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Supplementary Materials for

Gender and retention patterns among U.S. faculty

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This PDF file includes:

Supplementary Materials
Figs. S1 to S8
Tables S1 to S28
References

S1. Longitudinal Design

A. About the data

The data used in our longitudinal analyses originate from a census of U.S. tenure-track and tenured faculty members obtained under a Data Use Agreement with the Academic Analytics Research Center (AARC).

The census was obtained by filtering a larger census of U.S. faculty, which included temporary faculty. Our study includes only regular faculty members, i.e., those tenured or on the tenure track with titles of “assistant professor,” “associate professor,” and “full professor.” We filtered out and removed faculty with titles or ranks like “lecturer,” “instructor,” or teaching professors (all ranks), as well as faculty of unknown rank, and research, clinical, or visiting faculty.

The original longitudinal dataset contained annual employment records from 2011-2020 and doctoral degrees for all tenure-track faculty at all 392 doctoral degree-granting institutions in the U.S.

We cleaned (Section S1B), annotated (Section S1C), and preprocessed (Section S1D) the original longitudinal dataset, resulting in the final data used in our analyses. We then conducted a manual audit to assess potential attrition errors in our dataset (Section S1E).For each faculty member in the dataset, we utilized the following information in our analyses:

- **Retention, promotion, and attrition events**: A time series of their annual employment records from 2011 to 2020, including the institution they worked at each year (their employing institution) and their rank (assistant, associate, or full) at each year (Section S1D).
- **Career age**: The length of time (per year in their time series) since they received their doctoral degree. For example, a faculty member in 2015 who received their PhD in 2000 would have a career age of 15.
- **PhD year**: The year in which they received their doctoral degree.
- **Disciplines** (annotated, Section S1C): STEM/non-STEM, domains and fields
- **Gender** (annotated, Section S1C)
- **PhD country** (annotated, Section S1C): The country in which they received their doctoral degree
- **Prestige** (annotated, Section S1C): The relative prestige of their employing institution.

B. Data cleaning

De-duplication.

- We de-duplicated the names of doctoral degree-granting universities (e.g., “University of Oxford” = “Keble College”).
- We de-duplicated the names of departments that were (i) represented in different ways (e.g., “Department of Computer Science” = “Computer Science Department”) or (ii) were renamed within the study period (e.g., “USC School of Engineering” = “USC Viterbi School of Engineering”).

Individual-level cleaning.

- We removed outdated employment records. Rarely, some faculty members in the dataset appear as faculty members at multiple universities in a single year. These situations most likely represent a professor who has switched institutions, but whose old employing university (the university that they left) has not yet removed the professor from their public-facing employment records. These are residual records of employment, so we removed them, which removed 0.23% of total employment records. Records of employment preceding events where professors switched institutions were not removed.
- We imputed missing employment records. Rarely, some faculty members disappear from the dataset only to later reappear in the same department they left. While rare, it is important for us to understand and address these events, as our study is interested in gender differences between meaningful attrition events. We consider these situations to be spurious attrition events, and impute employment records

for the missing years using the academic rank the faculty member had prior to "leaving". Employment records were not imputed if they were listed at a department with no employment records in the given year. We imputed 1.3% of employment records, affecting 4.7% of people in the dataset.

Department-level cleaning.

- We removed departments that grew or shrank by more than 50% in a given year. Very rarely, faculty rosters were updated on a delay, with some departments having a relatively large number of faculty added or removed in a given year. Setting a threshold mitigates this artifact of data collection, although changing this arbitrary threshold did not change the qualitative results of the analysis.
- We removed departments with less than three unique people across all years, as a department with only one or two people may be a residual record of an old department that has been dissolved. However, changing this arbitrary threshold did not change the qualitative results of the analysis.

School-level cleaning.

- Medical schools were excluded since tenure at those schools often does not guarantee salaries.

These steps resulted in a reduced, but more robust dataset of 305,365 unique people from 12,113 unique departments. Additional technical details in [1]. We then preprocessed this dataset further to remove faculty with missing data for key covariates in our analysis, described in Section S1C.

C. Data annotation

Taxonomy annotations. We annotated each department with at least one taxonomic label at two levels: domain and field. This taxonomy allowed us to analyze faculty retention at each level, or to compare patterns between levels. **Table S1** contains the complete taxonomy of domains and fields. We then annotated each domain of study as a STEM or non-STEM domain.

In most cases, a single department received a single taxonomic annotation, but some interdisciplinary departments received multiple annotations. This choice is intentional—for example, a "Department of Physics and Astronomy" houses faculty members from both physics and astronomy, and is relevant to questions focused on the retention of faculty within both physics and astronomy. As a result, we include all appropriate taxonomic annotations for departments. For instance, the hypothetical department above, as well as its faculty members, would be included in both physics analyses and astronomy analyses. A focus on the individual instead of the department would be more informative, but would require us to have taxonomy annotations of individuals, rather than departments, which we do not have. In addition, many faculty members work across disciplinary lines and likely consider themselves to be members of multiple fields.

In cases where a university had multiple departments within the same field, those departments were collapsed into a single unit. For example, Carnegie Mellon's School of Computer Science has seven separate departments. In our taxonomic annotations, all seven departments were annotated as computer science and treated as a single unit in subsequent analyses of computer science.

Some fields are interdisciplinary by nature, with more ambiguous boundaries, and as a result have the potential to conceptually reside in multiple domains. For example, computer engineering could be reasonably included in the domain of mathematics & computing or in engineering. Similarly, educational psychology could be included in the domain of education or in the social sciences. For these ambiguous cases, we grouped each field with the domain that had the largest fraction of faculty whose doctoral university had a department in that domain. In other words, we group fields into domains using the heuristic that fields are best grouped into the domains in which their faculty members are most likely to have been trained.

Country annotations. The country of each doctoral degree-granting university was searched and obtained by hand. First, annotators on Amazon Mechanical Turk provided the initial annotations. The country of each doctoral degree-granting university was annotated by two different annotators. Inter-annotator agreement was above 99% and disagreements were resolved by hand. To ensure accuracy, the researchers did a second pass, which resulted in no alterations.

Prestige annotations. For each employing university, prestige ranks were calculated using the SpringRank algorithm [1,90], which assigns real-valued inferred ranks to institutions (as opposed to ordinal ranks), based on the network of their interactions with each other (specifically, the number of faculty who graduate from and are hired by each institution).

Career age. For each person-year record in our data, we defined the career age of a given faculty member in the given year as the year minus the year the faculty member received their doctoral degree. 29,872 faculty members (representing 9.8% of all faculty in our dataset) were missing doctoral degree years and were excluded from our analyses. We also excluded person-year records of faculty with a career age greater than 40 years, representing 6.4% of total person-years in our dataset, which excluded an additional 11,547 faculty from our dataset. We chose this threshold by assuming an average retirement age of 70 years old and an average PhD graduation age of 30 years old, in order to prevent possible distortion of our results (especially for full professors) by professors who stay in their positions past the typical retirement age.

Name-gender annotations. While Academic Analytics does provide gender labels for some of the faculty in their dataset, we chose to use a different gender annotation method for several reasons:

- The gender file we received from Academic Analytics had gender information for only 61% of faculty in our cleaned dataset of 305K faculty, while 39% had no gender information. This missing information necessitated that we use some approach to fill in the missing data (around 119K faculty).
- Out of the faculty for which Academic Analytics did provide us with gender information (N = 187K faculty), that gender information was only institution-provided for roughly 6% (around 11K) of them, with the remaining 94% (around 176K) were assigned by an algorithmic name-based gender classifier by Academic Analytics.
- The gender file we received from Academic Analytics had many "Unknown" gender labels, which disproportionately affect Asian faculty. We chose to use a classifier that uses a broader set of international name lists in order to increase the number of faculty we could include in our final data set, especially Asian faculty [39]. Out of the 15,719 faculty who were labeled as "Unknown" by Academic Analytics, our classifier was able to assign gender labels to 87% of them. By imputing missing data that is known to be biased, this approach decreases the possibility of errors and biases in our measurements of gendered attrition, because we have a more complete estimation of the culturally associated name-based genders of Asian faculty, who make up relatively large shares of STEM faculty, in particular. We find this method is comparable to the one used by Academic Analytics—out of the cases where both our method and Academic Analytics' method returned a man or woman gender label (N = 183K faculty), our labels aligned for 98% of records.

In order to estimate the gender of faculty members based on their first names, we used a classifier trained on 36 international data sources that captures the cultural association between a name and the gendered categories man and woman [39]. With this approach, we were able to assign estimated genders to 98.1% of the names in our dataset, with 65.9% of faculty estimated to be men from their first names, and 32.2% of faculty estimated to be women from their first names. 1.7% of faculty could not be matched with any names in the classifier's database, and the classifier was unable to resolve the gender for an additional 0.2% of faculty, so for these two groups their gender was not estimated and they were removed from the dataset (N = 8,561). This process is limited in that it falsely assumes gender is binary, and potentially assigns genders to faculty members that differ from how they identify. However, we decided to use this method since the rates of mis-gendering are relatively low (approximately 97% correspondence to self reported genders on a sample of 7,188 US faculty [91]) and it is free, open-source, with open data.

After removing faculty whose names could not be associated with a gender association using our classifier, we were left with a final dataset of 245,270 unique people from 11,688 unique departments and 391 institutions, which was used in our longitudinal analysis of attrition rates by career age **(Fig. 1)**. In the logistic regression, we excluded 5,321 faculty members (2.2%) who had a missing PhD country, resulting in a slightly reduced dataset of 239,949 unique people from 11,362 unique departments and 390 institutions **(Fig. 2)**.

	Domain	Field
STEM	Natural Sciences	Agronomy
		Anatomy
		Animal Sciences
		Astronomy
		Atmospheric Sciences
		Biochemistry
		Biology
		Biomedical Engineering
		Biophysics
		Biostatistics
		Cell Biology
		Chemical Engineering
		Chemistry
		Ecology
		Entomology
		Environmental Science
		Evolutionary Biology
		Food Science
		Forestry
		Geology
		Horticulture
		Marine Sciences
		Microbiology
		Molecular Biology
		Natural Resources
		Neuroscience
		Pathology
		Physics
		Plant Pathology
		Plant Sciences
		Soil Science
	Engineering	Aerospace Engineering
		Agricultural Engineering
		Civil Engineering
		Electrical Engineering
		Environmental Engineering
		Industrial Engineering
		Materials Engineering
		Mechanical Engineering

		Operations Research
		Systems Engineering
	Math & Computing	Computer Engineering
		Computer Science
		Information Science
		Information Technology
		Mathematics
		Statistics
	Medicine	**Epidemiology**
		Genetics
		Immunology
		Pharmaceutical Sciences
		Pharmacology
		Pharmacy
		Physiology
		Veterinary Medicine
Non-STEM	Humanities	Architecture
		Art History
		Asian Languages
		Asian Studies
		Classics
		Comparative Literature
		English Language
		French Language
		Germanic Language
		History
		Linguistics
		Music
		Near and Middle Eastern Languages
		Philosophy
		Religious Studies
		Slavic Language
		Spanish Language
		Theatre
		Theological Studies
		Urban & Regional Planning
	Social Sciences	Agricultural Economics
		Anthropology
		Criminal Justice
		Economics

	Educational Psychology
	Gender Studies
	Geography
	International Affairs
	Political Science
	Psychology
	Sociology
Health	Communication Disorders
	Environmental Health
	Exercise Science
	Health / PE
	Human Development
	Nursing
	Nutrition
	Public Health
	Social Work
	Speech and Hearing Sciences
Business	**Accounting**
	Business Administration
	Finance
	Management
	Management Information Systems
	Marketing
Education	Curriculum & Instruction
	Counselor Education
	Education Administration
	Education, General
	Special Education

Table **S1**: Taxonomy of disciplines. Bolded fields were surveyed (Section S2).

D. Data preprocessing

In order to identify who was promoted each year and who left each year, we analyzed each year-to-year transition.

For each pair of years (Year1, Year2) in [(2011, 2012), (2012, 2013)...(2019, 2020)], the following transitions were counted:

- *Promotion events.* People who were assistant professors in Year1 and associate professors in Year2 or people who were associate professors in Year1 and full professors in Year2. Invalid promotions (2 jumps) or demotions (**Fig S1B**) were not included.
- *Attrition events.* People who existed in the dataset in Year1 and did not exist in Year2.
- *Retention events.* People who existed in the dataset in Year1 and Year2.

In our dataset, any situation where a professor leaves academia for any reason counts as an attrition event, including faculty who retire, faculty who are let go, faculty who leave for an industry or government position, or faculty who pass away. This dataset does not allow us to identify the reasons behind these attrition events. We note that in our analyses, faculty who switch institutions within our set of 391 PhD-granting universities are not considered attrition events, even though they might be considered attrition events by the department or institution they left behind. We examine this important, although separate, aspect of faculty retention in Section S4C.

A faculty member who leaves our dataset can be counted as an attrition event at most once, or in other words, a faculty member who leaves academia multiple times will be considered an attrition event only upon leaving academia for the last time. A faculty member's last year of employment within the sample frame is considered the year of their attrition event when counting attrition events over time. Faculty members that switch disciplines but remain at the same university are not considered to be attrition events from disciplines they leave.

