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

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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.

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 undergraduate and PhD levels, but progress towards greater representation among tenure-track faculty has been much slower. Women have now 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 these slight changes in representation caused by hiring and attrition. A trend toward greater women's representation could be caused entirely by attrition, e.g., if relatively more men than women leave a field, entirely by hiring, e.g., if relatively more women are hired than men, or by a mixture of the two.

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, and we lack a clear prediction of how gender diversity may change in the future and

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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 [18–20]. 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 forecast 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 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. We organize these data into annual department-level faculty rosters. In turn, each department belongs to 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]. We added gender annotations to faculty using name-based gender classification for faculty names with high cultural name-gender associations (88%) [21], resulting in a dataset of $n = 268,769$ unique faculty, making up 1,768,118 person-years.

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 the tenure track for another job in academia, 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 to be hires or attritions.

A. Historical patterns of hiring and attrition

Most academic fields have become more gender diverse over time [8]. A field's demographic trends among hires can drive an increasing gender diversity within the field, and in many areas of study women's representation among PhD graduates has been growing for many years [22]. 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. S3) [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 [23, 24]. 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.

There are three distinct ways hiring and attrition can interact to produce an unchanging level of gender diversity. The first stable point is when a field's current gender diversity matches the gender diversity of new hires and new attritions ($\Delta_x = \Delta_y = 0$, the origin-point in Fig. 1). A second set of stable points occur when the concentration of men among new hires equals their concentration among attritions ($\Delta_x = -\Delta_y < 0$, the negatively sloped diagonal line in the second quadrant of Fig. 1). These stable

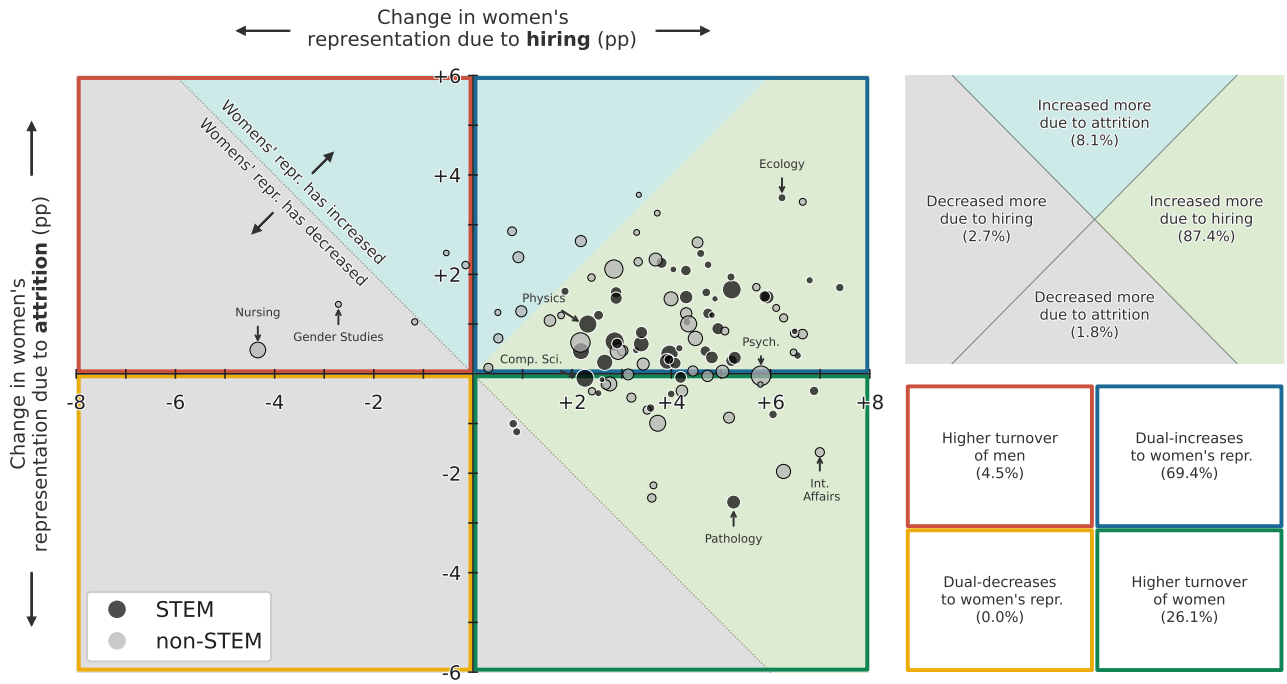

FIG. 1. Change in women's overall faculty representation for 111 academic fields between 2011–2020, decomposed into change due to hiring (horizontal axis) and change due to attrition (vertical axis, see supplement S1), showing that hiring increased women's representation for a large majority (87.4%) 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).

