Physics of Living Systems

Gendered hiring and attrition on the path to parity for academic faculty

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Abstract

Despite long-running efforts to increase gender diversity among tenured and tenure track faculty in the U.S., women remain underrepresented in most academic fields, sometimes dramatically so. Here we quantify the relative importance of faculty hiring and faculty attrition for both past and future faculty gender diversity using comprehensive data on the training and employment of 268,769 tenured and tenure-track faculty rostered at 12,112 U.S. PhD-granting departments, spanning 111 academic fields between 2011–2020. Over this time, we find that hiring had a far greater impact on women's representation among faculty than attrition in the majority (90.1%) of academic fields, even as academia loses a higher share of women faculty relative to men at every career stage. Finally, we model the impact of five specific policy interventions on women's representation, and project that eliminating attrition differences between women and men only leads to a marginal increase in women's overall representation—in most fields, successful interventions will need to make substantial and sustained changes to hiring in order to reach gender parity.

eLife assessment

Efforts to increase the representation of women in academia have focussed on efforts to recruit more women and to reduce the attrition of women. This study - which is based on analyses of data on more than 250,000 tenured and tenure-track faculty from the period 2011-2020, and the predictions of counterfactual models - shows that hiring more women has a bigger impact than reducing attrition. The study is an **important** contribution to work on gender representation in academia, and the evidence in support of the findings is **convincing**.

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Introduction

Faculty play a crucial role in educating future researchers, advancing knowledge, and shaping the direction of their fields. Diverse representation of social identities and backgrounds within the professoriate improves educational experiences for students [1, 2], accelerates innovation and problem-solving [3–5], and expands the benefits of scientific advances to a broader range of society [6, 7]. Gender equality in particular is a foundational principle for a fair and just society in which individuals of any gender identity are free to achieve their full potential. However, the composition of the professoriate has never been representative of the broader population, in part because higher education has remained unattractive or inaccessible to large segments of society [8–10].

Over the past 50 years, U.S. higher education has made substantial gains in women's representation at the under-graduate and PhD levels, but progress towards greater representation among tenure-track faculty has been much slower. Women have earned more than 50% of bachelor's degrees since 1981 [11], and now receive almost half of doctorates in the U.S. (46% in 2021) [12]. However, women comprise only 36% of all U.S. tenured and tenure-track faculty [8], and there are significant differences in women's representation across disciplines. For example, many fewer women earn PhDs in Science, Technology, Engineering, and Mathematics (STEM) fields (38%), compared to PhD recipients in non-STEM fields (59%) [12].

There are two primary ways by which women faculty representation changes: through hiring and through attrition. In our analysis of faculty demographics, faculty attrition refers to "all-cause attrition," which encompasses all the reasons that may lead someone to leave the professoriate, including retirement or being drawn to non-academic activities in the commercial sector. If the proportion of women among incoming hires is greater than the proportion of women among current faculty, then new hires will slightly increase the field's representation of women. On the other hand, if the proportion of women among faculty who leave their field is greater than the proportion of women among current faculty, then attrition will slightly decrease the field's representation of women. Because faculty often have very long careers, a trend in a field's overall gender representation is a cumulative integration, over many years, of the net differences in representation caused by a mixture of hiring and attrition.

Policies targeting gender parity can focus on changes to hiring, attrition, or both, and many have been tried. Hiring-focused policies include grants for diverse faculty recruitment [13], efforts to reduce bias in the hiring processes [14], and a range of other measures intended to increase women's representation at earlier educational and career stages. Attrition-focused policies include initiatives to reduce gender bias in the promotion and evaluation of faculty [15], efforts to diminish the gender wage gap among faculty [16], and diversity-focused grants for early and mid-career faculty research [17]. Some policies simultaneously impact hiring and attrition. For example, improvements to parental leave and childcare policies may lessen the attrition of women who become parents as faculty and also encourage more prospective women faculty to consider faculty careers.

Although both types of strategy can be important, their impact alone or together on historical trends in gender diversity remain unclear. Also, we lack a clear prediction of how gender diversity may change in the future and whether current trends, and the policies that support them, may ultimately achieve gender parity. Some studies have used empirically informed models of faculty hiring, attrition, and promotion to estimate the effectiveness of certain specific policy interventions [18–23]. However, most focus on a single institution, which tends to limit their generalizability to whole fields or to other institutions. Field-wide assessments and cross-field comparisons are necessary to provide a clear understanding of the overall patterns and their variations. Such broad comparative analyses would support evidence-based approaches to policy work and would shed new light on the causes and consequences of persistent gender inequalities among faculty.

In this study, we aim to quantify the individual and relative impacts of faculty hiring and attrition on the historical, counterfactual, and future representation of women faculty across fields and institutions. Our models and analyses are guided by a census-level dataset of faculty employment records spanning nearly all U.S.based PhD-granting institutions, including in 111 academic fields across the Humanities, Social Sciences, Natural Sciences, Engineering, Mathematics & Computing, Education, Medicine, Health, and Business. This wide coverage allows us to quantify broad patterns and trends in both hiring and attrition, across institutions and within fields and develop model-based extrapolations under a variety of possible policy interventions.

Results

We take three distinct approaches in our analysis of the relative importance of faculty hiring and faculty attrition for women's representation among tenure track faculty. First, we characterize the relative contributions of hiring and attrition to changes in women's representation across a range of academic fields over 2011–2020. Second, we model a hypothetical historical scenario over this same period in which we preserve demographic trends in hiring, but we eliminate "gendered attrition" by assigning equal attrition rates to men and women at each career stage. Here, gendered attrition refers only to the differences in the rates in which men and women at the same career stage leave academia. It does not refer to the absolute magnitude of the rates, which increases for both men and women in the late career as faculty approach an age where retirement is common. This counterfactual model provides data driven estimates of what different fields' gender diversity could have been, and hence provides a general estimate of the loss of diversity due to gendered attrition over this time. Finally, we use our hiring and attrition model to make quantitative projections of the potential impact of specific changes to faculty hiring and faculty attrition patterns on the future representation of women in academia, allowing us to assess the relative impact of practical or ambitious policy changes for achieving gender parity among faculty by field and in academia overall.

For these analyses, we use a census-level dataset of employment and education records for tenured and tenuretrack faculty in 12,112 PhD-granting departments across 392 PhD granting institutions in the United States from 2011-2020 [24]. We organize these data into annual department-level faculty rosters. In turn, each department belongs to at least one of 111 academic fields (e.g., Chemistry and Sociology) and one of 11 high-level groupings of related fields that we call domains (e.g., Natural Sciences and Social Sciences), enabling multiple levels of analysis. This dataset was obtained under a data use agreement with the Academic Analytics Research Center (AARC), and was extensively cleaned and preprocessed to support longitudinal analyses of faculty hiring and attrition [8] (see Methods for data cleaning details).

We added gender annotations to faculty using nomquamgender, an open source name-based gender classification package that is comparable in performance to the most reliable paid name-based gender classification services [25]. Gender annotations were applied to faculty names with high cultural name-gender associations (88%) [25], resulting in a dataset of n = 268, 769 unique faculty, making up 1,768,118 person-years. The methodology we use assigns only binary (woman/man) labels to faculty, even as we recognize that gender is nonbinary. This approach is a compromise due to the technical limitations of name-based gender methodologies and is not intended to reinforce a gender binary.

We define faculty hiring and faculty attrition to include all cases in which faculty join or leave a field or domain within our dataset. For example, hires include first-time tenure track faculty, and mid-career faculty who transition from an out-of-sample institution (e.g., from a non-U.S. or non PhD granting institution, or from industry). Examples of faculty attritions include faculty who leave for another job in academia to an institution outside the scope of our dataset (e.g., non-U.S. or non PhD granting), faculty who leave the tenure-track, faculty who move to another sector, and faculty who retire. Faculty who transition from one field to another are counted as an attrition from the first field and a hire into the new field. Finally, faculty who switch institutions but remain in-sample and in the same field are not counted as hires or attritions.

A. Historical impacts of hiring and attrition

Our data show a clear increase in women's representation between 2011 and 2020, increasing by an average of 4.8 percentage points (*pp*) across fields. Trends among new hires can drive increases in women faculty's representation, and in many fields women's representation among PhD graduates has been growing for many years [26]. At the same time, attrition can also drive increases in women's faculty representation if the trends run in the opposite direction, e.g., in many fields retiring faculty are more likely to be men than women (**Fig. S8**) [8]. However, attrition in the early- or mid-career stages may have the opposite effect if it is gendered, e.g., when women comprise a greater proportion of those leaving academia at these career stages [27, 28]. The balance of these inflows and outflows, relative to a field's current composition, determines whether women's overall representation will increase, decrease, or hold steady over time.

To investigate the effects of hiring and attrition on changes in women's representation between 2011 and 2020, we decomposed the total change in representation into separate hiring effects and attrition effects for each of our studied fields (**Fig. 1**, **Table S2**; see Methods). A total of 106 (95%) of 111 fields saw an increase in women's representation overall, with hiring contributing to increases in 106 of 111 fields (95%), and attrition contributing to increases in 82 of 111 fields (74%). In general, hiring was the larger cause of increases to women's representation, with greater effects in the majority (87.4%) of academic fields.

The effects of hiring do not always increase women's representation, nor do they always dominate the effects of attrition. For instance, hiring has contributed to negative changes in women's representation in 5 fields, including the majority-women fields of Nursing and Gender Studies. Our analysis also finds that 9 fields (8.1%) saw increases driven more by attrition than hiring, of which all are non-STEM fields.

The decomposition into hiring and attrition effects also shows that attrition can decrease women's representation, even if women's representation increases overall. In fact, faculty attrition decreased women's representation in 29 fields (26%) between 2011 and 2020 (**Fig. 1**, **Table S2**). These attrition-driven changes likely reflect a failure to retain early and mid-career women, as they are unlikely to be driven by retirements: among faculty, men are more likely to be at or near retirement age than women faculty due to historical demographic trends (**Fig. S8**). Indeed, of these fields, 25 (83%) of 29 are majority men, such that differential losses of women due to attrition move such fields away from parity. Nevertheless, despite net losses of women faculty to attrition, the effects of hiring were large enough to see overall increases in women's representation in 27 (93%) of 29 of these fields.

B. Quantifying the impact of gendered attrition

The fact that men are systematically more likely to be at or near retirement age than women across fields (**Fig. S8**; see also [8]) means that it is possible for all-cause attrition to cause a net-increase in women's representation (**Fig. 1**), even if women leave the academy at higher rates at every career stage. Indeed, recent work has shown that this is the case [28], a phenomenon termed *gendered attrition*. These findings together suggest that in some fields, women's representation might be higher had attrition been gender neutral over the past decade.

To estimate the potential impacts of gender-neutral attrition, we created a counterfactual model in which we fixed men's and women's attrition risks to be equal at every career age (see Methods). By initializing the model at our 2011 faculty census data, and preserving demo-graphic trends in hiring, we simulated $n = 500$ counterfactual demographic trajectories for 2011-2020 under gender-neutral attrition for each field. Here, our model bears an important resemblance to the seminal Leslie Matrix model used and adapted by demographers and ecologists (see, e.g. [29]), with a

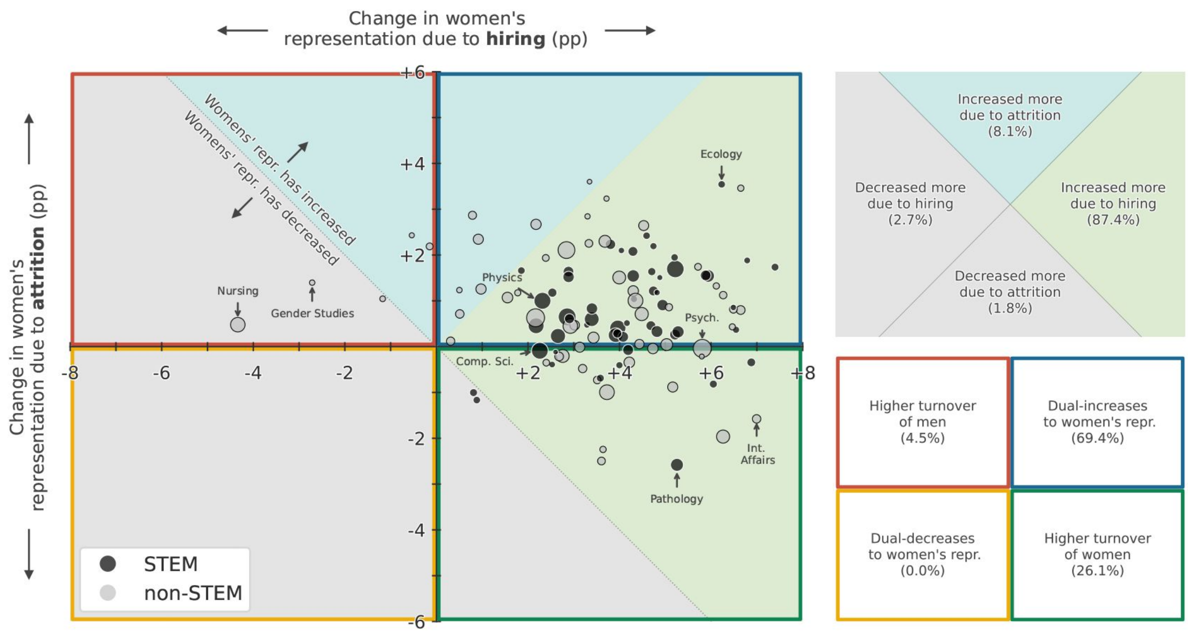

Figure 1.

Change in women's overall faculty representation for 111 academic fields between 2011–2020, decomposed into change due to hiring (horizontal axis) and change due to attrition (vertical axis, see Supplementary Sec. S1), showing that hiring increased women's representation for a large majority (87.4%) of fields, while it decreased women's representation for five fields. Point size represents the relative size of each field by number of faculty in 2020, and points are colored by STEM (black) or non-STEM (gray).

few notable differences to ensure the total faculty population size and the distribution of career ages at hiring match historical data (see Methods). From these trajectories, we quantified the effect of gendered attrition as the difference in women's representation between the real 2020 census and gender-neutral simulations, and labeled effects as significant only if 95% of simulations ended with either higher or lower representation of women. For instance, there were 1.83 *pp* fewer women in 2020 in Psychology due to a decade of significant gendered attrition (**Fig. 2A**; $p < 0.01$), whereas we find no significant gendered attrition in Ecology (**Fig. 2B**; $p = 0.24$).

A total of 16 fields exhibited significantly gendered attrition between 2011 and 2020 (circles, **Fig. 2C**). Of these, 15 fields, including Psychology, Philosophy, Chemistry, and Sociology, ended 2020 with fewer women than our gender-neutral attrition model predicted, while just one ended 2020 with fewer men (Gender Studies). Counterfactual simulations for the remaining 95 fields provided inconsistent outcomes, either towards greater or lesser representation of women faculty, for at least 5% of simulations (crosses in **Fig. 2C**, **Table S2**). In general, simulations for smaller fields tended to exhibit more variable outcomes which were consequently less often statistically significant.

To evaluate the effects of gendered attrition at a higher level of aggregation, we also estimated the impacts of gendered attrition for all STEM and all non-STEM fields, respectively. Gendered attrition was significant in both cases, decreasing women's representation by − 1.35 *pp* (STEM, $p < 0.01$) and − 1.99 *pp* (non-STEM, $p < 0.01$) relative to counterfactual simulations (**Fig. 2C**). Aggregating all fields, our counterfactual model estimates that gendered attrition has caused a net loss of 1378 women faculty from the PhD-granting sector of the U.S. tenure track between 2011 and 2020. Assuming 19.2 faculty per department (the mean department size in our dataset), this is an asymmetric loss of approximately 72 entire departments.

