, ϕ_f, to control for the considerable variation in research output across fields. Cohort fixed effects, κ_c, control for changes in publication expectations over time. To account for the effect of career span on research output identified by Huang et al. (2020), we control for career span and its interaction term with the female indicator. We cluster standard errors at the country level.

5. Results

5.1. Country culture and women's representation in science

Table 2 displays the results of estimating Model (1). In all columns of Table 2 Panel A, the coefficients on the culture proxies are positive and statistically significant at the 1% level. These associations are

[12] Cohn et al. (2022) recommend the Poisson model over zero-inflated Poisson or negative binomial regression because, although these alternatives may be more efficient in some settings, they do not admit separable group fixed effects. When group dummies are included as covariates, these alternative models are subject to the incidental parameters problem, potentially biasing all estimates.

Table 2
Country culture and women's representation in science.

Panel A

	Dependent variable: % Female			
	(1)	(2)	(3)	(4)
WEF EPO	0.318***			
	(4.793)			
LFP		0.132***		
		(3.660)		
WBL Workforce			0.077***	
			(3.259)	
AFI				0.106***
				(3.641)
log(GDP)	0.020***	0.024***	0.017**	0.015**
	(2.683)	(3.640)	(2.468)	(2.285)
Observations	1757	2104	2098	2108
Adjusted R^2	0.494	0.427	0.425	0.432
Fixed Effects	Field	Field	Field	Field

Panel B

	Dependent variable: % Female							
	STEM				Non-STEM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WEF EPO	0.355***				0.540***			
	(4.934)				(6.006)			
LFP		0.176***				0.289***		
		(3.092)				(4.077)		
WBL Workforce			0.072**				0.107***	
			(2.104)				(2.795)	
AFI				0.140***				0.201***
				(3.667)				(4.017)
Math gap	−0.042	−0.093	−0.091	−0.185**	0.050	−0.011	−0.007	−0.144
	(−0.492)	(−1.197)	(−1.008)	(−2.056)	(0.485)	(−0.120)	(−0.069)	(−1.471)
log(GDP)	−0.048***	−0.050***	−0.045***	−0.055***	−0.010	−0.020	−0.011	−0.023**
	(−4.425)	(−3.162)	(−3.483)	(−4.690)	(−0.740)	(−1.267)	(−0.898)	(−2.065)
Observations	662	750	760	760	622	686	695	695
Adjusted R^2	0.584	0.538	0.518	0.547	0.544	0.489	0.444	0.482
Fixed Effects	Field	Field	Field	Field	Field	Field	Field	Field

This table reports results of ordinary least squares regressions of women's representation in a country-field on country gender culture proxies. The data are at the country-field level, as detailed in Table 1. In Panel A, we control for *log(GDP)*. In Panel B, we add *Math gap* and report the results separately for STEM and Non-STEM fields. *% Female* is the percentage of women among all scientists in an academic field in a country. *WEF EPO* is the WEF Economic Participation and Opportunity index. *LFP* is the women's labor force participation divided by men's labor force participation. *WBL Workforce* is the Women Business Law workforce index. *AFI* is the Academic Freedom Index. *Math gap* refers to the difference between the average scores of boys and the average scores of girls on PISA math tests. *log(GDP)* is the logarithm of GDP per capita. T-statistics are calculated with standard errors clustered at the country level. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

also economically significant. For example, a one standard deviation increase in WEF EPO scores is associated with a 3.2 percentage point increase in the average representation of women in a scientific field in a country. In Peru (roughly the 25th percentile of the WEF EPO index), 27% of scientists are women. In Uganda (around the 75th percentile), it rises slightly to 29%. Australia, in the 90th percentile, shows significantly higher representation, with women making up 35% of scientists.

Consistent with studies on the effect of culture on female labor market outcomes (Boserup, 1970; Antecol, 2000; Fernández and Fogli, 2009; Blau et al., 2011; Alesina et al., 2013), our results suggest that countries with a more gender-equal work culture or greater academic freedom have a higher average representation of women in science across fields. These results are consistent with Chan and Torgler (2020) who report a positive Spearman correlation between gender-equal country culture and women's representation among top scientists using data from Ioannidis et al. (2020).

In Online Appendix Table OA2, we add *Math gap* to examine whether the results in Panel A of Table 2 are driven by endogeneity due to omitted gender gaps in math scores. Some argue that math gaps should be lower in more gender-equal countries although empirical findings on this are mixed (Guiso et al., 2008; Nollenberger et al., 2016; Kahn and Ginther, 2017; Stoet and Geary, 2018). Others argue that gender gaps in math scores are negatively correlated with women's representation in science, particularly in STEM fields. Since the regressions in Panel A do not include math gaps, it is possible that the coefficients on culture are biased upwards.

In columns (1)–(4) of Table OA2, we replicate the regressions in Panel A of Table 2 for the sample with available math gap data. We include math gaps in columns (5)–(8). In contrast to expectations, the results in Table OA2 show that regressions excluding math gaps tend to slightly underestimate, rather than overestimate, the coefficients on culture. Moreover, the coefficients on the math gaps are generally not statistically significant in our regressions.

In Panel B of Table 2, which shows results for STEM and Non-STEM fields separately, we show that math gaps also appear relatively less important for explaining women's representation than culture in the subsample of STEM fields. Thus, the association between gender culture and women's participation in science does not appear to be driven by gender disparities in math scores. In Online Appendix Table OA3, we show that these results are robust to using different measures of country culture, specifically the other three subindices of the WEF Gender Gap Index (Education, Health and Survival, and Political Empowerment), as well as *Fertility*. The fertility rate, the average number of children

Table 3
Field culture and women's representation among scientists.

Panel A

	Dependent variable: % Female			
	(1)	(2)	(3)	(4)
Ability belief	−0.204***			
	(−22.534)			
Ability belief (male)		−0.201***		−0.138***
		(−22.528)		(−14.280)
Ability belief (female)			−0.149***	−0.073***
			(−19.344)	(−8.643)
Observations	1667	1667	1667	1667
Adjusted R^2	0.454	0.428	0.406	0.445
Fixed Effects	Country	Country	Country	Country

Panel B

	Dependent variable: % Female					
	STEM			Non-STEM		
	(1)	(2)	(3)	(4)	(5)	(6)
Ability belief	−0.163***			−0.168***		
	(−9.708)			(−17.213)		
Ability belief (male)		−0.149***			−0.159***	
		(−10.641)			(−15.605)	
Ability belief (female)			−0.110***			−0.154***
			(−10.702)			(−17.628)
Observations	1090	1090	1090	520	520	520
Adjusted R^2	0.354	0.343	0.363	0.557	0.488	0.585
Fixed Effects	Country	Country	Country	Country	Country	Country

This table reports results of ordinary least squares regressions of women's representation in a country-field on field culture proxies. The data are at the country-field level, as detailed in Table 1. In Panel A, we analyze the full sample; in Panel B, we divide the sample into STEM and Non-STEM fields. *% Female* is the percentage of women among all scientists in an academic field in a country. *Ability belief* is the field-specific ability belief score from the survey conducted by Leslie et al. (2015). *Ability belief (male)* is the field-specific ability belief score of male respondents, while *Ability belief (female)* is the field-specific ability belief score of female respondents, both from the same survey. T-statistics are calculated with standard errors clustered at the country level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

a woman bears in her lifetime, as calculated by the United Nations, is a proxy for gender-related cultural norms with respect to child care (Fernández and Fogli, 2009).

In Panel B, the economic magnitudes of the coefficients in the Non-STEM subsample are higher than in the STEM subsample. For example, a one standard deviation increase in WEF EPO is associated with a 0.25 standard deviation increase in women's representation in STEM and a 0.34 standard deviation increase in women's representation in Non-STEM fields. Fig. 3(a)–(d) plots the unconditional averages of women's representation against country-level culture proxies. The figure illustrates that country culture is positively associated with women's representation in both STEM and Non-STEM fields, with the association appearing stronger in Non-STEM fields. Online Appendix Table OA4 shows that this finding is robust to using alternative definitions of STEM and Non-STEM fields. We examine potential explanations for these differences between STEM and Non-STEM fields in more detail below.

5.2. Field culture and women's representation in science

Table 3 shows results of estimating Model (2). In column (1) of Panel A, the coefficient on *Ability belief* is −0.204 and significant at the 1% level. It suggests that a one standard deviation increase in *Ability belief* is associated with a 6.5 percentage point decrease in women's representation in a field. Given that the average share of women in science is 33%, we consider this decrease to be economically meaningful.