points correspond to a high turnover of men, in which a gendered outflow of men among attritions is compensated by an equal sized gendered inflow of male faculty that replaces those who left. A third set of stable points occur in the symmetric case for high turnover among women, with a gendered inflow of women hires and equal-sized gendered outflow via attrition ($\Delta_x = -\Delta_y > 0$, the negatively sloped diagonal line in the fourth quadrant of Fig. 1). 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. Hence, a field's location within this state space characterizes both its current velocity toward or away from gender parity, and allows us to categorize a trend toward greater diversity as being more due to hiring ($\Delta_x > |\Delta_y|$) or more due to attrition ($|\Delta_x| < \Delta_y$).

In this first analysis, we quantify the relative historical impacts of these processes via a descriptive analysis in which we decompose the overall change in women's representation within each field into its hiring and attrition components (S1). Additionally, we measure aggregate differences between STEM and non-STEM fields, which makes our results more comparable to past studies of faculty retention [24].

Between 2011 and 2020, we find that both faculty hiring and faculty attrition have contributed to increases in women's representation in most academic fields (Fig. 1, Table S2). Hiring contributed to an increase in 106 of 111 fields (95%), and attrition drove a further increase in 82 of 111 fields (74%). Hiring was the larger cause of increases to women's representation in the majority (87.4%) of academic fields, and all of the fields (8.1%) in which attrition was the larger cause of increased gender diversity are non-STEM fields.

Although changes in women's representation across academic fields have been mostly positive in light of widespread efforts to increase faculty gender diversity, the cumulative 9-year changes seem modest in size (mean = +4.8 percentage points, or *pp*). There are also several fields in which hiring and attrition has led to decreases in women's representation. Faculty attrition decreased women's representation in 29 fields (26%) between 2011 and 2020, even though men are more likely to be at or near retirement age than women faculty due to historical demographic trends. Women represent the majority of faculty in only 5 of these 29 (17.2%). In contrast, hiring has contributed to negative changes in women's representation in only 5 fields, including 2 which have a majority of women among faculty, Nursing and Gender Studies.

B. Historical impact of gendered attrition

In our second analysis, we measure the historical impact of gendered attrition on women's faculty representation using a counterfactual model in which we preserve the historical demographic trends in faculty hiring but