For a given year, and for a given set of faculty who existed in the previous year, attrition *risk* is defined as the probability that each professor who existed in the previous year does not appear in the set in the current year. In other words, attrition risk represents the proportion of observed attrition events among all possible attrition events for the two-year period. Thus, attrition risks as stated in our analyses are annual per-capita risks of attrition. We compute average annual attrition risks by summing all attrition events and dividing by all possible attrition events. Similarly, annual promotion rates are formed by summing all promotion events and dividing by all possible promotion events.

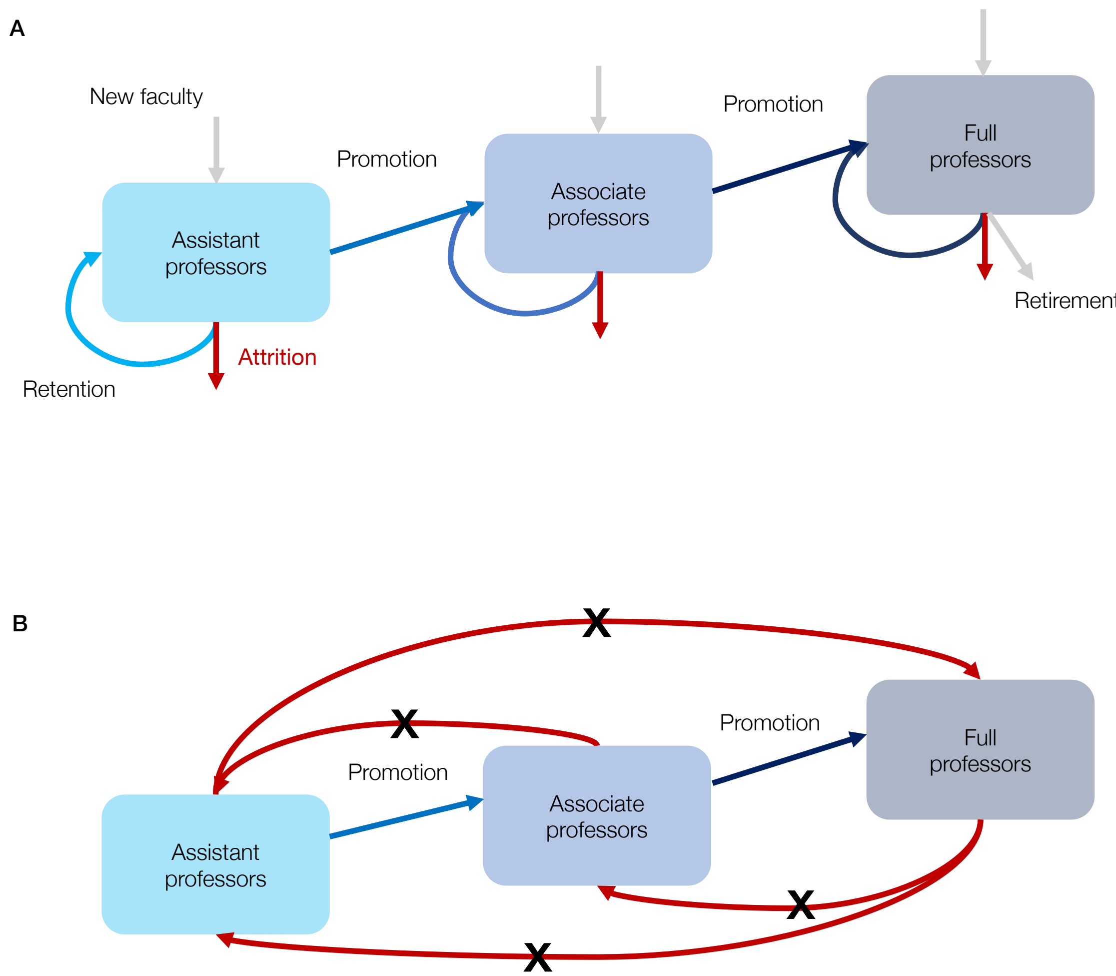

Figure **S1**: **Tenure-track pipeline processing. A.** The standard tenure-track faculty pipeline at an institution. **B.** During data cleaning, we remove invalid promotions (jumping from Assistant to Full Professor) and demotions, for simplicity and due to the rarity of these events.

E. Data errors and mitigation

As is common with administrative datasets, our census is not error-free. Data collection was primarily done in two ways: (i) faculty rosters were submitted to Academic Analytics by universities, and (ii) manual checks were conducted by Academic Analytics. Both of those methods are more accurate than methods like web scraping departmental websites, for example, where faculty can be listed online years after they left a university. However, both methods are susceptible to human error.

In our study, there are three main sources of error that could influence our measurement of attrition:

- **Misgendering**: faculty who self-identify with a given gender, but who were classified with a different gender label
- **Never tenure-track**: faculty who were recorded in the dataset as regular faculty (tenure-track or tenured), but who were actually temporary faculty such as teaching or visiting faculty
- **Didn't leave**: faculty who appeared to have left the dataset but who didn't actually leave

These errors could affect our results in two ways. First, spuriously annotated attritions could affect our reported attrition rates. Second, and more importantly to our primary findings, if such potential errors are, themselves, gendered in nature, our findings regarding gendered attrition could be distorted.

We assessed the magnitude and gendering of such "false positive attrition" errors in our data, via a manual audit. We first drew a stratified random sample of 240 faculty from the dataset who were classified as leaving, selecting equal numbers of men and women from each rank and academic domain. First, we used the pronouns faculty used in their online biographies to assess whether or not they had been misgendered. Next, we manually investigated their employment histories via extensive web searches (searching professional sites like LinkedIn, university websites, their professional homepages, their CV, evidence from professional events that identify their place of employment, etc.) to identify (i) the title of their position (whether or not they were never tenure-track faculty) and (ii) where and how they were employed after the "leaving" event in our data.

We also audited a complementary set of 240 faculty who did not appear to leave, again chosen using the same stratification procedure. This allowed us to compare rates of misgendering and never-tenure-track errors between those who did and did not appear to leave.

Our audit had two findings. First, we found no evidence to support a hypothesis that data errors were, themselves, gendered. In other words, our audit did not reveal that mislabeled attritions or mislabeled tenure-track titles were more likely for women than men. This suggests to us that our findings regarding the presence/absence of gendered attrition patterns are unlikely to be affected by mislabeling errors, allowing us to gain greater confidence in the integrity of our findings (see **Table S2** and **Table S3** for counts of errors for faculty who appeared to leave and didn't appear to leave the dataset, respectively; statistical significance was assessed using 2-proportion z-tests, but no gender differences were significant).

Second, our audit found that (i) there was no significant difference in the rate at which attritions vs non-attritions were misgendered (9/235 vs 13/231, $p = 0.36$), (ii) 11% of attritions vs 6.1% of non-attritions were never tenure-track faculty as far as one could infer from records on the Web, and (iii) 6% of faculty who "left" the AA sample frame didn't actually leave (half of whom had moved into part-time administrative roles but kept their faculty appointment). Our previous observation that errors in the data are not, themselves, gendered remains true. However, the presence of more never-tenure-track faculty among attritions (vs non-attritions), combined with false positive attritions, collectively suggest that our estimates of overall rates of attrition in Fig. 1A may be slightly inflated for both women and men overall.

Faculty who appeared to leave			Found	Misgendered	Never TT	Left	Ambiguous	Stayed
Non-STEM	Assistant	Men	20	2	2	17	1	0
Non-STEM	Assistant	Women	20	0	2	17	0	1
Non-STEM	Associate	Men	20	0	1	18	0	1
Non-STEM	Associate	Women	20	2	1	18	0	1
Non-STEM	Full	Men	20	0	0	18	0	2
Non-STEM	Full	Women	20	0	3	14	2	1
STEM	Assistant	Men	20	2	4	13	3	0
STEM	Assistant	Women	20	1	5	11	1	3
STEM	Associate	Men	19	1	4	12	3	0
STEM	Associate	Women	19	0	2	13	4	0
STEM	Full	Men	18	0	1	14	2	1
STEM	Full	Women	19	1	1	15	2	1
			235	**9**	**26**	**180**	**18**	**11**

Table **S2**: Counts of data errors recorded via a manual audit of $N = 240$ faculty who appeared to leave the dataset in STEM vs non-STEM domains. 235 faculty could be found online, but 5 people did not have any online presence. Out of those who could be found ($N = 235$), 9 were misgendered, and 26 were never tenure-track faculty. Out of those who were regular faculty ($N = 209$), there was online evidence indicating the given faculty member had left their job for 180 faculty (e.g., a LinkedIn profile showing the transition), evidence was ambiguous for 18 faculty (e.g., they were still listed on the departmental website, but had no other online presence), and there was online evidence indicating the given faculty member had stayed in their position for 11 faculty (e.g., a recent news article about them on their university's website).

Faculty who didn't appear to leave			Found	Misgendered	Never TT
Non-STEM	Assistant	Men	19	2	1
Non-STEM	Assistant	Women	19	0	0
Non-STEM	Associate	Men	20	3	0
Non-STEM	Associate	Women	20	0	0
Non-STEM	Full	Men	20	0	0
Non-STEM	Full	Women	19	0	1
STEM	Assistant	Men	19	1	2
STEM	Assistant	Women	19	4	5
STEM	Associate	Men	17	1	1
STEM	Associate	Women	19	1	1
STEM	Full	Men	20	0	2
STEM	Full	Women	20	1	1
			231	**13**	**14**

Table **S3**: Counts of data errors recorded via a manual audit of $N = 240$ faculty who did not appear to leave the dataset in STEM vs non-STEM domains. 231 faculty could be found online, but 9 people did not have any online presence. Out of those who could be found ($N = 231$), 13 were misgendered, and 14 were never tenure-track faculty.

S2. Survey Design & Administration

A. Participants

Participants were identified from the longitudinal dataset. We selected 29 different fields (out of 111 total fields) across the natural sciences, math and computing, engineering, social sciences, business, humanities, education, medicine and health (**Table S4**), representing 145,455 current and former tenure-track faculty, comprising 59.3% of the larger dataset. The fields were chosen to cover all of the nine domains analyzed in the longitudinal analysis. Within each domain, a mix of men-dominated fields (e.g., computer science) and women-dominated fields (e.g., nursing) were chosen, to the extent possible. Additionally, we aimed for a mix of large fields (e.g., biology) and medium fields (e.g., information science), and omitted very small fields (e.g., forestry) to avoid small sample sizes. Finally, we selected a mix of both commonly discussed fields in the retention literature (e.g., STEM fields like computer science) and less commonly discussed fields (e.g., education). We chose this selective strategy because we could not email all faculty in the longitudinal dataset due to financial constraints.

Participants fell into four possible target populations: current faculty who did not leave a position anytime after 2009, faculty who left academia, faculty who switched institutions but did not leave academia, and retired faculty (**Fig. S2**).

Participants were invited to participate in the survey through an email invitation, with initial invitations sent from late July 2021 to mid September 2021. Participants were sent two follow-up emails if they had not completed the survey, one week and two weeks after the initial invitation.

Email collection. We attempted to obtain email addresses for all faculty within the selected disciplines in a two step process. First, we utilized a web scraper to make automated web searches. For the faculty whose emails could not be found through this approach, we posted a task on Amazon Mechanical Turk, an online crowdsourcing marketplace. Mechanical Turk workers searched for publicly available email addresses of these remaining faculty members, with the option to indicate that they could not find the email. The authors conducted manual spot-checks to correct errors. Many former academics left forwarding addresses at their old email addresses that we then collected and sent an additional round of emails to. Through this process, email addresses for 50.2% of our full sample were found, resulting in a frame of 73,049 current and former tenure-track faculty (**Table S4**).

Responses. 73,049 people were contacted, but 1,600 emails failed or bounced, so 71,449 people had the chance to see the email invitation.

Although 11,908 people responded to the survey, 1,470 respondents did not fill out at least 80% of the survey, and 244 respondents were not in our survey frame, either indicating that they were not tenure-track faculty or that they left their positions before 2009, so these responses were removed from the analysis. Out of those who did not fill out at least 80% of the survey and who filled out the demographic information, no significant completion rate differences were found between men and women, or between white and non-white respondents.

Additionally, since all of our main analyses include binary gender, we removed 118 responses from people who did not specify their gender. We included non-binary faculty in analyses where we did not split by gender but did split by group (e.g., whether they left academia or switched institutions). But, since small sample sizes can prohibit reliable conclusions, we also removed responses from 1 person who said they are gender nonconforming, and 4 people who selected that they wanted to self-describe, but did not describe their gender.

After removing these responses, 10,071 people were included in our analysis, so our final response rate was 10,071 / (73,049 - 1600 - 244) = 14.1% (**Table S5**). Overall, our response rate mirrors other online surveys with email invitations conducted in the context of academia [88, 89]. The response rate was higher for former faculty (those who left academia or retired; 34%) than the average (**Table S6**).