In columns (2)–(4), we investigate the association between women's representation and men and women's field-specific ability belief scores. In column (4), we include both *Ability belief (male)* and *Ability belief (female)* as independent variables. Our results indicate that ability beliefs of both men and women are important.

In Online Appendix Table OA5, we control for field-level GRE math scores and obtain similar results. The coefficients on the ability belief variables remain statistically significant, although their economic magnitudes are reduced by about half. This suggests that the effect of ability belief is not solely driven by the higher math requirements of a field.[13]

Our findings are consistent with Leslie et al. (2015) who argue that the stereotype of women lacking the innate capacity to excel results in lower female representation in certain academic fields. Our results extend the results in Leslie et al. (2015) from the doctoral stage in the U.S. to global scientists at advanced stages of their careers. Our results also show that the field-level analyses in Leslie et al. (2015) and Adams and Xu (2023) are robust to controlling for country-level fixed effects which account for the potential effects of socialization that may occur within countries.

In columns (1)–(3) and (4)–(6) of Table 3 Panel B, we show results for the STEM and Non-STEM subsamples, respectively. The coefficients on all three ability belief measures are significantly negative in both STEM and Non-STEM subsamples.

The results in Panel B suggest that in STEM fields men's ability beliefs have a higher correlation with women's representation than women's beliefs, whereas in Non-STEM fields the correlations between men's and women's ability beliefs and women's representation are

[13] Since higher math requirements may be one of the mechanisms through which ability beliefs affect women's participation in science, controlling for GRE math scores could "over-control" for part of the effect we aim to capture. Thus, in our main specification we do not control for GRE math scores.

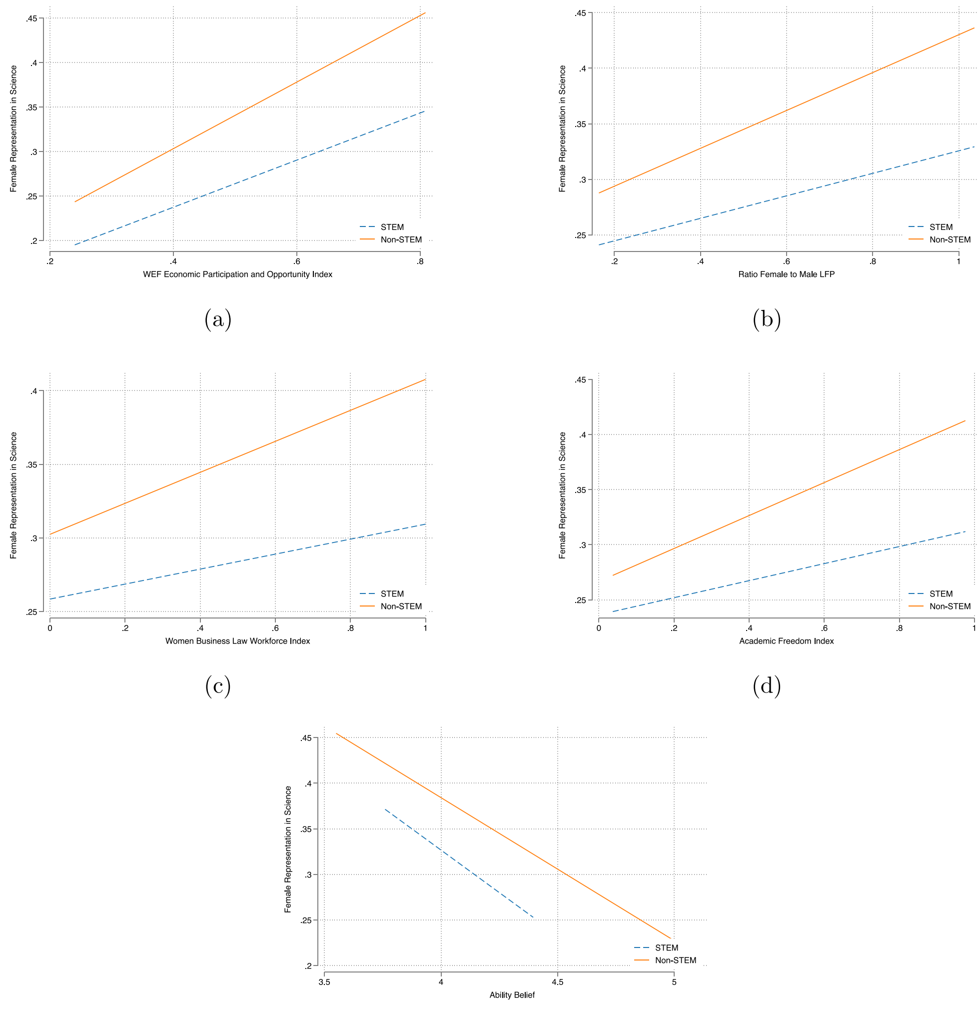

Fig. 3. Variation in women's representation in science by country culture in STEM and Non-STEM fields.
This figure shows the linear relationship between women's representation in science and proxies for country and field culture in STEM and Non-STEM fields. *% Female* is the percentage of women among all scientists in an academic field in a country. *WEF EPO* is the WEF Economic Participation and Opportunity index. *LFP* is the women's labor force participation divided by men's labor force participation. *WBL Workforce* is the Women Business Law workforce index. *AFI* is the Academic Freedom Index. *Ability belief* is the field-specific ability belief score from the survey conducted by Leslie et al. (2015). *STEM* is an indicator equal to one if the field is biology, biomedical research, chemistry, earth & environmental sciences, economics & finance, enabling & strategic technologies, engineering, information & communication, mathematics & statistics, or physics & astronomy.

similar. The likely source of this difference is that the correlation between *Ability belief (male)* and *Ability belief (female)* in the STEM subsample is 0.406, as compared to 0.953 in the Non-STEM sample. Thus, in STEM fields men and women tend to hold different beliefs about the importance of innate talent in achieving success, while in Non-STEM fields their beliefs align closely.[14]

In Table 4, we analyze both country- and field-level culture by adding interactions between country culture and ability beliefs to our Model (1) and including both country and field fixed effects. The coefficients on all four interaction terms are negative, which suggests that the impact of a noninclusive field culture is stronger in countries with more gender-equal cultures and greater academic freedom.

These results may help explain the gender equality paradox (Falk and Hermle, 2018; Stoet and Geary, 2018; Breda et al., 2020b) which is the phenomenon that gender differences in occupational choice and educational outcomes appear more pronounced in more egalitarian societies. Our results suggest that the egalitarianism of a country's culture and the egalitarianism of an occupation or field need not be the same, i.e., culture may be multi-dimensional. In this case, it is not hard to imagine that in more egalitarian societies, women have lower tolerance for noninclusive fields.[15] Thus, selection could help explain occupational choices. Importantly, this selection may be a manifestation of equality considerations, not a contradiction of equality considerations.

5.3. Shocks to academic freedom and women's representation in science

In Panel A of Fig. 4, we verify that the political events we discuss in Section 4.2 are associated with changes in the Academic Freedom

[14] In Leslie et al. (2015), the correlations between *Ability belief (male)* and *Ability belief (female)* are 0.328 and 0.558 in STEM and Non-STEM fields, respectively. The correlations in our data differ because our data are at country-field level, while the data in Leslie et al. (2015) are at field-level. Furthermore, our sample does not include all fields in Leslie et al. (2015).

[15] An example of women resisting intolerance comes from economics. Anja Samek, a professor of economics at UC San Diego started a petition to hold an anonymous platform that targets women in economics on EJMR (Ederer et al., 2023) legally accountable for harassment (Samek, 2023).

Table 4
Field culture and country culture interactions.

	Dependent variable: % Female			
	(1)	(2)	(3)	(4)
Ability belief × WEF EPO	−0.266***			
	(−3.094)			
Ability belief × LFP		−0.146***		
		(−2.626)		
Ability belief × WBL Workforce			−0.082***	
			(−2.909)	
Ability belief × AFI				−0.123***
				(−3.029)
Ability belief × log(GDP)	−0.022**	−0.020**	−0.015	−0.012
	(−2.184)	(−2.111)	(−1.646)	(−1.196)
Observations	1311	1580	1575	1582
Adjusted R^2	0.742	0.719	0.718	0.719
Fixed Effects	Country, Field	Country, Field	Country, Field	Country, Field

This table reports estimates of ordinary least squares model regressions of women's representation among scientists in a country-field on the interaction terms of field culture and the country culture proxies. The data are at the country-field level, as detailed in Table 1. *% Female* is the percentage of women among all scientists in an academic field in a country. *WEF EPO* is the WEF Economic Participation and Opportunity index. *LFP* is the women's labor force participation divided by men's labor force participation. *WBL Workforce* is the Women Business Law workforce index. *AFI* is the Academic Freedom Index. *Ability belief* is the field-specific ability belief score from the survey conducted by Leslie et al. (2015). *log(GDP)* is the logarithm of GDP per capita. T-statistics are calculated with standard errors clustered at the country level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Index. Panel A shows that academic freedom experienced discrete drops in levels in Brazil, China, and India, an increasing rate of decline in Mexico, and an increasing rate of improvement in Saudi Arabia, while in Hungary it continued to decline at a similar rate.