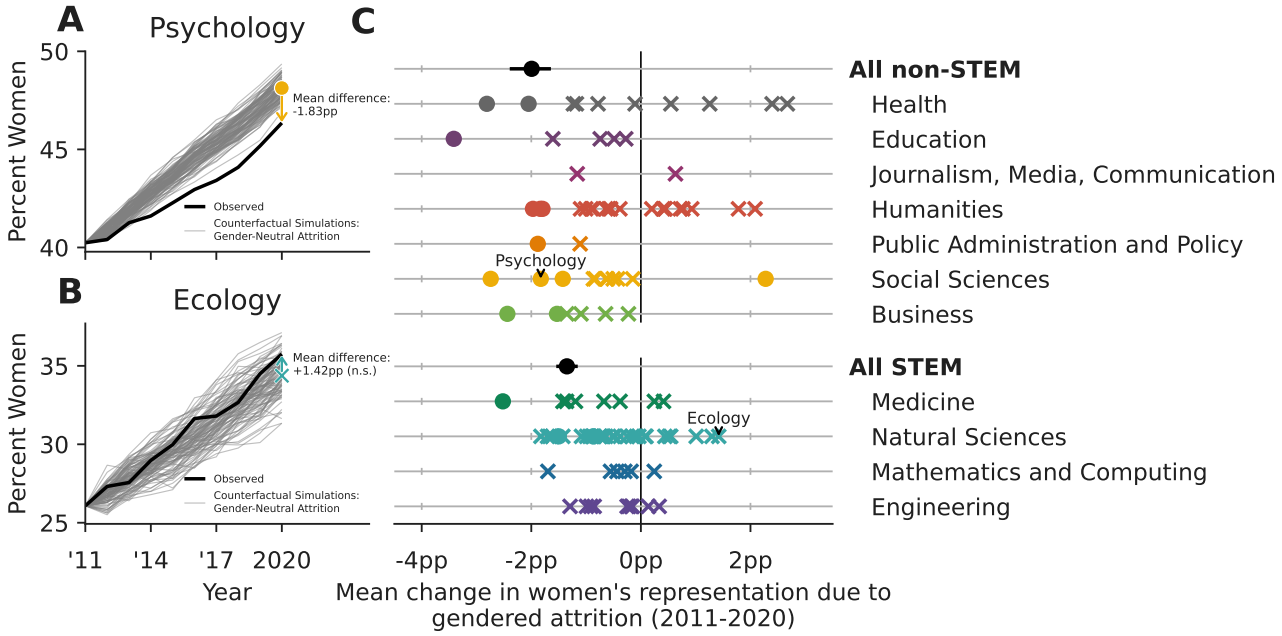

FIG. 2. Gendered faculty attrition has caused a differential loss of women faculty in both STEM and non-STEM fields. (A) Gendered attrition in psychology has caused a loss of -1.83 *pp* ($p < 0.01$) of women's representation between 2011-2020, relative to a counterfactual model with gender-neutral attrition (see supplement S2 B). 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, 16 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 (x-marks 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 stochastic simulations. No bars are included for field-level points to preserve readability.

set men's and women's attrition patterns to be equal for the academic years 2011–2020. We then measure the difference in each of 111 fields between the equal-attrition counterfactual and the observed historical pattern.

The empirical probability that a person leaves their academic career is known to vary with faculty career age. In particular, faculty attrition rates rise over the early career period to peak around 5-7 years after earning PhD, and then decline steadily until around 15-20 years post-PhD, after which, attrition rates increase again as faculty approach retirement. This pattern holds for both men and women, but women's overall rates are slightly higher than men's at every career stage [24]. In our counterfactual model we make attrition gender-neutral by eliminating the gendered aspect of these patterns, while preserving the rises and declines in attrition rates across faculty career ages, defined as years since earning a PhD (see supplement S2 B). Although the underlying attrition risk in the counterfactual model is the same function of career age for men and women, the simulated counts of faculty leaving are the result of weighted coin-flips for each faculty, each year. To capture this variability, we run 500 simulations of the counterfactual model for each field and record the resulting distribution of outcomes to define a null distribution against which we can characterize the relative likelihood of a field's observed gender representation, given gender-neutral attrition. For a detailed description of our methods, see supplement section S2 B.

Relative to this empirically-parameterized counterfactual model, we estimate that between 2011 and 2020, 15 fields, including Psychology, Philosophy, Chemistry, and Sociology, consistently decreased in women's representation across simulations, such that at least 95% of counterfactual simulations ended with greater representation of women in 2020 (circles in Fig. 2C). For example, in Psychology women would have, on average, represented an additional 1.83 *pp* of faculty if attrition risks had been gender-neutral (Fig. 2A). One field, Gender Studies, consistently increased women's representation as a result of gendered attrition. 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 (x-marks in Fig. 2C, Table S2).

Simulations for smaller fields tend to have more variable outcomes. This pattern is likely attributable to the smaller sample sizes at the field-level compared to the all STEM and all non-STEM aggregations, which exhibited large and significant losses in women's representation due to gendered attrition (-1.35 *pp*, $p < 0.01$ for STEM; -1.99 *pp*, $p < 0.01$ for non-STEM; Fig. 2C). This reality, paired with the relatively small differences in ob-