Representation. We evaluated the observable differences between the census and survey sample along four key variables: gender, academic rank, STEM vs non-STEM, and prestige (low vs high). Our respondent group exhibits some differences relative to the population, in that (i) full professors were somewhat overrepresented, (ii) assistant professors were somewhat underrepresented, and (iii) professors from higher-prestige institutions were somewhat overrepresented. Otherwise, our analysis suggests that the survey sample was broadly representative, including by gender, STEM vs non-STEM, and for associate professors (**Table S7**).

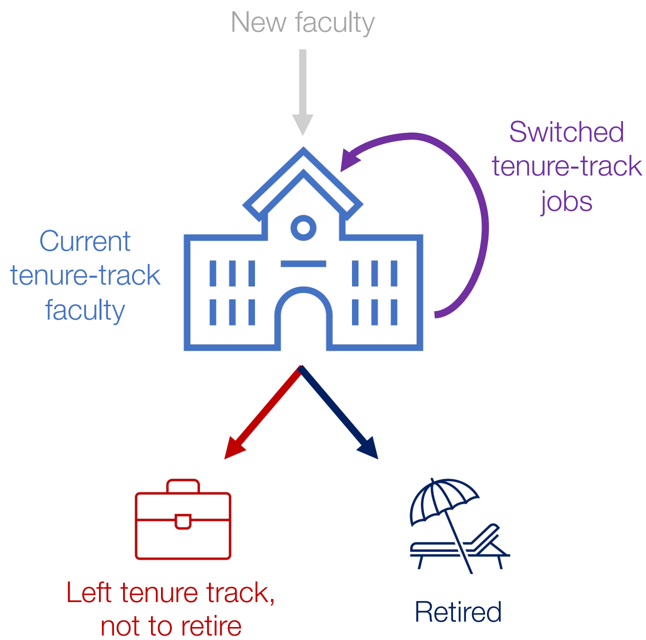

Figure **S2**: **Survey target populations.** We surveyed four target populations: current tenure-track faculty who did not leave a job anytime since 2009, faculty who switched tenure-track jobs, faculty who left the tenure track, not to retire, and faculty who retired. If respondents switched or left multiple times within our time period, we asked them to indicate the first time they switched or left, so for our purposes, these are four mutually exclusive target populations.

Domain	Field	Total Faculty	Emails Found	%
Natural Sciences	Astronomy	2978	1548	52.0
	Biochemistry	6546	2764	42.2
	Biology	9022	4451	49.3
	Biomedical Engineering	3273	1334	40.7
	Biostatistics	2333	955	40.9
	Chemistry	7138	3297	46.2
	Physics	7347	3261	44.3
Health	Nursing	6421	1399	21.8
	Social Work	3393	1347	40.0
Medicine	Epidemiology	2967	1059	35.7
	Pharmacology	3661	984	26.9
	Physiology	3821	1044	27.3
Humanities	History	7458	4305	57.7
	Linguistics	1336	706	52.8
	Philosophy	3668	2081	56.7
Social Sciences	Anthropology	4045	2004	49.5
	Economics	6311	3625	57.4
	Psychology	9119	6533	71.6
	Sociology	4888	2483	50.8
Engineering	Civil Engineering	4519	2530	56.0
	Mechanical Engineering	6677	3774	56.5
Business	Accounting	2978	1683	56.5
	Finance	3413	2007	58.8
	Management	5715	3475	60.8
	Marketing	2728	1464	53.7
Math & Computing	Computer Science	8608	5706	66.3
	Information Science	2173	707	32.5
	Mathematics	8582	5026	58.6
Education	Education, General	3943	1020	25.9
		145,455	**73,049**	**50.2**

Table **S4**: Number of faculty members in employment records in each field, and number of faculty whose email addresses could be found. % is the rate email addresses could be found per field.

Domain	Field	Frame	Responses	%
Natural Sciences	Astronomy	1548	275	17.8
	Biochemistry	2764	464	16.8
	Biology	4451	861	19.3
	Biomedical Engineering	1334	205	15.4
	Biostatistics	955	129	13.5
	Chemistry	3297	311	9.4
	Physics	3261	637	19.5
Health	Nursing	1399	183	13.1
	Social Work	1347	169	12.5
Medicine	Epidemiology	1059	175	16.5
	Pharmacology	984	127	12.9
	Physiology	1044	135	12.9
Humanities	History	4305	678	15.7
	Linguistics	706	134	19.0
	Philosophy	2081	314	15.1
Social Sciences	Anthropology	2004	384	19.2
	Economics	3625	353	9.7
	Psychology	6533	1087	16.6
	Sociology	2483	543	21.9
Engineering	Civil Engineering	2530	307	12.1
	Mechanical Engineering	3774	324	8.6
Business	Accounting	1683	215	12.8
	Finance	2007	205	10.2
	Management	3475	355	10.2
	Marketing	1464	181	12.4
Math & Computing	Computer Science	5706	559	9.8
	Information Science	707	119	16.8
	Mathematics	5026	494	9.8
Education	Education, General	1020	148	14.5
	73,049 - 1600 - 244 = 71,205		**10,071**	**14.1**

Table **S5**: Number of participants targeted in each field, and number of respondents. % is the response rate per field.

Type of event	N_{total}	$N_{selected-fields}$	$N_{respondents}$	%
Leaving academia or retiring	8,793	4,015	1,387	34%
Switching institutions	22,064	12,564	1,489	12%
Current faculty	203,586	54,626	7,195	13%

Table **S6**: The number of unique faculty who experience each type of event (leaving, switching, or staying) in the census dataset, the number of unique faculty who experience each type of event in our sample frame, and the number of survey respondents. % is the response rate per type of move.

		M	W	NB	Assistant	Associate	Full	High-prestige	N
STEM	Respondents	75.2	24.4	0.3	11.2	25.7	63.1	75.4	5,029
	Population	74.5	25.5	–	28.2	23.8	48.0	46.0	35,201
p-value					* $p < 0.001$	* $p < 0.01$	* $p < 0.001$	* $p < 0.001$	
Non-STEM	Respondents	55.0	44.6	0.4	15.6	29.5	54.9	78.3	5,042
	Population	54.6	45.4	–	29.0	30.6	40.4	48.6	36,004
p-value					* $p < 0.001$		* $p < 0.001$	* $p < 0.001$	

Table **S7**: Demographic attributes of faculty in STEM vs non-STEM domains. Proportions are reported for survey respondents and the survey frame, with statistical significance calculated using χ^2 two-tailed tests. The proportion in high-prestige institutions is calculated by selecting faculty who were in the top half of the prestige hierarchy.

B. Theoretical Framework

Our overall perspective is of the so-called "leaky pipeline", where women leave academia at higher rates than men at each stage of their careers [3]. Our survey solicited responses from current and former faculty about the role of various stressors within academia in faculty decisions to leave their tenure-track positions.

We investigate this question within the person-environment fit framework, which states that "stress arises not from the person or environment separately, but rather by their fit or congruence with one another" [53,54]. Within this framework, many theories have been developed (Model of person-organization fit [55,56]; Theory of work adjustment [49]; Holland's theory of vocational personalities and work environments [57,58]; Attraction-selection-attrition framework [59]).

Instead of measuring stress directly, we are interested in the sources of stress, or stressors. A stressor is a stimulus or event [60] that a person may consider challenging or threatening to their well-being [61]. Person-environment fit assumes that stressors are neither fully internal nor fully external, but that it is the fit of a particular person's cognitions, values, beliefs, and their work environment that can cause them to experience stress. For example, how stressed someone is about "obtaining funding" (the stressor) is not simply influenced by their personality (internal), but it is also not solely determined by the availability of grants (external).

The literature more broadly relates to the concepts of job satisfaction [92, 93] and well-being [94, 95]. Within academia, many studies have found that women report lower levels of job satisfaction than men [65, 92, 96, 97], although others have found no gender differences after controlling for other variables [98, 99]. However, here we focus on stressors because we are more interested in the reasons women leave than we are in identifying whether women are satisfied with their jobs. While the two concepts are related, what we want to know is why the "leaky pipeline" is evident on the tenure track.

Past studies have investigated some aspects of our question. For example, previous studies have identified several types of faculty stress [66, 100], but they don't align well with reasons for leaving a job. Additionally, many other studies of faculty have shown a gendered difference in stress, with women reporting higher levels of stress than men [48, 101, 102]. Many studies built upon this faculty job stress literature have also established the relationship between faculty job stress and the intention to leave, where a faculty member with more job stress is more likely to leave their job [96, 103–105]. While older, more general studies found that intention to leave a job predicts actually leaving [106, 107], and several studies have shown women and men academics intend to leave their jobs at similar rates [69, 103, 108] (although not all: see [23]) we know that is not always the case [15, 17, 109]. So, we are interested in actual reasons faculty leave. And many studies have specifically asked faculty to share the reasons why they left [26–30].

We designed our survey by specifically focusing on the reasons women leave faculty positions. In order to identify these reasons, we collected the most common reasons women academics left their jobs from the literature (i.e., a thematic analysis [110]; **Table S8**), and we defined these as our stressors. We grouped them into three categories after this review: professional stressors (e.g., obtaining research funding) [14, 23, 28–32, 62–69], work-life balance stressors (e.g., number of hours worked) [26–28, 31, 32, 38, 66, 67, 70–73, 103, 105], and climate stressors (e.g., how competitive academia is) [27–29, 32, 65, 66, 68, 69, 71, 74–76, 101, 105]. We were interested in how both current and former faculty experience(d) these stressors.

Theme	Item	Supporting Text
Professional	Expectations of scholarly productivity (e.g., publishing papers or books)	"professional advancement" was the top reason for leaving [29]; "...gender differences do exist, e.g., in scholarly productivity..." [62]; "When number of refereed publications were added to the model, differences by gender in retention...were no longer significant." [14]
Professional	Obtaining research funding or other external research support	"frustrations with research (funding difficulties,...) emerged as key factors associated with a decision to leave academic medicine" [28]
Professional	Expectations to work on specific research topics	"Women specialize less than men and thereby lose out on an important means of increasing their productivity." [63]
Professional	Lack of recognition of my scholarly achievements by my department and peers	"...scholarly devaluation was associated with higher intentions to leave the university..." [64]; "...perceptions of department...recognition...are more important to women faculty's satisfaction than male peers." [65]; "reward and recognition" was a dimension of perceived stress [66]
Professional	My salary	"low salary" [29], "salary" [30], "salary concerns" [31] listed as a top reason for leaving; "Additional measures to address gender discrimination could include...pay equity regardless of gender..." [67]
Professional	Low acceptance rates for scholarly work	"The literature suggests that not only do constant rejections demotivate the majority of academics, but also the funding allocation process in itself seems inefficient. The pressure on academics is so high that we tend to systematically over-estimate our success chances of our funding proposals, manuscripts and promotion requests." [68]
Professional	Poor administrative support (e.g., in grant-writing)	"low institutional support" [69]; "a lack of resources to support faculty work" [32]; "The findings suggest that the underrepresentation of women is more convincingly explained by an academic culture that provides women...limited support..." [23]
Work-life balance	Caring responsibilities (for children, partner, parents, etc.)	"...were much more likely to cite family-related reasons for leaving..." [27]; "A lack of role models for combining career and family responsibilities..." [28]; "stress of raising a family" was a key predictor for intending to leave academia [105]
Work-life balance	My partner's career constraints, ambitions, location, salary, etc.	"Committees actively considered women's—but not men's—relationship status when selecting hires." [70]; "Work–family conflict was the most frequently cited reason for leaving, with disproportionately more women than men giving this reason...typically referred to the difficulty of coordinating two careers." [26]; "Dominant explanations include... family and geographic reasons..." [71]

Work-life balance	Lack of time for hobbies and interests outside of work	"time constraints" was a dimension of perceived stress [66]
Work-life balance	Number of hours I worked per week	"time commitment" was a main correlate with intention to leave [103]
Work-life balance	Lack of adequate parental leave	"a lack of work–life balance policies and an environment to support them" [32]; "Additional measures to address gender discrimination could include offering paid parental leave..." [67]; "Women report that paid parental leave and adequate childcare are important factors in their recruitment and retention." [38]
Work-life balance	Difficulties having children (e.g., miscarriage, infertility, struggles with adoption or surrogacy)	"The risk of miscarriage was significantly higher in women with a history of exposure to psychological stress." [72]; "...work conditions in contemporary universities subject women graduate students and faculty members to high levels of stress such that work exacts an unsustainable toll on women's bodies...", including fertility [73]
Work-life balance	Personal issues (e.g., divorce, illness, etc.)	"personal/family reasons" was a top reason for leaving [31]
Climate	Dysfunctional departmental culture or leadership	"chairman/departmental leadership issues" [29], "a lack of consistent and quality leadership", "overall negative institutional and departmental environments" [32]; "an exclusionary and managerialist culture which marginalized and demoralized women", "poor leadership" [75] were listed as top reasons for leaving; "Attrition was associated with: perceived failure of the Department Chair to foster a climate of teaching, research, and service..." [74]; "departmental influence" was a dimension of perceived stress [66]; "Results indicate that women faculty...report less supportive relationships with their deans...", which was associated with psychological distress [101]
Climate	Feeling the need to prove myself	"Women reported greater susceptibility to [stereotype threat] than did men..." in academic medicine [76]
Climate	Feeling that people like me don't belong or fit in my department	"the institutional environment" [28], "work environment and fit" [71], "overall negative institutional and departmental environments." [32] , "...an exclusionary and managerialist culture which marginalized and demoralized women..." [75] were listed as top reasons for leaving; "Negative perceptions of the culture—unrelatedness, feeling moral distress at work, and lack of engagement—were associated with leaving for dissatisfaction." [69]; " a perceived lack of fit" was a key predictor for intending to leave academia [105]; "...perceptions of department fit... are more important to women faculty's satisfaction than male peers." [65]
Climate	Feeling that people like me don't belong or fit at my institution	Item modified from above

Climate	Feeling that people like me don't belong or fit in my academic field	Item modified from above
Climate	Harassment	"gender-based harassment/discrimination" was a top reason for leaving [27]
Climate	Discrimination	"gender-based harassment/discrimination" was a top reason for leaving [27]
Climate	How competitive academia is (e.g., constant criticism, comparisons, rejections, etc.)	"frustrations with research (..., competition)", "the institutional environment (described as noncollaborative and biased in favor of male faculty)" [28] were listed as top reasons for leaving; "We conclude that negative effects outweigh the potential gains which competitive systems bring about." [68]

Table **S8**: Thematic analysis of the literature to create the survey items.