C. Projecting future gender representation

Proposed strategies to increase faculty gender diversity often emphasize changes to hiring or retention. However, administrators and policymakers typically lack any ability to quantitatively evaluate a policy's long-term impact or to compare its outcomes against alternatives. In our third analysis, we therefore turn our counterfactual model, previously used to investigate the past, to investigate five projections capturing future hiring and attrition scenarios. These scenarios are not intended to predict or forecast precisely what will occur in the future, but instead serve to illustrate what could happen if a set of specific assumptions were held fixed. We operationalize a particular policy intervention by altering two parameters: faculty attrition risks, which can be gendered or gender-neutral, and the fraction of women among new hires, which can be maintained at 2011–2020 levels or increased over time. These scenarios are described in detail in Methods Sec. E. Across all scenarios, we hold the sizes of academic domains fixed at their 2020 values, initialize projections at empirical 2020 values, and project women's representation through 2060.

Even in the absence of interventions, our baseline projection using current hiring patterns and observed attrition (OA) shows a mean increase in women's representation of 2.8 *pp* (**Fig. 3**). Although the fraction of women among new hires has been increasing over time in some academic domains (Supplementary Sec. S2), here we do not extrapolate that trend into the future. Thus, this projection reflects demographic inertia, where it takes roughly a full career-length of time for the most recent, more gender diverse cohorts of newly hired faculty to fully replace all the older and less gender-diverse faculty cohorts [18, 30].

The gender-neutral attrition (GNA) scenario maintains the same assumption about hiring as the OA scenario, but alters the attrition risks to be equal for men and women at each career stage. This scenario therefore represents a set of policy interventions that entirely close the retention gap between women and men faculty. The resulting projected fraction of women faculty in the Natural Sciences domain in 2060 is 34.4%, representing a 6.4 *pp* increase from 2020 (**Fig. 3A**). Across all

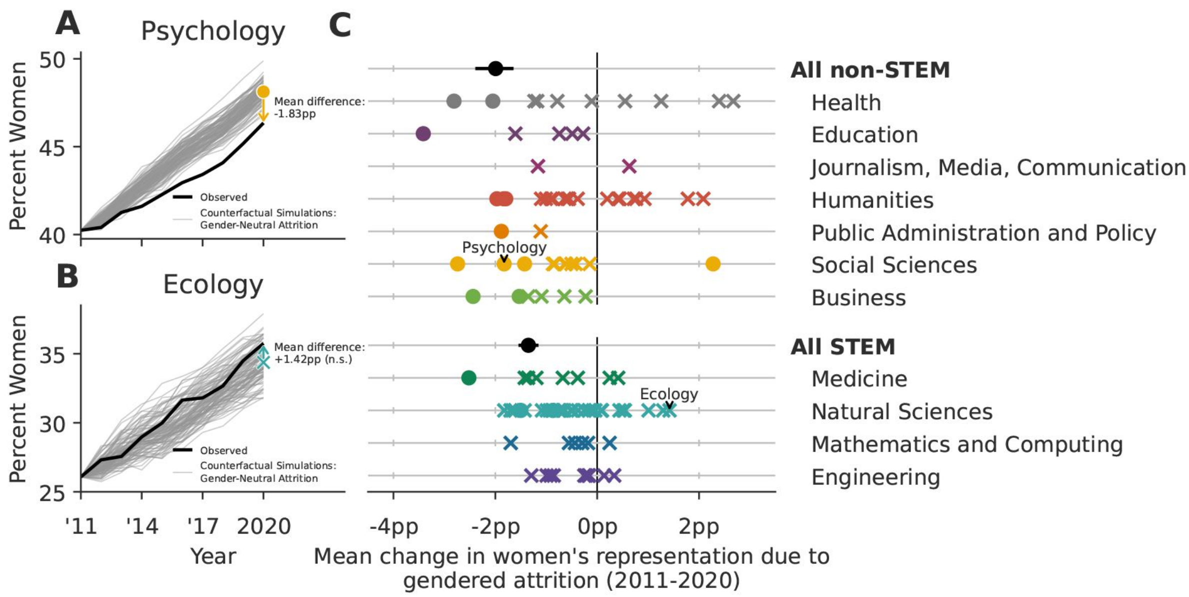

Figure 2.

Gendered faculty attrition has caused a differential loss of women faculty in both STEM and non-STEM fields. (A) Gendered attrition in psychology has caused a loss of − 1.83 *pp* ($p < 0.01$) of women's representation between 2011-2020, relative to a counterfactual model with gender-neutral attrition (see Methods Sec. C). In contrast, (B) gendered attrition in Ecology has not caused a statistically significant loss (+1.42 *pp*, $p = 0.24$). Relative to their field-specific counterfactual simulations, 15 academic fields and the STEM and non-STEM aggregations exhibit significant losses of women faculty due to gendered attrition (circles on figure; two-sided test for significance relative to the gender-neutral null distribution derived from simulation, $\alpha = 0.1$). The differences in the remaining 95 fields were not statistically significant (crosses on figure), but we note that their lack of significance is likely partly attributable to their smaller sample sizes at the field-level compared to the all STEM and all non-STEM aggregations, which exhibited large and significant differences. Error bars for the non-STEM and STEM aggregations contain 95% of $n = 500$ stochastic simulations. No bars are included for field-level points to preserve readability.

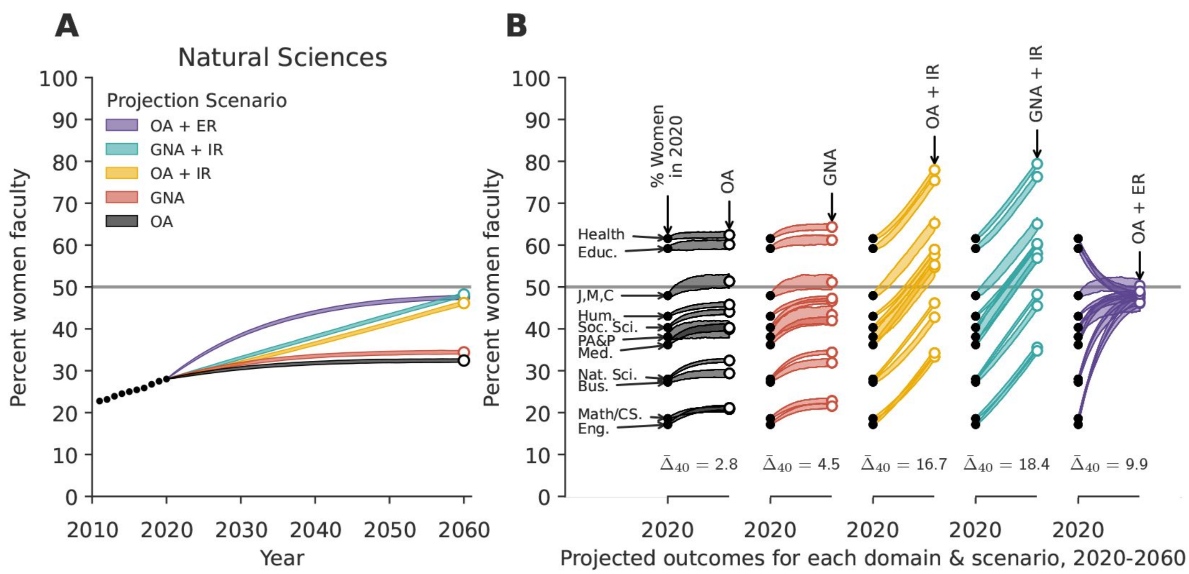

Figure 3.

(A) Observed (dotted line, 2011-2020) and projected (solid lines, 2021-2060) faculty gender diversity for Natural Sciences over time and (B) projections for 11 academic domains over 40 years under five policy scenarios. Line widths span the middle 95% of N = 500 simulations and $\bar{\Delta}_{40}$ gives the mean change in women's representation across domains over the 40-year period. Educ. = Education, J,M,C = Journalism, Media & Communications, Hum. = Humanities, Soc. Sci. = Social Sciences, and PA&P = Public Administration & Policy., Med. = Medicine, Nat. Sci. = Natural Sciences, Bus. = Business, Eng. = Engineering. See text for scenario explanations. OA = observed attrition, GNA = gender-neutral attrition, IR = increasing representation of women among hires (+0.5 *pp* each year), ER = equal representation of women and men among hires.

domains, the mean increase in women's representation relative to 2020 is 4.5 *pp* (**Fig. 3B**), exceeding the mean increase in the OA scenario by 1.7 *pp*. Nevertheless, in this scenario women are projected to remain underrepresented in most academic domains in 2060.

The increased representation (IR) scenarios alter new faculty hiring such that women's representation among new hires grows by +0.5 *pp* each year. This rate of growth ultimately increases women's representation among new hires by +20 *pp* by 2060, and is close to the median observed change 2011-2020 (+0.58 *pp*; **Supplementary Table S1**). Thus, for some domains, this scenario may not represent new action, but rather continued effects of current policies.

When increased representation among new hires is combined with observed attrition (OA+IR), the projected mean increase in women's overall representation is 16.7 *pp* (**Fig. 3**). The magnitude of this increase is the largest among these first three scenarios, exceeding the OA scenario's mean increase by 12.2 *pp*. We note, however, that these increases would grow women's representation beyond gender parity in Medicine, Social Sciences, Humanities, and Public Administration & Policy, and would maintain representation above parity in Health and Education (**Fig. 3**).

When increased representation among new hires is instead combined with gender-neutral attrition (GNA + IR), the projected mean increase in women's overall representation is 18.4 *pp* (**Fig. 3**), exceeding the OA + IR scenario by only 1.7 *pp*. These additional modest increases do not push any additional academic domains beyond gender parity (**Fig. 3**).

Finally, we consider a more radical intervention in which universities immediately and henceforth hire men and women faculty at equal rates (ER) but do not change attrition patterns (OA + ER). Overall, the projected mean increase in women's representation between 2020 and 2060 is 9.9 *pp* (**Fig. 3**), a result of all domains moving markedly toward parity. However, none of the academic domains is projected to achieve stable gender parity under this scenario because attrition remains gendered. In domains that are particularly male-dominated, such as Natural Sciences, this gender-parity hiring scenario causes the most rapid progress toward greater representation of women faculty of any of the scenarios (**Fig. 3A**).

Intentionally omitted is the scenario of equal-rate hiring and gender-neutral attrition (ER + GNA), for which conclusions can be drawn without simulation. Any academic domain with hiring at parity and equal retention rates between women and men is guaranteed to achieve stable parity, modulo stochastic effects, after one complete academic generation.

The five projection scenarios show that changes to hiring drive larger increases in the long-term representation of women faculty of a field. Most fields, and particularly those with the least gender diversity, cannot achieve equal representation by changing attrition patterns alone. In fact, our results suggest that even relatively modest annual changes in hiring tend to accumulate to substantial field-level changes over time. In contrast, eliminating gendered attrition leads to only modest changes in women's projected representation (**Fig. 3**).

Discussion

In this study, we used a decade of census-level employment data on U.S. tenured and tenure track faculty at PhD-granting institutions to investigate the relative impacts of faculty hiring versus all-cause faculty attrition on women's representation across academia. Toward this end, we answer three broad questions: (i) How have these two processes shaped gender representation across the academy over the decade 2011–2020? (ii) How might women's representation today have been different if gendered attrition among faculty were eliminated in 2011? And, how might we expect gender diversity among faculty to change over time under different future hiring and attrition scenarios?

The effects of hiring were stronger than the effects of attrition in changing women's representation among faculty over the decade 2011–2020. By separating hiring and attrition effects, we found that hiring served to increase women's representation in 96% of fields, while attrition (including retirement) served to increase women's representation in 74% of fields. However, these effects were not always synergistic, such that 26% of fields saw increases due to hiring amidst decreases due to attrition, while 5% of fields saw decreases due to hiring and increases due to attrition. In total, hiring effects dominated attrition effects in 90% of fields, 97% of which saw net increases in women's representation (**Fig. 1**). In contrast, attrition effects were stronger than hiring effects in just 10% of fields, yet 9 of these 11 nevertheless saw net increases in women's representation, including Linguistics, Theological Studies, and Art History. Only 5 (4.5%) fields saw decreased women's representation over same period, including Nursing and Gender Studies, both fields where women are over-represented (**Fig. 1**).

Our counterfactual analyses of the past decade's gender diversity trends, in which we preserved historical hiring trends but eliminated the effects of gendered attrition, indicate that U.S. academia as a whole has lost approximately 1378 women faculty because of gendered attrition. This number is both a small portion of academia (0.67% of the professoriate), and a staggering number of individual careers, enough to fully staff 72 nineteen-person departments. Because women are more likely to say they felt "pushed" out of academic jobs when they leave [28], each of these careers likely represents an unnecessary loss, both to the individual and to society, in the form of lost discoveries [3, 5–7], missing mentorship [1, 2], and many other contributions that scholars make. Moreover, although our study focuses narrowly on gender, past studies of faculty attrition [31–33] lead us to expect that a disproportionate share of these lost careers would be women of color.

The two findings above—that all-cause attrition served to increase women's representation in 74% of fields, while gendered attrition led to the net loss of an estimated 1378 women from the academy—seem at first glance to be at odds. However, the former reflects primarily the turnover and retirement of a previous generation of faculty [8], while the latter stems from observations that in most areas of the academy, women are at higher risk of leaving their faculty jobs than men of the same career age, i.e., gendered attrition [28]. Reconciling and quantifying these separate effects through models, parameterized by gender and career-age stratified empirical data, is therefore a key contribution of this work.

We find large and statistically significant effect sizes for gendered attrition at high levels of aggregation in our data, (e.g., all of academia, among all STEM or all non-STEM fields, and within domains), yet we often find smaller effects that are not statistically significant in constituent individual fields (**Fig. 2**; see also Ref. [28]). This pattern implies that there must be gendered effects within at least some of the constituent fields which may statistically indistinguishable from noise due to smaller population sizes and greater relative fluctuations in hiring. This perspective may therefore explain why field-specific studies of gendered faculty attrition sometimes reach conflicting conclusions [22, 28, 34–36], and suggests that future studies should seek larger samples sizes whenever possible. While this study cannot identify specific causal mechanisms that drive gendered attrition, the literature points to a number of possibilities, including disparities in the levels of support and value attributed to women and the scholarly work that women produce [37, 38], sexual harassment [39], workplace culture [28], work-life balance [40, 41], and the unequal impacts of parent-hood [42, 43]. Even in fields where we found no significant evidence that women and men leave academia at different rates, the reasons women and men leave may nevertheless be strongly gendered. For instance, past work has shown that men are more likely to leave faculty jobs due to attractive alternate opportunities ("pulls"), while women are more likely to leave due to negative workplace culture or work-life balance factors ("pushes") [28].

The relative importance of hiring vs attrition is also borne out in our projection scenarios. Indeed, we find that eliminating the gendered attrition gap, in isolation, would not substantially increase representation of women faculty in academia. Rather, progress toward gender parity depends far more heavily on increasing women's representation among new faculty hires, with the greatest change occurring if hiring is close to gender parity (**Fig. 3**).

