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INNOVATIONS IN SOCIAL PSYCHOLOGY

Field-Specific Ability Beliefs as an Explanation for Gender Differences in Academics' Career Trajectories: Evidence From Public Profiles on ORCID.org

Aniko Hannak¹, Kenneth Joseph², Daniel B. Larremore^{3, 4}, and Andrei Cimpian⁵

¹ Department of Informatics, University of Zürich

² Department of Computer Science and Engineering, University at Buffalo

³ Department of Computer Science, University of Colorado Boulder

⁴ BioFrontiers Institute, University of Colorado Boulder

⁵ Department of Psychology, New York University

Academic fields exhibit substantial levels of gender segregation. Here, we investigated differences in field-specific ability beliefs (FABs) as an explanation for this phenomenon. FABs may contribute to gender segregation to the extent that they portray success as depending on “brilliance” (i.e., exceptional intellectual ability), which is a trait culturally associated with men more than women. Although prior work has documented a relation between academic fields' FABs and their gender composition, it is still unclear what the underlying dynamics are that give rise to gender imbalances across academia as a function of FABs. To provide insight into this issue, we custom-built a new data set by combining information from the author-tracking service Open Researcher and Contributor ID (ORCID) with information from a survey of U.S. academics across 30 fields. Using this expansive longitudinal data set ($N_s = 86,879\text{--}364,355$), we found that women were underrepresented among those who enter fields with brilliance-oriented FABs and overrepresented among those who exit these fields. We also found that FABs' association with women's transitions across academic fields was substantially stronger than their association with men's transitions. With respect to mechanisms, FABs' association with gender segregation was partially explained by the fact that women encounter more prejudice in fields with brilliance-oriented FABs. With its focus on the dynamic patterns shaping segregation and its broad scope in terms of geography, career stage, and historical time, this research makes an important contribution toward understanding the factors driving gender segregation in academia.

Keywords: gender, segregation, academia, stereotypes, Big Data

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Aniko Hannak  <https://orcid.org/0000-0002-0612-6320>

Kenneth Joseph  <https://orcid.org/0000-0003-2233-3976>

Daniel B. Larremore  <https://orcid.org/0000-0001-5273-5234>

Andrei Cimpian  <https://orcid.org/0000-0002-3553-6097>

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Correspondence concerning this article should be addressed to Aniko Hannak, Department of Informatics, University of Zürich, Andreasstr. 15 / Office AND 2.60, 8050 Zürich, Switzerland, or Kenneth Joseph, Department of Computer Science and Engineering, University at Buffalo, 335 Davis Hall, Buffalo, NY 14260, United States, or Daniel B. Larremore, BioFrontiers Institute, University of Colorado Boulder, 3415 Colorado Avenue, Boulder, CO 80303, United States, or Andrei Cimpian, Department of Psychology, New York University, 6 Washington Place, New York, NY 10003, United States. Email: hannak@ifi.uzh.ch or kjoseph@buffalo.edu or daniel.larremore@colorado.edu or andrei.cimpian@nyu.edu

Gender segregation in academia remains substantial well into the 21st century, undermining gender equity in earnings and status (e.g., Blau & Kahn, 2017; Cheryan & Markus, 2020; England, 2010; Pelley & Carnes, 2020). Within psychology, most of the research conducted to understand gender segregation in the last few decades has focused on the narrower, but practically important, phenomenon of women's underrepresentation in science, technology, engineering, and mathematics (STEM; for reviews, see Cheryan et al., 2017; Schmader, 2023), in part because diversifying these fields is a priority for many governmental and international agencies (The Fawcett Society, 2019; United Nations, 2019). However, gender segregation is not unique to STEM fields. For example, only 27.4% of 2020 U.S. PhD recipients in philosophy, a humanities field, were women. At the other end of the spectrum, women made up 72.1% of U.S. PhD recipients in psychology¹ in the same year (National Science Foundation, 2020)—even though, interestingly, philosophy and psychology are “sibling disciplines,” similar in many substantive respects such as the topics studied (Cimpian & Leslie, 2017). Statistics such as these suggest that a broader perspective is needed to fully understand gender segregation in academia.

Here, we investigated a promising recent account of gender segregation that adopts this broader perspective and seeks to explain the gender imbalances in fields across the entire academic spectrum. This account appeals to field-specific ability beliefs (FABs) as a key factor underlying gender segregation in academia (e.g., Cimpian & Leslie, 2017; Leslie, Cimpian, et al., 2015). At the core of this account is the notion that academic fields—whether in STEM, social sciences, or the humanities—differ systematically in how their members think about success. In some fields, academics tend to view intellectual talent (“brilliance”) as necessary for success. In other fields, this belief is less common, and effort and dedication are seen as sufficient. Although gender-neutral on the surface, FABs contribute to gender segregation because brilliance is culturally associated with men more than women (e.g., Boutyline et al., 2023; Musto, 2019; Storage et al., 2020; Zhao et al., 2022), which makes fields with brilliance-oriented FABs more conducive to men's participation than to women's.²

There is by now substantial evidence for a relation between academic fields' FABs and their gender composition. For example, fields with more brilliance-oriented FABs graduate more men and fewer women both at the bachelor's level (e.g., Storage et al., 2016) and at the PhD level (e.g., Leslie, Cimpian, et al., 2015; Meyer et al., 2015). What is not yet understood, however, is what the underlying dynamics are that give rise to gender imbalances across academia as a function of FABs. For instance, do men find fields with brilliance-oriented FABs more appealing than women do, such that they are more likely to enter them in the first place? Alternatively (or in addition), are women more likely than men to exit fields with brilliance-oriented FABs? Questions such as these are central to the FAB account of gender segregation in academia, but they are also challenging to investigate: Answering them requires moving beyond cross-sectional correlations between FABs and gender ratios across fields and instead examining academics' career trajectories longitudinally, as they unfold over time. In part because scholars studying the FAB account of gender segregation have yet to identify the data and methods to study these longitudinal trajectories, questions about the career dynamics underlying how FABs shape gender segregation remain unexplored.

The main goal of the present research was to make headway on these important issues and provide, for the first time, insight into

how the dynamics of women's and men's transitions³ into and out of academic fields differ as a function of FABs, giving rise to the observed patterns of gender segregation. For purposes of this research, we will divide academics' career trajectories into a series of discrete “entry” and “exit” events. If an individual is in Field X at time *t* (e.g., as a college major) and in Field Y at time *t* + 1 (e.g., as a PhD student), we can describe this event as an entry into Field Y and an exit from Field X. Studying field entries helps illuminate the processes that lead to differential recruitment of women and men into a field. Studying field exits helps illuminate the processes that lead to differential attrition of women and men out of a field (or, conversely, differential retention of women and men into that field). Notably, the characteristics of a field that attract women or men into entering it, whether at the beginning of their careers or later, may be meaningfully different from the characteristics of a field that lead them to persist in (vs. leave) it (e.g., Cheryan et al., 2017; Xie & Shauman, 2003). From this dynamic perspective on gender segregation in academia, we asked the following questions (see also Figure 1):

Question 1a (Entry: Segregation): Are men more likely than women to enter fields with more brilliance-oriented FABs?

Question 1b (Exit: Segregation): Are women more likely than men to exit fields with more brilliance-oriented FABs?

The discussion above highlights another key question that the FAB account must answer but so far has not: Whether we should look to women or men to understand gender segregation. In psychology, gender segregation is often explained in terms of women's attitudes, abilities, and behaviors; in most cases, men are the presumed-neutral standard to which women are compared (for arguments on this point, see Cheryan & Markus, 2020; D. T. Miller et al., 1991). Here, we investigated the dynamic patterns underlying gender segregation without making a priori assumptions about who is responsible for these patterns. We were thus able to answer the questions below (see also Figure 1) and make another theoretical contribution to the FAB account.

Question 2a (Entry: Women vs. Men): Whose field entries do FABs predict better: women's or men's?

Question 2b (Exit: Women vs. Men): Whose field exits do FABs predict better: women's or men's?

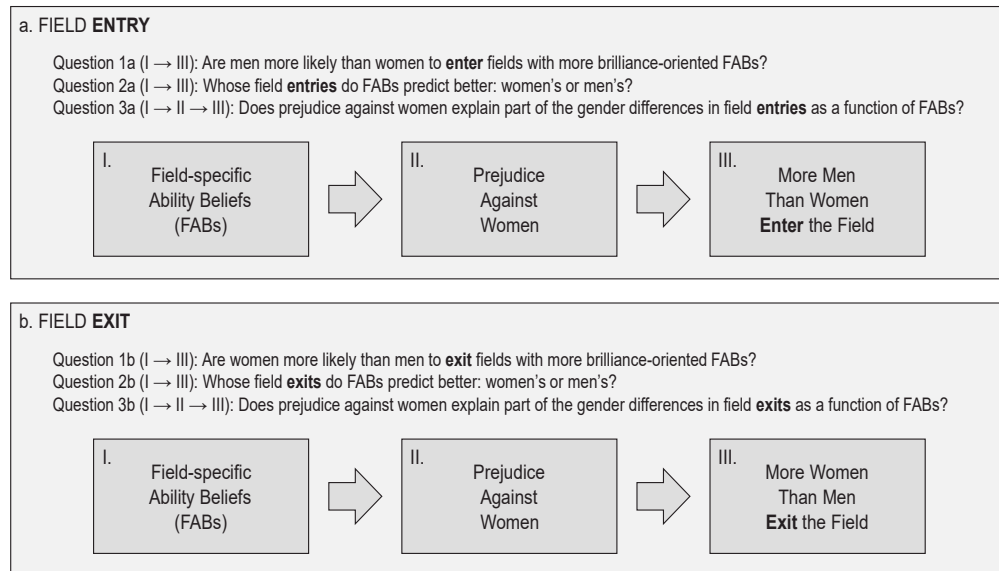
The final goal of the present research was to investigate the mechanisms that might explain the differences between women's and men's movements across fields as a function of FABs. From its initial formulation (Cimpian & Leslie, 2015; Leslie, Cimpian, et al., 2015), the FAB account of gender segregation has assigned a central role to prejudice against women as a mechanism by which FABs

¹ Following convention and precedent (e.g., Leslie, Cimpian, et al., 2015), we defined STEM as including the natural sciences (e.g., physics, biology, chemistry), engineering, mathematics, and computer science, but excluding the social and behavioral sciences (e.g., psychology, economics).