C. Survey questions

We designed our survey questions by specifically focusing on the reasons women leave faculty positions. In order to identify these reasons, we collected the most common reasons women academics left their jobs from the literature [14, 23, 26–32, 38, 62–76, 101, 103, 105] (Section S2B; **Table S8**), and we defined these as our stressors. We grouped them into three categories after this review: professional stressors (e.g., obtaining research funding), work-life balance stressors (e.g., number of hours worked), and climate stressors (e.g., how competitive academia is). We were interested in how both current and former faculty experience(d) these stressors.

Participants were asked questions about how frequently they experienced stressors from the three categories of stressors, a total of 22 items (**Table S9**). Former faculty were also asked, for each stressor, to check a box if that stressor contributed to their decision to leave their job, and current faculty were asked how much impact each broad category (professional, work-life balance, and climate) would have on a potential decision to leave their job ("No impact", "Minor impact", "Moderate impact", "Major impact").

Former faculty and faculty who switched institutions were asked if they left academia or switched institutions due to a push, pull, both, or neither, using the following question on the survey:

I changed positions because (check all that apply):

☐ I was unhappy, stressed, or otherwise unsatisfied, causing me to leave my previous position.

☐ I was drawn to, excited by, or otherwise attracted to my new position.

☐ I wanted to retire.

Similarly, current faculty were asked if they would leave academia due to a push, pull, both, or neither, using the following question on the survey:

Think about the reasons that might lead you to consider leaving your position (check all that apply):

☐ I am unhappy, stressed, or otherwise less than satisfied with my current position.

☐ I am drawn to, excited by, or otherwise attracted to a different position.

☐ I would not consider leaving.

This survey was approved by the University of Colorado Boulder Institutional Review Board (protocol 21-0293) and conducted online through the Qualtrics survey platform. In addition to the main questions, participants were also asked to answer a series of demographic questions, including questions about their self-identified gender, race, and parenthood status. The majority of the survey questions were optional, and those that were required (e.g., gender) had the option to mark "prefer not to say".

Instructions
Faculty who Left or Switched Institutions
Think about your day-to-day work in the year before you left this position. Try to recall the sources of stress you experienced for each of the categories below. Some stresses may be high but tolerable, or low but intolerable, so we ask that you also indicate whether that factor contributed to you leaving your job/switching institutions.
Current Faculty
Think about your day-to-day work in the last year. Try to recall the sources of stress you experienced for each of the categories below.
Survey items
How frequently did/do you experience stress due to:
Professional stress (stress associated with doing your job)
Expectations of scholarly productivity (e.g., publishing papers or books)
Obtaining research funding or other external research support
Expectations to work on specific research topics
Lack of recognition of my scholarly achievements by my department and peers
My salary
Low acceptance rates for scholarly work
Poor administrative support (e.g., in grant-writing)
Work-life stress (stress associated with balancing work and life)
Caring responsibilities (for children, partner, parents, etc.)
My partner's career constraints, ambitions, location, salary, etc.
Lack of time for hobbies and interests outside of work
Number of hours I work per week
Lack of adequate parental leave
Difficulties having children (e.g., miscarriage, infertility, struggles with adoption or surrogacy)
Personal issues (e.g., divorce, illness, etc.)
Climate stress (stress associated with the social climate of your institution and/or field)
Dysfunctional departmental culture or leadership
Feeling the need to prove myself
Feeling that people like me don't belong or fit in my **department**
Feeling that people like me don't belong or fit at my **institution**
Feeling that people like me don't belong or fit in my **academic field**
Harassment
Discrimination
How competitive academia is (e.g., constant criticism, comparisons, rejections, etc.)

Table **S9**: The survey items. All items were scored on a 5-point scale (1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = All the time), with the option for respondents to select "N/A" if that stressor does not apply to them.

D. Survey data cleaning

During data analysis, there were several data cleaning choices we made that re-classified several groups of responses in order to be as inclusive as possible and as clear as possible. However, no responses were removed during data cleaning.

Gender. 3 out of the 6570 men in our survey indicated they are transgender men, 1 out of the 3480 women in our survey indicated they are a transgender woman, and 1 out of the 3480 women in our survey indicated they are a woman and non-binary. While these 5 individuals used the "prefer to self-describe" box in order to describe their gender, we also included them in the binary gender categories that they mentioned in their descriptions. Including participants who self-reported these additional aspects of their gender identities into "men" and "women" categories allows us to respect their status as men and women [111].

Race. Respondents were given checkboxes corresponding to the U.S. Census race categories and asked to select all the categories they identified with. The options were: "American Indian or Alaskan Native", "Asian", "Black or African American", "Hispanic, Latino, or Spanish origin", "Native Hawaiian or other Pacific Islander", "White", "Other". These categories alone cannot encompass someone's entire racial identity, and we look forward to future survey methods that allow respondents to better represent their identity.

For each racial category a respondent identified with, they were included in that group. Most people only selected one group, and 525 respondents (5.2% of respondents) selected more than one. People who indicated that at least one of their racial identities was non-white were included in the "non-white" category, representing 1,747 respondents (17.4% of respondents).

Emerita/us faculty. Respondents were asked to indicate whether they were current or former faculty, along with their academic rank. Respondents who indicated that they are Emerita/us faculty were classified as retired, even if they said they were current faculty members, accounting for 71 respondents (0.7% of respondents).

S3. Longitudinal Analyses

A. Main logistic regression model (Fig. 2A)

We test for gendered differences in faculty attrition using a logistic regression model, which estimates the association of a professor's gender with whether they leave academia, while controlling for the professor's rank, as well as various aspects of their past training and current environment.

We fit a separate logistic regression model for each academic rank (assistant, associate, and full for attrition; assistant and associate for promotion) to the dataset described in SI Section S1 to model the probability p of faculty attrition (and separately, promotion), using faculty gender (0 = man, 1 = woman), career age (integer number of years since PhD), PhD year, PhD degree location (0 = non-U.S. degree, 1 = U.S. degree) and faculty employer prestige (scaled such that a 1 unit increase corresponds to a 1 decile increase up the prestige hierarchy, but note that each rank in the regression represents a unique institution; Section S1A):

$$logit(p) = \beta_0 + \beta_1[\text{Women}] + \beta_2[\text{Career age}] + \beta_3[\text{PhD year}] + \beta_4[\text{U.S. degree}] + \beta_5[\text{Prestige decile}]$$

Odds ratios. If attrition rates do not depend on gender, the odds that a woman leaves academia ($odds_W$) should be equal to the odds that a man leaves academia ($odds_M$), so $odds_W/odds_M$ (the odds ratio), which is equal to $\exp(\beta_1)$, should be 1. An odds ratio that is less than 1 means that men are more likely to leave academia than women, and an odds ratio that is greater than 1 means that women are more likely to leave academia than men.

We ran subgroup analyses for women's attrition from assistant, associate and full professor positions, both with and without adjusting for their PhD training, employer environment, and career age (**Table S10**). Significance was assessed using z-tests. Similarly, we ran subgroup analyses for women's promotion to associate and full professor positions, both with and without adjusting for their PhD training, employer environment, and career age (**Table S11**). Gendered odds ratios ($\exp(\beta_1)$) are visualized in **Fig. 2A**, top row.

We then ran additional subgroup analyses for women's attrition from assistant, associate and full professor positions, adjusting for their PhD training, employer environment, and career age, for STEM domains, non-STEM domains, and each of the nine individual domains (STEM: Natural Sciences, Engineering, Math & Computing, Medicine; non-STEM: Humanities, Social Sciences, Health, Business, Education). Gendered odds ratios ($\exp(\beta_1)$) are visualized in **Fig. 2A** and reported in **Tables S12-S14**. Similarly, we ran domain-level subgroup analyses for women's promotion to associate and full professor positions (**Tables S15-S16**). Tables containing the full domain-level model summaries (with all five covariates instead of just gender) are available upon request.

Population averages. Translating odds ratios to population averages to make sense of the results, we used the adjusted logistic regression model to compute the probability of attrition p for each person-year in the dataset, and then averaged those probabilities across relevant groups of interest. For example, in order to compute the average woman's likelihood of attrition compared to men from the assistant professor position, we average the probabilities of attrition across all person-years from women assistant professors in our dataset, $\overline{p_w}$, and all men assistant professors in our dataset, $\overline{p_m}$, and then obtain women's relative likelihood by calculating $\overline{p_w}/\overline{p_m}$. In this example, $\overline{p_w} = 0.055$ and $\overline{p_m} = 0.052$, so women assistant professors in academia as a whole are 6% more likely to leave than men assistant professors.

This is especially helpful for interpreting the association of prestige and attrition odds. For every 1 decile increase in prestige, the odds of attrition fall by 7%, 8%, and 13% for assistant, associate, and full professors, respectively (assistant: $\hat{\beta_1} = -0.07$, $\exp(\hat{\beta_1}) = 0.93$; associate: $\hat{\beta_1} = -0.08$, $\exp(\hat{\beta_1}) = 0.92$; full: $\hat{\beta_1} = -0.14$, $\exp(\hat{\beta_1}) = 0.87$; **Table S10**). This means a faculty member from the least prestigious institution, at decile 0, has 2.0x, 2.22x, and 4.0x higher odds of leaving the assistant, associate, and full professor ranks, respectively, than a faculty member from the most prestigious institution, at decile 10 (assistant: $1/\exp(\hat{\beta_1} * 10) = 2.01$, associate: $1/\exp(\hat{\beta_1} * 10) = 2.22$, full: $1/\exp(\hat{\beta_1} * 10) = 4.05$). But what does that mean for the population overall? To find out, we average the probabilities of attrition across all person-years from professors at the least prestigious institution, $\overline{p_0}$, and from professors at the most prestigious institution, $\overline{p_{10}}$, then compute the ratio. In this example, $\overline{p_0} = 0.08$ and $\overline{p_{10}} = 0.03$ for assistant professors, so assistant professors at the least prestigious institution are 2.5x more likely to leave than assistant professors at the most prestigious institution.

Attrition	**Assistant** ($N = 376,366$ person-years)							
	Unadjusted				Adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.06***	1.06	$(1.03, 1.09)$	3.9	0.06***	1.07	$(1.04, 1.10)$	4.4
Career age	–	–	–	–	0.05***	1.05	$(1.05, 1.06)$	17.1
PhD year	–	–	–	–	0.01*	1.01	$(1.00, 1.01)$	2.4
U.S. degree	–	–	–	–	−0.07**	0.93	$(0.89, 0.97)$	−3.3
Prestige decile	–	–	–	–	−0.07***	0.93	$(0.92, 0.93)$	−19.3
	Associate ($N = 459,541$ person-years)							
	Unadjusted				Adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.10***	1.11	$(1.07, 1.14)$	6.0	0.20***	1.22	$(1.18, 1.26)$	11.8
Career age	–	–	–	–	0.13***	1.13	$(1.12, 1.14)$	36.6
PhD year	–	–	–	–	0.06***	1.06	$(1.05, 1.07)$	17.4
U.S. degree	–	–	–	–	−0.03	0.97	$(0.92, 1.02)$	−1.1
Prestige decile	–	–	–	–	−0.08***	0.92	$(0.91, 0.93)$	−17.4
	Full ($N = 602,777$ person-years)							
	Unadjusted				Adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.18***	1.20	$(1.17, 1.23)$	13.1	0.31***	1.36	$(1.32, 1.40)$	21.6
Career age	–	–	–	–	0.14***	1.15	$(1.15, 1.16)$	51.9
PhD year	–	–	–	–	0.07***	1.07	$(1.06, 1.07)$	26.2
U.S. degree	–	–	–	–	0.27***	1.31	$(1.25, 1.37)$	11.6
Prestige decile	–	–	–	–	−0.14***	0.87	$(0.86, 0.87)$	−41.9

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S10**: Odds of women leaving academia as a whole as assistant professors, associate professors and full professors, calculated both with and without adjusting for training and environmental controls.