A limitation to this study is that it only considers tenured and tenure-track faculty at PhD granting institutions in the U.S. Non-tenure track faculty, including instructors, adjuncts, and research faculty, are an increasing portion of the professoriate [44, 45], and they may experience different trends in hiring and attrition, as may faculty outside the U.S. and faculty at institutions that do not grant PhDs. The results presented in this work will only generalize to these other populations to the extent that they share similar attrition rates, similar hiring rates, and similar current demographics. Notably, understanding how faculty hiring, faculty attrition, and faculty promotion [46] are shaping the gender composition of these populations is an important direction for future work.

Another important limitation of this work is that we focused our analysis at the level of entire fields and academic domains. However, hiring and attrition may play different roles in specific departments or in specific types of departments. These differences may be elucidated by future analyses of mid-career moves, in which faculty change institutions but stay in the same fields.

Faculty who belong to multiple marginalized groups (e.g. women of color) are particularly underrepresented and face unique challenges in academia [47]. The majority of women faculty in the U.S. are white [48], meaning the patterns in women's hiring and retention observed in this study are predominantly driven by this demographic. While attrition may not be the primary challenge for women's representation overall, it could still be a significant barrier for women of color and those from less privileged socioeconomic backgrounds. Additional data are needed to study trends in faculty hiring and faculty attrition across racial and socioeconomic groups.

More broadly, while this study has focused on a quantitative view of men's and women's relative representations, we note that equal representation is not equivalent to equal or fair treatment [49, 50]. Pursuing more diverse faculty hiring without also mitigating the causes that sustain existing inequities can act like a kind of "bait and switch," where new faculty are hired into environments that do not support their success, a dynamic that is believed to contribute to higher turnover rates for women faculty [51].

Our study's detailed and cross-disciplinary view of hiring and attrition, and their relative impacts on faculty gender diversity, highlights the importance of sustained and multifaceted efforts to increase diversity in academia. Achieving these goals will require a deeper understanding of factors that shape the demographic landscape of academia.

Methods

A. Data cleaning and preparation

Our analysis is based on a comprehensive dataset of U.S. faculty at PhD granting institutions, obtained through a data use agreement with the Academic Analytics Research Center (AARC). This dataset includes the employment records for all tenured and tenure-track faculty at all 392 U.S. doctoral-granting universities from 2011 to 2020, along with the year of each professor's terminal degree. To ensure the consistency and robustness of our measurements, we cleaned and preprocessed this dataset according to the following steps. For additional technical details relating to these steps, see Ref. [8]. For a manual audit to assess potential attrition errors in this dataset, see Ref. [28].

We first de-duplicated departments. This involved combining records due to: (i) variations in department names (e.g., “Computer Science Department” vs. “Department of Computer Science”) and (ii) departmental renaming events (e.g., “USC School of Engineering” vs. “USC Viterbi School of Engineering”).

Next, we annotated departments according to a two-level department taxonomy with lower level fields and higher level domains assignments to departments. While most departments were assigned a single annotation for each level of the taxonomy, some interdisciplinary departments received multiple annotations. This deliberate choice can reflect how a “Department of Physics and Astronomy” is relevant to both “Physics” within the “Natural Sciences” domain and “Astronomy” within the same domain. Therefore, we included all applicable annotations for such departments to capture their full scope, but note that domain-level analyses included such departments only once.

Then, we addressed certain interdisciplinary fields which could conceptually reside in multiple domains, e.g., Computer Engineering (potentially belonging to domains of either Mathematics & Computing or Engineering), and Educational Psychology (potentially belonging to domains of either Education or Social Sciences). To address this ambiguity, we employed a heuristic approach. Fields were assigned to the domain containing the largest proportion of faculty members whose doctoral universities housed a department within that domain. Thus, we grouped fields based on the domain where their faculty were most likely to have been trained. Supplementary Data **Table S2** contains a complete list of fields and domains.

In rare instances, faculty members temporarily disappeared from the dataset before reappearing in their original departments. We treated these as likely data errors and imputed the missing employment records. Missing records were filled in if the faculty member’s department had data for the missing years. Employment records were not imputed if they were associated with a department that did not have any employment records in the given year. Imputations affected 1.3% of employment records and 4.7% of faculty.

Next, we limited our analyses to departments consistently represented in the AARC data across the study period (2011-2020). This exclusion was necessary because not all departments were consistently recorded by AARC. Departments appearing in the majority of years within the study period were retained, resulting in the removal of 1.8% of employment records, 3.4% of faculty, and 9.1% of departments. This exclusion also resulted in the removal of 24 institutions (6.1%), primarily seminaries.

We next filtered the data to include only tenure-track faculty. This involved removing temporary faculty, including non-tenure-track instructors holding titles such as “lecturer,” “instructor,” or “teaching professor” at any rank, individuals with missing rank information, and faculty classified as “research,” “clinical,” or “visiting.” This filtering process resulted in a dataset solely comprised of tenured and tenure-track faculty holding the titles of “assistant professor,” “associate professor,” and “full professor.”

Finally, we defined career age for each person-year record in our dataset as the difference between the given year for the record and the year that the faculty member received their doctoral degree. However, doctoral year was missing for 29,872 faculty members (9.8% of faculty), necessitating their exclusion from the counterfactual analysis (results Sec. B) and the forecasting analysis (results Sec. C).

B. Decomposition of changes in representation into hiring and attrition

We decomposed the annual changes in women's representation (in units of proportion per year) within each field into hiring (δ_{hiring}) and attrition ($\delta_{attrition}$) components as follows. First, we define n_w and n_m as the counts of women and men faculty in the field in a given index year. Next, we let h_w and h_m be the counts of women and men that were hired between the index year and the following year, and similarly let x_w and x_m be the counts of women and men among faculty "all-cause" attritions between the index year and the following year. We then approximate δ_{hiring} and $\delta_{attrition}$ as

$$\delta_{hiring} = \frac{n_w + h_w}{n_w + h_w + n_m + h_m} - \frac{n_w}{n_w + n_m}$$

$$\delta_{attrition} = \frac{n_w - x_w}{n_w - x_w + n_m - x_m} - \frac{n_w}{n_w + n_m} \; .$$

These equations are developed in Supplementary Text S1. The annual changes δ_{hiring} and $\delta_{attrition}$ were summed, respectively, over 2011-2020 for each field, to construct **Fig. 1**.

C. Model of faculty hiring and attrition

We developed a model of annual faculty hiring and attrition structured by faculty career age (years since PhD) and gender, allowing model parameters to vary as a function of both. This model was used for both the counterfactual historical analysis, which investigated gendered attrition, and the projection of future scenarios, which investigated five stylized futures. Details of the particular parameterizations for each investigation follow this structural model description.

In this model, we track the number of people with a given career age a and gender g, with annual updates given by

$$n(a, g) \leftarrow n(a-1, g) + h(a, g) - x(a-1, g) \; , \qquad (1)$$

where h and x are hires and attritions, respectively. In each stochastic model realization, both h and x are drawn according to distributions that allow control over the extent to which hiring and attrition are (or are not) gendered processes.

We stochastically draw $h(a, g)$ and $h(a, \tilde{g})$ by first specifying the total number of hires that year $H(a)$. For each of the $H(a)$ hires, we draw gender annotations from independent Bernoulli trials with parameter $\psi(a, g)$. In this way, the ψ parameters control the extent to which hiring is gendered across career ages.

To calculate attritions $x(a-1, g)$, we subject each of the $n(a-1, g)$ sitting faculty to a career age and gender-stratified annual attrition risk $\phi(a-1, g)$, realizing the actual number of attritions from a binomial draw with n trials and parameter ϕ. The relative values of $\phi(a, g)$ and $\phi(a, \tilde{g})$ therefore control the extent to which attrition is gendered for a particular career age.

Thus, this model is stochastic, and after specifying initial conditions for the values of $\mathbf{n}$, one needs only values for the total hires $\mathbf{H}$, gendered hiring parameters ψ, and gendered attrition risk parameters ϕ to simulate stochastically, by iterating **Eq. (1)**.

D. Parameters for counterfactual model of 2011–2020

The goal of this model was to quantify the impact of gendered attrition over the period 2011–2020. As such, this model manipulated the parameters ϕ which control the extent to which attrition is gendered. To model a counterfactual scenario in which attrition was not gendered, we set women's and men's attrition risks to be identical $\phi(a, w) = \phi(a, m)$, taking on values estimated from empirical data in which gender was ignored, for each field (see below).

For each field, the model's faculty counts $\mathbf{n}$ were initialized using our 2011 faculty roster data, thereby matching all empirical 2011 values for both gender and career age. To ensure that a field's total faculty size grew or shrunk each year in a manner that exactly matched empirical changes, we first drew all attrition values x and then set the total number of new hires accordingly. Those new hires were assigned initial career ages drawn from the empirical age distribution of new hires, averaged over 2012-2020. Gendered hiring parameters ψ were set to values estimated from empirical data for each field (see below).

To parameterize $\psi(a, w, t)$, the probability that a new hire of career age a in year t is a woman, we used a logistic regression model fit to empirical hiring data for each field. Because the probability that a new hire is a woman varies non-linearly with career age (see **Supplementary Fig. S4**), the dependent variables in this model include new hires' career ages up to their fifth exponents and a linear term for the calendar year, which ranges from 2012 to 2020.

To parameterize $\phi(a, g, t)$, the probability that faculty of career age a and gender g experience attrition in year t, we used a logistic regression model trained on empirical attrition and retention data for each field. Because faculty attrition rates vary non-linearly with career age (see **Supplementary Fig. S3**), we include new hires' career ages up to their fifth exponents as dependent variables in the regression model, in addition to a linear term for the year, which ranges from 2012 to 2020. This regression model is fit to all observed cases of attrition and retention for both men and women together, for each field. Accordingly, men and women in our gender-neutral counterfactual model were subjected to the same age-varying attrition risks, eliminating the gendered aspect of these patterns, while preserving the rises and declines in attrition rates across faculty career ages.

To capture the distribution of counterfactual historical outcomes under gender neutral attrition, we drew 500 simulations of the years 2012–2020 for each field, recording women's representation at the end of each. See Supplementary Sec. S2 for details of model validation. This model was run for each field, independently. It was also run again for all STEM fields, and all non-STEM fields, with respective parameters estimated at those respective higher levels of data aggregation (**Fig. 2**).

E. Parameters for projection model of 2020–2060

The goal of this model was to quantify the effects of a set of five highly stylized scenarios for how hiring and attrition might evolve over the 40 years spanning 2020-2060. For scenarios with gender-neutral attrition (GNA), we set women's and men's attrition risks to be identical $\phi(a, w) = \phi(a, m)$, taking on values estimated from empirical data in which gender was ignored, for each academic domain. For scenarios with observed attrition (OA), we set women's and men's attrition risks to values estimated from empirical data in which gender was included, for each domain. For scenarios with equal representation of women and men among hires (ER), we set all ψ parameters to 0.5. And, for scenarios with increasing representation of women among hires (IR), we let the hiring parameters vary over time, such that the expected proportion of women among new hires increases by 0.5pp per year for each career age starting in 2020, i.e.,

$$\psi(a, w, t) = \psi(a, w, 2020) + 0.005(t - 2020) \ .$$

In the absence of one of the above manipulations, ϕ and ψ parameters were set to their empirical values, estimated from aggregated 2011-2020 data for each domain.

For each academic domain, the model's faculty counts $\mathbf{n}$ were initialized using our 2020 faculty roster data, thereby matching all empirical 2020 values for both gender and career age. Each domain's total faculty size was held fixed at 2020 values by setting the total number of new hires to be equal to the number of stochastically drawn attritions. This model was run for each domain, independently, using parameters estimated at the domain level accordingly.

To capture the distribution of outcomes in each projection scenario, we drew 500 simulations of the years 2020– 2060 for each academic domain, recording women's representation at the end of each (**Fig. 3**). See Supplementary Sec. S2 for details of model validation.

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Competing interests

None.

S1. Decomposition of change in gender diversity

We develop a method to decompose the change in each field's gender diversity into its two main components: change due to hiring, and change due to attrition. First, the fraction of faculty in a field that are women in any given year can be written as

$$\frac{n_w}{n_w + n_m}$$

where n_w and n_m are the number of women and men faculty in the field, respectively. An additional term could be added to account for nonbinary faculty representation if our data included nonbinary gender annotations, however the methodology we use [25] assigns only binary (woman / man) labels to faculty.

Then, in the following year, the new fraction of women faculty can be written as

$$\frac{n_w + h_w - x_w}{n_w + h_w - x_w + n_m + h_m - x_m}$$

where h_w and h_m are the numbers of women and men that were hired in the following year, respectively, and x_w and x_m are the number of women and men among faculty "all-cause" attritions (whether for retirement, or otherwise). The total change in women's representation between two academic years δ_{total}, can thus be written as

$$\delta_{total} = \frac{n_w + h_w - x_w}{n_w + h_w - x_w + n_m + h_m - x_m} - \frac{n_w}{n_w + n_m}$$

We decompose this total change into change due to hiring, δ_{hiring}, and change due to attrition, $\delta_{attrition}$, as follows:

$$\delta_{hiring} = \frac{n_w + h_w}{n_w + h_w + n_m + h_m} - \frac{n_w}{n_w + n_m}$$

$$\delta_{attrition} = \frac{n_w - x_w}{n_w - x_w + n_m - x_m} - \frac{n_w}{n_w + n_m}$$

This decomposition behaves intuitively. For example, if the share of women that are hired exceeds the fraction of women in the field prior to hiring, then δ_{hiring} will be positive. On the other hand, if the share of women that are hired is lower than the fraction of women in the field prior to hiring, then δ_{hiring} will be negative. If there are no hires, $\delta_{hiring} = 0$. Similar intuition can be applied for $\delta_{attrition}$.

We sum the change in representation due to hiring and attrition over each year between 2011 to 2020 to get the overall change in representation due to hiring, Δ_{hiring}, and attrition, $\Delta_{attrition}$.

One potential limitation of this decomposition is that Δ_{hiring} and $\Delta_{attrition}$ do not perfectly sum to the exact observed change in women's representation over a given range of years, Δ_{total}. Instead, there is a residual term

$$\Delta_{residual} = \Delta_{total} - \Delta_{hiring} - \Delta_{attrition}$$

Intuitively, we know that there should be a residual term, because the change in representation that results from a given cohort of new hires can depend upon the number of attritions observed in that year, and vice versa. If the residual terms are large, this decomposition would not be a good approximation of the total change in representation, and **Fig. 1** could be misleading. In **Fig. S1** we show that the residual terms are small (ranging from -0.51 *pp* to 1.14 *pp*, median = 0.2 *pp*), and thus the decomposition is a good approximation of the total change in women's representation.

A. Model Validation & Sensitivity Analysis

One way that we validate this model of faculty hiring and attrition is by starting the model in 2011, and comparing the resulting gender composition of faculty with the observed gender composition of faculty in 2020. In this validation, we use the same set of model parameters as in the gender-neutral counterfactual analysis (Sec. B), except attrition patterns are inferred separately for women faculty and men faculty. In other words, the attrition probabilities in this validation are not gender-neutral. We find that the observed outcomes are statistically indistinguishable from the model-based outcomes for all 111 fields, and for STEM and non-STEM aggregations (**Fig. S2**). This finding is not surprising, because the model is fit to the observed data, but it serves to validate the methods that we used to set the model's parameters (e.g., fitting logistic regression models to infer attrition risks and to infer the fraction of women faculty among new hires, as described in Methods Sec. D).