² In this article, we focus on the gender categories of woman and man, but we acknowledge that gender is not binary that many individuals do not identify with either of these categories (e.g., Hyde et al., 2019).

³ Throughout, we use the terms transition, move, and switch interchangeably to refer to an observed change in an academic's field.

Figure 1
Conceptual Diagram of the Hypothesized Relations Between FABs, Prejudice Against Women, and Gender Segregation Among Academics Who Are Entering (Upper Panel) and Exiting (Lower Panel) a Field



Note. FAB = field-specific ability beliefs.

give rise to gender segregation. According to this argument, the cultural stereotype that associates brilliance with men more than women (e.g., Bian et al., 2017, 2018a; Storage et al., 2020; Zhao et al., 2022) gives rise to doubts about whether women, regardless of their prior achievements, can succeed at the highest levels in fields with brilliance-oriented FABs. In turn, prejudiced attitudes of this sort pose an obstacle to women's participation in fields with brilliance-oriented FABs, contributing to gender segregation (see Figure 1). Although some of the basic associations predicted by this argument have already been documented (e.g., fields with more brilliance-oriented FABs exhibit more prejudice against women; Leslie, Cimpian, et al., 2015), to date there is no compelling answer to our third question:

Question 3a (Entry: Prejudice): Does prejudice against women explain part of the gender differences in field entries as a function of FABs?

Question 3b (Exit: Prejudice): Does prejudice against women explain part of the gender differences in field exits as a function of FABs?

As noted, answering the questions above requires access to individual-level, longitudinal information on academics' career trajectories, data that previous work on FABs has not found ways of gathering or analyzing. To overcome this obstacle, we drew on two unique data sets. First, we extracted longitudinal information on academic career trajectories from the biggest available collection of academic profiles: ORCID, which stands for "Open Researcher and Contributor ID." In addition to allowing us to track individual women's and men's movements across fields, our carefully curated ORCID data set was exceptionally broad, encompassing over 86,000 academics from as many as 30 fields across STEM, social sciences,

and the humanities; from virtually every country in the world; and with careers spanning more than six decades. Second, we linked these individual trajectories to a survey of U.S. academics from the same 30 fields (Leslie, Cimpian, et al., 2015). In this survey, academics rated, among other things, their fields' FABs and the extent to which women encounter prejudice within their fields. When combined, these two data sets offered unprecedented insight into the dynamic processes underlying gender segregation in academia, and the role that FABs play in it. Notably, we have made this data set freely available so that other researchers can build on the present work and/or explore other accounts of gender segregation.⁴ We are also sharing the code needed to recreate this data set from the raw data files that ORCID makes public every year: The rapid pace at which ORCID iDs are being adopted by academics everywhere (Petro, 2020) suggests that future scholars will have at their disposal an even more comprehensive snapshot of global academics.⁵

The FAB Account: Broader Theoretical Context, Prior Evidence

Academics' beliefs about the "ingredients" that are necessary for professional success differ by field. In some fields (e.g., philosophy, physics), many believe that success depends on "brilliance," a high level of intellectual ability (e.g., Leslie, Cimpian, et al., 2015; Storage et al., 2016). In other fields (e.g., psychology, education), brilliance is

⁴ All data and Python, R, and Stata code are available at https://github.com/kennyjoseph/ORCID_trajectories.

⁵ Although ORCID is growing rapidly, its present size is already large enough to produce stable estimates of the parameters of interest to us here. To illustrate, the analyses reported below were conducted on two versions of the ORCID data set, separated by 1.5 years. While the later data set was 40% larger than the earlier one, the results were materially the same across the two data sets.

less emphasized, and dedication and hard work are instead seen as sufficient for success. Because of cultural “brilliance = men” stereotypes that associate men more than women with brilliance (e.g., Bian et al., 2017, 2018a; Musto, 2019; Rivera & Tilcsik, 2019; Storage et al., 2020; Zhao et al., 2022) and portray women’s intellectual successes as rooted in effort (e.g., Del Pinal et al., 2017; Smith et al., 2013), FABs are argued to contribute to gender segregation, with more men than women in fields with brilliance-oriented FABs and more women than men in fields with effort-oriented FABs.

Broader Theoretical Context

It is useful to briefly situate the FAB account in the broader landscape of theoretical perspectives on gender segregation. Many prominent theoretical accounts agree that gender segregation arises in part because sociocultural factors (e.g., cultural stereotypes about the different interests and abilities of the average woman and man; Markus & Kitayama, 2010) create the perception of a “lack of fit” or “incongruity” between people of a particular gender and a particular professional context (e.g., Cheryan et al., 2015; Diekmann et al., 2017; Eagly & Karau, 2002; Hannover & Kessels, 2004; Heilman, 2012; Schmader, 2023; Van Vianen, 2018). For example, because girls are socialized to be more communal and altruistic than boys, they often perceive a lack of fit with STEM fields, which are culturally portrayed in ways that seem inconsistent with these self-views (e.g., scientists’ work is often portrayed as solitary; Diekmann et al., 2017). This perceived lack of fit might in turn diminish girls’ interest in pursuing careers in STEM (e.g., Master et al., 2021). In addition, to the extent that social others (e.g., peers, teachers) perceive a lack of fit between a particular gender and a particular career, they may display prejudice against the low-fit group (e.g., Eagly & Karau, 2002)—a further obstacle to the low-fit group’s pursuit of the relevant career.

Similar to these theoretical perspectives, the FAB account proposes that gender segregation is primarily the result of sociocultural factors. This account’s distinctive feature is the particular combination of factors that it emphasizes. The FAB account maintains that gender segregation in academia can be fruitfully understood as the product of two interlocking sets of cultural beliefs: (a) the beliefs of members of a field about what is required for success (namely, FABs) and (b) the pervasive “brilliance = men” stereotype (e.g., Bian et al., 2017; Zhao et al., 2022). In fields with more brilliance-oriented FABs, the “brilliance = men” stereotype creates a greater perceived fit or congruity with men than with women, which is in turn argued to give rise to gender segregation. Essentially, the goal of the present research is to flesh out this basic model and provide a deeper understanding of when these gender-differentiated perceptions of fit take their toll (field entry and/or exit), on whom they are acting more strongly in determining individual career paths (women vs. men), and through which mechanisms they are acting (e.g., prejudice against women).

Prior Evidence for the FAB Account

The initial studies motivated by the FAB account tested the basic prediction of a relationship between fields’ FABs and their gender composition. For example, Leslie, Cimpian, et al. (2015; see also Cimpian & Leslie, 2015) surveyed U.S. academics from 30 different fields and found that fields with more brilliance-oriented FABs

also had fewer women and more men obtaining PhDs ($r = -.60$). A similar negative relation was observed when examining fields in STEM and fields in the social sciences and humanities separately ($r_s = -.64$ and $-.62$, respectively). In addition, this relation remained significant when taking into account a number of other common explanations for gender segregation in academia (e.g., that women are underrepresented in fields that are more demanding in terms of work hours or more selective; Ceci & Williams, 2011; Ferriman et al., 2009). Subsequent work has replicated and extended these results. For example, some studies assessed FABs with new measures (e.g., via field-level differences in the use of the words “brilliant” and “genius” in anonymous reviews on RateMyProfessors.com; Storage et al., 2016) and in new populations (e.g., high school students, lay adults; Ito & McPherson, 2018; Meyer et al., 2015). Other studies used different indices of gender segregation, such as the gender ratios among bachelor’s degree recipients (Storage et al., 2016), whereas the initial studies examined PhD recipients, or gender differences in high school students’ intentions to pursue a field in college and as a career (Ito & McPherson, 2018).

Researchers have also theorized about the psychological mechanisms by which FABs give rise to gender segregation (e.g., Cimpian & Leslie, 2017). For instance, because of the stereotypes that associate brilliance with men more than women, brilliance-oriented FABs may pave the way for prejudice, such that members of fields with brilliance-oriented FABs may underestimate women’s abilities and provide them with fewer opportunities as a result. More generally, brilliance-oriented FABs may foster a “masculine” workplace atmosphere that undermines women’s psychological well-being and makes them feel they do not fit in (Cheryan & Markus, 2020). In addition, messages about the role of brilliance in success, combined with stereotypical gender associations, may encourage gender-based self-selection among aspiring or current members of a field (e.g., if such messages are appealing to men or off-putting to women). Some of these hypothesized mechanisms have received empirical support. For example, professional contexts in which brilliance is valued also prompt elevated levels of prejudice against women (for experimental evidence, see Bian et al., 2018a), as well as greater impostor feelings among women, feelings that are accompanied by a lower sense of belonging and lower self-efficacy (Muradoglu et al., 2022; Vial et al., 2022; see also Muenks et al., 2020; Porter & Cimpian, 2023). Portraying brilliance as important for success in a career was also found to undermine women’s (but not men’s) interest in that career, in part because it prompted women (but not men) to perceive that they would not fit in with others pursuing that career (Bian et al., 2018b).

In summary, the FAB account of gender segregation in academia builds on and extends previous theories that have appealed to sociocultural factors to explain this phenomenon. The distinctive feature of this account is its focus on the interlocking roles of FABs and “brilliance = men” stereotypes—two sociocultural factors that shape both individuals’ attributes (e.g., interests, self-views) and academic fields’ environments—as drivers of gender segregation.

The Present Research

The goal of the present research was to uncover the career dynamics by which FABs give rise to gender segregation in academia. Rather than using cross-sections of data as measures

of gender segregation (e.g., gender ratios among PhDs in a particular year), in the present research we were able to track individual academics' movements across fields as a function of the FABs of these fields. To obtain the information needed for this analysis, we built a new data set by combining information extracted from individual academic profiles on ORCID with information from a survey of U.S. academics from 30 fields in STEM, the social sciences, and the humanities. The overarching goal of uncovering the career dynamics by which FABs shape gender segregation led us to ask three pairs of questions (see Figure 1 for a graphical summary).