Promotion	**Associate** ($N = 356,642$ person-years)							
	Unadjusted				Adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	−0.08***	0.92	(0.90, 0.94)	−7.8	−0.08***	0.92	(0.90, 0.94)	−7.7
Career age	–	–	–	–	0.06***	1.07	(1.06, 1.07)	29.7
PhD year	–	–	–	–	0.01**	1.01	(1.00, 1.01)	2.6
U.S. degree	–	–	–	–	0.38***	1.46	(1.41, 1.51)	22.5
Prestige decile	–	–	–	–	0.03***	1.03	(1.02, 1.03)	10.3
	Full ($N = 444,354$ person-years)							
	Unadjusted				Adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	−0.13***	0.87	(0.85, 0.89)	−11.4	−0.13***	0.88	(0.86, 0.90)	−11.2
Career age	–	–	–	–	0.02***	1.02	(1.02, 1.03)	9.9
PhD year	–	–	–	–	0.02***	1.02	(1.02, 1.03)	9.5
U.S. degree	–	–	–	–	−0.17***	0.84	(0.81, 0.87)	−9.5
Prestige decile	–	–	–	–	0.09***	1.09	(1.08, 1.10)	29.0

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S11**: Odds of women being promoted to associate professor and full professor, calculated both with and without adjusting for training and environmental controls.

Attrition	**Assistant**, adjusted					
	N_{unique}	$N_{person-yrs}$	$\hat{\boldsymbol{\beta}_{\boldsymbol{W}}}$	$\exp(\hat{\boldsymbol{\beta}_{\boldsymbol{W}}})$	95% CI	z
Academia	$104,711$	$376,366$	0.06***	1.07	$(1.04, 1.10)$	4.4
STEM	$50,616$	$180,145$	-0.03	0.97	$(0.92, 1.01)$	-1.5
Natural Sciences	$28,007$	$100,731$	0.00	1.00	$(0.95, 1.06)$	0.1
Engineering	$11,138$	$39,136$	-0.17**	0.84	$(0.75, 0.94)$	-3.0
Math & Computing	$9,460$	$31,558$	-0.08	0.92	$(0.82, 1.03)$	-1.4
Medicine	$8,885$	$30,904$	0.01	1.01	$(0.92, 1.11)$	0.1
Non-STEM	$56,643$	$203,381$	0.10***	1.10	$(1.06, 1.14)$	4.8
Humanities	$14,647$	$53,480$	-0.01	0.98	$(0.91, 1.07)$	-0.4
Social Sciences	$14,897$	$52,885$	0.04	1.04	$(0.96, 1.13)$	1.1
Health	$13,264$	$45,305$	0.13**	1.14	$(1.05, 1.24)$	3.1
Business	$7,760$	$28,539$	0.16**	1.17	$(1.05, 1.30)$	2.9
Education	$5,979$	$20,174$	0.07	1.08	$(0.96, 1.21)$	1.2

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S12**: Odds of women leaving academia, STEM vs. non-STEM, and each of the nine domains, as assistant professors, adjusting for training and environmental controls.

Attrition	**Associate**, adjusted					
	N_{unique}	$N_{person-yrs}$	$\hat{\boldsymbol{\beta}_{\boldsymbol{W}}}$	$\exp(\hat{\boldsymbol{\beta}_{\boldsymbol{W}}})$	95% CI	z
Academia	$100,318$	$459,541$	0.20***	1.22	$(1.18, 1.26)$	11.8
STEM	$45,351$	$195,597$	0.11***	1.11	$(1.05, 1.18)$	3.8
Natural Sciences	$24,916$	$105,020$	0.05	1.06	$(0.98, 1.14)$	1.5
Engineering	$9,910$	$44,011$	0.08	1.08	$(0.93, 1.25)$	1.1
Math & Computing	$9,054$	$41,380$	0.24**	1.27	$(1.11, 1.46)$	3.5
Medicine	$7,744$	$30,817$	0.12*	1.13	$(1.01, 1.27)$	2.1
Non-STEM	$57,203$	$272,090$	0.22***	1.24	$(1.19, 1.29)$	10.0
Humanities	$18,642$	$95,957$	0.10*	1.11	$(1.02, 1.21)$	2.5
Social Sciences	$14,425$	$66,616$	0.11*	1.12	$(1.02, 1.23)$	2.5
Health	$10,983$	$46,422$	0.27***	1.31	$(1.20, 1.43)$	5.9
Business	$6,724$	$31,105$	0.02	1.02	$(0.90, 1.17)$	0.3
Education	$6,092$	$26,850$	0.12*	1.13	$(1.00, 1.27)$	2.0

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S13**: Odds of women leaving academia, STEM vs. non-STEM, and each of the nine domains, as associate professors, adjusting for training and environmental controls.

Attrition	**Full**, adjusted					
	N_{unique}	$N_{person-yrs}$	$\hat{\boldsymbol{\beta}_{\boldsymbol{W}}}$	$\exp(\hat{\boldsymbol{\beta}_{\boldsymbol{W}}})$	95% CI	z
Academia	$107,327$	$602,777$	0.31***	1.36	$(1.32, 1.40)$	21.6
STEM	$56,787$	$324,932$	0.10***	1.10	$(1.05, 1.16)$	4.0
Natural Sciences	$32,457$	$181,941$	0.08**	1.09	$(1.02, 1.15)$	2.6
Engineering	$12,477$	$73,275$	-0.03	0.97	$(0.85, 1.11)$	-0.4
Math & Computing	$11,075$	$66,245$	0.26***	1.29	$(1.14, 1.46)$	4.1
Medicine	$8,964$	$45,048$	-0.01	0.99	$(0.89, 1.10)$	-0.2
Non-STEM	$53,140$	$289,116$	0.33***	1.39	$(1.34, 1.44)$	18.1
Humanities	$16,799$	$93,862$	0.20***	1.23	$(1.15, 1.31)$	6.2
Social Sciences	$15,406$	$85,923$	0.29***	1.33	$(1.24, 1.43)$	7.6
Health	$9,003$	$43,698$	0.30***	1.35	$(1.24, 1.46)$	7.2
Business	$6,855$	$38,270$	0.26***	1.30	$(1.15, 1.46)$	4.3
Education	$4,909$	$23,460$	0.22***	1.25	$(1.12, 1.38)$	4.2

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S14**: Odds of women leaving academia, STEM vs. non-STEM, and each of the nine domains, as full professors, adjusting for training and environmental controls.

Promotion			**Associate**, adjusted			
	N_{unique}	$N_{person-yrs}$	$\hat{\boldsymbol{\beta}_{\boldsymbol{W}}}$	$\exp(\hat{\boldsymbol{\beta}_{\boldsymbol{W}}})$	95% CI	z
Academia	$100,405$	$356,642$	-0.08***	0.92	$(0.90, 0.94)$	-7.7
STEM	$48,372$	$170,859$	-0.15***	0.86	$(0.83, 0.89)$	-9.5
Natural Sciences	$26,825$	$95,662$	-0.15***	0.86	$(0.82, 0.89)$	-7.2
Engineering	$10,728$	$37,316$	-0.03	0.97	$(0.90, 1.04)$	-0.8
Math & Computing	$9,039$	$29,926$	0.00	1.00	$(0.93, 1.08)$	0.1
Medicine	$8,364$	$28,979$	-0.11**	0.89	$(0.83, 0.96)$	-2.9
Non-STEM	$54,480$	$192,550$	-0.09***	0.92	$(0.89, 0.94)$	-6.4
Humanities	$14,199$	$51,160$	-0.07**	0.93	$(0.89, 0.98)$	-2.8
Social Sciences	$14,364$	$50,278$	-0.05	0.95	$(0.91, 1.01)$	-1.7
Health	$12,590$	$42,355$	-0.08*	0.92	$(0.86, 0.98)$	-2.5
Business	$7,531$	$26,997$	-0.04	0.96	$(0.88, 1.04)$	-1.0
Education	$5,704$	$18,900$	-0.03	0.97	$(0.89, 1.06)$	-0.6

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S15**: Odds of women being promoted to associate professor, STEM vs. non-STEM, and each of the nine domains, adjusting for training and environmental controls.

Promotion	**Full**, adjusted					
	N_{unique}	$N_{person-yrs}$	$\hat{\boldsymbol{\beta}}_{\boldsymbol{W}}$	$\exp(\hat{\boldsymbol{\beta}}_{\boldsymbol{W}})$	95% CI	z
Academia	$97,824$	$444,354$	-0.13***	0.88	$(0.86, 0.90)$	-11.2
STEM	$44,149$	$189,310$	-0.05**	0.95	$(0.92, 0.99)$	-2.7
Natural Sciences	$24,188$	$101,504$	-0.06**	0.94	$(0.89, 0.98)$	-2.8
Engineering	$9,700$	$42,748$	-0.00	0.99	$(0.92, 1.08)$	-0.1
Math & Computing	$8,875$	$40,231$	-0.08	0.92	$(0.84, 1.00)$	-2.0
Medicine	$7,467$	$29,586$	-0.01	0.99	$(0.91, 1.07)$	-0.3
Non-STEM	$55,841$	$262,885$	-0.08***	0.92	$(0.89, 0.95)$	-5.5
Humanities	$18,348$	$93,601$	-0.13***	0.88	$(0.83, 0.92)$	-4.7
Social Sciences	$14,108$	$64,631$	-0.11***	0.90	$(0.84, 0.95)$	-3.6
Health	$10,573$	$44,046$	-0.04	0.96	$(0.89, 1.04)$	-0.9
Business	$6,571$	$29,966$	-0.06	0.94	$(0.85, 1.04)$	-1.1
Education	$5,915$	$25,593$	0.01	1.01	$(0.91, 1.12)$	0.2

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S16**: Odds of women being promoted to full professor, STEM vs. non-STEM, and each of the nine domains, adjusting for training and environmental controls.

B. Prestige x gender interaction (Figs. 2B-D)

While our main model described in SI Section S3A and visualized in **Fig. 2A** has no interaction terms, we created an additional model with the same covariates, but with an interaction term between prestige and gender, in order to allow attrition risk to vary differently across the prestige hierarchy for women and men:

$$\begin{aligned} logit(p) = \beta_0 &+ \beta_1[\text{Women}] + \beta_2[\text{Career age}] + \beta_3[\text{PhD year}] + \beta_4[\text{U.S. degree}] + \beta_5[\text{Prestige decile}] \\ &+ \beta_6[\text{Prestige decile x Women}] \end{aligned}$$

We ran subgroup analyses for women's attrition from assistant, associate and full professor positions in academia as a whole, adjusting for their PhD training, employer environment, career age, and the interaction between prestige and gender (**Table S17**). Significance was assessed using z-tests. The gender coefficient β_1 in this model represents women's attrition relative to men's at the least prestigious institution in our dataset (i.e., where prestige = 0). The prestige coefficient β_5 represents the change in men's attrition risk for each additional prestige decile. The interaction coefficient β_6 represents the additional change in women's attrition risk for each additional prestige decile. Since all interaction coefficients are negative and significant (**Table S17**), that means that while men are less likely to leave higher-prestige institutions than lower prestige-institutions, women are even less likely than men to leave higher-prestige institutions.

We then ran additional subgroup analyses for women's attrition from assistant, associate and full professor positions, adjusting for their PhD training, employer environment, and career age, for STEM domains (**Table S18**) and non-STEM domains (**Table S19**) separately.

We calculated population averages by computing the probabilities for each person-year of attrition. Then, for each relevant subgroup, with 3 [assistant, associate, full] x 2 [women, men] x 2 [STEM, non-STEM] x 10 [each prestige decile] = 360 subgroups total, we averaged across all faculty within a given subgroup to get the average probabilities for each subgroup shown in **Figs. 2B-D**.

Attrition, **Academia**	**Assistant** ($N = 376,366$ person-years), adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.14∗∗∗	1.16	$(1.07, 1.25)$	3.7
Career age	0.05∗∗∗	1.05	$(1.05, 1.06)$	17.1
PhD year	0.01∗	1.01	$(1.00, 1.01)$	2.4
U.S. degree	−0.07**	0.93	$(0.89, 0.97)$	−3.3
Prestige decile	−0.07∗∗∗	0.93	$(0.92, 0.94)$	−12.8
Women x Prestige decile	−0.02∗	0.98	$(0.97, 1.00)$	−2.2
	Associate ($N = 459,541$ person-years), adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.41∗∗∗	1.51	$(1.38, 1.65)$	9.0
Career age	0.12∗∗∗	1.13	$(1.13, 1.14)$	36.6
PhD year	0.06∗∗∗	1.06	$(1.05, 1.06)$	17.4
U.S. degree	−0.03	0.97	$(0.92, 1.02)$	−1.1
Prestige decile	−0.06∗∗∗	0.94	$(0.93, 0.95)$	−9.8
Women x Prestige decile	−0.04∗∗∗	0.95	$(0.94, 0.97)$	−5.0
	Full ($N = 602,777$ person-years), adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.40∗∗∗	1.49	$(1.38, 1.61)$	10.3
Career age	0.14∗∗∗	1.15	$(1.15, 1.16)$	51.9
PhD year	0.07∗∗∗	1.07	$(1.06, 1.07)$	26.2
U.S. degree	0.27∗∗∗	1.31	$(1.25, 1.37)$	11.6
Prestige decile	−0.13∗∗∗	0.87	$(0.87, 0.88)$	−33.3
Women x Prestige decile	−0.02∗	0.98	$(0.97, 1.00)$	−2.5

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S17**: Odds of women leaving academia as a whole as assistant professors, associate professors and full professors, adjusting for training and environmental controls and for an interaction between prestige and gender.