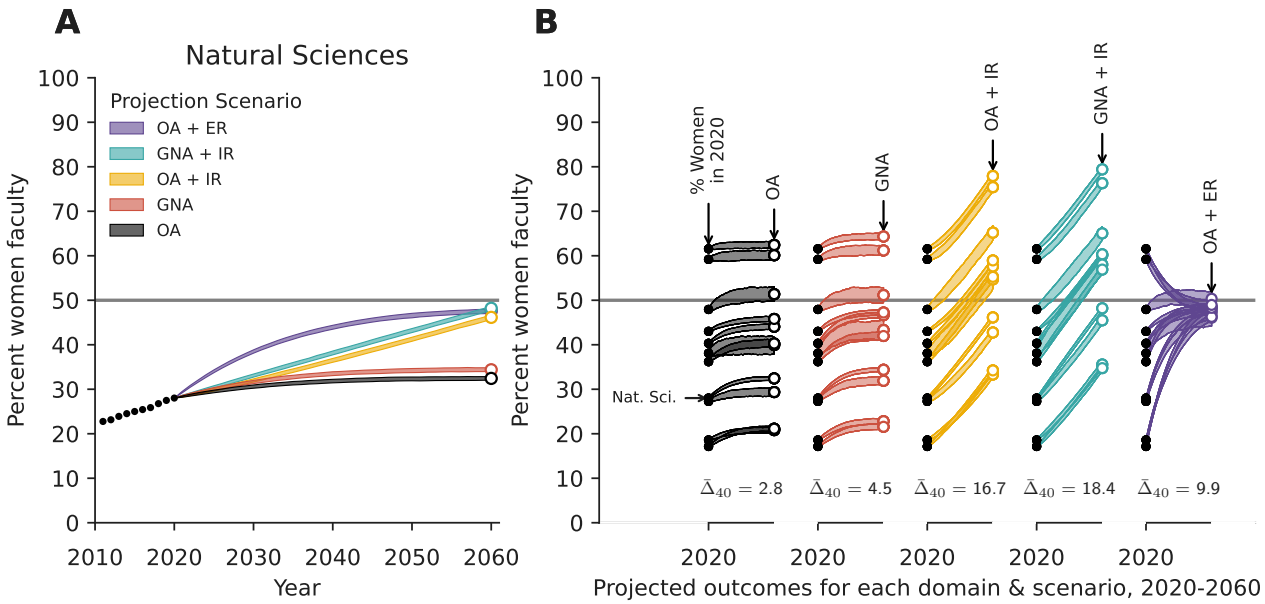

FIG. 3. (A) Observed (dotted line, 2011-2020) and projected (solid lines, 2021-2060) faculty gender diversity for natural sciences over time and (B) projections for 10 academic domains over 40 years under five policy scenarios. Line widths span the middle 95% of simulations and $\bar{\Delta}_{40}$ gives the mean change in women's representation across domains over the 40-year period. See text for scenario explanations. OA = observed attrition, GNA = gender-neutral attrition, IR = increasing representation of women among hires (+0.5% each year), ER = equal representation of women and men among hires.

served attrition rates between men and women faculty, makes it difficult to robustly identify when underlying attrition risks are gendered in smaller samples of faculty, e.g., within a single institution or department. As a consequence, the utility of employment-record based data is limited to revealing large-scale patterns only, and deeper, more qualitative studies are needed to understand gendered effects at smaller scales [24].

Across fields, our counterfactual model estimates that the average impact of gendered attrition has caused a net loss of 1378 women faculty across all fields of study between 2011 and 2020. Assuming 19.2 faculty per department (the mean department size in our dataset), this is an asymmetric loss of about 71.8 entire departments.

C. Projecting future gender representation

Often a proposed strategy or policy for increasing gender diversity among faculty will emphasize a change to hiring or to retention. However, 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 use our counterfactual model to answer several specific questions about the potential long-term impact of different interventions on hiring and/or attrition. In these experiments, 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 current levels or increased over time.

Via the two parameters, we define and evaluate five distinct scenarios: (i) a baseline lower-bound scenario in which no interventions are made and rates take their historical values, (ii-iv) three scenarios representing achievable interventions to attrition and hiring, and finally (v) a scenario that maximizes how quickly gender parity could be reached. For each scenario and for each of 11 academic domains, we make a model-based projection of the fraction of women faculty under each intervention. These scenarios are described in detail in the supplementary materials (Sec. S2 C).

The baseline "observed attrition" (OA) projection (Fig. 3) represents a scenario in which no interventions are taken. Instead, attrition risks and the fraction of new hires that are women are assumed to remain constant at the average observed values for 2011-2020. We note that in a subset of academic domains, the fraction of women among new hires has been increasing over time (supplement S3). In this scenario, we do not extrapolate that trend into the future. Despite this assumption, our model projects that the fraction of women faculty in the OA case will increase slightly between 2020 and 2060 in all 10 academic domains (average change = 2.8 *pp*, Fig. 3B). This prediction reflects a kind of "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, 25]. The resulting effect size over the 40-year projection period is relatively small compared to the observed increases in women's representation between 2011–

2020 because we used the average new-hire gender diversity over that period to parameterize the model (change across academia overall = 4.4 *pp*).

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 as we did in our second analysis above (Fig. 3). Hence, this scenario represents a set of policy interventions that entirely close the retention gap between women and men faculty. The resulting projected fraction women faculty in the natural sciences domain in 2060 is 34.4%, representing a 6.4 *pp* increase from 2020 (Fig. 3). Across all 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 by 2060.