Questions 1a (Entry: Segregation) and 1b (Exit: Segregation) asked whether FABs predict gender segregation among those who enter a field and those who exit a field, respectively. Our ability to track ORCID users across the span of their educational and employment histories allowed us to evaluate FABs' role at these distinct points where gender segregation can arise.

Whereas the first question focuses on when (i.e., at which points in academics' careers) FABs predict the emergence of gender segregation, Questions 2a (Entry: Women vs. Men) and 2b (Exit: Women vs. Men) tackle the question of who FABs act on. These questions were intended in part as a corrective to the common assumption that men's behavior is the "default" that needs no explanation (Cheryan & Markus, 2020; D. T. Miller et al., 1991). This male-centric bias (e.g., Bailey et al., 2019, 2022) has often led researchers and policymakers to assume that gender segregation, especially as it manifests in women's underrepresentation in STEM, is largely a function of women's attitudes and behaviors (e.g., women are not confident enough in their abilities), and thus that women are the ones who need to change in order to desegregate academia. In the present research, we were able to examine separately the ways in which women's versus men's movements across fields contribute to gender segregation in academia.

Finally, Questions 3a (Entry: Prejudice) and 3b (Exit: Prejudice) delve deeper into the mechanisms that may explain the role of FABs as a gender-segregating force among those who are entering and exiting a field, respectively. Specifically, we focused on prejudice against women as a candidate mechanism. Small-scale experimental evidence suggests that professional contexts that are oriented to brilliance and genius elicit prejudice against women (Bian et al., 2018a). However, no research to date has used data on actual academics to investigate whether the prejudice women encounter explains why women's and men's career trajectories might diverge as a function of FABs. Our individual-level, longitudinal data set on ORCID users' career trajectories allows us to do precisely this.

Method

Identifying Field Entries and Exits: The New ORCID Data Set

We tested the role of FABs in gender segregation using a new data set created from public profiles on ORCID, which were augmented with field characteristics obtained from a survey of academics (Leslie, Cimpian, et al., 2015). Since ORCID does not collect field, career status, or gender information from its users, we had to infer these metadata. We processed ORCID data in three steps: (a) cleaning the data; (b) inferring the roles, fields, and likely

perceived gender of each ORCID user; and (c) identifying field entries and exits (see Section 1 in the Supplemental Materials).

Starting with an initial 9,600,248 unique ORCID users with 8,146,175 affiliations with particular departments, we first removed (a) users without a first and last name, which we needed to estimate likely perceived gender; (b) affiliations that did not include a department name or equivalent, which we needed to infer a user's academic field; or (c) affiliations that lacked either a position/role (e.g., "bachelor's degree," "postdoc") or an associated date, which we needed to infer the sequence of fields with which an ORCID user was affiliated—and thus which fields they entered and exited. These filtering steps resulted in 3,988,331 remaining affiliations from 1,287,228 users.

We inferred roles, fields, and cultural name–gender associations using three distinct algorithms. First, a role was assigned to each affiliation from the following list of roles: bachelor's, master's/postgraduate, PhD, postdoc, professor/department head, or unknown (see Section 1-A in the Supplemental Materials). The mapping between these roles' various aliases and names in other languages was done by recursively accumulating a list of hand-checked aliases.

Second, a field was assigned to each affiliation using a rule-based matching algorithm (see Section 1-B in the Supplemental Materials). We discarded any affiliation that had (a) no matching field, (b) two or more matching fields, or (c) one matching field that was not among the list of 30 fields surveyed by Leslie, Cimpian, et al. (2015). This conservative approach resulted in 1,768,238 affiliations among 965,603 users.⁶

Third, we inferred name–gender associations using a cultural consensus model (Batchelder & Romney, 1988; Van Buskirk et al., 2022) that computed the Bayesian posterior probability that a person's name was culturally understood to belong to a woman or a man based on data from 30 different sources, ranging from the U.S. Social Security Administration's names database to a list of the world's Olympic Athletes (see Section 1-D in the Supplemental Materials). Names that did not appear in any of the reference data sets were submitted to Genni (Torvik & Agarwal, 2016), a service that takes into account the perceived ethnicity of first and last names to improve estimates of gender from first names. Finally, names with posterior probabilities or Genni scores of ≥ 0.9 or ≤ 0.1 were labeled as being likely to be associated with a woman or a man, respectively.⁷ Names with scores between 0.1 and 0.9 were not included in our analyses (18.8% of names). We were able to make name–gender associations for 809,988 of the 965,603 users with at least one affiliation linked to an academic field in our survey data, resulting in 1,480,407 affiliations from 809,988 people.

As a reliability check, 600 ORCID profiles were chosen uniformly at random and provided to both the cultural consensus model and a panel of research assistants who coded perceived gender, via pronoun usage and photographs, based on a web search of

⁶ Each affiliation was also labeled with a geographic region, based on the classifications provided by the United Nations Statistics Division (2010; see Section 1-C in the Supplemental Materials).

⁷ We acknowledge that it is impossible to determine the gender of any individual person using this method. Rather, the application of gendered labels to ORCID identifiers represents an aggregate probability that a given name will be culturally perceived to match a binary gender. Although we use "men" and "women" as shorthand to describe this aggregate probability in our article, these labels should only be used in aggregate as they may misrepresent the gender of any given individual.

Table 1

The Measures of Field-Specific Ability Beliefs and Perceived Prejudice Against Women From Leslie, Cimpian, et al.'s (2015) Survey of Academics

Field-specific Ability Beliefs

Being a top scholar of [my field] requires a special aptitude that just can't be taught.

If you want to succeed in [my field], hard work alone just won't cut it; you need to have an innate gift or talent.

With the right amount of effort and dedication, anyone can become a top scholar in [my field]. (R)

When it comes to [my field], the most important factors for success are motivation and sustained effort; raw ability is secondary. (R)

Perceived Prejudice Against Women^a

Women face more challenges than men if they pursue careers in [my field].

[My field] as a discipline is welcoming to women. (R)

Other academics in [my field] tend to think that even though it's not politically correct to say it, men are often more suited than women to do high-level work in [my field].

Note. (R) indicates items that were reverse-scored. Responses were given on a 7-point scale (1 = strongly disagree to 7 = strongly agree). The title of each measure is bolded.

^a Participants also saw the item, "Personally, I think that even though it is not politically correct to say it, men are often more suited than women to do high-level work in [my field]," but this item was not included in the composite measure of perceived prejudice because it did not cohere with the other three.

individuals' names and their recent institutional employment. The gender ratios in this sample were indistinguishable between the model and the research assistants (37.87% and 37.95% women), with disagreement on only 1.7% of coded individuals.

We identified field entries and exits among the 1,480,407 affiliations by sorting each individual's affiliations by date whenever possible, or by role sequence when no dates were provided (see Section 1-E and Figure S1 in the Supplemental Materials). Field entries and exits were identified from these ordered affiliation trajectories. For instance, if an individual obtained a BA in sociology and a PhD in computer science (see Figure S1), this would be recorded as an entry into computer science and an exit out of sociology. If an individual switched fields multiple times, all entries and exits would be recorded.⁸ This resulted in a final data set of 112,132 field entry/exit combinations (e.g., enter computer science + exit sociology) from 86,879 individuals.

Measuring FABs

To test the role of FABs in gender segregation among academics, we needed to associate academic fields with quantitative measurements of their FABs. These data were imported from Leslie, Cimpian, et al. (2015) survey of academics. Their FAB measure consisted of four face-valid items (e.g., "Being a top scholar of [my field] requires a special aptitude that just can't be taught," "With the right amount of effort and dedication, anyone can become a top scholar in [my field]" [reverse-coded]; see Table 1). Participants rated endorsement with these items (1 = strongly disagree to 7 = strongly agree) both from their own perspective ("Personally, I think that ...") and from the perspective of other academics in their field ("Other academics in my field think that ..."). The self and other items were presented as separate blocks, and the order of the blocks was counterbalanced. Item order within these two blocks was randomized. Responses to the self items and the other items were correlated at $r = .59$, $p < .001$, so the eight items were averaged into a single composite ($\alpha = .83$). Higher scores on this composite

indicate more brilliance-oriented FABs; lower scores indicate more effort-oriented FABs.

The survey respondents were 1,820 professors, graduate students, and postdoctoral researchers in 30 disciplines, including nine social sciences (e.g., political science, psychology, sociology), nine humanities (e.g., philosophy, archeology, art history), and 12 STEM disciplines (e.g., chemistry, computer science, engineering; see Table S1 in the Supplemental Materials for a full list of fields). The respondents were recruited from nine geographically diverse, research-intensive universities (five private, four public) from the United States. Participants completed the survey anonymously online and were only asked about their own field. The responses from participants within a field were averaged, resulting in a set of 30 FAB scores (one per field).

Does this field-averaged measure reliably capture differences between fields in their FABs? The reliability of group-averaged measures (which this is an instance of) is assessed with a particular type of intra-class correlation coefficient (ICC), the ICC(2) (LeBreton & Senter, 2008; Lüdtke et al., 2009), which is a function of the variance that can be explained at the group (vs. the individual) level and the number of respondents per group; the higher these two quantities, the higher the reliability of the group-averaged measure. The ICC(2) ranges from 0 to 1, with values above .70 indicating strong reliability by conventional standards (LeBreton & Senter, 2008). The reliability of the FAB measure exceeded this threshold, $ICC(2) = .86$.