Attrition, **STEM**	**Assistant** ($N = 180,145$ person-years), adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.13*	1.14	(1.01, 1.30)	2.0
Career age	0.06***	1.06	(1.05, 1.07)	14.1
PhD year	0.02***	1.02	(1.01, 1.03)	4.7
U.S. degree	−0.12***	0.89	(0.84, 0.94)	−4.4
Prestige decile	−0.06***	0.94	(0.92, 0.95)	−8.5
Women x Prestige decile	−0.03**	0.96	(0.94, 0.99)	−2.7
	Associate ($N = 195,597$ person-years), adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.28**	1.32	(1.12, 1.55)	3.3
Career age	0.13***	1.13	(1.12, 1.15)	23.9
PhD year	0.06***	1.06	(1.05, 1.07)	12.0
U.S. degree	−0.07*	0.93	(0.87, 0.99)	−2.1
Prestige decile	−0.03**	0.97	(0.95, 0.99)	−3.2
Women x Prestige decile	−0.03*	0.96	(0.93, 1.00)	−2.2
	Full ($N = 324,932$ person-years), adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.08	1.09	(0.94, 1.25)	1.2
Career age	0.14***	1.16	(1.15, 1.16)	36.1
PhD year	0.06***	1.07	(1.06, 1.07)	17.3
U.S. degree	0.26***	1.30	(1.23, 1.37)	9.1
Prestige decile	−0.12***	0.88	(0.87, 0.89)	−21.0
Women x Prestige decile	0.00	1.00	(0.98, 1.03)	0.2

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S18**: Odds of women leaving STEM domains as assistant professors, associate professors and full professors, adjusting for training and environmental controls and for an interaction between prestige and gender.

Attrition, **non-STEM**	**Assistant** ($N = 203,381$ person-years), adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.13*	1.14	$(1.03, 1.25)$	2.6
Career age	0.05***	1.05	$(1.04, 1.06)$	12.1
PhD year	-0.00	1.00	$(0.99, 1.00)$	-0.7
U.S. degree	-0.13**	0.87	$(0.81, 0.94)$	-3.4
Prestige decile	-0.06***	0.94	$(0.92, 0.95)$	-9.3
Women x Prestige decile	-0.01	0.99	$(0.97, 1.01)$	-0.7
	Associate ($N = 272,090$ person-years), adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.38***	1.46	$(1.31, 1.63)$	6.8
Career age	0.13***	1.13	$(1.12, 1.14)$	28.6
PhD year	0.05***	1.06	$(1.05, 1.06)$	13.0
U.S. degree	-0.11*	0.90	$(0.82, 0.99)$	-2.2
Prestige decile	-0.08***	0.92	$(0.90, 0.93)$	-10.4
Women x Prestige decile	-0.03**	0.96	$(0.94, 0.99)$	-3.1
	Full ($N = 289,116$ person-years), adjusted			
	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.41***	1.50	$(1.37, 1.64)$	8.8
Career age	0.16***	1.16	$(1.15, 1.17)$	39.1
PhD year	0.07***	1.07	$(1.07, 1.08)$	20.8
U.S. degree	0.03	1.03	$(0.95, 1.11)$	0.7
Prestige decile	-0.14***	0.87	$(0.86, 0.87)$	-26.3
Women x Prestige decile	-0.01	0.98	$(0.97, 1.00)$	-1.8

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S19**: Odds of women leaving non-STEM domains as assistant professors, associate professors and full professors, adjusting for training and environmental controls and for an interaction between prestige and gender.

C. Robustness checks

C1. Fixed effects for each academic field

We found that women are more likely to be employed as faculty in academic domains and fields with higher overall attrition rates, regardless of gender (**Fig. S3**). The correlations between the fraction of women in each field and the average annual attrition risk in each field were moderate for assistant and associate professors ($R = 0.447$ and $R = 0.425$, respectively, both $p < 0.001$; **Fig. S3D-E**), and strong for full professors ($R = 0.618$, $p < 0.001$; **Fig. S3F**). Our analysis cannot isolate the reasons for this correlation, which is an interesting puzzle for future work, and relates to broader existing work on occupational gender segregation [112, 113].

However, we wanted to know how much of the gendered difference in the academia-level retention rates was due to these cross-field differences in overall attrition rates. Comparing the average woman in academia to the average man in academia is our main goal, but if the entire gender effect is due to cross-field differences, that would imply different policy interventions than if there is still a difference in retention for women and men in the same field. The covariate-adjusted odds ratio of gendered attrition that we estimate for academia as a whole is equivalent to a population-weighted average over fields, representing the likelihood that a uniformly random woman professor would leave academia, compared to a man in the same PhD cohort, at the same career age and rank, and at the same institution. Including fixed effects in the model would adjust for field differences and effectively give each field equal weight in the estimate of the gender effect.

To investigate this further, we added 111 fixed effects, one for each academic field, to our main model predicting the odds of attrition (**Fig. 2A, Table S20A**). We found that the gender coefficient was eliminated for assistant professors (**Table S20B**), meaning that the entire gender effect in academic retention of assistant professors can be attributed to cross-field differences in retention, e.g., the unequal distribution of women across high- and low-turnover fields. We also found that the gender coefficients for associate and full professors were reduced substantially, but not eliminated (**Table S20B**), implying that while cross-field differences in retention are associated with much of the gendered differences in retention, there still exist disparities in retention for tenured women vs. men in the same field, at the same institution.

Domain-level gender composition vs. statistical significance of domain-level odds ratios. Interpreting the odds ratios at the domain level (**Fig. 2A**), is there a relationship between the gender composition of a domain and how likely it is that women in that domain are more likely to leave than men?

To investigate the potential relationship between a domain's gender composition and the relative attrition/promotion odds for women vs men, we checked the correlations between the two. We found no significant correlations, but we did observe differences in patterns for attrition vs promotion. For attrition, the general trend is that domains with greater fractions of women are also the domains with the highest odds ratios of women leaving vs men (**Fig. S4**). For promotion, it does look like the domains with some of the highest (education) and lowest (engineering) fractions of women are less likely to show significant gender differences in the annual odds (**Fig. S5**). However, there are domains with more moderate fractions of women that also do not show significant differences (e.g., social sciences for promotion to associate, and medicine for promotion to full), and there are some domains with high and low fractions of women that do show significant differences (e.g., health for promotion to associate, and math & computing for promotion to full). These patterns are interesting and we hope future work will investigate them further.

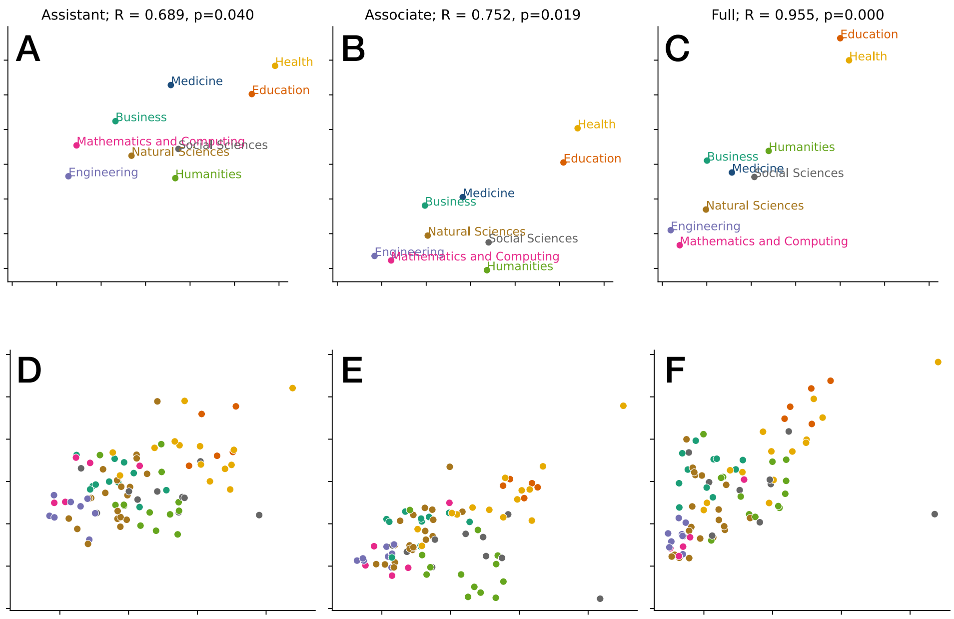

Figure **S3**: **Discipline-level attrition risks and the fraction of women in each discipline. A-C**. The fraction of women employed in each domain, at each academic rank, averaged across 2011-2020, vs. the average annual attrition risk for a faculty member in each domain, at each academic rank, regardless of gender. **D-F**. The fraction of women employed in each field, at each academic rank, averaged across 2011-2020, vs. the average annual attrition risk for a faculty member in each field, at each academic rank, regardless of gender. Fields are colored by their containing domains.

A. Main Results	Attrition						Promotion			
	Assistant		Associate		Full		Associate		Full	
	$\exp(\hat{\beta})$	95% CI	$\exp(\hat{\beta})$	95% CI	$\exp(\hat{\beta})$	95% CI	$\exp(\hat{\beta})$	95% CI	$\exp(\hat{\beta})$	95% CI
Women	1.07∗∗∗	(1.04, 1.10)	1.22∗∗∗	(1.18, 1.26)	1.36∗∗∗	(1.32, 1.40)	0.92∗∗∗	(0.90, 094)	0.88∗∗∗	(0.86, 0.90)
Career age	1.05∗∗∗	(1.05, 1.06)	1.13∗∗∗	(1.12, 1.14)	1.15∗∗∗	(1.15, 1.16)	1.07∗∗∗	(1.06, 1.07)	1.02∗∗∗	(1.02, 1.03)
PhD year	1.01∗	(1.00, 1.01)	1.06∗∗∗	(1.05, 1.07)	1.07∗∗∗	(1.06, 1.07)	1.01**	(1.00, 1.01)	1.02∗∗∗	(1.02, 1.03)
U.S. degree	0.93**	(0.89, 0.97)	0.97	(0.92, 1.02)	1.31∗∗∗	(1.25, 1.37)	1.46∗∗∗	(1.41, 1.51)	0.84∗∗∗	(0.81, 0.87)
Prestige decile	0.93∗∗∗	(0.92, 0.93)	0.92∗∗∗	(0.91, 0.93)	0.87∗∗∗	(0.86, 0.87)	1.03∗∗∗	(1.02, 1.03)	1.09∗∗∗	(1.08, 1.10)
B. Fixed field	Attrition						Promotion			
	Assistant		Associate		Full		Associate		Full	
	$\exp(\hat{\beta})$	95% CI	$\exp(\hat{\beta})$	95% CI	$\exp(\hat{\beta})$	95% CI	$\exp(\hat{\beta})$	95% CI	$\exp(\hat{\beta})$	95% CI
Women	1.01	(0.98, 1.04)	1.09∗∗∗	(1.05, 1.13)	1.17∗∗∗	(1.14, 1.21)	0.92∗∗∗	(0.91, 0.94)	0.95∗∗∗	(0.93, 0.98)
Career age	1.05∗∗∗	(1.05, 1.06)	1.14∗∗∗	(1.13, 1.14)	1.16∗∗∗	(1.15, 1.17)	1.09∗∗∗	(1.08, 1.09)	1.02∗∗∗	(1.02, 1.03)
PhD year	1.00∗	(1.00, 1.01)	1.06∗∗∗	(1.05, 1.07)	1.07∗∗∗	(1.07, 1.08)	1.01∗∗∗	(1.00, 1.01)	1.02∗∗∗	(1.02, 1.03)
U.S. degree	0.86∗∗∗	(0.83, 0.90)	0.90∗∗∗	(0.85, 0.95)	1.13∗∗∗	(1.07, 1.18)	1.29∗∗∗	(1.24, 1.33)	0.91∗∗∗	(0.87, 0.94)
Prestige decile	0.93∗∗∗	(0.92, 0.94)	0.91∗∗∗	(0.91, 0.92)	0.87∗∗∗	(0.86, 0.87)	1.04∗∗∗	(1.03, 1.04)	1.10∗∗∗	(1.09, 1.10)

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S20**: Regression coefficients presented as odds ratios for (A) the main results, (B) with fixed effects for each of the 111 academic fields included additional predictors.