In the next scenario, we alter new faculty hiring such that there are increases in representation (IR) of women faculty among new hires by a modest +0.5% each year while maintaining the gendered attrition of the OA scenario (Fig. 3, OA + IR). This rate of increase is close to what many academic fields have achieved over the past 10 years in increasing gender diversity among faculty (see supplement S3) and ultimately increases women's representation among new hires by +20% by 2060. For such domains, this scenario may not represent new action, but rather continued use of current policies. Across all domains the projected mean increase in women's representation between 2020 and 2060 across all domains is 16.7 *pp* (Fig. 3B). The magnitude of this increase is the largest among these first three scenarios, exceeding the OA scenario's mean increase by 12.2 *pp*. These increases would increase women's representation beyond gender parity in four domains: Medicine, Social Sciences, Humanities, and Public Administration & Policy.

Next, we combine the modifications of the GNA and IR scenarios: the attrition risks for men and women are set to be the equal at each career stage, and women's representation among new hires increases by +0.05% each year (Fig. 3, GNA + IR). Under this scenario, the projected mean increase in women's representation between 2020 and 2060 across all domains is 18.4 *pp* (Fig. 3B), which exceeds the mean increase in the previous scenario by 1.7 *pp*. These additional modest increases do not push any additional academic domains beyond gender parity.

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 (Fig. 3, OA + ER). In the Education and Health domains women are currently overrepresented among faculty, and hence hiring new faculty at gender parity causes a decrease in women's representation toward parity. Across all domains, the projected mean increase in women's representation between 2020 and 2060 is 9.9 *pp* (Fig. 3B). At the same time, none of the academic domains will achieve gender parity under this scenario because attrition remains gendered. On the other hand, 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).

Across all five scenarios, we find that changes to hiring drive the largest improvement in the long-term gender diversity of a field. Our results indicate that most fields, and particularly those with the least gender diversity, cannot achieve equal representation by only changing attrition patterns. In fact, our results suggest that even relatively modest annual changes in hiring tend to accumulate to substantial field-level improvements over time. In contrast, eliminating gendered attrition leads to only modest changes in projected field-level gender diversity (Fig. 3). This contrast highlights the different loci of interventions that target hiring vs. attrition. Mitigating gendered attrition preserves the contributions of current faculty to a field's gender diversity (and their corresponding contributions to scholarship), while more gender-equal hiring sets an upper limit for a field's gender diversity over the long term. As a result, gender equity in a field can only be achieved by efforts on both.

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 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 and in both broad academic domains and in individual fields, over the decade 2011–2020? (ii) How might women's representation today have been different if gendered-attrition among faculty were eliminated in 2011? (iii) And, how should we expect gender diversity among faculty to change over time, under different future hiring and attrition scenarios?

Over the decade 2011–2020, our data show that academia as a whole and most individual fields have become more gender diverse. For most fields, this change occurred primarily because of hiring more gender diverse faculty. Nevertheless, about 8% of fields increased their women's representation more because of faculty attrition than because of who they hired. These fields include Linguistics, Theological Studies, and Art History. In contrast, about 4.5% of fields decreased their women's representation over same period by their combination of hiring and attrition. These fields include Nursing and Gender Studies, both fields where women are over-represented (Fig. 1). This heterogeneity across fields illustrates the utility of taking a comparative approach to studying questions of faculty demographic trends: it reveals the broad variability of trends and patterns and helps surface hypotheses as to why some differences are small while others are not.

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, being 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 [24], 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 [26–28] lead us to expect that a disproportionate share of these lost careers would be women of color.

It is notable that 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, while we often find smaller effects that are not statistically significant in the constituent individual fields (Fig. 2, and Ref. [24]). This pattern implies that the gendered effects must also exist within the constituent fields, but tend to be obscured by their smaller sample sizes and greater relative fluctuations in hiring. This perspective may also explain why field-specific studies of gendered attrition sometimes reach conflicting conclusions about the presence of gendered differences among faculty [24, 29–31].

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 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).

We note that our study modeled faculty hiring and faculty attrition as independent processes. Past work suggests however that they can be linked. Hiring new faculty from underrepresented social groups can depend on the same cultural and environmental factors that drive gendered attrition. Hence, successful efforts to ameliorate the causes of gendered attrition are likely to also improve efforts to hire more women faculty. Such interactions between attrition and hiring underscore a need for future work to identify the mechanisms driving faculty to leave their tenure-track positions, and women faculty in particular.