With respect to validity, academics' ratings of their fields' FABs were correlated with a different face-valid measure of the same construct—the frequency of the adjectives "genius" and "brilliant" in 14 million anonymous reviews of instructors in these fields on the website RateMyProfessors.com, $r = .62$, $p = .006$ (Storage et al., 2016). That is, the fields that academics in Leslie, Cimpian, et al.'s (2015) survey rated as having more brilliance-oriented FABs were

⁸ Transitivity was not used to create additional switches. That is, a sequence of affiliations in fields $X \rightarrow Y \rightarrow Z$ was recorded as only $X \rightarrow Y$ and $Y \rightarrow Z$, but $X \rightarrow Z$ would not be included.

also the fields in which college students used the words “brilliant” and “genius” more often to evaluate their instructors. Also pertinent to the question of validity, the FAB measure predicted the proportions of women and African Americans among PhD recipients in the United States (as reported by the U.S. National Science Foundation [NSF]; Leslie, Cimpian, et al., 2015), a result that has been replicated with other samples of respondents (Ito & McPherson, 2018; Meyer et al., 2015; Muradoglu et al., 2022) and when adjusting for nonresponse bias (Leslie, Cimpian, et al., 2015; for more information on nonresponse bias, see Berg, 2010).

Here, we used U.S. participants’ FABs to predict the career trajectories of a global sample of academics. Although integrating the U.S. FAB data with the global ORCID data considerably expanded the scope of the conclusions we were able to draw about gender segregation in academia, we recognize the limitations of using the beliefs of a U.S. sample to predict the behavior of academics from other parts of the world (e.g., Gelfand et al., 2004; Henrich et al., 2010). To guard against ethnocentric biases in the interpretation of our findings, we conducted a series of robustness checks in which we split the ORCID sample by geographical region and tested whether U.S. academics’ FABs have a different relation with academics’ career trajectories depending on their location (see the later section titled “Probing Generalizability: Geography, Career Stage, and Time.”). In light of these results, we return to and evaluate our decision to use U.S. academics’ beliefs to predict gender segregation among non-U.S. academics in the Discussion.

Measuring Perceived Prejudice Against Women

To measure the extent to which prejudice against women is perceived to be prevalent in a field, we capitalized on a measure collected by Leslie, Cimpian, et al. (2015; e.g., “Women face more challenges than men if they pursue careers in [my field],” “[My field] as a discipline is welcoming to women” [reverse-scored]; see Table 1). This measure tapped academics’ perceptions of prejudice against women in their respective fields rather than their personal prejudice, which distinguishes it from some of the instruments used to measure prejudice in social psychology (e.g., the Modern Sexism Scale; Swim et al., 1995). Instead, Leslie, Cimpian, et al.’s (2015) measurement strategy is consistent with a long tradition in industrial/organizational psychology, where it is relatively common to ask participants to report on the level of prejudice and discrimination they perceive in their organizations (for reviews, see Burkard et al., 2002; Shen & Dhanani, 2015).⁹ As was the case for the FAB items, academics answered the four items in this measure only with respect to their own field.

A parallel analysis (Horn, 1965) suggested retaining two components; the first component explained 44.8% of the variance, and the second explained 27.9%. Three of the items loaded onto the first component (all loadings >.52), and the fourth loaded by itself onto the second component (loading = .80). We dropped this item from further consideration and proceeded with the three that loaded onto the first component (see Table 1). We averaged these three items into a participant-level perceived prejudice composite (Cronbach’s α = .63), which we then averaged across members of a field to create a field-level composite. The reliability of this field-averaged measure was high, ICC(2) = .88, indicating that it strongly differentiated

between fields in the extent to which they were perceived to exhibit prejudice against women.

As reported by Leslie, Cimpian, et al. (2015), fields with more brilliance-oriented FABs scored significantly higher on perceived prejudice against women, $r = .42$, $p = .021$. This result is consistent with the possibility that prejudice against women is a candidate mechanism by which FABs contribute to gender segregation in academia. In the present work, we used the ORCID data set to evaluate this possibility by determining the extent to which FABs’ relation to gender segregation, both in terms of who enters a field (Question 3a) and in terms of who exits (Question 3b), is explained by the perception that women face more prejudice in fields with brilliance-oriented FABs.

Analytic Strategy

We performed two separate sets of analyses: one on field entries (Questions 1a–3a) and one on field exits (Questions 1b–3b). After these main analyses, explained below, we report several supplementary analyses intended to explore the robustness and generalizability of our findings, as well as address potential concerns about the ORCID data (specifically, potential sampling biases).

In the first set of main analyses, which focused on field entries, we analyzed all instances in the ORCID data in which an academic entered one field in the focal set of 30 from another field in this set. Specifically, we modeled field-entry behavior as a choice among the 29 fields in our sample (excluding the field being departed): Given that an academic is departing a certain field, which of the other 29 fields in our sample will they enter, and how does their probability of entering a field depend on their gender and the field’s FABs?

In the second set of main analyses, which focused on field exits, we compared all instances in the ORCID data in which two consecutive affiliations of an academic (e.g., bachelor’s → PhD) were in different fields (e.g., sociology → computer science) with instances in which two consecutive affiliations were in the same field (e.g., sociology → sociology): Does a field’s FABs predict whether an ORCID user exits that field, and do they do so differentially for women and men? Note that the logic of this analysis involves comparing academics who exit a field with those who stay in that field across consecutive affiliations. The latter group was not included in the first set of analyses, which was premised on an academic leaving a field and entering another one. Thus, the analyses of field exits relied on a larger segment of ORCID users ($N = 364,355$) relative to the analyses of field entries ($N = 86,879$).

All analyses were performed in Stata 16.1 (StataCorp, 2019a) or R Version 4.0.3 (R Core Team, 2020), including the packages ggplot2 (Wickham, 2016), tidyverse (Wickham et al., 2019), and data.table (Dowle & Srinivasan, 2022). In all models, standard errors were robust to heteroskedasticity and took into account the clustering in the data, which occurred because some ORCID users made multiple field entries or exits. The FAB and prejudice

⁹ For instance, James et al.’s (1994) Workplace Prejudice/Discrimination Inventory includes items such as “At work minority employees receive fewer opportunities.” Similarly, Hegarty and Dalton’s (1995) Organizational Diversity Inventory includes items such as “Many people in my organization are biased against people who are gay.” To take another example, Larkey’s (1996) Workforce Diversity Questionnaire includes items such as “You can just feel a difference in the way some people are treated or talked to because they are different.”

predictors were mean-centered and scaled by dividing by two standard deviations (SDs). With this scaling, a regression coefficient can be interpreted as indicating the change in the dependent variable that accompanies a change from -1 SD to $+1$ SD in the predictor (Gelman, 2008).

Results

FABs and Field Entries

Our first set of main analyses focused on the relation between FABs and gender segregation in field entries (i.e., among the academics who are being recruited into a field). We report the results of two statistical models that differed in only one respect: whether they included the variable tracking perceived prejudice against women as a predictor. The first, simpler model did not include this variable. We will use this model to answer Question 1a (Entry: Segregation) and Question 2a (Entry: Women vs. Men). The second model included the perceived prejudice variable. We will use this model to answer Question 3a (Entry: Prejudice).

Answering Question 1a (Entry: Segregation) and Question 2a (Entry: Women vs. Men)

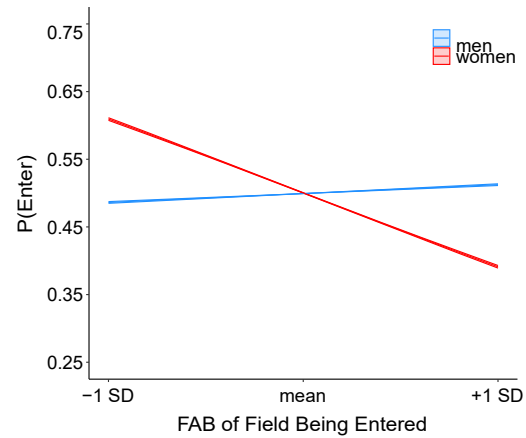
We performed a conditional logistic regression (e.g., StataCorp, 2019b; Wooldridge, 2010) in which we modeled the probability that an academic entered one of the 29 possible destination fields in our data set (excluding their current field at the time) on the basis of their gender (0 = man, 1 = woman), the FAB variable, and the two-way interaction between gender and FAB. The model also included a categorical variable indicating whether a field was in STEM or not (see Table S1 in the Supplemental Materials; 0 = non-STEM, 1 = STEM), which was mean-centered and interacted with ORCID user gender. Given that STEM fields generally have more brilliance-oriented FABs than fields outside of STEM (Leslie, Cimpian, et al., 2015), adding this indicator variable—as was done in previous work (e.g., Leslie, Cimpian, et al., 2015; Meyer et al., 2015; Storage et al., 2016)—ensured that the results we observed for FABs were not confounded by the STEM versus non-STEM distinction. Conversely, this model revealed whether FABs explain the gender differences in entering STEM versus non-STEM fields or, instead, whether the STEM/non-STEM distinction explains unique variance in academics' field-entry behavior, even after adjusting for FABs.

The answer to Question 1a (Entry: Segregation) hinges on the interaction between gender and FAB in this model. If we find that the Gender $\times$ FAB interaction is significant (i.e., that the association between FABs and field entry differs significantly for women vs. men), that would suggest that FABs act as a gender-segregating force when academics are entering a field (i.e., at the recruitment stage). In contrast, if the Gender $\times$ FAB interaction is not significant, then FABs are not contributing to gender segregation at field entry. The answer to Question 2a (Entry: Women vs. Men), which concerns whether FABs provide a better explanation for women's or men's patterns of field entry, can be found by inspecting (the absolute values of) the simple slopes of FABs within each gender—specifically, whether the FAB variable is a substantially stronger predictor of field entry for one gender than for the other.