We additionally validate the model by comparing the projected 2060 faculty career age distributions for Natural Sciences from **Fig. 3** with the observed career age distribution for Natural Sciences in 2020 (**Fig. S3**). We find that the projected 2060 career age distributions are similar to the observed 2020 career age distribution for Natural Sciences (shown in **Fig. S3**) and for the additional academic domains.

We perform a sensitivity analysis to test the robustness of our results to changes in the model's parameters. In particular, we test the robustness of our counterfactual results to different models of attrition risks and to different models of the fraction of women among new hires. First, we fit several alternative models to the empirical attrition risks (**Fig. S4**) and to the fractions of women among new hires (**Fig. S5**) to validate our choice of including career age up to its fifth power as a predictor in these logistic regression models. Then, we test the robustness of our counterfactual results to changes in the model's parameters by running the counterfactual analysis with the alternative model in which we only include career age up to its third power. This alternate model is less likely to overfit the data, and even tends to underfit the observed correlation structures between attrition risk and career age (**Fig. S4**, **Fig. S5**). Nevertheless, we find that the results are robust to these changes (**Fig. S6**).

S2. Gender diversity of hires over time

In academia overall, the fraction of women faculty among hires has been increasing on average over the past decade, at a rate of around 0.91 *pp/year* (**Fig. S7**), however, these rates of change are not uniform across academic domains. **Table S1** shows regression results for trends in women's representation among hires for 11 academic domains. While women's representation has been increasing in 6 of the 11 domains over time at rates up to 1.30 *pp/year*, the remaining 5 domains have not exhibited significant trends (**Table S1**).

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Figure S1.

The change in gender diversity between 2011 and 2020 can be approximately decomposed into parts due to hiring and attrition for each academic field, but there is a leftover residual term. In practice, we find that the residual term tends to be very small, such that the decomposition is nearly ideal. The dotted line represents an ideal decomposition, where the change in women's representation among faculty due to hiring and attrition perfectly matches the total observed change.

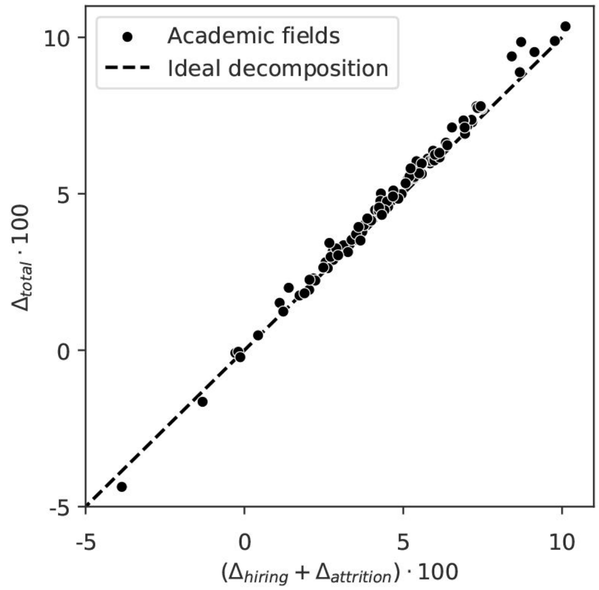
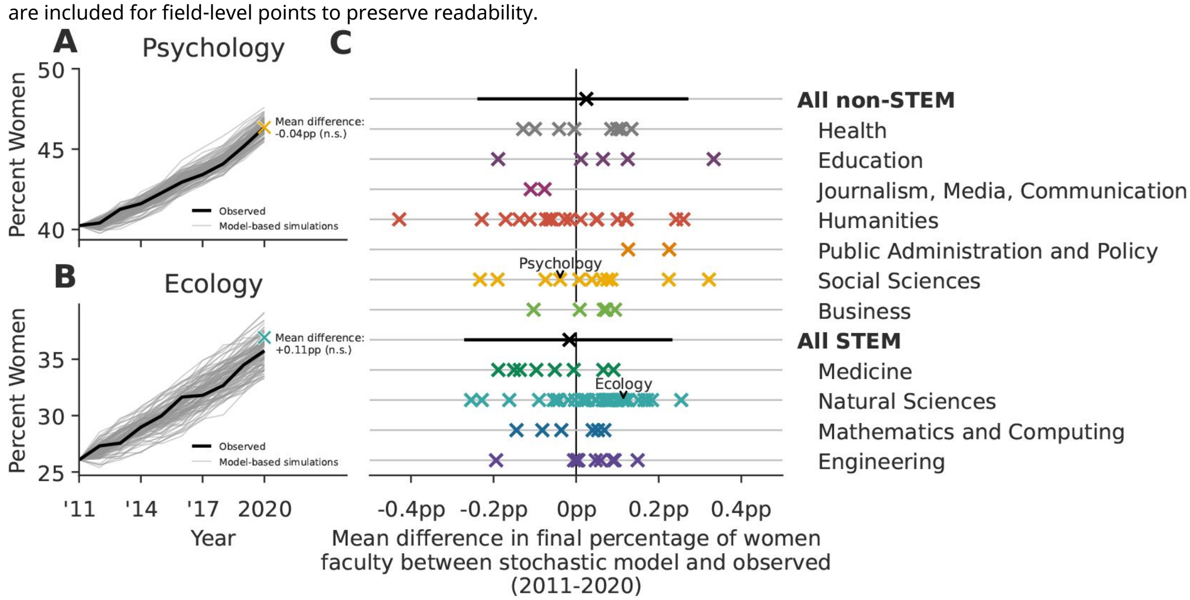


Figure S2.

Model validation: Differences between observed gender diversity outcomes and model-based outcomes. (A) The mean outcomes of model-based simulations in psychology differ from the observed outcomes by − 0.04*pp*, and (B) in Ecology by +0.11*pp*, but these differences are not statistically significant. (C) Gender diversity outcomes from model-based simulations of hiring and attrition are statistically indistinguishable from observed gender diversity outcomes for all 111 fields, and for STEM and non-STEM aggregations, based on a two-sided test for significance relative to the model-based null distribution derived from simulation, $\alpha = 0.1$). Error bars for the non-STEM and STEM aggregations contain 95% of stochastic simulations. No bars are included for field-level points to preserve readability.



Academic Domain	Estimated Annual Change (pp)	p
Mathematics and Computing	0.25	0.095
Social Sciences	1.18**	0.006
Natural Sciences	1.30***	0.000
Engineering	0.95***	0.000
Health	0.58*	0.020
Humanities	1.18**	0.002
Public Administration and Policy	0.22	0.717
Business	0.38	0.089
Medicine	0.98**	0.009
Journalism, Media, Communication	0.49	0.173
Education	0.34	0.057
Academia Overall	0.91***	0.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S1.

Trends in women's representation among new hires from 2012 to 2020 for 11 academic domains, along with academia overall. We use linear regression to measure the expected change in women's concentration among new hires each year, and find that women's representation has been increasing in 6 of the 11 domains over time, at rates ranging from 0.58 *pp* to 1.30 *pp* per year. The remaining 5 domains have not exhibited significant linear trends. Overall, the fraction of women among hires has been increasing in academia over time (**Fig. S7**). These findings are qualitatively replicated using logistic regression, so we present the linear regression results here for enhanced interpretability.

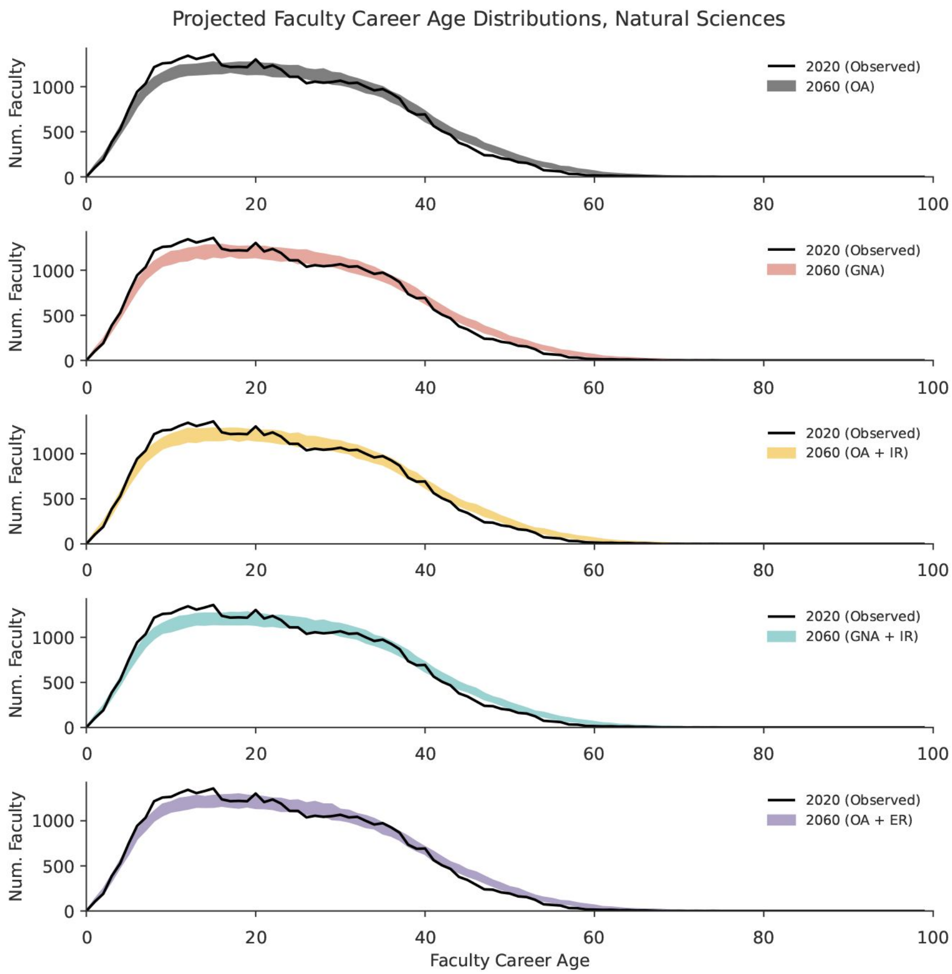


Figure S3.

Model validation: Projected 2060 faculty career age distributions for Natural Sciences from **Fig. 3** are similar to the observed career age distribution for Natural Sciences in 2020, for each projection scenario. Line widths for the simulated scenarios span the middle 95% of simulations. OA = observed attrition, GNA = gender-neutral attrition, IR = increasing representation of women among hires (+0.5 *pp* each year), ER = equal representation of women and men among hires.

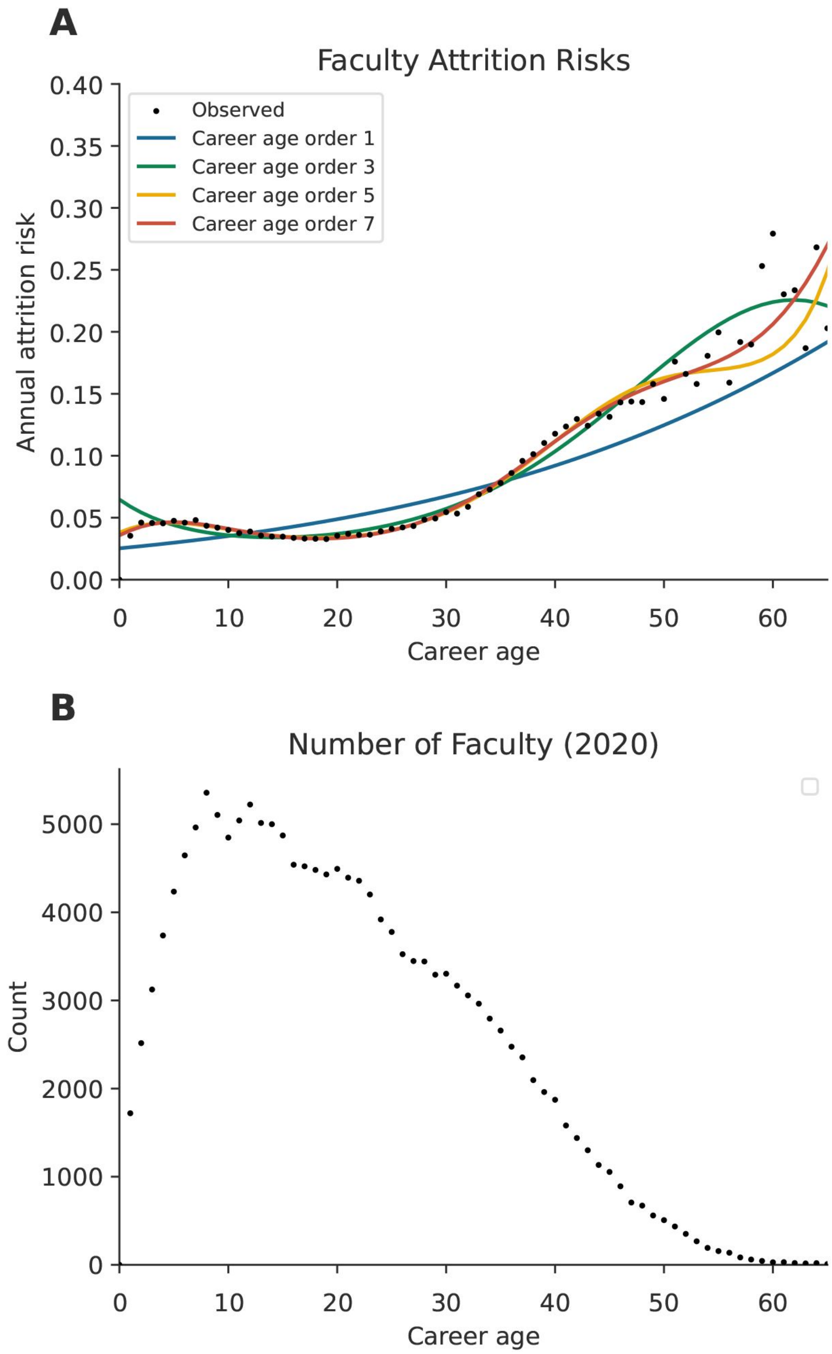


Figure S4.

Model selection. (A) Four logistic regression models fit to observed faculty attrition data. Each model includes career age up to a different power, e.g., the model labeled "Career age order 3" includes career age up to its third power: $logit(p) = \beta_0 + \beta_1 a + \beta_2 a^2 + \beta_3 a^3 + \beta_4 t$ where a represents career age and t represents year (see Methods Sec. D for details). The pattern in observed attrition risk becomes more noisy at higher career ages, because (B) there are relatively low numbers of faculty at the highest observed career ages.