While this study cannot identify specific causal mechanisms that drive gendered attrition, there is a substantial literature that points to a number of possibilities. For instance, a gendered disparity in the level of support and value attributed to women and the scholarly work that women produce [32, 33], sexual harassment [34], workplace culture [24], work-life balance [35, 36], and the unequal impacts of parenthood [37, 38]. Even in fields where we have found little 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") [24].

Another 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 [39, 40], and they may experience different trends in hiring and attrition, as may faculty at institutions that do not grant PhDs. Understanding how faculty hiring and faculty attrition are shaping the gender composition of these populations is an important direction for future work.

Faculty who belong to multiple marginalized groups (e.g. women of color) are particularly underrepresented and face unique challenges in academia [41]. The majority of women faculty in the U.S. are white [42], 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 is 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 [43, 44]. 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 [45].

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.

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

$$\frac{n_w + h_w - a_w}{n_w + h_w - a_w + n_m + h_m - a_m}$$

where h_w and h_m are the numbers of women and men that were hired in the following year, respectively, and a_w and a_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

$$\delta_{total} = \frac{n_w + h_w - a_w}{n_w + h_w - a_w + n_m + h_m - a_m} - \frac{n_w}{n_w + n_m}$$

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

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

$$\delta_{attrition} = \frac{n_w - a_w}{n_w - a_w + n_m - a_m} - \frac{n_w}{n_w + n_m}$$

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, and thus the decomposition is a good approximation of the total change in women's representation.

S2. MODEL OF HIRING AND ATTRITION

A. Model description

We develop a model of faculty hiring and attrition to facilitate testing of counterfactual scenarios (S2 B) and to make projections about the impacts of potential policy interventions on women's representation (S2 C). We start with simple update equations, which track the flow of faculty from a given demographic group (i.e., men or women) through faculty career ages:

$$n_\alpha \leftarrow n_{\alpha-1} + h_\alpha - a_{\alpha-1}$$

where the left arrow represents the passing of an academic year, n_α is the number of faculty in career age α (defined as years since receiving a PhD), h_α is the number of new hires into career age α, and $a_{\alpha-1}$ is the number of faculty in career age $\alpha - 1$ who left their faculty jobs. Then, we reparameterize the update equations to streamline counterfactual analyses and projections:

$$n_\alpha \leftarrow n_{\alpha-1} + H_\alpha \psi_\alpha - n_{\alpha-1}\phi_{\alpha-1}$$

where H_α is the total number of faculty hired into career age α across all demographic groups (i.e., men and women) in the given year, ψ_α is the probability that a given new hire is in the specific demographic group for the update equation (e.g., women), and $\phi_{\alpha-1}$ is the probability that faculty of career age $\alpha - 1$ leave their faculty jobs.

In our analyses, we experiment with changing the two parameters ψ_α and $\phi_{\alpha-1}$, which modulate the demographic diversity of hires, and the dynamics of attrition, respectively. After modeling the flow of faculty through career ages for men and women for a given set of parameters separately using the above equation, we can then calculate the overall gender diversity for each year. This is a probabilistic model in which hiring and attrition outcomes are determined by weighted coin flips, so we repeat this process many times (500 trials) under each set of parameters to measure average effects in addition to outcome variability.

B. Counterfactual Analysis

We use the model outlined in S2 A to conduct a counterfactual analysis for each academic field, in which women and men have the same risks of attrition (Fig. 2). To do this, we alter the parameter $\vec{\phi}$, a vector of faculty attrition risks (i.e., underlying attrition probabilities) at each