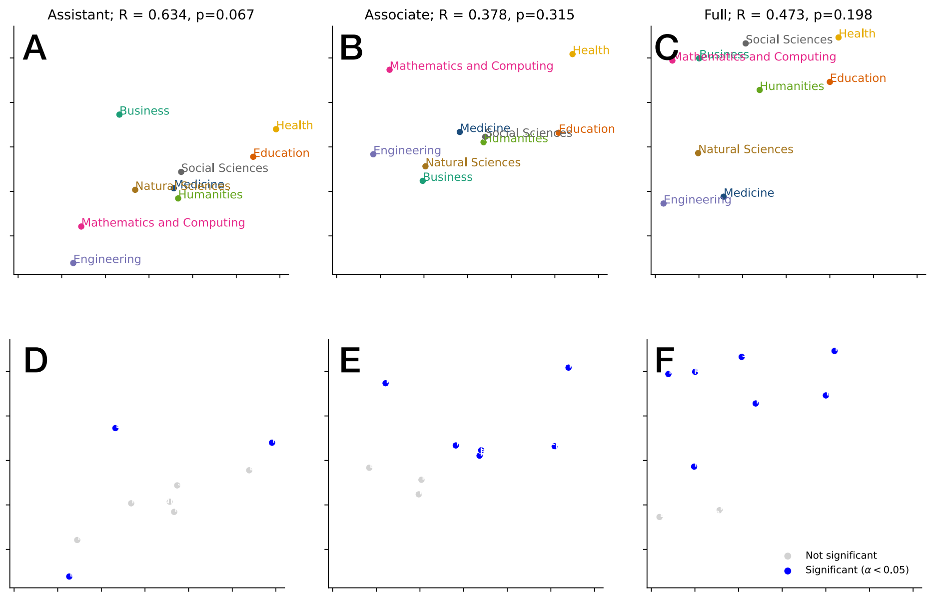

Figure **S4**: **Discipline-level attrition odds and the fraction of women in each discipline. A-C**. The fraction of women employed in each domain, at each academic rank, averaged across 2011-2020, vs. the gendered odds ratio of leaving each domain, at each academic rank, colored by domain. **D-F**. The fraction of women employed in each domain, at each academic rank, averaged across 2011-2020, vs. the gendered odds ratio of leaving each domain, at each academic rank, colored by statistical significance.

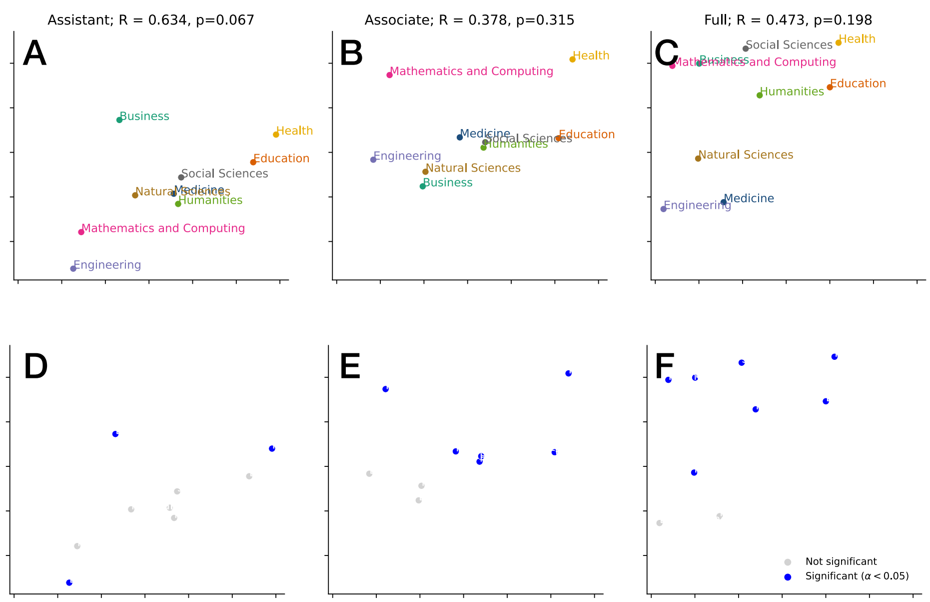

Figure **S5**: **Discipline-level promotion odds and the fraction of women in each discipline. A-B**. The fraction of women employed in each domain, at each academic rank, averaged across 2011-2020, vs. the gendered odds ratio of being promoted in each domain, at each academic rank, colored by domain. **C-D**. The fraction of women employed in each domain, at each academic rank, averaged across 2011-2020, vs. the gendered odds ratio of being promoted in each domain, at each academic rank, colored by statistical significance.

C2. Excluding older faculty (presumed retirements)

Although the purpose of our study is not to examine individual causes of attrition, but instead to consider the phenomenon of gendered attrition from the broadest possible perspective, or "all-cause attrition", we wondered whether gendered attrition in the later-career of faculty reflects gendered differences in retirement ages, i.e., perhaps women retire from the workforce at younger ages than do men.

To investigate this, we conducted two robustness checks. The first was re-running our main model only including faculty with career age ≤ 15. The second was identical, but with career age ≤ 25. On these two samples of younger faculty, we nevertheless find results in strong agreement with the larger analysis, showing that on average, women are more likely than men to leave (**Table S21**).

	Main Results		Robustness Checks			
	Career age ≤ 40		Career age ≤ 15		Career age ≤ 25	
	$\exp(\hat{\boldsymbol{\beta}})$	95% CI	$\exp(\hat{\boldsymbol{\beta}})$	95% CI	$\exp(\hat{\boldsymbol{\beta}})$	95% CI
Associate	$1.22{*}{*}{*}$	$(1.18, 1.26)$	$1.19{*}{*}{*}$	$(1.13, 1.26)$	$1.26{*}{*}{*}$	$(1.21, 1.32)$
Full	$1.36{*}{*}{*}$	$(1.32, 1.40)$	$1.39{*}{*}{*}$	$(1.24, 1.55)$	$1.46{*}{*}{*}$	$(1.39, 1.54)$

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S21**: Gender coefficients for associate and full professors presented as odds ratios for the main results, and for robustness checks run on faculty with career age ≤ 15 and with career age ≤ 25.

C3. Excluding the last two years of data (imputation procedure)

Our data cleaning and imputation procedure used an assumption that “you only leave once” (Section S1D), meaning that if someone disappears and then reappears, we don’t count them as leaving academia, even if they may have actually left their job to work in industry temporarily and then returned (to the same institution or to a different one). Hence our analysis should be robust to faculty taking temporary leaves to work in industry or government.

However, this approach may make mistakes for faculty who leave but have not returned by the end of our sample frame, and if they haven’t come back yet, we may incorrectly assume they have left academia forever.

To investigate these potential errors, we ran a robustness check for **Fig. 2A**, recalculating all results using only the years 2011-2018 instead of the full data 2011-2020. We found that most of the point estimates remain the same or shift only slightly (including in engineering); the main difference between these analyses was larger confidence intervals with the smaller dataset, as expected (**Table S22**).

	Main Results Years 2011–2020		Robustness Check Years 2011–2018	
	$\exp(\hat{\boldsymbol{\beta}})$	95% CI	$\exp(\hat{\boldsymbol{\beta}})$	95% CI
Assistant	1.07***	$(1.04, 1.10)$	1.11***	$(1.06, 1.15)$
Associate	1.22***	$(1.18, 1.26)$	1.17***	$(1.12, 1.23)$
Full	1.36***	$(1.32, 1.40)$	1.32***	$(1.27, 1.37)$

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S22**: Gender coefficients for assistant, associate and full professors presented as odds ratios for the main results, and for a robustness check run on faculty records from 2011-2018.

C4. Age of first tenure-track job

A limitation of defining career age as the age since someone received their PhD is that by comparing faculty at the same career age, we may not be comparing faculty as the same career progression. For example, one faculty member with a career age of 7 could be just starting their tenure-track job while another could be preparing their tenure packet. This is not relevant to our study unless those career age differences are gendered, e.g., if women were to start their tenure-track jobs earlier than men, on average, or vice versa.

Gendered pursuit of, or experiences in, postdoc positions are not well captured in our faculty-level data, and hence those effects are effectively "upstream" of our data. Previous evidence indicates that women and men in computer science, business, and history on average start their first tenure-track faculty job at similar biological ages, suggesting that postdoc'ing may not be gendered on average. Using survey responses from a past study in our group [91], we expanded this analysis to additional fields (anthropology, biology, physics/astronomy, psychology, and sociology), and found the same nongendered pattern in biological age for the beginning of a first faculty job (age 33), without significant differences across fields. Of course, this analysis does not indicate whether there is gendered attrition between PhD year and first faculty job, and previous evidence in computer science suggests that there is an effect there [62]. We adjust for PhD year in our longitudinal analyses to help account for this potential difference, but expanding analyses like ours of gendered attrition to postdocs is an important direction for future work.

D. The role of productivity in attrition

We wanted to know how much of the observed gendered differences in retention were associated with individual levels of productivity. Prior work has suggested that individual productivity may play a role in gendered retention patterns [14, 21], but has also found that gendered patterns still hold in promotion even after controlling for productivity [114]. Interested in probing this line of thinking, we started to implement a supplemental productivity analysis. However, we drew the conclusion that such an analysis is not (yet) feasible while appropriately accounting for what is known about endogenous and exogenous variation in productivity, which we now explain in more detail.

First, individual productivity is associated with or even driven by a variety of factors:

- Individual publication rates vary substantially in magnitude as a result of the faculty's location in the prestige hierarchy [40], in large part because faculty at more prestigious institutions have larger research groups, which causes greater productivity, but only in academic fields with collaborative norms (vs non-collaborative norms) [41]. In addition, men exhibit both greater productivity and larger research groups [41].
- The average productivity of individuals varies non-linearly over the course of a faculty career, following a rapid rise, and then a slow decline, regardless of their institutional prestige (but, institutional prestige shifts this average pattern up or down in scale, and moderates the speed of initial increase, and the rate of subsequent decline). However, only a minority of individual faculty have productivity trajectories that closely follow this average "canonical trajectory", and instead individual faculty—even lifelong academics—exhibit a diverse range of productivity patterns [42], on both a year-to-year basis and cumulatively over time.
- Individual publication rates are influenced by other individual-level factors such as parenthood, especially motherhood [38] and social networks [44], and both the timing of parenthood and the social capital of collaborators are important but difficult to observe or estimate. In addition, gendered differences in work-time expectations (e.g., more time spent on service or in middle-author roles [43]) can impact publication rates as well.

As a result of these factors, when we sought to map out a hypothetical causal diagram for an analysis that includes productivity, we realized that there were a great number of potential hypotheses for causality and confounding in this system. Designing a regression framework that would properly account for these time-varying, prestige-dependent, field-specific, historical and contingent factors would be highly complicated, and it would still not clearly identify the hypothesized relationship between productivity and attrition.

Continuing this line of reasoning, we can imagine a simple causal link, whereby low productivity causes attrition (e.g. through dismissal or failure to be reappointed/promoted), or a more complex causal structure whereby low productivity and attrition are both driven by a third variable that is driven by gender (e.g. through excessive service requirements, work-life balance, workplace climate, or significant public outreach). Were we to include productivity in a regression model and then see gendered differences in retention disappear (or persist), we would be poorly positioned to accurately explain these results.

We also noted a great deal of potential freedom in operationalizing productivity. It is not clear theoretically or empirically which operationalization would have more causal relevance, and it is plausible that different operationalizations are more or less relevant at different career stages. For instance, we might hypothesize that a pre-tenure assistant professor's attrition may be explained by their total cumulative productivity post-hire, e.g., because of the particular expectations associated with tenure evaluations. In contrast, a post-tenure associate professor's attrition may have more to do with cumulative productivity only over the most recent N years. Multiple zero-publication years may be an indicator of increased likelihood of attrition, although it could also indicate a move into a more administrative role, such as department chair, that would not be related to potential attrition (and in fact could be oppositely correlated).

In summary, we believe that there is no straightforward operationalization of productivity (for the purposes of analyzing retention), nor a set of clear and identifiable causal mechanisms to test with our current data that would yield reliable and clearly interpretable results. We believe that this area of inquiry would be valuable to explore in future work.

S4. Survey Analysis

A. Pushes and pulls

Former faculty ($N = 433$ faculty who left academia and $N = 954$ retirees) were asked if they left academia due to a push, pull, both, or neither, using the following question on the survey:

I changed positions because (check all that apply):

☐ I was unhappy, stressed, or otherwise unsatisfied, causing me to leave my previous position.

☐ I was drawn to, excited by, or otherwise attracted to my new position.

☐ I wanted to retire.

Similarly, current faculty ($N = 7,195$) were asked if they would leave academia due to a push, pull, both, or neither, using the following question on the survey:

Think about the reasons that might lead you to consider leaving your position (check all that apply):

☐ I am unhappy, stressed, or otherwise less than satisfied with my current position.

☐ I am drawn to, excited by, or otherwise attracted to a different position.

☐ I would not consider leaving.

In our survey, 10,071 faculty saw the question, and faculty who switched institutions ($N = 1,489$) were asked the same question as former faculty, but switching institutions is a different aspect of retention, so they were excluded from the main analysis, but supplementary results can be found in Section S4C.

In the main analysis, 8,582 current and former faculty saw the question, but 1,310 faculty members (15%) with a missing degree year or a career age greater than 40 were excluded. In addition, former faculty who only said "I wanted to retire" (N = 401) and current faculty who said "'I would not consider leaving" (N = 1,623) were excluded from this analysis (**Table S23**). Finally, 329 respondents (4%) skipped the question as it was an optional question. This left 4,919 current and former faculty who were included in the push/pull multivariate regression analysis.