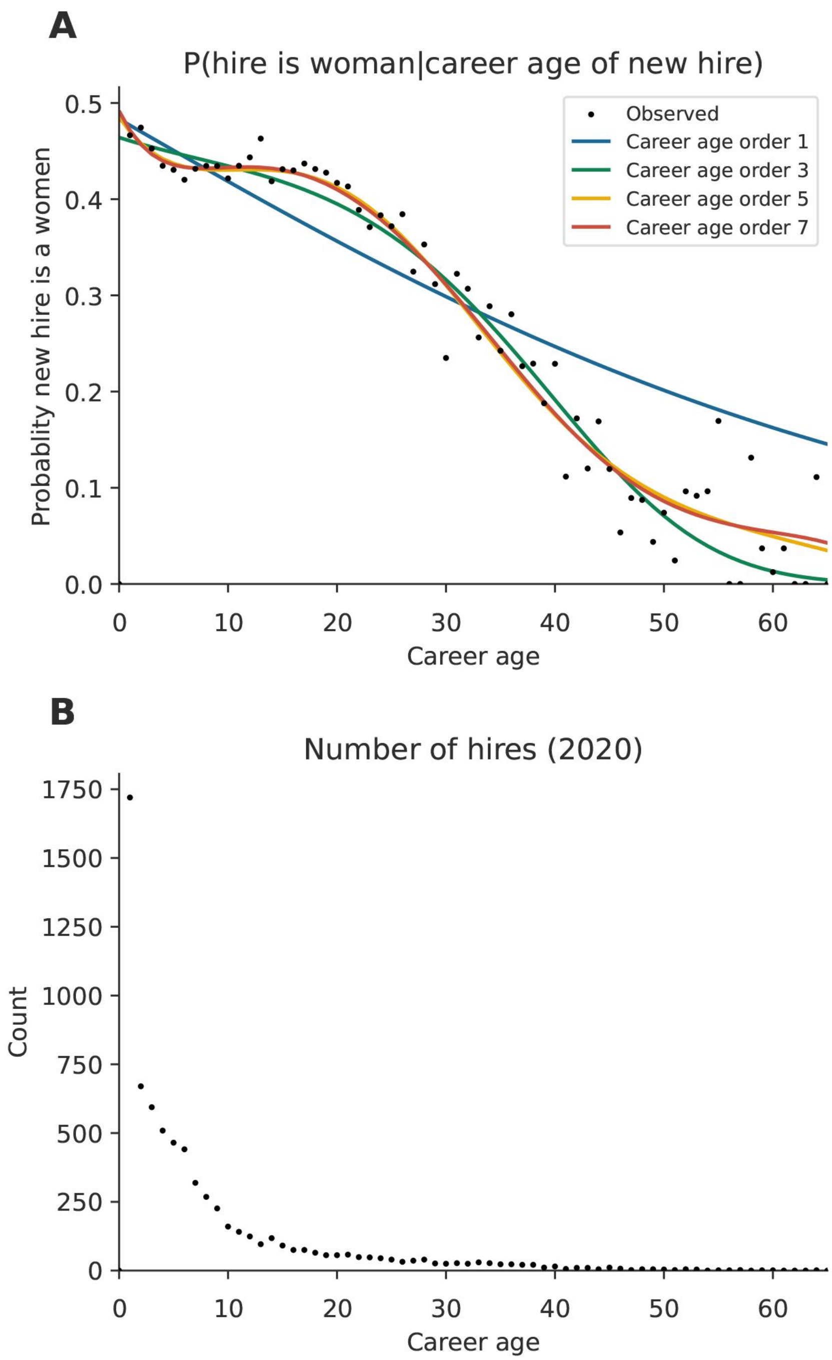


Figure S5.

Model selection. (A) Four logistic regression models fit to observed faculty hiring data, where the outcome variable is the gender of the faculty hire (1 = woman, 0 = man). Each model includes career age up to a different power, e.g., the model labeled "Career age order 3" includes career age up to its third power: $logit(p) = \beta_0 + \beta_1 a + \beta_2 a^2 + \beta_3 a^3 + \beta_6 t$ where a represents career age and t represents year (see Methods Sec. D for details). The pattern in the gender representation among new faculty hires becomes more noisy at higher career ages, because (B) there are relatively low numbers of faculty hired at higher career ages.

Figure S6.

Sensitivity analysis: Replicating the counterfactual analysis from results Sec. B using career age up to its third power in the associated logistic regressions model, instead of the fifth power (see Supplementary Sec. S1 A for details). Findings under this parameterization are qualitatively very similar to those presented in **Fig. 2**, indicating that the results are robust to modest changes to model parameterization.

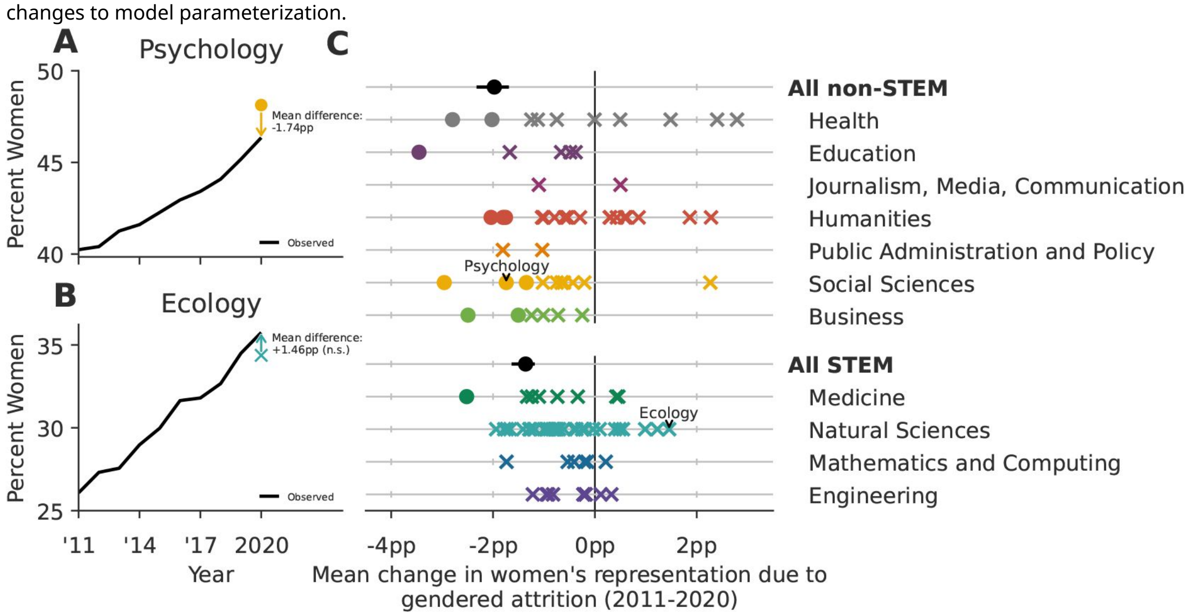
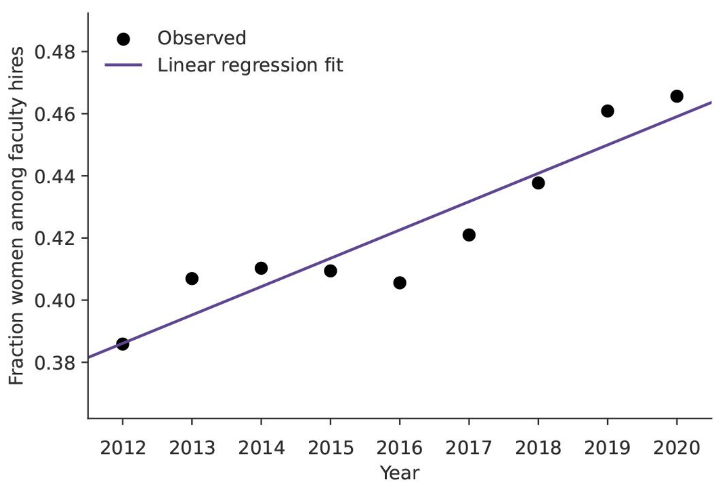


Figure S7.

Fraction of women among tenure-track faculty hires over time at U.S. PhD granting institutions. Women's share of new hires is observed to increase at around 0.91 *pp* annually (t-test, $p < 0.001$), measured by an ordinary least squares regression fit (shown in purple).



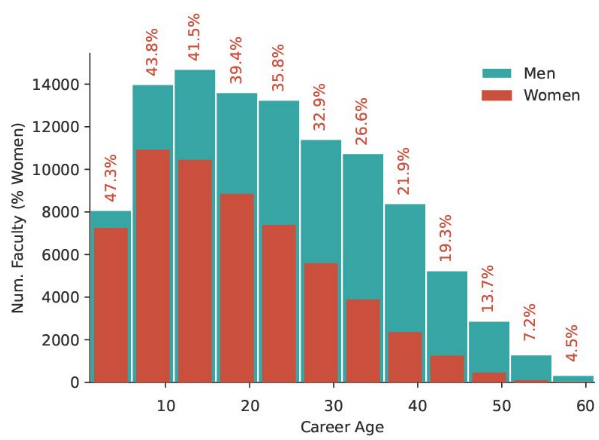


Figure S8.

Career age distribution of women (red) and men (blue) tenured and tenure-track faculty across all academic fields. Career age is measured as the number of years since earning a PhD. There are substantially more men faculty with high career ages than women faculty.

Field	Observed Δ_{hiring}	Observed $\Delta_{\text{attrition}}$	Est. $\Delta_{\text{gendered attrition}}$
Health			
Environmental Health Sciences	+6.65	+3.46	+2.40 (−1.03, +5.60)
Nursing	−4.34	+0.48	+0.55 (−0.59, +1.65)
Public Health	+4.48	+0.71	−0.11 (−1.89, +1.60)
Human Development and Family Sciences	+3.19	−0.48	−2.81 (−5.44, −0.25)
Speech and Hearing Sciences	+3.30	+2.84	+2.67 (−0.81, +6.31)
Exercise Science, Kinesiology, Rehab, Health	+6.26	−1.96	−2.05 (−3.63, −0.27)
Nutrition Sciences	+0.31	+0.12	−1.18 (−3.62, +1.37)
Communication Disorders and Sciences	+6.11	+1.32	+1.26 (−1.77, +4.99)
Health, Physical Education, Recreation	+2.40	−0.35	−0.78 (−4.34, +2.52)
Social Work	+4.73	−0.04	−1.23 (−3.21, +0.60)
Education			
Education	+1.55	+1.07	−0.28 (−2.21, +1.62)
Special Education	+3.64	−2.24	−3.41 (−6.84, −0.28)
Education Administration	+0.91	+2.34	−0.74 (−2.84, +1.51)
Counselor Education	+5.08	+0.86	−0.49 (−3.36, +2.49)
Curriculum and Instruction	+0.97	+1.26	−1.61 (−3.70, +0.22)
Journalism, Media, Communication			
Communication	+3.43	+0.20	−1.16 (−3.01, +0.80)
Mass Communications and Media Studies	+4.30	+1.22	+0.63 (−1.61, +2.73)
Humanities			
Theological Studies	+0.51	+0.71	−0.91 (−3.07, +1.02)
Asian Languages	−0.54	+2.43	+1.78 (−1.91, +5.32)
Slavic Languages and Literatures	+3.34	+3.60	+0.93 (−3.00, +5.18)
Classics and Classical Languages	+3.33	+2.25	+0.20 (−2.14, +2.69)
French Language and Literature	+0.50	+1.23	−0.38 (−3.69, +3.30)
Germanic Languages and Literatures	+3.72	+3.23	+2.08 (−1.44, +5.76)
Theatre Literature, History and Criticism	+0.79	+2.87	+0.40 (−4.04, +4.58)
Art History and Criticism	+2.18	+2.67	+0.44 (−1.85, +2.86)
Asian Studies	−1.17	+1.04	+0.72 (−2.84, +3.90)
History	+2.84	+2.11	−0.64 (−1.69, +0.44)
Urban and Regional Planning	+5.71	+1.74	−1.01 (−4.53, +2.34)
Linguistics	−0.15	+2.19	+0.44 (−2.12, +3.29)
English Language and Literature	+2.17	+0.63	−1.80 (−2.80, −0.80)
Near and Middle Eastern Languages and Cultures	+5.80	−0.22	−0.87 (−4.87, +3.41)
Music	+3.72	−0.99	−1.10 (−2.54, +0.47)
Philosophy	+5.03	+0.04	−1.84 (−3.37, −0.24)
Religious Studies	+2.68	−0.22	−1.97 (−4.28, +0.08)
Comparative Literature	+1.78	+1.17	−0.58 (−4.04, +2.40)
Spanish Language and Literature	+2.39	+1.94	−0.55 (−3.09, +1.98)
Architecture	+4.53	+2.64	+0.77 (−2.31, +3.72)
Public Administration and Policy			
Public Policy	+5.16	−0.88	−1.88 (−3.85, +0.23)
Public Administration	+6.49	+0.82	−1.11 (−3.71, +1.62)
Social Sciences			
Sociology	+3.99	+1.51	−1.43 (−2.92, +0.03)
Gender Studies	−2.71	+1.40	+2.28 (−0.56, +5.25)
Anthropology	+3.68	+2.30	−0.42 (−1.94, +1.31)
Political Science	+4.35	+1.00	−0.15 (−1.41, +0.98)
International Affairs	+6.99	−1.58	−2.74 (−5.31, −0.33)
Geography	+6.65	+0.80	−0.51 (−2.26, +1.82)
Psychology	+5.81	−0.04	−1.83 (−2.82, −0.74)

Continued on next page

Table S2

Changes in Women’s Representation through Hiring, Attrition, and Gendered Attrition in Academic Fields (2011-2020).

Observed changes in women’s representation resulting from hiring and attrition, expressed in percentage points (*pp*), based on data from **Fig. 1**, and the estimated average change in women’s representation due to gendered attrition as depicted in **Figure 2**, accompanied by the 2.5 percentile and 97.5 percentiles of simulations in parentheses. The analysis covers 111 academic fields.

Agricultural Economics	+6.46	+0.43	−0.87 (−4.10, +1.76)
Educational Psychology	+3.51	−0.73	−0.84 (−3.75, +2.13)
Economics	+2.93	+0.45	−0.61 (−1.66, +0.50)
Criminal Justice and Criminology	+6.26	+1.12	−0.63 (−3.47, +2.28)
Business			
Accounting	+3.02	+0.47	−1.35 (−3.37, +0.61)
Marketing	+4.43	+0.06	−1.09 (−3.11, +0.99)
Management Information Systems	+3.61	−2.50	−2.44 (−4.61, −0.10)
Finance	+3.13	−0.01	−0.64 (−2.26, +0.88)
Business Administration	+4.21	−0.34	−0.23 (−1.98, +1.67)
Management	+2.76	−0.20	−1.53 (−2.94, +0.17)
Medicine			
Genetics	+4.31	+1.04	+0.25 (−2.77, +3.00)
Pharmaceutical Sciences	+6.88	−0.34	−1.42 (−3.78, +0.96)
Epidemiology	+3.95	+0.29	−0.67 (−3.04, +1.59)
Pharmacology	+2.91	+0.61	−0.38 (−2.19, +1.36)
Pharmacy	+10.25	−1.54	−1.36 (−4.17, +1.52)
Physiology	+5.21	+0.26	−1.19 (−3.05, +0.72)
Veterinary Medical Sciences	+10.34	−1.92	−2.52 (−4.31, −0.74)
Immunology	+3.80	+2.23	+0.41 (−1.55, +2.35)
Natural Sciences			
Entomology	+6.49	+0.85	−1.42 (−4.55, +1.21)
Soil Science	+4.04	+2.10	+0.52 (−2.46, +3.38)
Anatomy	+6.05	−0.82	−1.61 (−4.11, +0.84)
Natural Resources	+4.70	+1.64	+0.09 (−2.23, +2.49)
Plant Sciences	+4.74	+2.19	+1.01 (−1.61, +3.68)
Plant Pathology	+4.88	+1.51	−1.70 (−4.92, +1.69)
Biophysics	+4.00	−0.41	−0.75 (−3.31, +1.71)
Food Science	+4.16	+0.51	−1.08 (−4.07, +2.03)
Pathology	+5.25	−2.58	−1.50 (−3.14, +0.04)
Horticulture	+2.60	−0.12	−1.66 (−5.07, +1.69)
Biostatistics	+3.58	−0.69	−0.68 (−3.49, +2.02)
Agronomy	+4.82	+1.18	−0.93 (−3.96, +1.68)
Animal Sciences	+7.40	+1.74	−0.51 (−2.68, +1.63)
Forestry and Forest Resources	+6.54	+0.37	−1.82 (−4.83, +0.71)
Geology	+5.93	+1.54	−0.38 (−1.85, +1.03)
Biological Sciences	+5.22	+1.69	−0.04 (−1.07, +0.92)
Physics	+2.32	+1.00	−0.25 (−1.00, +0.50)
Chemistry	+3.96	+0.40	−0.87 (−1.77, +0.02)
Biochemistry	+3.91	+0.25	−0.89 (−2.22, +0.40)
Chemical Engineering	+4.08	+0.21	−0.87 (−2.38, +0.63)
Environmental Sciences	+5.88	+1.56	−0.64 (−2.62, +1.16)
Atmospheric Sciences and Meteorology	+4.59	+2.42	+1.30 (−1.00, +3.30)
Biomedical Engineering	+4.29	+2.08	+0.44 (−1.38, +2.40)
Microbiology	+5.28	+0.32	−0.99 (−2.51, +0.59)
Cell Biology	+4.82	+0.33	−0.48 (−2.06, +1.11)
Marine Sciences	+5.20	+1.95	−0.08 (−2.85, +2.44)
Astronomy	+2.89	+1.52	+0.08 (−1.22, +1.35)
Evolutionary Biology	+6.79	+1.88	+0.54 (−2.10, +3.21)
Ecology	+6.23	+3.54	+1.42 (−0.88, +3.92)
Neuroscience	+4.19	−0.07	−0.75 (−2.63, +1.02)
Molecular Biology	+3.40	+0.83	−0.16 (−1.83, +1.53)
Mathematics and Computing			
Statistics	+2.89	+1.64	+0.24 (−1.43, +1.72)
Mathematics	+2.86	+0.65	−0.44 (−1.22, +0.41)
Computer Engineering	+2.66	+0.23	−0.18 (−1.08, +0.79)
Computer Science	+2.26	−0.09	−0.55 (−1.51, +0.32)
Information Technology	+0.88	−1.17	−0.29 (−2.68, +2.01)
Information Science	+0.81	−1.00	−1.70 (−4.20, +1.05)
Engineering			