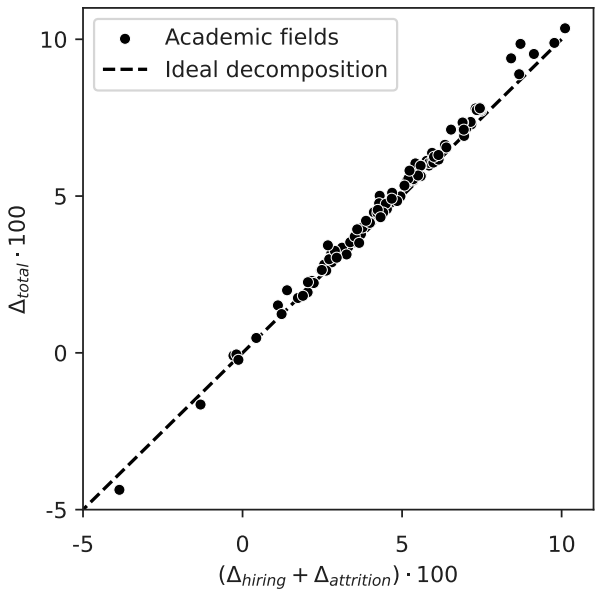

FIG. S1. The change in gender diversity between 2011 and 2020 can be approximately decomposed into parts due to hiring and attrition for each academic field, but there is a leftover residual term. In practice, we find that the residual term tends to be very small, such that the decomposition is nearly 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.

career age, while keeping all other model parameters close to their observed values.

There are many ways that women's and men's attrition risks can be equal. For example, men's attrition risk can be set to women's for each career age, such that men's risk would tend to increase in most fields. On the other hand, women's risk can be set to be equal to that of men. We present our analysis of the intermediate possibility, in which all faculty are assigned the "pooled" risk, which is the average attrition risk between men and women faculty.

To calculate the pooled risk, we train a logistic regression model to capture the high level trends in faculty attrition for each field. One key benefit of this approach is that it allows the robust inference of faculty attrition risks in each field for each career age, even for career ages where there is little or no observed data.

We allow attrition risks to vary non-linearly as a function of career age by including faculty career age, α, as a predictor in each logistic regression model, up to its fifth power. We find that this allows the shapes of attrition risks for each field to fit expected patterns [24], still without overfitting in fields with fewer data (checked using 5-fold cross validation with a Brier score loss metric). Furthermore, we include the academic year as a predictor in each model which allows inferred attrition risks to change linearly with time. The regression model takes the following form:

$$logit(p) = \beta_0 + \beta_1\alpha + \beta_2\alpha^2 + \beta_3\alpha^3 + \beta_4\alpha^4 + \beta_5\alpha^5 + \beta_6 Y$$

where Y is the academic year of a potential attrition event. We train these models on observed attrition-risk data for men and women together for each field, then use the learned parameters to infer the "gender-neutral" attrition risk for faculty at each academic year and career age.

We use this same approach to infer the fraction of women faculty among new hires for each field, but rather than training the logistic regression model on possible faculty attrition events, we use hiring events (e.g., hiring event is 1 if a woman is hired, or 0 if a man is hired).

The final parameter that we fit is $\vec{H}$, the number of faculty hired into each career age in each year. We choose to scale the number of hires each year such that the resulting field size aligns with the observed value for each given year. However, our qualitative results are robust to the reasonable alternative, which is to use the observed number of hires each year, and allow the field size to deviate from observed values as a function of the counterfactual attrition dynamics. It is additionally assumed that the career age of new hires follows the average career age distribution of hires that is observed over the course of 2011-2020.

Finally, we quantify the estimated effect size of gendered attrition for each field over the observed time period by plugging the inferred parameters into the update equation presented in S2 A, and running 500 counterfactual simulations for each set of parameters. We compare the observed fraction of women faculty in 2020 with the modeled fraction of women faculty where attrition risks are equal, and plot this difference in Figure 2. In the text, we also discuss the net difference between the observed number and the modeled number of women in academia, across all fields.

C. Projections Analysis

We create projections for the gender diversity outcomes of academic domains under several scenarios of hiring and attrition dynamics using the model outlined in S2 A. To test the impact of changes to attrition dynamics, we adjust $\vec{\phi}$, the vector of faculty attrition risks at each career age. To test the impact of changes to hiring, we make adjustments to $\vec{\psi}$, the fraction of faculty hired into each career age that are women.

We use the average hiring and attrition rates for each career age and gender as the baseline for our projections. There are two key benefits to this approach. First, by simply using average values, we do not make implicit assumptions about trends in the data, which allows us to explicitly and clearly state assumptions in the subsequent scenarios. For example, over the course of 2011-2020, new hires in the natural sciences have been growing more gender diverse over time (see supplement sec. S3), which likely reflects ongoing efforts to increase faculty diversity in that domain. For our baseline projection (labeled: "OA", Fig. 3), we assume that hiring dynamics will remain at their average values, instead of inferring trends (i.e., with a regression model) which may vary in direction and size across academic domains. Second, this simple approach is suitable to this analysis because at the level of academic domains we have sufficient data coverage to make reliable estimates for the average attrition and hiring probabilities at each career age (i.e., without the need to construct a model for each domain, as in S2 B).