The two-way Gender $\times$ FAB interaction was significant, $b = -0.99$, $SE = 0.02$, $p < .001$ (see Figure 2). Men were more likely to

Figure 2

The Predicted Probability That an Academic Enters a Field as a Function of Its FABs, Separately for Women (Red) Versus Men (Blue)



Note. Following a conditional logistic regression, predicted probabilities can only be calculated if a fixed effect (i.e., intercept) of 0 is assumed (StataCorp, 2019b), which leads to unrealistically high values of the predicted probabilities. In interpreting this figure, readers should discount the absolute values of the predicted probabilities and base their interpretation instead on the relative differences between the predicted probabilities at various levels of FABs. The error bands represent standard errors but are not easily visible because the size of the data set allows precise estimation. FAB = field-specific ability beliefs. See the online article for the color version of this figure.

enter a field as FABs increased, $b = 0.11$, $SE = 0.01$, $p < .001$. In contrast, women's probability of entering a field decreased as a function of FABs, $b = -0.89$, $SE = 0.02$, $p < .001$. More concretely, the change from 1 SD below the mean in FABs to 1 SD above the mean was accompanied by a .03 increase in the probability of entering a field for men and a .22 decrease in this probability for women.

These findings suggest straightforward answers to Questions 1a (Entry: Segregation) and 2a (Entry: Women vs. Men): First, FABs are in fact acting as a gender-segregating force at the field-entry stage. Second, FABs seem to explain women's field-entry behavior better than men's: While men's probability of entering a field remained fairly constant across the FAB spectrum (with only a modest increase), women were substantially more likely than men to enter fields with effort-oriented FABs and substantially less likely than men to enter fields with brilliance-oriented FABs (see Figure 2).

This model also revealed a significant interaction between gender and STEM, $b = -0.83$, $SE = 0.01$, $p < .001$. Both men and women were more likely to enter STEM (vs. non-STEM) fields, consistent with the reality that STEM fields are much bigger (e.g., Dasler et al., 2017), but the STEM versus non-STEM difference was significantly larger for men, $b = 1.01$, $SE = 0.01$, $p < .001$, than for women, $b = 0.18$, $SE = 0.01$, $p < .001$. Men's probability of entering a STEM field was .25 greater than their probability of entering a non-STEM field; for women, this difference was only .04. Given that this difference was observed even after adjusting for FABs, it suggests that the more brilliance-oriented FABs that are observed in STEM fields are not the only reason why men are more likely than women to enter these fields. We return to this point in the Discussion.

Answering Question 3a (Entry: Prejudice)

Is the fact that women (vs. men) enter fields with effort-oriented FABs more than fields with brilliance-oriented FABs explained by the different levels of prejudice women might expect to encounter in these fields? To answer this question (i.e., Question 3a), we added the variable tracking perceived prejudice against women and its interaction with ORCID users' gender as predictors of field entry in the model above. The answer to Question 3a hinges on what happens to the Gender $\times$ FAB interaction when these two terms are added to the model. If the Gender $\times$ FAB interaction term is substantially reduced in magnitude, then that would suggest that FABs' relation to gender segregation at the field-entry stage is partly explained by perceived prejudice against women.

Unsurprisingly, the two-way Gender $\times$ Perceived Prejudice interaction was significant, with women entering fields with more perceived prejudice against women less often than men, $b = -0.71$, $SE = 0.01$, $p < .001$. Crucially for Question 3a (Entry: Prejudice), the Gender $\times$ FAB interaction was substantially reduced in magnitude, $b = -0.65$, $SE = 0.02$, $p < .001$ (compare with $b = -0.99$ above). Perceived prejudice against women explained approximately 34.4% of the gender difference in the relation between FABs and field entry. However, the fact that the Gender $\times$ FAB interaction was still significant in this model suggests that there are additional factors as well (beyond prejudice) that explain why women are more likely than men to enter fields with effort-oriented FABs and less likely than men to enter fields with brilliance-oriented FABs.

It is also noteworthy that the reduction in the magnitude of the Gender $\times$ STEM interaction was minimal in this model, $b = -0.78$, $SE = 0.01$, $p < .001$ (only a 5.3% reduction, compared to 34.4% for FABs). This result suggests that perceived prejudice is a more potent explanation for why fields with brilliance-oriented FABs attract more men than women than for why STEM fields do (at least after accounting for the variance attributable to FABs).

FABs and Field Exits

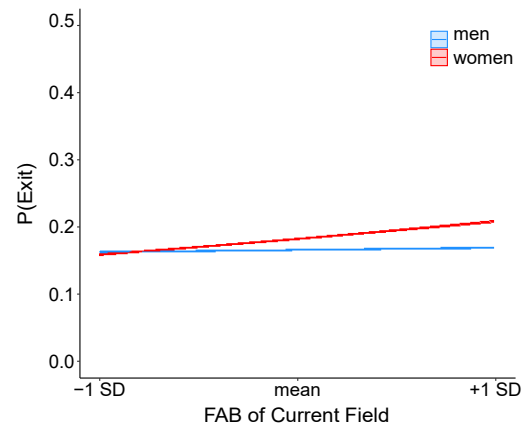
Our second set of main analyses focused on the relation between FABs and gender segregation in field exits. As before, we report the results of two statistical models that differed only in whether they included the prejudice variable. The simpler model will be used to answer Question 1b (Exit: Segregation) and Question 2b (Exit: Women vs. Men), whereas the model with prejudice as an additional predictor will be used to answer Question 3b (Exit: Prejudice).

Answering Question 1b (Exit: Segregation) and Question 2b (Exit: Women vs. Men)

We used a logistic regression to model the probability that two consecutive affiliations of an ORCID user are in the same field (0 = stay) or in different fields (1 = exit) on the basis of the ORCID user's gender, the FAB variable, and the two-way interactions between user gender and FAB.¹⁰ The model also included a mean-centered STEM versus non-STEM indicator variable and its interaction with ORCID users' gender. As previously mentioned, this analysis relied on a larger segment of ORCID users ($N = 364,355$) relative to the previous analysis ($N = 86,879$) because an investigation of field-exit patterns requires that we compare the academics who exit a field and those who stay in that field. In

Figure 3

The Predicted Probability That an Academic Exits a Field as a Function of Its FABs, Separately for Women (Red) Versus Men (Blue)



Note. The error bands represent standard errors but are not easily visible because the size of the data set allows precise estimation. FAB = field-specific ability beliefs. See the online article for the color version of this figure.

contrast, investigating field-entry patterns necessitated that we focus exclusively on the subset of academics who are looking for a new field.

The logic of the mapping between Questions 1b (Exit: Segregation) and 2b (Exit: Women vs. Men) and the results of this model was the same as before: Determining whether the Gender $\times$ FAB interaction is significant will answer Question 1b: namely, do FABs segregate field exits? Comparing (the absolute values of) the simple slopes of FABs within each gender will answer Question 2b: namely, are FABs a stronger predictor of women's field exits or men's field exits?

The two-way Gender $\times$ FAB interaction was significant, $b = 0.30$, $SE = 0.02$, $p < .001$ (see Figure 3). Both women, $b = 0.35$, $SE = 0.01$, $p < .001$, and men, $b = 0.05$, $SE = 0.01$, $p < .001$, were more likely to exit fields with more brilliance-oriented FABs, but this relationship was significantly stronger among women. To illustrate the magnitude of these differences, the probability of a woman exiting a field that was 1 SD above the mean value of FAB was .05 higher than her probability of exiting a field that was 1 SD below the mean. In contrast, men's probability of exiting was only .007 higher in fields at 1 SD above versus below the mean—less than one sixth of the corresponding increase for women.

These findings suggest clear answers to Questions 1b (Exit: Segregation) and 2b (Exit: Women vs. Men): First, and similar to the results for field entries, FABs are acting as a gender-segregating force at the field-exit stage. Second, and also similar to the results for field entries, FABs seem to explain women's field exits better than men's: While men's probability of exiting a field changed very little

¹⁰ This operationalization of field exits focuses on whether an academic exits a particular field of academia for another. Since ORCID is an author-tracking service, and since nonacademic careers place less emphasis on publications, the ORCID data set is not well suited to capturing whether an academic exits academia altogether.

as a function of FABs, women were substantially more likely than men to exit fields with brilliance-oriented FABs (see Figure 3).

In this model, the interaction between gender and STEM was not significant, $b = 0.01$, $SE = 0.02$, $p = .49$. Notably, this interaction was significant without the FAB variable in the model, $b = 0.19$, $SE = 0.02$, $p < .001$, and was driven by the expected pattern of men being significantly less likely to exit STEM (vs. non-STEM) fields relative to women. The fact that the Gender $\times$ STEM interaction became nonsignificant when FABs were added to the model suggests that the differences between the gendered field-exit patterns of STEM and non-STEM fields were explained by FABs.

Answering Question 3b (Exit: Prejudice)

We can again ask whether women's higher probability of exiting fields with brilliance-oriented FABs is explained by the prejudice women encounter in these fields. To answer this question, we added the variable tracking perceived prejudice against women and its interaction with ORCID users' gender to the model just described.

Unsurprisingly, the two-way Gender $\times$ Perceived Prejudice interaction was significant, with women exiting fields with more perceived prejudice against women more often than men, $b = 0.23$, $SE = 0.02$, $p < .001$. Crucially for Question 3b (Exit: Prejudice), the Gender $\times$ FAB interaction was substantially reduced in magnitude, $b = 0.16$, $SE = 0.02$, $p < .001$ (compare with $b = 0.30$ above). Perceived prejudice explained approximately 40.1% of the gender difference in the relation between FABs and field exits. Comparing this percentage to that observed for field entry (34.4%) suggests that prejudice plays a similarly central role in explaining why FABs segregate entry into and exit out of a field.

Robustness Checks

Our findings so far provide, for the first time, insight into the career dynamics that underlie the patterns of gender segregation observed as a function of FABs. In the present section, we describe four additional sets of analyses intended to probe the robustness and generalizability of these findings.

Taking Into Account the FABs of the Source and Destination Fields Simultaneously

Our previous analyses showed that FABs predict gender differences in the fields that academics enter and, separately, in the fields that academics exit. The present robustness check explores whether FABs also predict gender differences in career trajectories when simultaneously taking into account the FABs of the fields being exited (the "source fields") and the fields being entered (the "destination fields"). This added precision in assessing how FABs relate to gender differences in career trajectories comes at a cost, however: Because the unit of analysis is now a field transition (rather than an instance of entering a field or exiting a field), this analysis can no longer disentangle the role of FABs at the field-entry versus field-exit stages.