Continued on next page

Table S2 (continued)

Mechanical Engineering	$+3.39$	$+0.60$	-0.18 (-1.09, $+0.75$)
Systems Engineering	$+3.29$	$+0.48$	-1.29 (-3.85, $+1.15$)
Aerospace Engineering	$+2.53$	$+1.18$	$+0.33$ (-1.27, $+1.93$)
Electrical Engineering	$+2.18$	$+0.46$	-0.22 (-1.11, $+0.66$)
Agricultural Engineering	$+4.74$	$+1.22$	-0.16 (-1.96, $+1.44$)
Operations Research	$+2.53$	-0.39	-0.99 (-3.44, $+1.32$)
Environmental Engineering	$+4.94$	$+0.91$	-0.91 (-2.30, $+0.52$)
Civil Engineering	$+4.30$	$+1.54$	-0.25 (-1.51, $+1.07$)
Materials Engineering	$+4.68$	$+0.46$	-0.85 (-2.76, $+0.80$)
Industrial Engineering	$+1.86$	$+1.66$	$+0.14$ (-2.25, $+2.54$)

Table S2 (continued)

Field	Women	Men	Pct. Women
Health			
Environmental Health Sciences	285	430	39.9
Nursing	3531	515	87.3
Public Health	1813	1555	53.8
Human Development and Family Sciences	765	486	61.2
Speech and Hearing Sciences	352	184	65.7
Exercise Science, Kinesiology, Rehab, Health	1612	1555	50.9
Nutrition Sciences	722	604	54.4
Communication Disorders and Sciences	450	215	67.7
Health, Physical Education, Recreation	356	427	45.5
Social Work	1308	696	65.3
Education			
Education	1301	857	60.3
Special Education	452	277	62.0
Education Administration	986	840	54.0
Counselor Education	566	405	58.3
Curriculum and Instruction	1204	654	64.8
Journalism, Media, Communication			
Communication	1054	1208	46.6
Mass Communications and Media Studies	947	1093	46.4
Humanities			
Theological Studies	324	958	25.3
Asian Languages	189	257	42.4
Slavic Languages and Literatures	198	186	51.6
Classics and Classical Languages	513	596	46.3
French Language and Literature	291	253	53.5
Germanic Languages and Literatures	244	264	48.0
Theatre Literature, History and Criticism	574	615	48.3
Art History and Criticism	1006	912	52.5
Asian Studies	237	344	40.8
History	2071	3008	40.8
Urban and Regional Planning	335	506	39.8
Linguistics	404	467	46.4
English Language and Literature	2968	2918	50.4
Near & Middle Eastern Langs. & Cultures	160	268	37.4
Music	1239	2747	31.1
Philosophy	788	1773	30.8
Religious Studies	446	900	33.1
Comparative Literature	354	364	49.3
Spanish Language and Literature	438	409	51.7
Architecture	606	1205	33.5
Public Administration and Policy			
Public Policy	687	1146	37.5

Table S3

Number of faculty by field and gender, 2020.

Estimated counts of women and men faculty based on 2020 faculty rosters and name-based gender inference [25].

Public Administration	446	645	40.9
Social Sciences			
Sociology	1501	1483	50.3
Gender Studies	474	82	85.3
Anthropology	1305	1291	50.3
Political Science	1345	2702	33.2
International Affairs	426	851	33.4
Geography	482	933	34.1
Psychology	2826	3215	46.8
Agricultural Economics	171	532	24.3
Educational Psychology	555	463	54.5
Economics	804	3039	20.9
Criminal Justice and Criminology	466	588	44.2
Business			
Accounting	536	1186	31.1
Marketing	516	1069	32.6
Management Information Systems	231	867	21.0
Finance	377	1503	20.1
Business Administration	546	1473	27.0
Management	880	2136	29.2
Medicine			
Genetics	324	612	34.6
Pharmaceutical Sciences	444	912	32.7
Epidemiology	778	747	51.0
Pharmacology	512	1268	28.8
Pharmacy	567	639	47.0
Physiology	620	1446	30.0
Veterinary Medical Sciences	956	1281	42.7
Immunology	677	1303	34.2
Natural Sciences			
Entomology	191	494	27.9
Soil Science	163	506	24.4
Anatomy	387	763	33.7
Natural Resources	340	877	27.9
Plant Sciences	250	656	27.6
Plant Pathology	166	446	27.1
Biophysics	223	689	24.5
Food Science	353	474	42.7
Pathology	1199	1868	39.1
Horticulture	117	394	22.9
Biostatistics	457	676	40.3
Agronomy	149	526	22.1
Animal Sciences	337	749	31.0
Forestry and Forest Resources	229	655	25.9
Geology	770	2098	26.8
Biological Sciences	1895	3656	34.1
Physics	800	4364	15.5
Chemistry	1024	3671	21.8
Biochemistry	1001	2884	25.8
Chemical Engineering	405	1692	19.3
Environmental Sciences	624	1416	30.6
Atmospheric Sciences and Meteorology	267	757	26.1
Biomedical Engineering	426	1284	24.9
Microbiology	884	1815	32.8
Cell Biology	844	1699	33.2
Marine Sciences	279	722	27.9
Astronomy	416	1937	17.7
Evolutionary Biology	293	521	36.0
Ecology	370	662	35.9
Neuroscience	721	1443	33.3

Table S3 (continued)

Molecular Biology	732	1669	30.5
Mathematics and Computing			
Statistics	474	1598	22.9
Mathematics	1072	4688	18.6
Computer Engineering	584	3581	14.0
Computer Science	885	4291	17.1
Information Technology	211	759	21.8
Information Science	404	723	35.8
Engineering			
Mechanical Engineering	562	3428	14.1
Systems Engineering	152	654	18.9
Aerospace Engineering	209	1364	13.3
Electrical Engineering	613	3914	13.5
Agricultural Engineering	378	1386	21.4
Operations Research	149	632	19.1
Environmental Engineering	517	1854	21.8
Civil Engineering	585	2217	20.9
Materials Engineering	340	1439	19.1
Industrial Engineering	212	838	20.2

Table S3 (continued)

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Editors

Reviewing Editor
Peter Rodgers
eLife, Cambridge, United Kingdom

Senior Editor
Peter Rodgers
eLife, Cambridge, United Kingdom

Reviewer #1 (Public Review):

Summary
This is an interesting paper that concludes that hiring more women will do more to improve the gender balance of (US) academia than improving the attrition rates of women (which are usually higher than men's). Other groups have reported similar findings, i.e. that improving hiring rates does more for women's representation than reducing attrition, but this study uses a larger than usual dataset that spans many fields and institutions so it is a good contribution to the field.

The paper is much improved and far more convincing as a result of the revisions made by the authors.

Strengths
A large data set with many individuals, many institutions and fields of research.
A good sensitivity analysis to test for potential model weaknesses.

Weaknesses
Only a single country with a very specific culture and academic system.
Complex model fitting with many steps and possible places for model bias.

https://doi.org/10.7554/eLife.93755.2.sa1

Reviewer #3 (Public Review):

Summary
This study investigates the roles of faculty hiring and attrition in influencing gender representation in U.S. academia. It uses a comprehensive dataset covering tenured and tenure-track faculty across various fields from 2011 to 2020. The study employs a counterfactual model to assess the impact of hypothetical gender-neutral attrition and projects future gender representation under different policy scenarios. The analysis reveals that hiring has a more significant impact on women's representation than attrition in most fields and highlights the need for sustained changes in hiring practices to achieve gender parity.

The revisions made by the authors have improved the paper.

Strengths
Overall, the manuscript offers significant contributions to understanding gender diversity in academia through its rigorous data analysis and innovative methodology.

The methodology is robust, employing extensive data covering a wide range of academic fields and institutions.

Weaknesses
The primary weakness of the study lies in its focus on U.S. academia, which may limit the generalizability of its findings to other cultural and academic contexts. Additionally, the counterfactual model's reliance on specific assumptions about gender-neutral attrition could affect the accuracy of its projections.

Additionally, the study assumes that whoever disappeared from the dataset is attrition in academia. While in reality, those attritions could be researchers who moved to another country or another institution that is not indexed by AA.

https://doi.org/10.7554/eLife.93755.2.sa0

Author response:

The following is the authors' response to the original reviews.

Your editorial guidance, reviews, and suggestions have led us to make substantial changes to our manuscript. While we detail point-by-point responses in typical fashion below, I wanted to outline, at a high level, what we've done.

(1) Methods. Your suggestions led us to rethink our presentation of our methods, which are now described more cohesively in a new methods section in the main text.

(2) Model Validation & Robustness. Reviewers suggested various validations and checks to ensure that our findings were not, for instance, the consequence of a particular choice of parameter. These can be found in the supplementary materials.

(3) Data Cleaning & Inclusion/Exclusion. Finally, based on feedback, our new methods section fully describes the process by which we cleaned our original data, and on what grounds we included/excluded individual faculty records from analysis.

> > ***eLife assessment***
> >
> > *Efforts to increase the representation of women in academia have focussed on efforts to recruit more women and to reduce the attrition of women. This study - which is based on analyses of data on more than 250,000 tenured and tenure-track faculty from the period 2011-2020, and the predictions of counterfactual models - shows that hiring more women has a bigger impact than reducing attrition. The study is an important contribution to work on gender representation in academia, and while the evidence in support of the findings is solid, the description of the methods used is in need of improvement.*
>
> ***Reviewer #1 (Public Review):***
>
> *Summary and strengths*
>
> *This is an interesting paper that concludes that hiring more women will do more to improve the gender balance of (US) academia than improving the attrition rates of women (which are usually higher than men's). Other groups have reported similar findings but this study uses a larger than usual dataset that spans many fields and institutions, so it is a good contribution to the field.*

We thank the reviewer for their positive assessment of the contributions of our work.

> *Weaknesses*
>
> *The paper uses a mixture of mathematical models (basically Leslie matrices, though that term isn't mentioned here) parameterised using statistical models fitted to data. However, the description of the methods needs to be improved significantly. The author should consider citing Matrix Population Models by Caswell (Second Edition; 2006; OUP) as a general introduction to these methods, and consider citing some or all of the following as examples of similar studies performed with these models:*

> *Shaw and Stanton. 2012. Proc Roy Soc B 279:3736-3741*
>
> *Brower and James. 2020. PLOS One 15:e0226392*
>
> *James and Brower. 2022. Royal Society Open Science 9:220785 Lawrence and Chen. 2015.*
>
> *[http://128.97.186.17/index.php/pwp/article/view/PWP-CCPR-2015-008]*
>
> *Danell and Hjerm. 2013. Scientometrics 94:999-1006*

We have expanded the description of methods in a new methods section of the paper which we hope will address the reviewer's concerns.

We agree that our model of faculty hiring and attrition resembles Leslie matrices. In results section B, we now mention Leslie matrices and cite Matrix Population Models by Caswell, noting a few key differences between Leslie matrices and the model of hiring and attrition presented in this work. Most notably, in the hiring and attrition model presented, the number of new hires is not based on per-capita fertility constants. Instead, population sizes are predetermined fixed values for each year, precluding exponential population growth or decay towards 0 that is commonly observed in the asymptotic behavior of linear Leslie Matrix models.

We have additionally revised the main text to cite the listed examples of similar studies (we had already cited James and Brower, 2022). We thank the reviewer for bringing these relevant works to our attention.

> *The analysis also runs the risk of conflating the fraction of women in a field with gender diversity! In female-dominated fields (e.g. Nursing, Education) increasing the proportion of women in the field will lead to reduced gender diversity. This does not seem to be accounted for in the analysis. It would also be helpful to state the number of men and women in each of the 111 fields in the study.*

We have carefully examined the manuscript and revised the text to correctly differentiate between gender diversity and women's representation.

We have additionally added a table to the supplemental materials (Tab. S3) that reports the estimated number of men and women in each of the 111 fields.

> ***Reviewer #2 (Public Review):***
>
> *Summary:*
>
> *This important study by LaBerge and co-authors seeks to understand the causal drivers of faculty gender demographics by quantifying the relative importance of faculty hiring and attrition across fields. They leverage historical data to describe past trends and develop models that project future scenarios that test the efficacy of targeted interventions. Overall, I found this study to be a compelling and important analysis of gendered hiring and attrition in US institutions, and one that has wide-reaching policy implications for the academy. The authors have also suggested a number of fruitful future avenues for research that will allow for additional clarity in understanding the gendered, racial, and socioeconomic disparities present in US hiring and attrition, and potential strategies for mitigating or eliminating these disparities.*

We thank the reviewer for their positive assessment of the contributions of our work.