Panel B plots the share of female scientists around the events. In Brazil, women's representation in science is relatively high, consistent with broader trends in Latin America. It rose from around 38% in 2008 to 41% in 2018. However, since 2019, this growth has stalled and the share of women remains around 41%. In China, women's representation in science rose steadily since 2008, with larger increases before 2015, and has since remained relatively stable at about 29%. In Hungary, India and Mexico, women's representation in science rose prior to state intervention and continued to grow afterward, but at a slightly slower pace. In contrast, Saudi Arabia saw a sharp increase in women's representation after 2016: from roughly 12% in 2015 to about 18% in 2022.

Some government interventions explicitly targeted disciplines with relatively high female participation, such as gender studies. As a result, the changes observed in Panel B may reflect mechanical changes in the set of fields. Thus, we examine the share of female scientists in STEM and Non-STEM fields separately in Panels C and D. While in some countries the shocks to academic freedom appear to have relatively little effect on the trends in women's overall representation, e.g., in Hungary, India, and Mexico, Panels C and D suggest that the effects may be larger for certain fields. For example, the trend for STEM in China seems flatter after the shock than in Non-STEM, and there is a noticeable drop in Non-STEM in Mexico after the shock. Overall, we believe that the case study provides suggestive evidence that shocks to academic freedom may have persistent effects on women's representation in science, consistent with a causal effect of culture.

In Online Appendix Figure OA1, we provide a more in-depth analysis by comparing trends in these six countries to trends in the four nearest-neighbor matched countries by region and numbers of scientists. The blue lines indicate "shocked" countries and the gray lines indicate matched countries. Panel A of Figure OA1 confirms that the events we examine can be considered to be shocks to academic freedom in five out of six countries, as academic freedom in matched countries evolved more smoothly over this period. Since academic freedom in Hungary was declining well before the event, the comparison to matched countries suggests that the biggest shocks to academic freedom happened much earlier than our event day. Even for "shocked" countries, however, Panel B shows that it would be difficult to argue that there are parallel trends in women's representation prior to the shocks. Some "shocked" countries also have systematically lower representation despite having generally higher levels of academic freedom, consistent with our argument that multiple dimensions of culture affect women's representation. For this reason, we focus on a pre/post analysis, rather than a difference-in-difference analysis.

The case of Saudi Arabia might lend itself most readily to a difference-in-difference interpretation, as one could argue there are parallel trends prior to the shock. The relative steeper increase in the slope of women's representation around the shock in Saudi Arabia is consistent with a causal effect of academic freedom on women's representation - with the drop in the level of representation in matched countries potentially reflecting a spillover effect due to migration.

5.4. Transitioning to individual level data

Before turning to the analysis of mechanisms of cultural transmission using the individual-level data, we first verify that culture operates in a similar way for the top 2% of scientists as for scientists generally. We aggregate the individual-level data to the country-field level and estimate Model (1) and Model (2) in this data. We also perform a similar exercise with the ORCID data, which is not restricted to the top 2% of scientists.

Table 5 shows that the effects of culture are similar among the top 2% of scientists as in Table 2. This is not driven by differences in sample composition, as restricting the sample in Table 2 to the same countries and fields as in the individual data leads to similar results (see Online Appendix Table OA6).[16] Results using aggregated ORCID data are also similar (see Online Appendix Table OA7). Thus, we conclude that the individual data should be informative about the mechanisms of cultural transmission that operate more generally.

5.5. Mechanisms for cultural transmission

5.5.1. Country culture and women's migration

Fig. 5 compares the association between the unconditional probability of moving to a destination country and its culture for men

[16] We note that *Ability belief (female)* loses significance among top scientists, although the coefficient remains negative. The differences between top scientists and other scientists would be interesting to explore in further work.

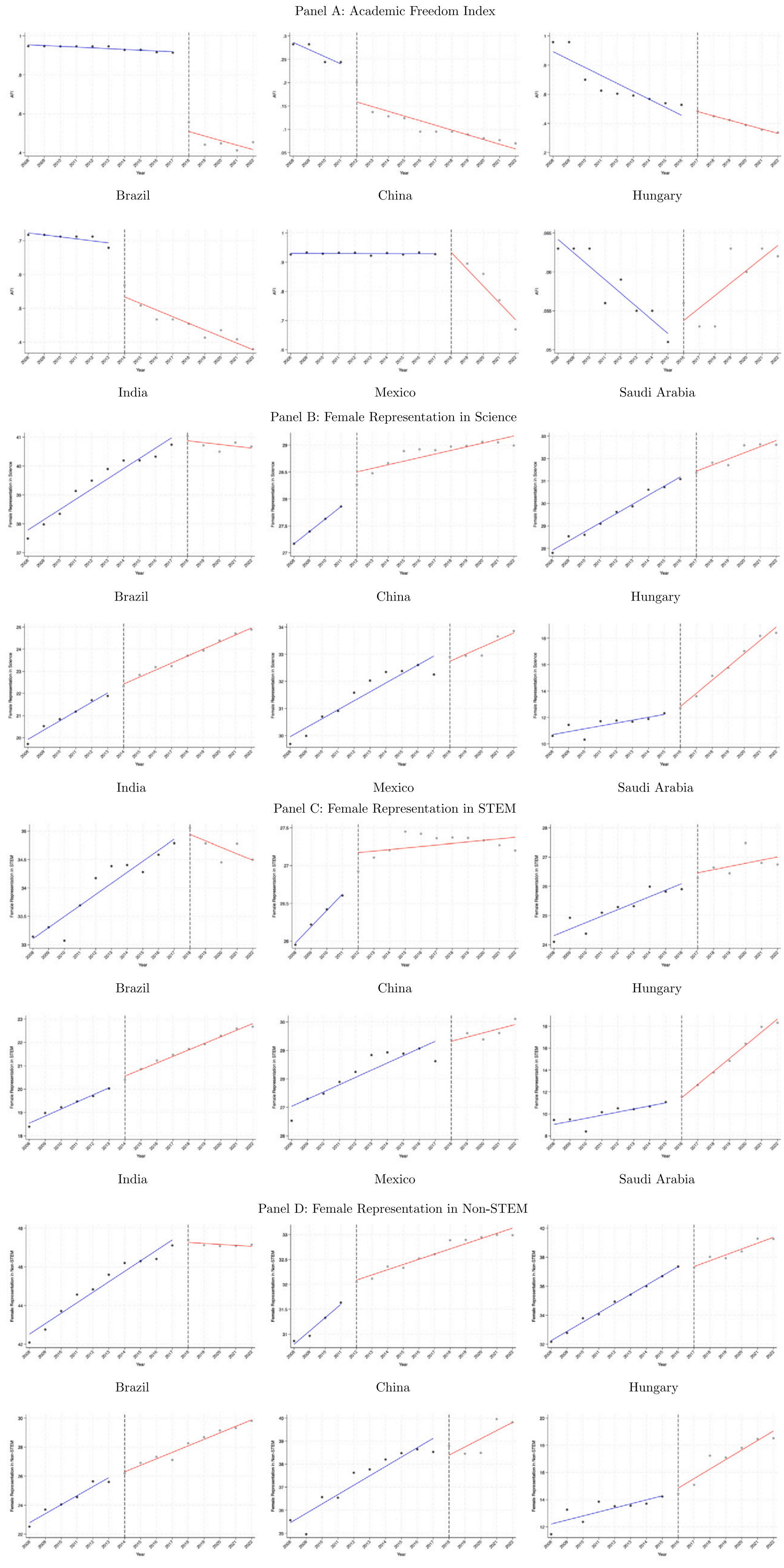

Fig. 4. Women's representation in science around political turnovers or reforms.
This figure shows the Academic Freedom Index (AFI), female representation in science, and female representation in STEM and Non-STEM fields around political turnovers or reforms: Brazil (2018, Bolsonaro), China (2012, Xi), Hungary (2017, restrictions on CEU and gender studies), India (2014, Modi), Mexico (2018, López Obrador), and Saudi Arabia (2016, Vision 2030 reform). Each subfigure plots scatter points before and after the turnover/reform and linear fitted lines for both periods.