Figure 4 depicts the field transitions observed among the academics in our data set, with fields sorted according to FABs. We see that most upstream (low $\rightarrow$ high FAB) arcs are blue in color and most downstream (high $\rightarrow$ low FAB) arcs are red in color. This indicates

that men are more likely than women to move up the FAB gradient (i.e., toward fields with more brilliance-oriented FABs) and, conversely, that women are more likely than men to move down this gradient.

For a formal test, we used a logistic regression model in which we predicted the gender of an individual moving between two fields (0 = man, 1 = woman) on the basis of a gradient for FABs. This gradient was calculated as the difference between the FAB score for the destination field and the FAB score for the source field.¹¹ Consistent with our other results so far, women were significantly more likely than men to move down the FAB gradient, toward fields that placed less emphasis on brilliance, $b = -0.46$, $SE = 0.02$, $p < .001$. The probability that an academic transitioning between fields was a woman was .10 lower for transitions that were 1 SD above the mean FAB gradient (i.e., more upstream) relative to transitions that were 1 SD below the mean (i.e., more downstream).

Assessing Competing Explanations

Do FABs explain unique variance in women's and men's career trajectories, above and beyond other field characteristics that could also contribute to gender segregation in academia? In particular, following Leslie, Cimpian, et al. (2015) and using the data that they collected, we compared the FAB account with three alternative accounts: that women are underrepresented relative to men in academic fields (a) that are particularly demanding in terms of workload (e.g., Ferriman et al., 2009; Hakim, 2006; McCabe et al., 2019; Rhoads, 2004), (b) that rely on "systemizing" relative to "empathizing" (e.g., Billington et al., 2007; Greenberg et al., 2018), and (c) that are particularly selective (e.g., Ceci & Williams, 2011; Stewart-Williams & Halsey, 2021; Summers, 2005). In Section 2 of the Supplemental Materials, we provide additional theoretical background for these alternative accounts and detail how they were operationalized and measured.

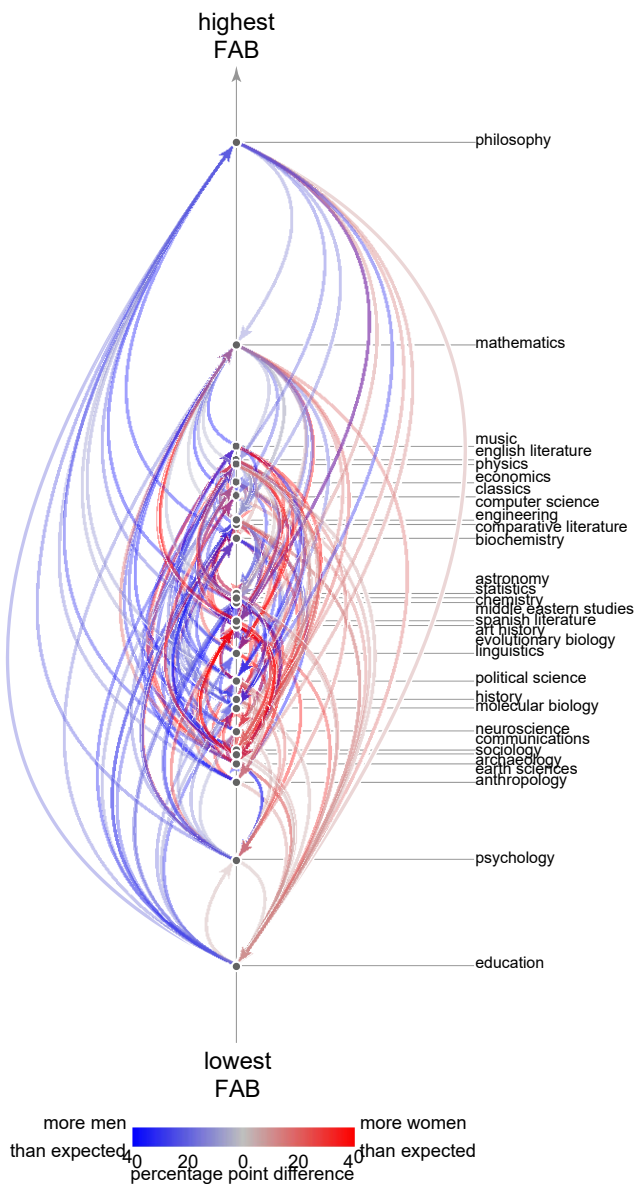
Variables pertaining to these three alternative accounts, along with their interactions with academics' gender, were added to the models on field entries and exits, as described in the corresponding earlier sections. We found that the key results involving FABs (specifically, the Gender $\times$ FAB interactions) were robust to the addition of the variables pertaining to competing accounts (see Table S5 in the Supplemental Materials): As before, we found that women were less likely than men to enter fields with brilliance-oriented FABs, $b = -0.96$, $SE = 0.02$, $p < .001$, and were also more likely than men to exit fields with brilliance-oriented FABs, $b = 0.58$, $SE = 0.02$, $p < .001$.

Probing Generalizability: Geography, Career Stage, and Time

In the third set of robustness checks, we explored whether FABs predict gender differences in the fields that academics enter and exit

¹¹ The model also included a STEM gradient (ranging from -1 = transition from a STEM to a non-STEM field to 1 = transition from a non-STEM to a STEM field), which was mean-centered, and indicator variables for all but one of the 30 source fields. Including these indicator variables adjusts for differences in the gender composition of the source fields and thus for differences among them in the probability that the individuals who switch are women.

Figure 4
Transitions Between Fields as a Function of FABs



Note. The more red versus blue an arc, the greater the proportion of women versus men, respectively, transitioning between the two fields relative to expectations. Fields are displayed vertically in descending order of FABs, with more brilliance-oriented FABs at the top. Transitions up and down the gradient are displayed on the left and right of the vertical axis, respectively. For simplicity, we only display the arcs for which the gender of the transitioning individuals differed significantly from what would be expected given the gender composition of the source field, according to a z-test for differences in proportions. FAB = field-specific ability beliefs. See the online article for the color version of this figure.

when analyzing separately key subsets of the data: (a) field transitions involving institutions from Northern America (U.S. and Canada), Latin America and the Caribbean, Europe, and Asia, (b) field transitions from bachelor's or master's programs to PhD programs and from PhD programs to postdoctoral positions or

professorships, and (c) field transitions that occurred before (and including) the year 2000 and after 2000. We chose 2000 as a split point in this last robustness check because it is a salient marker (i.e., the transition to a new century and millennium); because it is far enough in the past that we can reasonably expect before versus after differences; and because it splits the data into two segments that are roughly (but not perfectly) matched in size. Importantly, however, using other years as split points (e.g., the median year for a transition in the ORCID data set) led to similar results.

The results are illustrated in Figure 5, using odds ratios rather than log-odds coefficients for ease of interpretation. (Odds ratios can be obtained by exponentiating the log-odds coefficients from logistic regression models.) The top row of this figure presents the FAB odds ratios from the field-entry and field-exit models on the full data set, split by gender.¹² The FAB odds ratios as a function of geography are presented in rows 2–5, as a function of career stage in rows 6 and 7, and as a function of time in rows 8 and 9. The extent to which the Key Gender $\times$ FAB interaction generalizes can be assessed by comparing the FAB odds ratios for women and men across the levels of each potential moderator (e.g., geography). Figure 5 reveals that the Gender $\times$ FAB interaction is observed across geography,¹³ career stage, and time. While the magnitude of the gender differences did fluctuate somewhat across subsets, men were significantly more likely than women to enter fields with more brilliance-oriented FABs and women were significantly more likely than men to exit these fields across all subsets of the data examined.

Investigating Potential Sampling Bias in the ORCID Data: Four Numerical Experiments With Synthetic Data

ORCID users are not a uniform random sample of world academics. As a result, ORCID usership could be biased in ways that make it difficult to generalize from this sample to the population of interest (i.e., world academics). Considering that our research questions concern gender differences in academics' movements across fields, the sampling biases that would be most problematic for our purposes here pertain to potential over- or underrepresentation of scholars (a) of a certain gender and/or (b) from certain fields relative to their share of world academics.

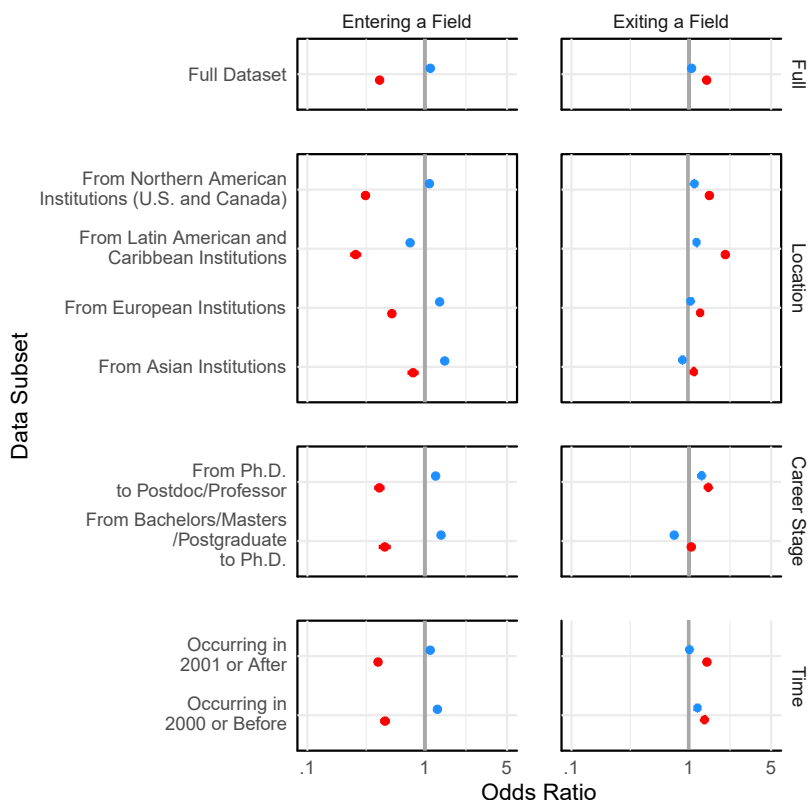
To investigate sampling biases with respect to gender, we calculated field-level gender ratios among ORCID users in our data and compared them with analogous gender ratios reported by authoritative sources—in particular, the U.S. National Science Foundation (2017). We found that field-level gender ratios among American PhD recipients, as reported by the NSF, were highly correlated ($r = .86$) with the gender ratios observed among the subset of ORCID users who approximate the characteristics of NSF's sample (i.e., users with recent affiliations with U.S. universities). This result speaks against the presence of pervasive sampling bias with respect to gender.