> *Strengths:*

> *In this study, LaBerge et al use data from over 268,000 tenured and tenure-track faculty from over 100 fields at more than 12,000 PhD-granting institutions in the US. The period they examine covers 2011-2020. Their analysis provides a large-scale overview of demographics across fields, a unique strength that allows the authors to find statistically significant effects for gendered attrition and hiring across broad areas (STEM, non-STEM, and topical domains).*
>
> *LaBerge et al. find gendered disparities in attrition-using both empirical data and their counterfactual model-that account for the loss of 1378 women faculty across all fields between 2011 and 2020. It is true that "this number is both a small portion of academia... and a staggering number of individual careers," as ." - as this loss of women faculty is comparable to losing more than 70 entire departments. I appreciate the authors' discussion about these losses-they note that each of these is likely unnecessary, as women often report feeling that they were pushed out of academic jobs.*
>
> *LaBerge et al. also find-by developing a number of model scenarios testing the impacts of hiring, attrition, or both-that hiring has a greater impact on women's representation in the majority of academic fields in spite of higher attrition rates for women faculty relative to men at every career stage. Unlike many other studies of historical trends in gender diversity, which have often been limited to institution-specific analyses, they provide an analysis that spans over 100 fields and includes nearly all US PhD-granting institutions. They are able to project the impacts of strategies focusing on hiring or retention using models that project the impact of altering attrition risk or hiring success for women. With this approach, they show that even relatively modest annual changes in hiring accumulate over time to help improve the diversity of a given field. They also demonstrate that, across the model scenarios they employ, changes to hiring drive the largest improvement in the long-term gender diversity of a field.*
>
> *Future work will hopefully - as the authors point out - include intersectional analyses to determine whether a disproportionate share of lost gender diversity is due to the loss of women of color from the professoriate. I appreciate the author's discussion of the racial demographics of women in the professoriate, and their note that "the majority of women faculty in the US are white" and thus that the patterns observed in this study are predominately driven by this demographic. I also highly appreciate their final note that "equal representation is not equivalent to equal or fair treatment," and that diversifying hiring without mitigating the underlying cause of inequity will continue to contribute to higher losses of women faculty.*
>
> *Weaknesses*
>
> *First, and perhaps most importantly, it would be beneficial to include a distinct methods section. While the authors have woven the methods into the results section, I found that I needed to dig to find the answers to my questions about methods. I would also have appreciated additional information within the main text on the source of the data, specifics about its collection, inclusion and exclusion criteria for the present study, and other information on how the final dataset was produced. This - and additional information as the authors and editor see fit - would be helpful to readers hoping to understand some of the nuance behind the collection, curation, and analysis of this important dataset.*

We have expanded upon the description of methods in a new methods section of the paper.

We have also added a detailed description of the data cleaning steps taken to produce the dataset used in these analyses, including the inclusion/exclusion criteria applied. This detailed description is at the beginning of the methods section. This addition has substantially enhanced the transparency of our data cleaning methods, so we thank the reviewer for this suggestion.

> *I would also encourage the authors to include a note about binary gender classifications in the discussion section. In particular, I encourage them to include an explicit acknowledgement that the trends assessed in the present study are focused solely on two binary genders - and do not include an analysis of nonbinary, genderqueer, or other "third gender" individuals. While this is likely because of the limitations of the dataset utilized, the focus of this study on binary genders means that it does not reflect the true diversity of gender identities represented within the professoriate.*
>
> *In a similar vein, additional context on how gender was assigned on the basis of names should be added to the methods section.*

We use a free, open-source, and open-data python package called nomquamgender (Van Buskirk et al, 2023) to estimate the strengths of (culturally constructed) name-gender associations. For sufficiently strong associations with a binary gender, we apply those labels to the names in our data. We have updated the main text to make this approach more apparent.

We have also added language to the main text which explicitly acknowledges that our approach only assigns binary (woman/man) labels to faculty. We point out that this is a compromise due to the technical limitations of name-based gender methodologies and is not intended to reinforce a gender binary.

> *I do think that some care might be warranted regarding the statement that "eliminating gendered attrition leads to only modest changes in field-level diversity" (Page 6). while I do not think that this is untrue, I do think that the model scenarios where hiring is "radical" and attrition is unchanged from present (equal representation of women and men among hires (ER) + observed attrition (OA)) shows that a sole focus on hiring dampens the gains that can otherwise be addressed via even modest interventions (see, e.g., gender-neutral attrition (GNA) + increasing representation of women among hires (IR)). I am curious as to why the authors did not include an additional scenario where hiring rates are equal and attrition is equalized (i.e., GNA + ER). The importance of including this additional model is highlighted in the discussion, where, on Page 7, the authors write: "In our forecasting analysis, we find that eliminating the gendered attrition gap, in isolation, would not substantially increase representation of women faculty in academia. Rather, progress towards gender parity depends far more heavily on increasing women's representation among new faculty hires, with the greatest change occurring if hiring is close to gender parity." I believe that this statement would be greatly strengthened if the authors can also include a comparison to a scenario where both hiring and attrition are addressed with "radical" interventions.*

Our rationale for omitting the GNA + ER scenario in the presented analysis is that we can reason about the outcomes of this scenario without the need for computation; if a field has equal inputs of women and men faculty (on average) and equal retention rates between women and men (on average), then, no matter the field's initial age and gender distribution of faculty, the expected value for the percentage of women faculty after all of the prior faculty have retired (which may take 40+ years) is exactly 50%. We have updated the main text to discuss this point.

> ***Reviewer #3 (Public Review):***
>
> *This manuscript investigates the roles of faculty hiring and attrition in influencing gender representation in US academia. It uses a comprehensive dataset covering tenured and*

> *tenure-track faculty across various fields from 2011 to 2020. The study employs a counterfactual model to assess the impact of hypothetical gender-neutral attrition and projects future gender representation under different policy scenarios. The analysis reveals that hiring has a more significant impact on women's representation than attrition in most fields and highlights the need for sustained changes in hiring practices to achieve gender parity.*
>
> *Strengths:*
>
> *Overall, the manuscript offers significant contributions to understanding gender diversity in academia through its rigorous data analysis and innovative methodology.*
>
> *The methodology is robust, employing extensive data covering a wide range of academic fields and institutions.*
>
> *Weaknesses:*
>
> *The primary weakness of the study lies in its focus on US academia, which may limit the generalizability of its findings to other cultural and academic contexts.*

We agree that the U.S. focus of this study limits the generalizability of our findings. The findings that we present in this work will only generalize to other populations–whether it be to an alternate industry, e.g., tech workers, or to faculty in different countries–to the extent that these other populations share similar hiring patterns, retention patterns, and current demographic representation. We have added a discussion of this limitation to the manuscript.

> *Additionally, the counterfactual model's reliance on specific assumptions about gender-neutral attrition could affect the accuracy of its projections.*

Our projection analysis is intended to illustrate the potential gender representation outcomes of several possible counterfactual scenarios, with each projection being conditioned on transparent and simple assumptions. In this way, the projection analysis is not intended to predict or forecast the future.

To resolve this point for our readers, we now introduce our projections in the context of the related terms of prediction and forecast, noting that they have distinct meanings as terms of art: On one hand, prediction and forecasting involve anticipating a specific outcome based on available information and analysis, and typically rely on patterns, trends, or historical data to make educated guesses about what will happen. Projections are based on assumptions and are often presented in a panel of possible future scenarios. While predictions and forecasts aim for precision, projections (which we make in our analysis) are more generalized and may involve a range of potential outcomes.

> *Additionally, the study assumes that whoever disappeared from the dataset is attrition in academia. While in reality, those attritions could be researchers who moved to another country or another institution that is not included in the AARC (Academic Analytics Research Centre) dataset.*

In our revision, we have elevated this important point, and clarified it in the context of the various ways in which we count hires and attritions. We now explicitly state that “We define faculty hiring and faculty attrition to include all cases in which faculty join or leave a field or domain within our dataset.” Then, we enumerate the number of situations that could be counted as hires and attritions, including the reviewer’s example of faculty who move to another country.

> ***Reviewer #1 (Recommendations For The Authors):***
>
> *Section B: The authors use an age structured Leslie matrix model (see Caswell for a good reference to these) to test the effect of making the attrition rates or hiring rates equal for men and women. My main concern here is the fitting techniques for the parameters. These are described (a little too!) briefly in section S1B. Some specific questions that are left hanging include:*
>
> *A 5th order polynomial is an interesting choice. Some statistical evidence as to why it was the best fit would be useful. What other candidate models were compared? What was the "best fit" judgement made with: AIC, r^2? What are the estimates for how good this fit is? How many data points were fitted to? Was it the best fit choice for all of the 111 fields for men and women?*

We use a logistic regression model for each field to infer faculty attrition probabilities across career ages and time, and we include the career age predictor up to its fifth power to capture the career-age correlations observed in Spoon et. al., Science Advances, 2023. For ease of reference, we reproduce the attrition risk curves in Fig S4.

We note that faculty attrition rates start low and then reach a peak around 5-7 years after earning PhD, and then decline until around 15-20 years post-PhD, after which, attrition rates increase as faculty approach retirement.

This function shape starts low and ends high, and includes at least one local minimum, which indicates that career age should be odd-ordered in the model and at least order-3, but only including career age up to its 3rd order term tended to miss some of the overserved career-age/attrition correlations. We evaluated the fit using 5-fold cross validation with a Brier score loss metric, and among options of polynomials of degree 1, 3, 5, or 7, we found that 5th order performed well overall on average over all fields (even if it was not the best for every field), without overfitting in fields with fewer data. Example fits, reminiscent of the figure from Spoon et al, are now provided in Figs S4 and S5.

While the model fit with fifth order terms may not be the best fit for all 111 fields (e.g., 7th order fits better in some cases), we wanted to avoid field-specific curves that might be overfitted to the field-specific data, especially due to low sample size (and thus larger fluctuations) on the high career age side of the function. Our main text and supplement now includes justifications for our choice to include career age up to its fifth order terms.

> *You used the 5th order logistic regression (bottom of page 11) to model attrition at different ages. The data in [24] shows that attrition increases sharply, then drops then increases again with career age. A fifth order polynomial on its own could plausibly do this but I associate logistic regression models like this as being monotonically increasing (or decreasing!), again more details as to how this worked would be useful.*

Our first submission did not explain this point well, but we hope that Supplementary Figures S4 and S5 provide clarity. In short, we agree of course that typical logistic regression assumes a linear relationship between the predictor variables and the log odds of the outcome variable. This means that the relationship between the predictor variables and the probability of the outcome variable follows a sigmoidal (S-shaped) curve. However, the relationship between the predictor variables and the outcome variable may not be linear.

To capture more complex relationships, like the increasing, decreasing and then increasing attrition rates as a function of career age, higher-order terms can be added to the logistic regression model. These higher-order terms allow the model to capture nonlinear relationships between the predictor variables and the outcome variable — namely the nonmonotonic relationship between rates of attrition and career age — while staying within a logistic regression framework.

> *"The career age of new hires follows the average career age distribution of hires" did you use the empirical distribution here or did you fit a standard statistical distribution e.g. Gamma?*

We used the empirical distribution. This information has been added to the updated methods section in the main text.

> *How did you account for institution (presumably available)? Your own work has shown that institution types plays a role which could be contributing to these results.*

See below.

> *What other confounding variables could be at play here, what is available as part of the data and what happens if you do/don't account for them?*

A number of variables included in our data have been shown to correlate with faculty attrition, including PhD prestige, current institution prestige, PhD country, and whether or not an individual is a “self-hire,” i.e., trained and hired at the same institution (Wapman et. al., Nature, 2022). Additional factors that faculty self-report as reasons for leaving academia include issues of work-life balance, workplace climate, and professional reasons, and in some cases to varying degrees between men and women faculty (Spoon et. al., Sci. Adv., 2023).

Our counterfactual analysis aims to address a specific question: how would women’s representation among faculty be different today if men and women were subjected to the same attrition patterns over the past decade? To answer this question, it is important to account for faculty career age, which we accept as a variable that will always correlate strongly with faculty attrition rates, as long as the tenure filter remains in place and faculty continue to naturally progress towards retirement age. On the other hand, it is less clear why PhD country, self-hire status, or any of the other mentioned variables should necessarily correlate with attrition rates and with gendered differences in attrition rates more specifically. While some or all of these variables may underlie the causal roots of gendered attrition rates, our analysis does not seek to answer causal questions about why faculty leave their jobs (e.g., by testing the impact of accounting for these variables in simulations per the reviewers suggestion). This is because we do not believe the data used in this analysis is sufficient to answer such questions, lacking comprehensive data on faculty stress (Spoon et. al., Sci. Adv., 2023), parenthood status, etc.

> *What career age range did the model use?*

The career age range observed in model outcomes are a function of the empirically derived attrition rates for faculty across academic fields. The highest career age observed in the AARC data was 80, and the faculty career ages that result from our model simulations and projections do not exceed 80.

We have also added the distribution of faculty across career ages for the projection scenario model outputs in the supplemental materials Fig. S3 (see response to your later comment regarding career age for further details). Looking at these distributions, it is observed that very few faculty have career age > 60, both in observation and in our simulations.

> *What was the initial condition for the model?*

Empirical 2011 Faculty rosters are used as the initial conditions for the counterfactual analysis, and 2020 faculty rosters are these as the initial conditions for the projections analysis. This information has been added to the descriptions of methods in the main text.

> *Starting the model in 2011 how well does it fit the available data up to 2020?*

Thank you for this suggestion. We ran this analysis for each field starting in 2011, and found that model outcomes were statistically indistinguishable from the observed 2020 faculty gender compositions for all 111 academic fields. This finding is not surprising, because the model is fit to the observed data, but it serves to validate the methods that we used to extract the model's parameters. We have added these results to the supplement (Fig. S2).

> *What are the sensitivity analysis results for the model? If you have made different fitting decisions how much would the results change? All this applied to both the hiring and attrition parameters estimates.*

We model attrition and hiring using logistic regression, with career age included as an exogenous variable up to its fifth power. A natural question follows: what if we used a model with career age only to its first or third power? Or to higher powers? We performed this sensitivity analysis, and added three new figures to the supplement to present these findings:

First, we show the observed attrition probabilities at each career age, and four model fits to attrition data (Supplementary Figs S4 and S5). The first model includes career age only to its first power, and this model clearly does not capture the full career age / attrition correlation structure. The second model includes career age to its third power, which does a better job of fitting to the observed patterns. The third model includes career age up to its fifth power, which appears to very modestly improve upon the former model. The fourth model includes career age up to its seventh power, and the patterns captured by this model are largely the same as the 5th-power model up to career age 50, beyond which there are some notable differences in the inferred attrition probabilities. These differences would have relatively little impact on model outcomes because the vast majority of faculty have a career age below 50.

Second, we show the observed probability that hires are women, conditional on the career age of the hire. Once again, we fit four models to the data, and find that career age should be included at least up to its fifth order in order to capture the correlation structures between career age and the gender of new hires. However, limited differences result from including career age up to the 7th degree in the model (relative to the 5th degree).

As a final sensitivity analysis, we reproduce Fig. 2, but rather than including career age as an exogenous variable up to its fifth power in our models for hiring and attrition, we include career age up to its third power. Findings under this parameterization are qualitatively very similar to those presented in Fig. 2, indicating that the results are robust to modest changes to model parameterization (shown in supplement Fig. S6).

> *Far more detail in this and some interim results from each stage of the analysis would make the paper far more convincing. It currently has an air of "black box" too much of the analysis which would easily allow an unconvinced reader to discard the results.*

We have added more detailed descriptions of the methods to the main text. We hope that the changes made will address these concerns.

> *Section C: You use the Leslie model to predict the future population. As the model is linear the population will either grow exponentially (most likely) or dwindle to zero. You*

> *mention you dealt with this by scaling the average value of H to keep the population at 2020 levels? This would change the ratio of hiring to attrition. How did this affect the timescale of the results. If a field had very minimal attrition (and hence grew massively over the time period of the dataset) the hiring rate would have to be very small too so there would be very little change in the gender balance. Did you consider running the model to steady state instead?*

We chose the 40 year window (2020-2060) for this projection analysis because 40 years is roughly the timespan of a full-length faculty career. In other words, it will take around 40 years for most of the pre-existing faculty from 2020 to retire, such that the new, simulated faculty will have almost entirely replaced all former faculty by 2060.