Table 5
Culture and women's representation among top scientists.

	Dependent variable: % Top female							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WEF EPO	0.212***							
	(4.376)							
LFP		0.115***						
		(3.641)						
WBL Workforce			0.069***					
			(3.209)					
AFI				0.094***				
				(4.399)				
Ability belief					−0.159***			
					(−9.860)			
Ability belief (male)						−0.163***		−0.148***
						(−10.014)		(−8.545)
Ability belief (female)							−0.084***	−0.021
							(−6.730)	(−1.511)
log(GDP)	−0.004	−0.006	−0.004	−0.006				
	(−0.414)	(−0.730)	(−0.494)	(−0.686)				
Observations	738	785	796	797	585	585	585	585
Adjusted R^2	0.374	0.357	0.352	0.354	0.267	0.258	0.181	0.259
Fixed Effects	Field	Field	Field	Field	Country	Country	Country	Country

This table replicates the results in Table 2 Panel A and Table 3 Panel A, using country–field level data aggregated from individual-level data on top scientists. *% Top female* is the percentage of women among top scientists in an academic field in a country. *WEF EPO* is the WEF Economic Participation and Opportunity index. *LFP* is the women's labor force participation divided by men's labor force participation. *WBL Workforce* is the Women Business Law workforce index. *AFI* is the Academic Freedom Index. *log(GDP)* is the logarithm of GDP per capita. T-statistics are calculated with standard errors clustered at the country level. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

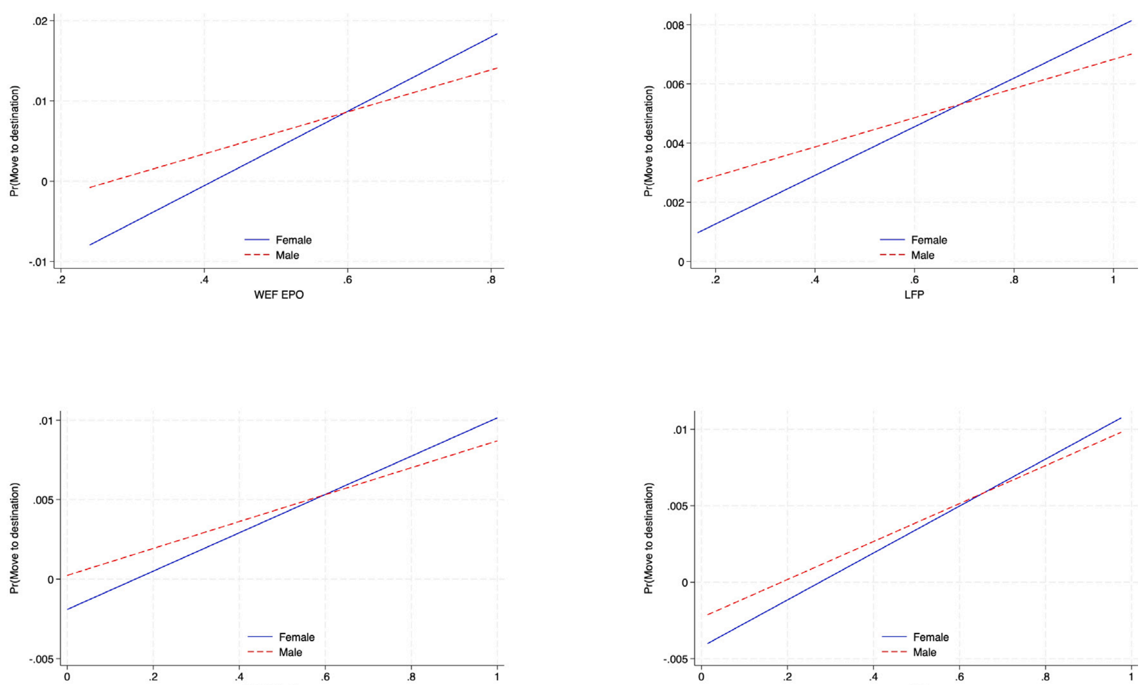

Fig. 5. Migration probability by culture.
This figure plots the unconditional probability of moving to a destination country for men and women against the culture of the destination country. The sample includes only migrated scientists in the individual-level Scopus data *WEF EPO* is the WEF Economic Participation and Opportunity index. *LFP* is the women's labor force participation divided by men's labor force participation. *WBL Workforce* is the Women Business Law workforce index. *AFI* is the Academic Freedom Index.

and women. Both men and women are more likely to move to destinations with greater gender equality and higher academic freedom. However, women's decisions appear more sensitive to cultural factors, as illustrated by the steeper slope of the blue lines.

Table 6 Panel A reports the results of estimating Model (3).[17] In columns (1)–(4), we examine the migration choices of scientists across

[17] Coefficients showing 0.000 are smaller than 0.001.

Table 6
Country culture and women's migration choices.

Panel A

	Dependent variable: Working country											
	All fields				STEM				Non-STEM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female	−0.010**	−0.004**	−0.002**	−0.003**	−0.003	−0.001	−0.001	−0.001	−0.010**	−0.004**	−0.002**	−0.003**
	(−2.503)	(−2.349)	(−2.034)	(−2.391)	(−0.860)	(−0.579)	(−0.567)	(−0.880)	(−2.383)	(−2.584)	(−2.218)	(−2.452)
WEF EPO	0.057***				0.053***				0.063***			
	(11.685)				(10.849)				(12.458)			
Female * WEF EPO	0.010**				0.003				0.011**			
	(2.335)				(0.566)				(2.330)			
LFP		0.019***				0.018***				0.021***		
		(19.801)				(16.474)				(26.268)		
Female * LFP		0.002**				0.000				0.002***		
		(2.113)				(0.190)				(2.649)		
WBL Workforce			0.007***				0.007***				0.008***	
			(6.065)				(5.838)				(6.361)	
Female * WBL Workforce			0.002**				0.002**				0.002*	
			(2.243)				(2.100)				(1.776)	
AFI				0.011***				0.010***				0.013***
				(17.758)				(13.413)				(31.165)
Female * AFI				0.001**				0.001				0.001
				(2.191)				(1.227)				(1.613)
log(GDP)	0.008***	0.007***	0.006***	0.006***	0.008***	0.007***	0.005***	0.006***	0.009***	0.007***	0.006***	0.006***
	(44.243)	(46.533)	(39.981)	(46.203)	(38.189)	(40.307)	(35.600)	(42.050)	(54.221)	(56.712)	(47.275)	(51.331)
Female * log(GDP)	0.000**	0.000**	0.000	0.000*	0.000	0.000	−0.000	0.000	0.000**	0.000**	0.000	0.000**
	(2.308)	(2.366)	(0.454)	(1.663)	(1.119)	(0.799)	(−0.550)	(0.384)	(2.107)	(2.407)	(0.711)	(1.982)
Observations	1,696,135	2,404,087	2,389,338	2,374,589	1,010,390	1,432,118	1,423,332	1,414,546	685,745	971,969	966,006	960,043
Adjusted R-squared	0.016	0.012	0.011	0.011	0.015	0.012	0.010	0.011	0.018	0.013	0.011	0.012
Country (Origin) Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

	Dependent variable: Working country (ORCID)			
	(1)	(2)	(3)	(4)
Female	−0.008**	−0.006***	−0.001	−0.002**
	(−2.551)	(−3.492)	(−1.625)	(−2.448)
WEF EPO	0.029***			
	(4.658)			
Female * WEF EPO	0.009**			
	(2.433)			
LFP		0.012***		
		(5.788)		
Female * LFP		0.005***		
		(4.340)		
WBL Workforce			0.005***	
			(5.879)	
Female * WBL Workforce			0.003***	
			(4.160)	
AFI				0.007***
				(5.443)
Female * AFI				0.005***
				(6.208)
log(GDP)	0.007***	0.006***	0.005***	0.005***
	(26.724)	(26.496)	(41.830)	(37.023)
Female * log(GDP)	0.000**	0.000***	−0.000	−0.000*
	(2.479)	(2.704)	(−1.106)	(−1.785)
Observations	2,048,694	2,911,302	2,893,331	2,875,360
Adjusted R-squared	0.010	0.009	0.009	0.009
Country (Origin) Fixed Effects	Yes	Yes	Yes	Yes
Field Fixed Effects	Yes	Yes	Yes	Yes
PhD Cohort Fixed Effects	Yes	Yes	Yes	Yes