Concerns about over- or undersampling of certain fields are assuaged by a recent study on ORCID adoption (Dasler et al., 2017) that was funded by the European Commission as part of an effort to systematically integrate ORCID iDs into article and data

¹² Essentially, this is the same information as in Figures 2 and 3.

¹³ The global scope of this association is perhaps surprising, given that FABs were measured from a U.S. academic cohort. We return to this point in the Discussion.

Figure 5
Women's and Men's FAB Odds Ratios in the Full Data Set (Top Row) and Across
Different Subsets of the Data



Note. The odds ratios for women are depicted in red, and the odds ratios for men are depicted in blue. Error bars represent 95% CIs but are not easily visible because the size of the data set allows precise estimation. The x axis is on a logarithmic scale. The differences between women's and men's odds ratios (i.e., the Gender $\times$ FAB interactions) are statistically significant in all subsets of the data. FAB = field-specific ability beliefs; CI = confidence interval. See the online article for the color version of this figure.

submission services. Dasler et al. (2017) compared the composition of the ORCID usership against a reference data set of authors compiled from the Web of Science database, which arguably provides the closest approximation possible to the population of interest (i.e., world academics). Dasler and colleagues concluded that the distribution of disciplines in ORCID data set is "broadly similar" to that in the Web of Science data set (p. 28). For example, scholars from the natural sciences made up 38% of all authors with ORCID iDs and 39% of all authors represented in the Web of Science. Looking at the broad distinction between STEM and non-STEM fields, over 90% of the authors on ORCID were from STEM fields (specifically, the natural, health, and applied sciences) and less than 10% were from the humanities and social sciences, percentages that roughly match those observed on Web of Science and thus reflect actual size differences between these domains of scholarly activity.

The evidence above suggests that the ORCID sample is likely to provide a representative snapshot of world academics. However, since this evidence is far from definitive, we went on to investigate more systematically how sampling biases, if present, would in turn bias our estimation of gender differences in career trajectories as a

function of FABs.¹⁴ For purposes of this investigation, we conducted a series of numerical experiments with synthetic data that simulated possible, unforeseen sampling biases in the ORCID data. These simulations are described in detail in Section 3 of the Supplemental Materials. Here, we provide a brief summary.

As a first step, we generated a synthetic data set of career trajectories that was meant to represent the population of world academics. These trajectories incorporated a certain relationship between FABs and women's (vs. men's) transitions across fields. Next, we drew biased samples from this complete data set, one sample per numerical experiment. This sampling process was meant to simulate the way in which the sample of ORCID users might also be biased relative to the entire population of world academics. The size of the synthetic samples across our numerical

¹⁴ In this section, we used the modeling strategy that simultaneously takes into account the FABs of the fields that academics exit and enter, which provides the most precise way of assessing how FABs relate to gender differences in career trajectories. This strategy is also simpler, requiring a single model rather than separate models for field entries and exits.

experiments was fixed to be exactly the size of our ORCID sample of field transitions. In the last step, we tested whether the bias in these sampling procedures detracted from our ability to produce unbiased estimates of the “true” relationships that we had built into the complete synthetic data set (i.e., the population). We increased the severity of the sampling bias across experiments to map out the extent of bias that can be tolerated in the ORCID sample before our estimation strategy is no longer effective.

The first numerical experiment simulated a close-to-ideal situation in which our sample is simply a random subset of the broader population, equal in size to the ORCID data set of field transitions. The second numerical experiment added more bias to the sampled data, simulating a situation in which ORCID adoption rates vary across fields. In the synthetic data for this experiment, the size of the samples of transitions between any two fields was heterogeneous, with counts varying between 0× and 2× the average. Thus, the overall number of transitions in the synthetic data set for this experiment was the same as in the previous experiment, but the transitions were distributed heterogeneously between fields. Much like the previous experiment, the third numerical experiment simulated a situation in which ORCID users are a variable and noisy sample of the broader population (i.e., transitions were again sampled at rates between 0× and 2× the average), but with an additional constraint: This experiment also assumed that there is gender bias in ORCID adoption, such that one gender is more likely to have ORCID profiles than the other, with said gender bias varying randomly across fields. Finally, the fourth numerical experiment was identical to the previous one, but with an extra layer of sampling bias intended to reflect systematically higher ORCID usage among some academic fields than others. In this case, we simulated lower rates of ORCID adoption among academics who are currently in, or have ever been in, STEM fields. This bias was inspired by Dasler et al.’s (2017) findings that ORCID iDs are slightly undersampling STEM fields and oversampling the social sciences and humanities. In this final experiment, sampling rates for STEM fields were chosen uniformly between 0× and 0.5× the average; for other fields, sampling rates were between 1.5× and 2× the average. (Note, however, that the same conclusion would hold if transitions between STEM fields were over- rather than undersampled instead.)

Across all numerical experiments, and for a variety of choices of assumed “true” relationships between FABs and gender segregation, we found that the estimated relationships were a close match to the relationships built into the complete data set, prior to the addition of bias (see Figure S2 in the Supplemental Materials). In other words, a range of gender- and field-related sampling biases did not interfere with the ability of our analyses to accurately estimate the relationships built into the population data. Thus, these numerical experiments suggest that the data and our statistical approach provide valid evidence on gender differences in academics’ movements across fields.

Discussion

Gender segregation in academia is a persistent global phenomenon. Analyzing the single largest data set of academic profiles, we investigated differences in the migration of women and men across a range of fields in STEM, the social sciences, and the humanities to advance theory on gender segregation in academia. Our investigation was guided by a recently proposed account of this phenomenon, at the heart of which is the idea that differences

in FABs (i.e., the extent to which fields view intellectual talent as necessary for success) are an important engine of gender segregation in academia. Because common stereotypes associate brilliance and genius with men more than women (Bian et al., 2017; Musto, 2019; Rivera & Tilcsik, 2019; Storage et al., 2020), a belief that on the surface seems unbiased—namely, the belief that success in a given field requires brilliance—is likely to have a differential impact on women’s and men’s career trajectories, giving rise to segregation.

The present research answered three important questions about the role of FABs in gender segregation, greatly expanding the evidence bearing on this account. Questions 1a (Entry: Segregation) and 1b (Exit: Segregation) concerned whether FABs act as a gender-segregating force among the academics who enter a field and among the academics who exit a field, respectively. Our results suggested that the answer to both questions is “yes.” Women were underrepresented among those who enter fields with brilliance-oriented FABs and overrepresented among those who exit these fields. Prior work had not been able to conclusively establish whether FABs relate to gender segregation at both of these points in academics’ careers, so the present findings contribute an important element to theory on this topic. We also note that this was not a foregone conclusion: It is often the case that the characteristics of a field that lead different numbers of women and men to enter it are not the same as the characteristics that lead to differential attrition for women and men (e.g., Cheryan et al., 2017; Xie & Shauman, 2003). In this case, however, it seems that FABs are influential at both earlier and later points in academics’ relationships with their fields.

Questions 2a (Entry: Women vs. Men) and 2b (Exit: Women vs. Men) asked whether FABs provide a better explanation for women’s or for men’s trajectories in academia—another issue that prior research on the FAB account left open. We found that FABs’ relation to men’s movements across academic fields was substantially weaker than their relation to women’s movements. The fact that men are not targeted by negative stereotypes about their intellectual abilities (e.g., Storage et al., 2020) may make them less attuned to FABs, which may in turn diminish the role of these beliefs in shaping men’s career trajectories. This granular insight into the dynamics of gender segregation highlights the value of an investigation such as ours, in which scholars are observed longitudinally across transitions between fields that span the academic spectrum and whose various characteristics we can quantify. Nevertheless, hints of an asymmetry in the relation of FABs with women’s versus men’s outcomes can be found in prior work as well. For instance, whereas women report less interest in novel professional opportunities when these opportunities are described as requiring brilliance (vs. various control attributes), men’s interest is much more weakly affected by these messages (in the opposite direction; Bian et al., 2018b). Similarly, women’s feelings of being an impostor increase more steeply as a function of their fields’ FABs than men’s do (Muradoglu et al., 2022), a pattern that mirrors the present finding that women’s probability of exiting a field increases more steeply than men’s as a function of FABs.

Questions 3a (Entry: Prejudice) and 3b (Exit: Prejudice) contributed to theory on the psychological mechanisms underlying the role of FABs in gender segregation. Our results indicated that prejudice against women explains a substantial portion of FABs’ relation to gender segregation at both field entry and exit—between 30% and 40%. In other words, fields with more brilliance-oriented FABs both

attract and retain fewer women in part because their members (are perceived to) exhibit prejudice against women. Practically, the present findings suggest that intervention efforts intended to desegregate academia might fruitfully be targeted at the prejudiced attitudes of members of fields with brilliance-oriented FABs, as well as at the more fundamental beliefs that give rise to these negative attitudes: The belief that intellectual talent is required for success, and the stereotype that women have less intellectual potential than men.