For three out of five of our projection scenarios (OA, GNA, OA+ER), the point at which observed faculty are replaced by simulated faculty represents steady state. One way to check this intuition is to observe the asymptotic behavior of the trajectories in Fig. 3B; the slopes for these 3 scenarios nearly level out within 40 years.

The other two scenarios (OA + IR, GNA+IR) represent situations where women's representation among new hires is increasing each year. These scenarios will not reach steady state until women represent 100% of faculty. Accordingly, the steady state outcomes for these scenarios would yield uninteresting results; instead, we argue that it is the relative timescales that are interesting.

> *What did you do to check that your predictions at least felt realistic under the fitted parameters? (see above for presenting the goodness of fit over the 10 years of the data).*

We ran the analysis suggested in a prior comment (Starting the model in 2011 how well does it fit the available data up to 2020?) and found that model outcomes were statistically indistinguishable from the observed 2020 faculty gender compositions for all 111 academic fields, plus the "All STEM" and "All non-STEM" aggregations.

> *You only present the final proportion of women for each scenario. As mentioned earlier, models of this type have a tendency to lead to strange population distributions with wild age predictions and huge (or zero populations). Presenting more results here would assuage any worries the reader had about these problems. What is the predicted age distribution of men and women in the long term scenarios? Would a different method of keeping the total population in check have yielded different results? Interim results, especially from a model as complex as this one, rather than just presenting a final single number answer are a convincing validation that your model is a good one! Again, presenting this result will go a long way to convincing readers that your results are sound and rigorous.*

Thank you for this suggestion. We now include a figure that presents faculty age distributions for each projection scenario at 2060 against the observed faculty age distribution in 2020 (pictured below, and as Fig. S3 in the supplementary materials). We find that the projected age distributions are very similar to the observed distributions for natural sciences (shown) and for the additional academic domains. We hope this additional validation will inspire confidence in our model of faculty hiring and attrition for the reviewer, and for future readers.

In Fig S3, line widths for the simulated scenarios span the central 95% of simulations.

> *Other people have reached almost identical conclusions (albeit it with smaller data sets) that hiring is more important than attrition. It would be good to compare your conclusions with their work in the Discussion.*

We have revised the main text to cite the listed examples of similar studies. We thank the reviewer for bringing these relevant works to our attention.

> *General comments:*
>
> *What thoughts have you given to non-binary individuals?*
>
> *Be careful how you use the term "gender diversity"! In many countries "Gender diverse" is a term used in data collection for non-binary individuals, i.e. Male, female, gender diverse. The phrase "hiring more gender diverse faculty" can be read in different ways! If you are only considering men and women then gender balance may be a better framework to use.*

We have added language to the main text which explicitly acknowledges that our analysis focuses on men and women due to limitations in our name-based gender tool, which only assigns binary (woman/man) labels to faculty. We point out that this is a compromise due to the technical limitations of name-based gender methodologies and is not intended to reinforce a gender binary.

We have also taken additional care with referring to "gender diversity," per reviewer 1's point in their public review.

> ***Reviewer #2 (Recommendations For The Authors):***
>
> *Data availability: I did not see an indication that the dataset used here is publicly available, either in its raw format or as a summary dataset. Perhaps this is due to the sensitive nature of the data, but regardless of the underlying reason, the authors should include a note on data availability in the paper.*

The dataset used for these analyses were obtained under a data use agreement with the Academic Analytics Research Center (AARC). While these data are not publicly available, researchers may apply for data access here: https://aarcresearch.com/access-our-data.

We also added a table to the supplemental materials (Tab. S3) that reports the estimated number of men and women in each of the 111 fields.

Additionally, a variety of summary statistics based on this dataset are available online, here: https://github.com/LarremoreLab/us-faculty-hiring-networks/tree/main

> *Gender classification: Was an existing package used to classify gender from names in the dataset, or did the authors develop custom code to do so? Either way, this code should be cited. I would also be curious to know what the error rate of these classifications are, and suggest that additional information on potential biases that might result from automated classifications be included in the discussion, under the section describing data limitations. The reliability of name-based gender classification is particularly of interest, as external gender classifications such as those applied on the basis of an individual's name - may not reflect the gender with which an individual self-identifies. In other words, while for many people their names may reflect their true genders, for others those names may only reflect their gender assigned at birth and not their self-perceived or lived gender identity. Nonbinary faculty are in particular invisibilized here (and through any analysis that assigns binary gender on the basis of name). While these considerations do not detract from the main focus of the study - which was to utilize an existing dataset classified only on the basis of binary gender to assess trends for women faculty-these limitations should be addressed as they provide additional context for the interpretation of the results and suggest avenues for future research.*

We use a free, open-source, and open-data python package called nomquamgender (Van Buskirk et al, 2023) to estimate the strengths of (culturally constructed) name-gender associations. For sufficiently strong associations with a binary gender, we apply those labels to the names in our data. We have updated the main text to make this approach more apparent.

We have also added language to the main text which explicitly acknowledges that our approach only assigns binary (woman/man) labels to faculty. We point out that this is a compromise due to the technical limitations of name-based gender methodologies and is not intended to reinforce a gender binary.

As we mentioned in response to the public review, we use a free and open source python package called nomquamgender to estimate the strengths of name-gender associations, and we apply gender labels to the names with sufficiently strong associations with a binary gender. This package is based on a paper by Van Buskirk et. al. 2023, "An open-source cultural consensus approach to name-based gender classification," which documents error rates and potential biases.

We have also added language to the main text which explicitly acknowledges that our approach only assigns binary (woman/man) labels to faculty. We point out that this is a compromise due to the technical limitations of name-based gender methodologies and is not intended to reinforce a gender binary.

> *Page 1: The sentence beginning "A trend towards greater women's representation could be caused..." is missing a conjunction. It should likely read: "A trend towards greater women's representation could be caused entirely by attrition, e.g., if relatively more men than women leave a field, OR entirely by hiring..."*

We have edited the paragraph to remove the sentence in question.

> *Pages 1-2: The sentence beginning "Although both types of strategy..." and ending with "may ultimately achieve gender parity" is a bit of a run-on; perhaps it would be best to split this into multiple sentences for ease of reading.*

We have revised this run-on sentence.

> *Page 2: See comments in the public review about a methods section, the addition of which may help to improve clarity for the readers. Within the existing descriptions of what I consider to be methods (i.e., the first three paragraphs currently under "results"), some minor corrections could be added here. First, consider citing the source of the dataset in the line where it is first described (in the sentence "For these analyses, we exploit a census-level dataset of employment and education records for tenured and tenure-track faculty in 12,112 PhD-granting departments in the United States from 2011-2020.") It also may be helpful to include context here (or above, in the discussion about institutional analyses) about how "departments" can be interpreted. For example, how many institutions are represented across these departments? More information on how the authors eliminated the gendered aspect of patterns in their counterfactual model would be helpful as well; this is currently hinted at on page 4, but could instead be included in the methods section with a call-out to the relevant supplemental information section (S2B).*

We have added a citation to Academic Analytics Research Center's (AARC) list of available data elements to the data's introduction sentence. We hope this will allow readers to familiarize themselves with the data used in our analysis.

Faculty department membership was determined by AARC based on online faculty rosters. 392 institutions are represented across the 12,112 departments present in our dataset. We have updated the main text to include this information.

Finally, we have added a methods section to the main text, which includes information on how the gendered aspect of attrition patterns were eliminated in the counterfactual model.

> *Page 2: Perhaps some indication of how many transitions from an out-of-sample institution might be helpful to readers hoping to understand "edge cases."*

In our analysis, we consider all transitions from out-of-sample institutions to in-sample institutions as hires, and all transitions away from in-sample institutions–whether it be to an out of sample institution, or out of academia entirely–as attritions. We choose to restrict our analysis of hiring and attrition to PhD granting institutions in the U.S. in this way because our data do not support an analysis of other, out-of-sample institutions.

> *I also would have liked additional information on how many faculty switched institutions but remained "in-sample and in the same field" - and the gender breakdowns of these institutional changes, as this might be an interesting future direction for studies of gender parity. (For example, readers may be spurred to ask: if the majority of those who move institutions are women, what are the implications for tenure and promotion for these individuals?)*

While these mid-career moves are not counted as attritions in the present analysis, a study of faculty who switch institutions but remain (in-sample) as faculty could shed light on issues of gendered faculty retention at the level of institutions. We share the reviewer's interest in a more in depth study of mid-career moves and how these moves impact faculty careers, and we now discuss the potential value of such a study towards the end of the paper. In fact, this subject is the topic of a current investigation by the authors!

> *Page 3: I was confused by the statement that "of the three types of stable points, only the first point represents an equitable steady-state, in which men and women faculty have equal average career lengths and are hired in unchanging proportions." Here, for example, computer science appears to be close to the origin on Figure 1, suggesting that hiring has occurred in "unchanging proportions" over the study interval. However, upon analysis of Table S2, it appears that changes in hiring in Computer Science (+2.26 pp) are relatively large over the study interval compared to other fields. Perhaps I am reading too literally into the phrase that "men and women faculty are hired in unchanging proportions" - but I (and likely others) would benefit from additional clarity here.*

We had created an arrow along with the computer science label in Fig. 1, but it was difficult to see, which is likely the source of this confusion. This was our fault, and we have moved the "Comp. Sci." label and its corresponding arrow to be more visible in Figure 1.

Changes in women's representation in Computer Science due to hiring over 2011 - 2020 was +2.26 pp as the reviewer points out, but, consulting Fig. 1 and the corresponding table in the supplement, we observe that this is a relatively small amount of change compared to most fields.

> *Page 3: If possible it may be helpful to cite a study (or multiple) that shows that "changes in women's representation across academic fields have been mostly positive." What does "positive" mean here, particularly when the changes the authors observe are modest? Perhaps by "positive" you mean "perceived as positive"?*

We used the term positive in the mathematical sense, to mean greater than zero. We have reworded the sentence to read “women's representation across academic fields has been mostly increasing…” We hope this change clarifies our meaning to future readers.

> *Page 3: The sentence that ends with "even though men are more likely to be at or near retirement age than women faculty due to historical demographic trends" may benefit from a citation (of either Figure S3 or another source).*

We now cite the corresponding figure in this sentence.

> *Page 4: The two sentences that begin with "The empirical probability that a person leaves their academic career" would benefit from an added citation.*

We have added a citation to the sentences.

> *Figure 3: Which 10 academic domains are represented in Panel 3B? The colors in appear to correspond to the legend in Panel 3A, but no indication of which fields are represented is provided. If possible, please do so - it would be interesting and informative to be able to make these comparisons.*

This was not clear in the initial version of Fig. 3B, so we now label each domain. For reference, the domains represented in 3B are (from top to bottom):

- Health
- Education
- Journalism, Media, Communication
- Humanities
- Social Sciences
- Public Administration and Policy
- Medicine
- Business
- Natural Sciences
- Mathematics and Computing
- Engineering

> *Page 6: Consider citing relevant figure(s) earlier up in paragraph 2 of the discussion. For example, the first sentence could refer to Figure 1 (rather than waiting until the bottom of the paragraph to cite it).*

Thank you for this suggestion, we now cite Fig. 1 earlier in this discussion paragraph.

> *Page 10: A minor comment on the fraction of women faculty in any given year-the authors assume that the proportion of women in a field can be calculated from knowing the number of women in a field and the number of men. This is, again, true if assuming binary genders but not true if additional gender diversity is included. It is likely that the number of nonbinary faculty is quite low, and as such would not cause a large change in*

> *the overall proportions calculated here, but additional context within the first paragraph of S1 might be helpful for readers.*

We have added additional context in the first paragraph of S1, explaining that an additional term could be added to the equation to account for nonbinary faculty representation if our data included nonbinary gender annotations. Thank you for making this point.

> *Page 10: Please include a range of values for the residual terms of the decomposition of hiring and attrition in the sentence that reads "In Figure S1 we show that the residual terms are small, and thus the decomposition is a good approximation of the total change in women's representation."*

These residual terms range from -0.51pp to 1.14pp (median = 0.2pp). We have added this information to the sentence in question.

> *Page 12: It may be helpful to readers to include a description of the information contained in Table S2 in the supplemental text under section S3.*

We refer to table S2 twice in the main text (once in the observational findings, and once for the counterfactual analysis), and the contents of table S2 are described thoroughly in the table caption.

> ***Reviewer #3 (Recommendations For The Authors):***
>
> *(1) There is a potential limitation in the generalizability of the findings, as the study focuses exclusively on US academia. Including international perspectives could have provided a more global understanding of the issues at hand.*

The U.S. focus of this study limits the generalizability of our findings, as non-U.S. other faculty may exhibit differences in hiring patterns, retention patterns, and current demographic representations. We have added a discussion of this limitation to the manuscript. Unfortunately, our data do not support international analyses of hiring and attrition.

> *(2) I am not sure that everyone who disappeared from the AARC dataset could be count as "attrition" from academia. Indeed, some who disappeared might have completely left academia once they disappeared from the AARC dataset. Yet, there's also the possibility that some professors left for academic positions in countries outside of the US, or US institutions that are not included in the AARC dataset. These individuals didn't leave academia. Furthermore, it is also possible that these scholars who moved to an institution outside of US or not indexed by AARC are gender specific. Therefore, analyses that this study conducts should find a way to test whether the assumption that anyone who disappeared from AARC is indeed valid. If not, how will this potentially challenge the current conclusions?*

The reviewer makes an important point: faculty who move to faculty positions in other countries and faculty who move to non-PhD granting institutions, or to institutions that are otherwise not included in the AARC data are all counted as attritions in our analysis. We intentionally define hiring and attrition broadly to include all cases in which faculty join or leave a field or domain within our dataset.

The types of transitions that faculty make out of the tenure track system at PhD granting institutions in the U.S. may correlate with faculty attributes, like gender. For example, women or men may be more likely to transition to tenure track positions at non-U.S. institutions. Nevertheless, these types of career transition represent an attrition for the system of study, and a hire for another system. Following this same logic, faculty who transition from one field to another field in our analysis are treated as an attrition from the first field and a hire into the new field.

By focusing on "all-cause" attrition in this way, we are able to make robust insights for the specific systems we consider (e.g.,, STEM and non-STEM faculty at U.S. PhD granting institutions), without being roadblocked by the task of annotating faculty departures and arbitrating which should constitute "valid" attritions.

> *(3) It would be very interesting to know how much of the attribution was due to tenure failure. Previous studies have suggested that women are less likely to be granted tenure, which makes me wonder about the role that tenure plays in the gendered patterns of attrition in academia.*

We note that faculty attrition rates start low and then reach a peak around 5-7 years after earning PhD, and then decline until around 15-20 years post-PhD, after which, attrition rates increase as faculty approach retirement. The first local maximum appears to coincide roughly with the tenure clock timing, but we can only speculate that these attritions are tenure related. Our dataset is unfortunately not equipped to determine the causal mechanisms driving attrition.

We reproduce the attrition risk curve in the supplementary materials, Fig. S4:

> *(4) The dataset used doesn't fully capture the complexities of academic environments, particularly smaller or less research-intensive institutions (regional universities, historically black colleges and universities, and minority-serving institutions). This could be potentially added to the manuscript for discussions.*

We have added this point to the description of this study's limitations in the discussion.

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