This table reports results of linear probability model regressions of *Working country* on the interaction terms between *Female* and the country culture proxies in the sample of individual-country pairwise observations. The sample includes scientists who we define as having migrated from their origin countries. *Working country* is an indicator equal to one if a scientist works in the country. *Female* is an indicator equal to one if a scientist is female. *WEF EPO* is the WEF Economic Participation and Opportunity index. *LFP* is the women's labor force participation divided by men's labor force participation. *WBL Workforce* is the Women Business Law workforce index. *AFI* is the Academic Freedom Index. *log(GDP)* is the logarithm of GDP per capita. In Panel A, the sample consists of individual-level scientists from Ioannidis et al. (2019, 2020). Columns (1)–(4) include all fields; columns (5)–(8) focus on STEM fields; columns (9)–(12) focus on Non-STEM fields. In Panel B, the regressions use the ORCID data. PhD cohort refers to the decade in which a scientist was awarded their PhD degree. t-statistics are calculated with standard errors clustered at the origin country level. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Country culture and research output.

	Dependent variable: Number of papers											
	All fields				STEM				Non-STEM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female	1.116	1.026	1.179	0.965	0.997	0.856	1.094	0.822	0.857	0.765	0.855	0.712
	(0.408)	(0.135)	(0.555)	(−0.179)	(−0.011)	(−0.972)	(0.267)	(−0.815)	(−0.541)	(−0.946)	(−0.560)	(−1.284)
Career span	1.047***	1.047***	1.047***	1.047***	1.052***	1.052***	1.052***	1.052***	1.042***	1.042***	1.042***	1.042***
	(35.932)	(37.461)	(37.898)	(37.770)	(30.220)	(31.159)	(31.577)	(31.527)	(26.701)	(27.645)	(27.543)	(27.529)
Female × WEF EPO	1.194				1.333*				1.215*			
	(1.557)				(1.849)				(1.737)			
Female × LFP		1.285***				1.384***				1.192		
		(2.617)				(3.011)				(1.261)		
Female × WBL Workforce			1.083**				1.116*				1.095*	
			(2.334)				(1.818)				(1.758)	
Female × AFI				0.947				0.936				0.953
				(−0.588)				(−0.617)				(−0.404)
Female × Career span	0.999**	0.999**	0.999**	0.999**	1.000	1.000	1.000	1.000	0.999	0.999	0.999	0.999
	(−2.198)	(−2.223)	(−2.220)	(−2.056)	(−0.183)	(−0.225)	(−0.262)	(−0.056)	(−1.237)	(−1.177)	(−1.194)	(−1.116)
Female × log(GDP)	0.965	0.966	0.965	0.995	0.970	0.979	0.971	1.012	0.985	0.996	0.990	1.019
	(−1.175)	(−1.597)	(−1.242)	(−0.288)	(−1.032)	(−1.145)	(−0.861)	(0.456)	(−0.464)	(−0.139)	(−0.353)	(0.736)
Observations	124 703	125 482	125 642	125 648	67 253	67 704	67 825	67 825	57 450	57 778	57 817	57 823
Pseudo R2	0.379	0.379	0.379	0.379	0.336	0.337	0.337	0.337	0.422	0.422	0.422	0.422
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports results of Poisson regressions of *Number of papers* on the interaction between *Female* and the country culture proxies. Estimated coefficients are expressed as incidence rate ratios. The sample is at the individual level and is described in Table 1. Columns (1)–(4) include all fields; columns (5)–(8) focus on STEM fields; columns (9)–(12) focus on non-STEM fields. *Number of papers* is the cumulative number of papers a scientist published between 1960 and 2019. *WEF EPO* is the WEF Economic Participation and Opportunity index. *LFP* is the women's labor force participation divided by men's labor force participation. *WBL Workforce* is the Women Business Law workforce index. *AFI* is the Academic Freedom Index. *Female* is an indicator equal to one if a scientist is female. *Career span* is the number of years between the year of the first publication and the year of the last publication of a scientist. *log(GDP)* is the logarithm of GDP per capita. Z-statistics are calculated with standard errors clustered at the country level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

all fields. In columns (5)–(12), we run the tests separately for STEM and Non-STEM fields. In columns (1)–(4), the coefficients on *log(GDP)* are positive, which suggests that there may be more scientific opportunities in more developed economies. The interactions between *Female* and *log(GDP)* are not always positive, and the economic magnitudes are small, which suggests that the effect of economic development is not necessarily more pronounced for women. In contrast, the coefficients on the measures of working country culture and their interactions with *Female* are always positive and generally statistically significant. Thus, countries with a gender-equal culture appear to attract male and female scientists, but the effect is especially pronounced for female scientists.

Columns (5)–(12) suggest that the role of culture is stronger for women in Non-STEM fields than in STEM fields. We believe that this contrast raises interesting questions for future research. We examine one potential contributing factor to this difference relating to the nature of work in STEM and Non-STEM fields in Table 9 below.

In Panel B of Table 6 we replicate the analysis in columns (1)–(4) of Panel A using ORCID data. Consistent with the results in Panel A, the coefficients on the interaction terms between the female indicator and the culture proxies are all significantly positive.

The results remain robust when we restrict the sample to countries for which all four culture proxies are available (see Online Appendix Table OA8). The results are also similar when we estimate Model (3) in an unconditional sample which incorporates "staying", i.e., the working country is the same as the origin country, as a migration choice (see Online Appendix Table OA9).

5.5.2. Culture and women's research output

Table 7 reports the results of estimating Model (4). The samples we use in columns (1)–(4), (5)–(8), and (9)–(12) are the full sample, the STEM subsample, and the Non-STEM subsample, respectively. The coefficients on the interaction terms are greater than one and generally statistically significant for all culture measures except academic freedom. The results suggest that women in countries with more equal gender cultures write more papers. But we note that the economic and statistical significance fluctuates based on the specific measure of cultural gender equality we use and by STEM or Non-STEM classification.

In Table 8, we examine the association between field culture and research output. Column (1) reports results for scientists in all fields; columns (2) and (3) focus on scientists in STEM and Non-STEM fields. In column (1), the coefficient on the interaction term is above one, implying that a one unit increase in *Ability belief* corresponds to 18 percentage points lower gender gap in the number of papers. Since higher *Ability belief* indicates a less inclusive field culture, this result contradicts the findings in Table 7. In columns (2) and (3), we show that this positive correlation is driven by STEM fields. In Non-STEM fields, the gender output gap is smaller in fields with a more inclusive culture. In Online Appendix Tables OA11 and OA10, we report similar results using OLS regressions.

We posit that the differences we observe between STEM and Non-STEM fields may be attributable to a higher bar for women in STEM fields (e.g., Hengel, 2022). One driver of this bar may be different co-authoring patterns in STEM fields. Table 9 shows that the percentage of co-authored papers among top scientists is notably higher in STEM fields than in Non-STEM fields. As Sarsons (2017), Sarsons et al. (2021) show, co-authorship can introduce an attribution bias in performance assessment. When papers have multiple authors, women may need to produce more papers to reach the same career milestones as their male counterparts. As ability beliefs increase, this co-author attribution bias may become harder to overcome.

6. Conclusion

Many argue that increasing the pipeline of women entering doctoral programs will improve women's representation in science. To improve the pipeline, many policies and programs focus on education, particularly in STEM subjects (Meoli et al., 2024). While the representation of

Table 8
Field culture and research output.

	Dependent variable: Number of papers		
	All fields (1)	STEM (2)	Non-STEM (3)
Female	0.452**	0.635	1.531
	(−2.460)	(−1.072)	(0.741)
Career span	1.047***	1.051***	1.041***
	(31.336)	(26.692)	(25.478)
Female × Ability belief	1.176***	1.095**	0.802**
	(4.988)	(2.452)	(−2.247)
Female × Career span	0.999*	1.000	0.999
	(−1.681)	(−0.551)	(−0.829)
Female × log(GDP)	1.000	0.996	1.022
	(0.013)	(−0.108)	(0.722)
Observations	107 473	59 725	47 748
Pseudo R2	0.370	0.334	0.395
Country Fixed Effects	Yes	Yes	Yes
Field Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes

This table reports results of Poisson regressions of *Number of papers* on the interaction terms of *Female* and *Ability belief*. Estimated coefficients are expressed as incidence rate ratios. The sample is at the individual level and is described in Table 1. Column (1) includes all fields; column (2) focuses on STEM fields; column (3) focuses on non-STEM fields. *Number of papers* is the cumulative number of papers a scientist published between 1960 and 2019. *Ability belief* is the field-specific ability belief scores obtained from the survey conducted by Leslie et al. (2015). *Female* is an indicator equal to one if a scientist is female. *Career span* is the number of years between the year of the first publication and the year of the last publication of a scientist. *log(GDP)* is the logarithm of GDP per capita. Z-statistics are calculated with standard errors clustered at the country level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Single authored papers by field.