For each academic domain, we input the average attrition and hiring parameters, for men and women separately, into the update equations described in S2 A and iterate for 40 years, ending in 2060. We choose to scale $\vec{H}$, the number of faculty hired into each career age in each year, so that the resulting number of faculty in each domain remains at its observed 2020 value. We run many forecasts for each scenario in order to measure the variability in outcomes, in addition to the average trends, then finally, we plot the resulting fractions of faculty that are women in each domain in Fig. 3.

This process is repeated for four additional scenarios. For the gender-neutral attrition (GNA) scenarios, we use the pooled average attrition risk between both men and women, rather than calculating attrition risks separately. For the OA + IR scenario, we leave attrition risks gendered (i.e., not pooled), but increase the share of women among new hires for each year by a half of a percentage point. This level of annual increase falls within the rates observed across domains (supplement sec. S3). In the following scenario, we combine the former two, by using pooled attrition risks, and increasing women's representation among new hires each year (GNA + IR). In the final scenario, women and men are equally likely to be hired across all career ages.

S3. 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. S2), 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).

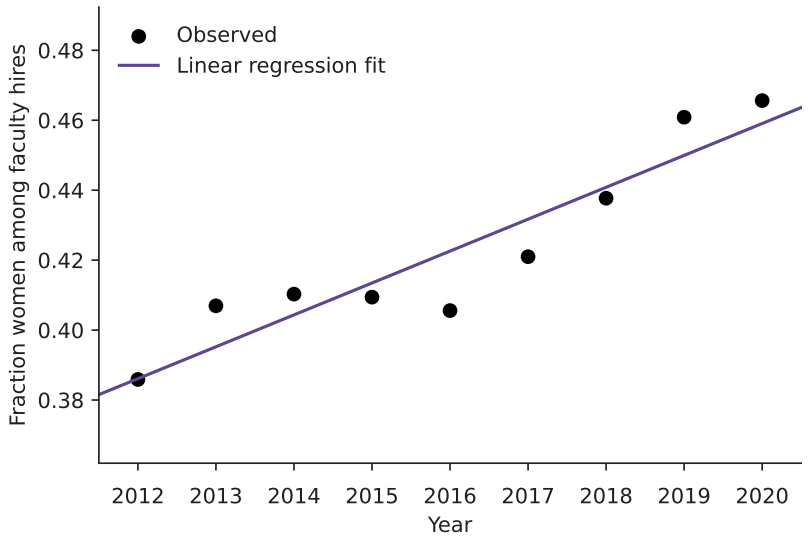

FIG. S2. Fraction of women among tenure-track faculty hires over time at U.S. PhD granting institutions. Women's share of new hires is observed to increase at around 0.91 *pp* annually ($p < 0.001$), measured by an ordinary least squares regression fit (shown in purple).

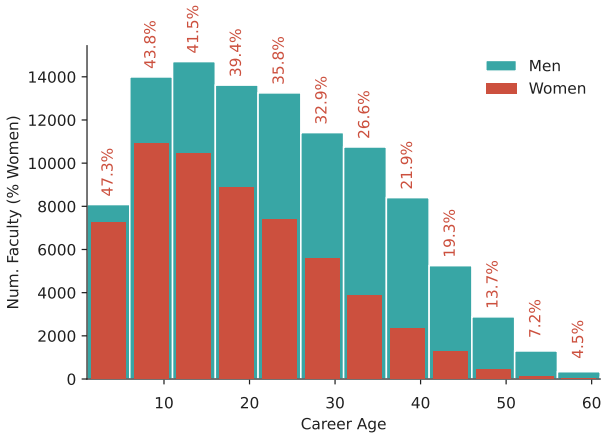

FIG. S3. Career age distribution of women (red) and men (blue) tenured and tenure-track faculty across all academic fields. Career age is measured as the number of years since earning a PhD. There are substantially more men faculty with high career ages than women faculty.

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. S2). These findings are qualitatively replicated using logistic regression, so we present the linear regression results here for enhanced interpretability.

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.

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)

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TABLE S2 – Continued from previous page

Field	Observed Δ_{hiring}	Observed $\Delta_{\text{attrition}}$	Est. $\Delta_{\text{gendered attrition}}$
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 from previous page

Field	Observed Δ_{hiring}	Observed $\Delta_{\text{attrition}}$	Est. $\Delta_{\text{gendered attrition}}$
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)