Although substantial, the portion of FABs' association with gender segregation that was explained by prejudice against women was far from 100%, suggesting that other mechanisms are at play as well. For instance, it is possible that brilliance-oriented FABs communicate a lack of fit to young women much earlier in life, diverting them from the path to these fields considerably before concerns about encountering prejudice would even be relevant. In fact, the roots of women's underrepresentation among those who aspire to careers in fields with brilliance-oriented FABs may stretch all the way back to childhood: When unfamiliar activities are described as being for children who "are really, really smart," 6- and 7-year-old girls show less interest in them relative to boys of the same age; in contrast, when the same activities are described as being for children who "try really, really hard," no gender differences are observed (Bian et al., 2017). Among young adults as well, messages about the importance of brilliance to success undermine women's interest in various professional opportunities by signaling a lack of fit with others in those professional contexts (Bian et al., 2018b).

In interpreting the results pertaining to prejudice, we have so far assumed the causal model depicted in Figure 1, in which prejudice against women is a result of brilliance-oriented FABs and a proximal cause of women's underrepresentation among those who enter and stay in fields with such FABs. However, the present data are correlational and do not allow for empirical claims about the causal ordering of these variables. For instance, our results are also compatible with a causal model in which prejudice causes FABs rather than the other way around: Perhaps more brilliance-oriented FABs arise in fields that already exhibit stronger prejudice against women, as a way of rationalizing these negative attitudes (e.g., Haidt, 2001; Sidanius & Pratto, 1999). Additional research is needed to adjudicate between these possibilities.

Confidence in our answers to Questions 1–3 was boosted by several robustness checks. For instance, FABs explained unique variance in the career dynamics underlying gender segregation, beyond other field-level characteristics that have been proposed to contribute to this phenomenon. This is an informative result because fields that differ in their FABs might differ in other respects as well, such as their workload, selectivity, or the extent to which they focus on people versus things. The fact that FABs remained significant predictors of gender segregation after adjusting for other segregation-relevant field characteristics, which were themselves assessed with reliable and valid instruments (see Section 2 of the Supplemental Materials), bolsters the conclusion that FABs provide a distinct explanation for gender segregation, not reducible to other previously proposed factors.

We also conducted a thorough generalizability check to determine whether FABs explained the career dynamics underlying gender segregation in different regions of the world, at different career stages, and at different points in time. It was important to perform this check because, among other reasons, there are systematic differences

in the gender composition of academic fields across countries (e.g., Breda et al., 2018, 2020; Charles & Bradley, 2009; Charles & Grusky, 2005; D. I. Miller et al., 2015), as well as historical trends in the extent to which women and men differ in the skills needed for various academic careers (e.g., Hyde & Mertz, 2009; Xie & Shauman, 2003) and are subject to stereotypes relevant to these careers (e.g., Charlesworth & Banaji, 2019; Eagly et al., 2020). The gender differences in the relations between FABs and academics' career trajectories (at both field entry and exit) were observed across these different dimensions (see Figure 5), speaking again to the robustness of FABs as an explanation for gender segregation. Few other accounts of gender segregation have been tested with respect to their generalizability across all three of these key dimensions (geography, career stage, and historical time), which highlights the value and rigor of the current investigation.

Returning to the topic of possible confounds, it is noteworthy that all of our models included a variable tracking whether a field was in STEM or not. Adjusting for this variable meant that our conclusions about the role of FABs as a gender-segregating force were not confounded by the STEM/non-STEM distinction. In other words, fields with more brilliance-oriented FABs did not attract and retain fewer women than men simply because they were in STEM.

The simultaneous inclusion of the FAB and STEM variables in models predicting academics' career trajectories also allowed us to make inferences in the opposite direction—about whether the differences between STEM and non-STEM fields in their gender composition are explainable by differences in their FABs. The evidence on this point was mixed. FABs did in fact explain why men were less likely to exit STEM (vs. non-STEM) fields relative to women. However, this was not the case when we analyzed field entries. Women were still significantly less likely to enter STEM (vs. non-STEM) fields than men even after accounting for FABs. Together, this evidence suggests that FABs provide a partial, but not complete, explanation for the longstanding gender gaps in STEM fields. This conclusion is consistent with previous data on this question. For example, Leslie, Cimpian, et al. (2015) similarly found that FABs do not explain the difference in the gender composition of PhDs from STEM versus non-STEM fields (see Model 2 in Leslie, Cimpian, et al., 2015; Table 1). In light of the present evidence, it seems likely that the unique variance accounted for by the STEM/non-STEM distinction comes primarily from the field-entry stage—that is, the fact that STEM fields attract more men than women. While many factors probably feed into this recruitment-side imbalance, a promising explanation for it comes from recent research on a nationally representative sample of U.S. high school students, which found that STEM careers were a "default" for many young men, who aspired to and pursued these careers regardless of their achievement in STEM courses or their attitudes toward these fields (J. R. Cimpian et al., 2020).

More broadly, the present research serves as a useful reminder that social biases can "go underground" and become more subtle but nevertheless retain the power to shape people's lives. Blatant stereotypes about women's competence have waned over time (Eagly et al., 2020; see also Charlesworth & Banaji, 2022). Yet, more subtle gender stereotypes about brilliance and genius are alive and well (e.g., Boutyline et al., 2023; Storage et al., 2020; Zhao et al., 2022). Combined with seemingly gender-neutral field-specific beliefs about the necessary ingredients for success, these stereotypes

remain a powerful force in segregating academia well into the 21st century.

Finally, it is noteworthy that our approach here provides an update to the common metaphor of a “leaky pipeline.” Most pipeline analyses compare the proportions of women and men at consecutive stages in the professional trajectory of a field’s members (e.g., bachelor’s degrees vs. PhD degrees; Ceci et al., 2014; Miller & Wai, 2015). In these analyses, a field’s pipeline is said to be leaking women (or men) if the proportion of women (or men) in the field declines from one career stage to the next. Although useful, this approach is intrinsically limited by the fact that it cannot provide insight into why gaps emerge when they do. In contrast, our approach engages with the dynamic complexities of the “branching pipeline” of women’s and men’s career trajectories (Fuhrmann et al., 2011), pushing toward a deeper understanding of gender segregation in academia.

Limitations and Directions for Future Research

An important limitation of this work is that FABs measured at a single time point (namely, around 2015; Leslie, Cimpian, et al., 2015) were used to predict field entries and exits that occurred (sometimes considerably) earlier or later. Notably, there was no substantial drop in FABs’ predictive validity for transitions that occurred 15 years or more earlier (compare the bottom two rows of Figure 5). Nevertheless, the characteristics of a field may change over time (Cheryan et al., 2017), so research that measures FABs at multiple time points and relates them dynamically to the observed levels of gender segregation across fields would be valuable. A related limitation of the data is that FABs were measured from a sample of U.S. academics (Leslie, Cimpian, et al., 2015) rather than from a global sample. If FABs varied across countries or regions, we would not be able to take these variations into account when analyzing the patterns underlying gender segregation. Future surveys of academics with a broader geographical scope could, when combined with ORCID profiles, provide a more precise test of the FAB account.

In light of this limitation, it is striking that U.S. academics’ FABs emerged as a reliable predictor of career trajectories not just for academics from the United States and Canada but also for academics from other parts of the world (see Figure 5). What explains this pattern of results? One possibility is that FABs about a field are generally shared by academics from that field, regardless of where they reside. Given that academics from different countries have regular opportunities to interact with one another at professional conferences and exchange ideas in the pages of their disciplinary journals, it seems plausible that there would be general consensus within a field about the characteristics that are believed to be required for success. Alternatively, perhaps non-Western academics who have ORCID iDs represent a more Western-facing segment of the academics in their respective countries, whose beliefs are thus more in sync with those of U.S. academics. Such a selection effect would explain why U.S. academics’ FABs were predictive of gender differences in the career trajectories of ORCID users from other parts of the world. Further research is needed to disentangle these possibilities.

ORCID is an author-tracking service, so any conclusions about gender segregation in academia based on an analysis of ORCID apply more readily to the research-oriented segment of academia

than to the teaching-oriented segment, where it is less common to publish. This is another constraint on the generality of the conclusions that can be drawn from the present data. In addition, the information available via ORCID does not indicate when an academic has switched from a full- to a part-time position or left academia altogether, processes that also contribute to gender segregation (e.g., Cech & Blair-Loy, 2019).

The present research considered the FAB account in the context of several other explanations for gender segregation in academia, but it obviously did not, and could not, consider all explanations that have been proposed on this topic. Testing additional theoretical perspectives with these data is a fruitful direction for future work. For instance, it would also be important to investigate differences between fields in their communal goal affordances (i.e., working with and helping others) as an alternative (or complementary) explanation for the observed patterns of gender segregation (e.g., Diekmann et al., 2010). Prior theory and evidence (for a summary, see Diekmann et al., 2017) suggests that women (vs. men) should be more likely to enter and less likely to exit fields that facilitate their members’ pursuit of communal goals. It is in principle possible that fields with more brilliance-oriented FABs recruit and retain fewer women because they are perceived to be less compatible with the pursuit of communal goals.

Finally, the inclusion of a STEM indicator variable in our analyses assumes that STEM disciplines are a monolithic group. However, there are important differences among this group in the extent of gender segregation and the climate that women face (e.g., Cheryan et al., 2017; J. R. Cimpian et al., 2020; National Academies of Sciences, Engineering, & Medicine, 2018). In particular, computer science, engineering, and physics remain more segregated than the rest of the STEM fields and are particularly likely to exhibit “masculine cultures” that undermine women’s psychological safety (Cheryan et al., 2017; Cheryan & Markus, 2020). In future work, it will be important to use the ORCID data set to examine the differences among STEM fields in order to understand why some have moved toward gender desegregation while others have not.

Conclusion

In the present research, we created a new, expansive data set of career trajectories and used it to examine gender segregation in academia as a dynamic phenomenon shaped by how women and men move differentially across fields. We found that the differences between fields in the extent to which they value intellectual talent were a major contributor to the observed patterns of gender segregation. The effects of these FABs were partially explained by the fact that fields that valued brilliance were also perceived to be more prejudiced toward women. This research makes a substantial contribution to scientific understanding of gender segregation in academia, and it contributes methodologically as well by making available a useful new data set and the tools to work with it.

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