Field	STEM	% Single authored papers
Biology	1	8%
Biomedical Research	1	6%
Chemistry	1	4%
Earth & Environmental Sciences	1	9%
Economics	1	25%
Enabling & Strategic Technologies	1	5%
Engineering	1	8%
Information & Communication Technologies	1	8%
Mathematics & Statistics	1	23%
Physics & Astronomy	1	8%
Agriculture, Fisheries & Forestry	0	6%
Built Environment & Design	0	19%
Business	0	18%
Clinical Medicine	0	6%
Communication & Textual Studies	0	50%
Historical Studies	0	48%
Philosophy & Theology	0	65%
Psychology & Cognitive Sciences	0	13%
Public Health & Health Services	0	12%
Social Sciences	0	35%
Visual & Performing Arts	0	59%
STEM fields		8%
Non-STEM fields		11%

This table reports the share of single authored papers in STEM and Non-STEM fields. *% Single authored papers* is the percentage of single authored papers by a scientist.

women at the PhD level has improved, it is less clear that science has become more diverse (Lundberg and Stearns, 2019; Huang et al., 2020; Berland et al., 2023; Mulders et al., 2024; Iaria et al., 2024). Using data over the 20th century, Iaria et al. (2024) document substantial gender gaps in representation and promotion in academia. As Baron et al. (2024) highlight, simply focusing on increased representation is unlikely to close these gender gaps. Huang et al. (2020) go so far as to question the sustainability of academic careers for women.

Our evidence points to reasons why academic careers might not be sustainable or attractive for women. Societal culture and field-specific culture may make it difficult for women to pursue scientific careers in both STEM and Non-STEM fields. Since culture is nurture, not nature, our results suggest more generally that the conduct of science and innovation in countries and fields may be hampered by man-made constraints. Instead of simply educating women and girls, policies that change field-specific and scientific culture (e.g., Audretsch et al., 2024) and improve women's rights and the rights of other minorities in science could lead to more inclusive science and higher rates of innovation.

Table A.1
Variable definition.

Variable	Definition	Source
	Country-field characteristics	
% Female	Women's representation in an academic field in a country among scientists with at least 5 publications	ICSR
Number of scientists	The number of scientists with at least 5 publications in an academic field in a country	ICSR
% Top female	Women's representation in an academic field in a country among the top 2% ranked scientists with at least 5 publications in Scopus	Ioannidis et al. (2019, 2020)
Number of top scientists	The number of top scientists in an academic field in a country	Ioannidis et al. (2019, 2020)
	Country characteristics	
WEF EPO	World Economic Forum Economic Participation and Opportunity index, measured in the first available year (2006)	World Economic Forum
LFP	The ratio of female to male labor force participation rates, measured in the first available year (1990)	World Bank
WBL	Women Business Law workforce index, measured in the first available year (1970)	World Bank
AFL	Academic Freedom Index	FAU Erlangen-Nürnberg and V-Dem Institute
log(GDP)	The natural logarithm of GDP per capita, measured in 1960	Maddison Project Database
Math gap	Boys' average PISA math scores minus girls' average PISA math scores, measured in the year when a country was first covered in PISA.	OECD
	Field characteristics	
Ability belief	Field-specific ability belief score	Leslie et al. (2015)
Ability belief (male)	Field-specific ability belief score for male survey respondents	Leslie et al. (2015)
Ability belief (female)	Field-specific ability belief score for female survey respondents	Leslie et al. (2015)
STEM	An indicator equal to one if the field is Biology, Biomedical Research, Chemistry, Earth & Environmental Sciences, Economics, Enabling & Strategic Technologies, Engineering, Information & Communication, Mathematics & Statistics, or Physics & Astronomy.	ICSR and Ioannidis et al. (2019, 2020)
Field	A scientific discipline according to Science-Metrix classification. We use the field classification from Ioannidis et al. (2019, 2020) except for economics. We separate economics and finance from economics and business since economics and finance are classified as STEM fields and the rest of the business is classified as Non-STEM field.	ICSR and Ioannidis et al. (2019, 2020)
GRE math	The field's average quantitative GRE score	Ginther and Kahn (2015)
	Individual characteristics	
Female	An indicator equal to one if a scientist is female	Ioannidis et al. (2019, 2020), Genderize.io
Number of papers	The number of papers by a scientist between 1960 and 2019	Ioannidis et al. (2019, 2020)
Number of single authored papers	The number of single-authored papers by a scientist	Ioannidis et al. (2019, 2020)
Cohort	The decade in which scientists published their first publication. The first cohort also includes those scientists whose first publications appeared before 1940.	Ioannidis et al. (2019, 2020)
PhD cohort	The decade in which a scientist was awarded their PhD degree	Bohannon and Doran (2017)
Career span	The number of years between the year of first publication and the year of last publication	Ioannidis et al. (2019, 2020)
Country	The country where a scientist is working.	Bohannon and Doran (2017), Ioannidis et al. (2019, 2020)
Country (Origin)	The scientist's country of origin, identified based on nationality or work history	Bohannon and Doran (2017), Ioannidis et al. (2019, 2020), Nationalize.io
Migrated	An indicator equal to one if a scientist's origin country differs from the working country in 2019 in the individual-level data, and if a scientist's country of first job differs from the working country in 2016 in the ORCID data	Bohannon and Doran (2017), Ioannidis et al. (2019, 2020), Nationalize.io

This table provides the definitions of variables used in our analysis.

CRediT authorship contribution statement

Renée B. Adams: Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization. **Jing Xu:** Writing – review & editing, Writing – original draft, Software, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process: During the preparation of this work the authors used ChatGPT in order to help identify country-level shocks to academic freedom and for minor grammar and coding checks. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Table A.1

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.respol.2025.105400.

Data availability

The authors do not have permission to share data.

References

Adams, R.B., Kräussl, R., Navone, M., Verwijmeren, P., 2021. Gendered prices. Rev. Financ. Stud.34 (8), 3789–3839.

Adams, R.B., Lowry, M., 2022a. The culture of the finance profession: Evidence from the 2020/2021 American finance association survey. Working Paper.

Adams, R.B., Lowry, M., 2022b. What's good for women is good for science: Evidence from the American finance association. Rev. Corp. Financ. Stud. 11 (3), 554–604.

Adams, R.B., Lowry, M., 2022c. Women's committee: Organizations and women's discontent. RES Q. Newsl. https://res.org.uk/committee/women-s-committee-organizations-and-women-s-discontent (accessed January 20, 2025).

Adams, R.B., Xu, J., 2023. The inequality of finance. Rev. Corp. Financ. 3 (1–2), 35–68.

Alesina, A., Giuliano, P., Nunn, N., 2013. On the origins of gender roles: Women and the plough. Q. J. Econ. 128 (2), 469–530.

Anastasiadou, A., Kim, J., Sanlitürk, A.E., de Valk, H., Zagheni, E., 2023. Sex- and gender-based differences in the migration process: A systematic literature review. Working Paper.

Antecol, H., 2000. An examination of cross-country differences in the gender gap in labor force participation rates. Labour Econ. 7 (4), 409–426.

Antman, F.M., 2018. Women and migration. In: Averett, S.L., Argys, L.M., Hoffman, S.D. (Eds.), The Oxford Handbook of Women and the Economy. Oxford University Press, Oxford, pp. 731–748.

Audretsch, D.B., Fisch, C., Franzoni, C., Momtaz, P.P., Vismara, S., 2024. Academic freedom and innovation. PLoS One 19 (6), e0304560.

Bagues, M., Sylos-Labini, M., Zinovyeva, N., 2017. Does the gender composition of scientific committees matter? Am. Econ. Rev. 107 (4), 1207–1238.

Baron, J., Ganglmair, B., Persico, N., Simcoe, T., Tarantino, E., 2024. Representation is not sufficient for selecting gender diversity. Res. Policy 53 (6), 104994.

Berland, O., Harman, O., Moreau-Kastler, N., 2023. Pipelines or pyramids: A review of barriers for women in economics. Working paper.

Bertrand, M., 2011. Chapter 17 - new perspectives on gender. In: Card, D., Ashenfelter, O. (Eds.), In: Handbook of Labor Economics, vol. 4, Part B, Elsevier, pp. 1545–1592.

Bikard, M., Fernandez-Mateo, I., Mogra, R., 2025. Standing on the shoulders of (male) giants: Gender inequality and the technological impact of scientific ideas. Adm. Sci. Q. 70 (3), 695–732.

Blau, F., Kahn, L., Papps, K., 2011. Gender, source country characteristics, and labor market assimilation among immigrants: 1980–2000. Rev. Econ. Stat. 93 (1), 43–58.

Bohannon, J., Doran, K., 2017. Introducing ORCID. Science 356, 691–692.

Boserup, E., 1970. Women's Role in Economic Development. Allen & Unwin.

Breda, T., Grenet, J., Monnet, M., Van Effenterre, C., et al., 2020a. Do female role models reduce the gender gap in science?: Evidence from French high schools. Working paper.

Breda, T., Jouini, E., Napp, C., Thebault, G., 2020b. Gender stereotypes can explain the gender-equality paradox. Proc. Natl. Acad. Sci. 117 (49), 31063–31069.

Catala, A., 2015. Democracy, trust, and epistemic justice. Monist. 98 (4), 424–440.

Ceci, S.J., Ginther, D.K., Kahn, S., Williams, W.M., 2014. Women in academic science: A changing landscape. Psychol. Sci. Public Interes. Suppl. 15 (3), 75–141.

Ceci, S.J., Kahn, S., Williams, W.M., 2023. Exploring gender bias in six key domains of academic science: An adversarial collaboration. Psychol. Sci. Public Interes. 24 (1), 15–73.

Cetina, K.K., 1999. Epistemic Cultures: How the Sciences Make Knowledge. Harvard University Press.

Chan, H.F., Torgler, B., 2020. Gender differences in performance of top cited scientists by field and country. Scientometrics 125 (3), 2421–2447.

Charles, M., Bradley, K., 2009. Indulging our gendered selves? Sex segregation by field of study in 44 countries. Am. J. Sociol. 114 (4), 924–976.

Cheung, H.Y., Chan, A.W., 2007. How culture affects female inequality across countries: An empirical study. J. Stud. Int. Educ. 11 (2), 157–179.

Cimpian, A., Leslie, S.J., 2015. Women in science. Response to comment on "expectations of brilliance underlie gender distributions across academic disciplines". Science 349 (6246), 391c.

Clancy, M., 2021a. Gender and what gets researched, New Things Under the Sun. https://mattsclancy.substack.com/p/gender-and-what-gets-researched (accessed January 20, 2025).

Clancy, M., 2021b. More science leads to more innovation, New Things under Sun. https://mattsclancy.substack.com/p/more-science-leads-to-more-innovation (accessed January 20, 2025).

Cohen, P., 2025. The World Is Wooing U.S. Researchers Shunned by Trump, The New York Times. https://www.nytimes.com/2025/05/14/business/economy/trump-research-brain-drain.html (accessed May 20, 2025).

Cohn, J.B., Liu, Z., Wardlaw, M.I., 2022. Count (and count-like) data in finance. J. Financ. Econ. 146 (2), 529–551.

Cortes, P., Pan, J., 2018. Occupation and gender. In: Averett, S.L., Argys, L.M., Hoffman, S.D. (Eds.), The Oxford Handbook of Women and the Economy. Oxford University Press, Oxford, pp. 425–452.

Cuevas, A., Rumin, R.C., Desmet, K., Ortuño-Ortin, I., 2025. 238, 107165.

Dillon, S., 2005. Harvard chief defends his talk on women. The New York Times. https://www.nytimes.com/2005/01/18/us/harvard-chief-defends-his-talk-on-women.html (accessed January 20, 2025).

Dodson, B., 2021. Gender and gender relations in skilled migration: more than a matter of brains. In: The Palgrave Handbook of Gender and Migration. Springer, pp. 203–220.

Eagly, A.H., Wood, W., 1999. The origins of sex differences in human behavior: Evolved dispositions versus social roles. Am. Psychol. 54 (6), 408–423.

Eckel, C.C., Gangadharan, L., Grossman, P.J., Xue, N., 2020. The gender leadership gap: Insights from experiments. In: Chaudhuri, A. (Ed.), Research Agenda in Experimental Economics. In: Elgar Research Agenda Series, Edward Elgar, Cheltenham, UK, pp. 137–162.

Ederer, F., Goldsmith-Pinkham, P., Jensen, K., 2023. Anonymity and identity online. Working Paper.

Falk, A., Hermle, J., 2018. Relationship of gender differences in preferences to economic development and gender equality. Science 362 (6412), eaas9899.

Fernández, R., 2007. Women, work, and culture. J. Eur. Econ. Assoc. 5 (2-3), 305–332.

Fernández, R., Fogli, A., 2009. Culture: An empirical investigation of beliefs, work, and fertility. Am. Econ. J.: Macroecon. 1 (1), 146–177.

Fleury, A., 2016. Understanding Women and Migration: A Literature Review. Working Paper.

Fortunato, S., Bergstrom, C.T., Börner, K., Evans, J.A., Helbing, D., Milojević, S., Petersen, A.M., Radicchi, F., Sinatra, R., Uzzi, B., Vespignani, A., Waltman, L., Wang, D., Barabási, A.L., 2018. Science of science. Science 359 (6379), eaao0185.

Fourcade, M., Ollion, E., Algan, Y., 2015. The superiority of economists. J. Econ. Perspect. 29 (1), 89–114.

Franklin, S., 1995. Science as culture, cultures of science. Annu. Rev. Anthr. 24 (1), 163–184.

Fricker, M., 1999. Epistemic oppression and epistemic privilege. Can. J. Philos. Suppl. Vol. 25, 191–210.

Fryer, Jr., R.G., Levitt, S.D., 2010. An empirical analysis of the gender gap in mathematics. Am. Econ. J.: Appl. Econ. 2 (2), 210–240.

Ginther, D.K., Kahn, S., 2015. Comment on "Expectations of brilliance underlie gender distributions across academic disciplines". Science 349 (6246), 391b.

Giorcelli, M., Lacetera, N., Marinoni, A., 2022. How does scientific progress affect cultural changes? A digital text analysis. J. Econ. Growth 27 (4), 415–452.

Guiso, L., Monte, F., Sapienza, P., Zingales, L., 2008. Culture, gender, and math. Science 320 (5880), 1164–1165.

Halpern, D.F., Benbow, C.P., Geary, D.C., Gur, R.C., Hyde, J.S., Gernsbacher, M.A., 2007. The science of sex differences in science and mathematics. Psychol. Sci. Public Interes. 8 (1), 1–51.

Hengel, E., 2022. Publishing while female: are women held to higher standards? Evidence from peer review. Econ. J. 132 (648), 2951–2991.

Hofstede, G., 2001. Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations, vol. 41, Sage Publications, pp. 861–862.

Huang, J., Gates, A.J., Sinatra, R., Barabási, A.L., 2020. Historical comparison of gender inequality in scientific careers across countries and disciplines. Proc. Natl. Acad. Sci. 117, 4609–4616.

Iaccarino, M., 2003. Science and culture: Western science could learn a thing or two from the way science is done in other cultures. EMBO Rep. 4 (3), 220–223.

Iaria, A., Schwarz, C., Waldinger, F., 2024. Gender gaps in academia: Global evidence over the twentieth century. Working paper.

Ioannidis, J.P.A., Baas, J., Klavans, R., Boyack, K.W., 2019. A standardized citation metrics author database annotated for scientific field. PLOS Biology 17 (8), e3000384.

Ioannidis, J.P.A., Boyack, K.W., Baas, J., 2020. Updated science-wide author databases of standardized citation indicators. PLOS Biology 18 (10), e3000918.

Kaasa, A., 2021. Merging Hofstede, Schwartz, and Inglehart into a single system. J. Cross-Cultural Psychol. 52 (4), 339–353.

Kahn, S., Ginther, D., 2017. Women and science, technology, engineering, and mathematics (STEM): Are differences in education and careers due to stereotypes, interests, or family? In: The Oxford Handbook of Women and the Economy. Oxford University Press, pp. 767–798.

Kang, J.C., 2025. What's the point of Trump's war on D.E.I.? New Yorker. https://www.newyorker.com/news/fault-lines/whats-the-point-of-trumps-war-on-diversity-equality-inclusion (accessed May 20, 2025).

King, D.A., 2004. The scientific impact of nations. Nature 430 (6997), 311–316.

Kinzelbach, K., Lindberg, S.I., Pelke, L., Spannagel, J., 2023. Academic Freedom Index 2023 Update. FAU Erlangen-Nürnberg and V-Dem Institute.

Koffi, M., 2021. Gendered citations at top economic journals. In: AEA Papers and Proceedings, 111, 60–64.

Kozlowski, D., Larivière, V., Sugimoto, C.R., Monroe-White, T., 2022. Intersectional inequalities in science. Proc. Natl. Acad. Sci. 119 (2), e2113067119.

Krieger, T., Renner, L., Schmid, L., 2020. The individual level: Sorting effects. In: Environmental Conflicts, Migration and Governance. Bristol University Press, Bristol, UK, pp. 103–120.

Lerman, K., Yu, Y., Morstatter, F., Pujara, J., 2022. Gendered citation patterns among the scientific elite. Proc. Natl. Acad. Sci. 119 (40), e2206070119.

Leslie, S.J., Cimpian, A., Meyer, M., Freeland, E., 2015. Expectations of brilliance underlie gender distributions across academic disciplines. Science 347 (6219), 262–265.

Lockhart, J., King, M., Munsch, C., 2023. Name-based demographic inference and the unequal distribution of misrecognition. Nat. Hum. Behav. 7, 1084–1095.

Long, J.S., 1990. The origins of sex differences in science. Soc. Forces 68 (4), 1297–1316.

Long, J.S., Allison, P.D., McGinnis, R., 1993. Rank advancement in academic careers: Sex differences and the effects of productivity. Am. Sociol. Rev. 58 (5), 703–722.

Lundberg, S., Stearns, J., 2019. Women in economics: Stalled progress. J. Econ. Perspect. 33 (1), 3–22.

Manly, C.A., Wells, R.S., Kommers, S., 2018. The influence of STEM definitions for research on women's college attainment. Int. J. STEM Educ. 5, 45.

Master, A., Meltzoff, A.N., Cheryan, S., 2021. Gender stereotypes about interests start early and cause gender disparities in computer science and engineering. Proc. Natl. Acad. Sci. 118 (48), e2100030118.

May, R.M., 1997. The scientific wealth of nations. Science 275 (5301), 793–796.

Mendes, C.H., de Brito, A.S., Angotti, B., Sales, F.R., Reis, L.S., de Vasconcelos, N.P., 2020. Academic freedom in Brazil: A case study on recent developments. https://gppi.net/assets/GPPi_LAUT_2020_Academic_Freedom_in_Brazil.pdf (accessed January 20, 2025).

Meoli, A., Piva, E., Righi, H., 2024. Missing women in STEM occupations: The impact of university education on the gender gap in graduates' transition to work. Res. Policy 53 (8), 105072.

Miller, D.I., Eagly, A.H., Linn, M.C., 2015. Women's representation in science predicts national gender-science stereotypes: Evidence from 66 nations. J. Educ. Psychol. 107 (3), 631–644.

Mulders, A.M., Hofstra, B., Tolsma, J., 2024. A matter of time? Gender and ethnic inequality in the academic publishing careers of Dutch PhDs. Quant. Sci. Stud. 5 (3), 487–515.

Naghsh-Nejad, M., Young, A.T., 2014. Female brain drains and women's rights gaps: A gravity model analysis of bilateral migration flows. Working Paper.

Nielsen, M.W., Bloch, C.W., Schiebinger, L., 2018. Making gender diversity work for scientific discovery and innovation. Nat. Hum. Behav. 2 (10), 726–734.

Nollenberger, N., Rodríguez-Planas, N., Sevilla, A., 2016. The math gender gap: The role of culture. Am. Econ. Rev. 106 (5), 257–261.

Norris, P., 2025. Professors are the enemy: Two faces of academic freedom. Working paper.

Parey, M., Ruhose, J., Waldinger, F., Netz, N., 2017. The selection of high-skilled emigrants. Rev. Econ. Stat. 99 (5), 776–792.

Phillips, K.W., Medin, D., Lee, C.D., Bang, M., Bishop, S., Lee, D., 2014. How diversity works. Sci. Am. 311 (4), 42–47.

Piazza, A., Rendine, S., Zei, G., Moroni, A., Cavalli-Sforza, L.L., 1987. Migration rates of human populations from surname distributions. Nature 329 (6141), 714–716.

Powell, W.W., Snellman, K., 2004. The knowledge economy. Annu. Rev. Sociol. 30 (1), 199–220.

Richardson, S.S., Reiches, M.W., Bruch, J., Boulicault, M., Noll, N.E., Shattuck-Heidorn, H., 2020. Is there a gender-equality paradox in science, technology, engineering, and math (STEM)? Commentary on the study by Stoet and Geary (2018). Psychol. Sci. 31 (3), 338–341.

Ritz, S.A., Greaves, L., 2024. We need more-nuanced approaches to exploring sex and gender in research. Nature 629 (8010), 34–36.

Rossi, A.S., 1965. Women in science: Why so few? Social and psychological influences restrict women's choice and pursuit of careers in science. Science 148 (3674), 1196–1202.

Rossiter, M.W., 1997. Which science? Which women? Osiris 12, 169–185.

Ruyssen, I., Salomone, S., 2018. Female migration: A way out of discrimination? J. Dev. Econ. 130 (C), 224–241.

Samek, A., 2023. Request to the AEA to assist in action against libel and threats on EJMR. https://x.com/AnyaSamek/status/1661227432685477894. (accessed January 20, 2025).

Sarsons, H., 2017. Recognition for group work: Gender differences in academia. Am. Econ. Rev. 107 (5), 141–145.

Sarsons, H., Gërxhani, K., Reuben, E., Schram, A., 2021. Gender differences in recognition for group work. J. Political Econ. 129 (1), 101–147.

Schiebinger, L., 1987. The history and philosophy of women in science: A review essay. J. Women Cult. Soc. 12 (2), 305–332.

Schwartz, S.H., 1999. A theory of cultural values and some implications for work. Appl. Psychol. 48 (1), 23–47.

Schwartz, S.H., Rubel-Lifschitz, T., 2009. Cross-national variation in the size of sex differences in values: effects of gender equality. J. Pers. Soc. Psychol. 97 (1), 171–185.

Siniscalchi, M., Veronesi, P., 2020. Self-image bias and lost talent. Working Paper.

Stoet, G., Geary, D.C., 2018. The gender-equality paradox in science, technology, engineering, and mathematics education. Psychol. Sci. 29 (4), 581–593.

Straza, T., Scan, G., 2024. Changing the Equation: Securing STEM Futures for Women. Tech. rep., UNESCO, https://unesdoc.unesco.org/ark:/48223/pf0000391384. (accessed January 20, 2025).

Sweetser, A.G., Petry, G.H., 1981. A history of the seven academic finance associations and their contributions to development of the discipline. Financ. Manag. 10 (2), 46–70.

Warren, J.R., 2019. How much do you have to publish to get a job in a top sociology department? Or to get tenure? Trends over a generation. Sociol. Sci. 6 (7), 172–196.

Wilson, L., 2018. State control over academic freedom in Hungary threatens all universities. (accessed August 1, 2025).

World Bank, 2023. Women, Business and the Law 2023. World Bank, Washington, DC.

Wright, J., 2024. The hierarchy in economics and its implications. Econ. Philos. 40 (2), 257–278.

Yang, Y., Tian, T.Y., Woodruff, T.K., Jones, B.F., Uzzi, B., 2022. Gender-diverse teams produce more novel and higher-impact scientific ideas. Proc. Natl. Acad. Sci. 119 (36), e2200841119.

Zhao, X., Akbaritabar, A., Kashyap, R., Zagheni, E., 2023. A gender perspective on the global migration of scholars. Proc. Natl. Acad. Sci. 120 (10), e2214664120.

Zheng, H., Li, W., Wang, D., 2022. Expertise diversity of teams predicts originality and long-term impact in science and technology. Working paper.

Zuckerman, H., Cole, J.R., 1984. The productivity puzzle: Persistence and change in patterns of publication of men and women scientists. Adv. Motiv. Achiev. 2, 217–258.