	N	Push	Pull	Both	Neither
Current faculty	6,162	30.2%	19.7%	23.7%	26.4%
STEM women	875	36.1%	16.4%	28.1%	19.4%
Non-STEM women	1,375	34.4%	16.8%	25.1%	23.7%
STEM men	2,272	29.2%	20.6%	22.3%	27.9%
Non-STEM men	1,560	24.9%	23.0%	21.8%	30.3%
Former faculty	781	26.9%	9.1%	12.7%	51.3%
STEM women	87	31.0%	8.0%	21.8%	39.0%
Non-STEM women	169	40.8%	6.5%	8.3%	44.4%
STEM men	303	19.8%	9.6%	14.8%	55.8%
Non-STEM men	182	20.9%	11.5%	8.8%	58.8%

Table **S23**: Fraction of current and former (left academia or retired) faculty between career ages 1–40 who left or would leave due to a push, a pull, both, or neither ("I would not consider leaving" for current faculty and "I wanted to retire" for former faculty). Rows sum to 100.

We used the smaller dataset described above in order to assess the relative importance of gender, institutional prestige and academic domain, adjusting for career age, on feeling pushed or pulled. We excluded people who did not consider leaving or who only wanted to retire in order to only compare people who considered leaving or left due to positive/negative forces to each other.

We fit separate logistic regression models to the dataset to model the probability p of feeling pushed out of a faculty position (1 = only pushed, 0 = only pulled, or both pushed and pulled), and separately, feeling pulled towards a better position (1 = only pulled, 0 = only pushed, or both pushed and pulled), using faculty gender (0 = man, 1 = woman), career age (integer number of years since PhD), whether they are in a STEM or non-STEM domain (0 = non-STEM, 1 = STEM), and faculty employer prestige (scaled such that a 1 unit increase corresponds to a 1 decile increase up the prestige hierarchy, but note that each rank in the regression represents a unique institution; Section S1A):

$$logit(p) = \beta_0 + \beta_1[\text{Women}] + \beta_2[\text{Career age}] + \beta_3[\text{STEM}] + \beta_4[\text{Prestige decile}]$$

If feeling pushed out of a faculty position does not depend on gender, the odds that a woman feels pushed ($odds_W$) should be equal to the odds that a man feels pushed ($odds_M$), so $odds_W/odds_M$ (the odds ratio), which is equal to $\exp(\beta_1)$, should be 1. An odds ratio that is less than 1 means that men are more likely to feel pushed than women, and an odds ratio that is greater than 1 means that women are more likely to feel pushed than men (**Table S24**).

Feeling pushed	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.37***	1.44	(1.28, 1.63)	6.0
Career age, t (decades)	0.26***	1.30	(1.22, 1.38)	8.5
Prestige decile	−0.03**	0.97	(0.95, 0.99)	−2.7
STEM	0.03	1.03	(0.92, 1.16)	0.6
Feeling pulled	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	−0.50***	0.61	(0.53, 0.70)	−7.0
Career age, t (decades)	0.07*	1.08	(1.01, 1.15)	2.2
Prestige decile	0.04*	1.04	(1.01, 1.07)	2.9
STEM	−0.17*	0.84	(0.74, 0.96)	−2.5

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S24**: Odds of feeling only pushed out and only pulled towards a better position, adjusting for gender, career age, prestige decile, and whether in a STEM domain or not.

We added an additional covariate to the model to see if being a parent of children under the age of 18 (especially mothers) had an association with being pushed or pulled (**Table S25**):

$$\begin{aligned} logit(p) = \beta_0 &+ \beta_1[\text{Women}] + \beta_2[\text{Career age}] + \beta_3[\text{Prestige decile}] + \beta_4[\text{STEM}] \\ &+ \beta_5[\text{Parents}] \\ &+ \beta_6[\text{Women x Parents (Mothers)}] \end{aligned}$$

Feeling pushed	$\hat{\boldsymbol{\beta}}$	$\exp(\hat{\boldsymbol{\beta}})$	95% CI	z
Women	0.43***	1.53	(1.31, 1.79)	5.3
Career age	0.22***	1.25	(1.17, 1.34)	6.7
Prestige decile	−0.03**	0.97	(0.95, 0.99)	−2.6
STEM	0.04	1.04	(0.93, 1.17)	0.7
Parents of children under 18	−0.13	0.88	(0.75, 1.03)	−1.6
Mothers of children under 18	−0.17	0.84	(0.66, 1.06)	−1.4
Feeling pulled	$\hat{\boldsymbol{\beta}}$	$\exp(\hat{\boldsymbol{\beta}})$	95% CI	z
Women	−0.46***	0.63	(0.52, 0.76)	−4.8
Career age	0.15***	1.16	(1.08, 1.25)	4.0
Prestige decile	0.04**	1.04	(1.01, 1.07)	2.7
STEM	−0.18**	0.83	(0.73, 0.95)	−2.7
Parents of children under 18	0.37***	1.45	(1.22, 1.72)	4.3
Mothers of children under 18	−0.03	0.97	(0.74, 1.28)	−0.2

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S25**: Odds of feeling only pushed out and only pulled towards a better position, adjusting for gender, career age, prestige decile, whether in a STEM domain or not, whether a parent of kids under 18 or not, and whether a mother of kids under 18 or not.

Similarly, we added an additional covariate to the model to see if being a a faculty member of color (faculty who self-identified as "American Indian or Alaskan Native", "Asian", "Black or African American", "Hispanic, Latino, or Spanish origin", or "Native Hawaiian or other Pacific Islander") had an association with being pushed or pulled (**Table S26**):

$$\begin{aligned} logit(p) = \beta_0 &+ \beta_1[\text{Women}] + \beta_2[\text{Career age}] + \beta_3[\text{Prestige decile}] + \beta_4[\text{STEM}] \\ &+ \beta_5[\text{People of color}] \\ &+ \beta_6[\text{Women x People of color (Women of color)}] \end{aligned}$$

Feeling pushed	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	0.38***	1.47	(1.29, 1.67)	5.7
Career age	0.26***	1.30	(1.22, 1.38)	8.5
Prestige decile	−0.03**	0.97	(0.95, 0.99)	−2.7
STEM	0.03	1.03	(0.92, 1.16)	0.6
People of color	0.07	1.08	(0.88, 1.32)	0.7
Women of color	−0.10	0.90	(0.66, 1.23)	−0.6
Feeling pulled	$\hat{\beta}$	$\exp(\hat{\beta})$	95% CI	z
Women	−0.47***	0.63	(0.54, 0.73)	−6.0
Career age	0.08*	1.08	(1.01, 1.16)	2.3
Prestige decile	0.04**	1.04	(1.01, 1.07)	2.9
STEM	−0.17*	0.84	(0.74, 0.96)	−2.5
People of color	0.21*	1.23	(1.00, 1.52)	2.0
Women of color	−0.16	0.85	(0.59, 1.21)	−0.9

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S26**: Odds of feeling only pushed out and only pulled towards a better position, adjusting for gender, career age, prestige decile, whether in a STEM domain or not, whether a faculty member is a person of color, and whether a faculty member is a woman of color.

Finally, we added fixed effects for academic domain to the models, but few individual domains were significant predictors, with the exception of Health in the push model, and Math & Computing, Natural Sciences, and Social Sciences in the pull model (**Table S27**):

Feeling pushed	$\hat{\boldsymbol{\beta}}$	$\exp(\hat{\boldsymbol{\beta}})$	95% CI	z
Women	0.34***	1.41	$(1.25, 1.59)$	5.5
Career age	0.27***	1.31	$(1.23, 1.39)$	8.8
Prestige decile	−0.03*	0.97	$(0.95, 0.99)$	−2.6
Business intercept [reference]	−0.95***	0.39	$(0.29, 0.51)$	−6.5
Education intercept	0.28	1.32	$(0.77, 2.24)$	1.0
Engineering intercept	0.21	1.23	$(0.91, 1.65)$	1.4
Heath intercept	0.52**	1.69	$(1.16, 2.46)$	2.7
Humanities intercept	0.00	1.00	$(0.77, 1.30)$	0.0
Math & Computing intercept	0.24	1.28	$(0.99, 1.66)$	1.8
Medicine intercept	−0.14	0.86	$(0.56, 1.33)$	−0.6
Natural Sciences intercept	0.11	1.12	$(0.90, 1.40)$	1.0
Social Sciences intercept	0.14	1.15	$(0.92, 1.45)$	1.2
Feeling pulled	$\hat{\boldsymbol{\beta}}$	$\exp(\hat{\boldsymbol{\beta}})$	95% CI	z
Women	−0.47***	0.62	$(0.54, 0.72)$	−6.6
Career age	0.07*	1.08	$(1.01, 1.15)$	2.2
Prestige decile	0.04**	1.04	$(1.01, 1.06)$	2.7
Business intercept [reference]	−0.98***	0.37	$(0.27, 0.51)$	−6.2
Education intercept	−0.53	0.59	$(0.31, 1.12)$	−1.6
Engineering intercept	−0.27	0.76	$(0.55, 1.04)$	−1.7
Heath intercept	−0.11	0.89	$(0.59, 1.36)$	−0.5
Humanities intercept	−0.12	0.89	$(0.68, 1.17)$	−0.8
Math & Computing intercept	−0.47**	0.62	$(0.47, 0.82)$	−3.3
Medicine intercept	−0.22	0.80	$(0.50, 1.27)$	−0.9
Natural Sciences intercept	−0.37**	0.69	$(0.54, 0.87)$	−3.2
Social Sciences intercept	−0.35**	0.71	$(0.55, 0.90)$	−2.8

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table **S27**: Odds of feeling only pushed out and only pulled towards a better position, adjusting for gender, career age, and prestige decile, with fixed effects for each of the nine academic domains.

B. Reasons for leaving

Former faculty. First, we removed two of the original 22 survey items from the analysis from the work-life balance category due to very low response rates and concerns about item reliability: difficulties having children and lack of adequate parental leave. This left the three categories unbalanced, so we did not count each reason equally in our analysis of the reasons former faculty left. Instead, we computed weighted reason scores for each subgroup of faculty.

For each person and for each reason they selected, we calculated a "reason weight" instead of using a weight of 1 for each reason. For each reason r a person selected, the reason weight w_r is:

$$w_r = \frac{1}{n_{category}}$$

Since there are 7 professional reasons, 5 work-life balance reasons, and 8 workplace climate reasons, $n_{prof} = 7$, $n_{work-life} = 5$, and $n_{climate} = 8$.

For each person, the sum of their reasons must sum to 1, so the final normed reason weight is:

$$w_{r-normed} = \frac{w_r}{\sum_{w_r}}$$

Now, each person who gave at least one reason for leaving gets 1 point total, and the reasons within that one point can be distributed differently based on the number of reasons they selected and the number of reasons in the categories they selected. For example, if a women who left academia selected 2 reasons for leaving, with one from work-life balance (number of hours worked), and one from workplace climate (harassment), counting each reason equally would mean 50% of the reasons (1/2) she left academia were due to work-life balance, and 50% of the reasons (1/2) were due to workplace climate. However, after weighting the reasons by the number of reasons in each category and the number of reasons she selected, 61.5% of the reasons she left academia were due to work-life balance, and 38.5% of the reasons were due to workplace climate:

Reason	Category	$n_{category}$	w_r	/	$\sum_{w_r}$	=	$w_{r-normed}$	%
Number of hours	Work-life balance	5	$\frac{1}{5} = 0.2$	/	0.325	=	0.615	61.5%
Harassment	Workplace climate	8	$\frac{1}{8} = 0.125$	/	0.325	=	0.385	38.5%
			0.325				1.000	100%

After computing the weighted reason scores for each person, we calculate the fraction of reasons selected from each category by each subgroup (e.g., women who left academia), with N people in the subgroup:

$$F_{category} = \frac{\sum_{w_{r-normed}}}{N}$$

For example, let's assume our full sample consists of three women who left academia. After computing the weighted reason scores for each person, each person has a total of 1 point consisting of different fractions of reasons from each of the three categories:

	$w_{r-normed}$			
Person	Professional	Work-life balance	Climate	
1	0.2	0.6	0.2	1.0
2	0.1	0.2	0.7	1.0
3	0.3	0.1	0.6	1.0

We can then compute $F_{category}$ for each of the three categories of reasons by summing the weighted reason scores across all faculty in the subgroup, and dividing by the total number of faculty in the subgroup:

Category	Person	$w_{r-normed}$				
Professional	1	0.2				
	2	0.1				
	3	0.3				
		$\sum w_{r-normed}$	/	N	=	F_{prof}
		0.6	/	3	=	0.2
Work-life balance	1	0.6				
	2	0.2				
	3	0.1				
		$\sum w_{r-normed}$	/	N	=	$F_{work-life}$
		0.9	/	3	=	0.3
Climate	1	0.2				
	2	0.7				
	3	0.6				
		$\sum w_{r-normed}$	/	N	=	$F_{climate}$
		1.5	/	3	=	0.5
						1.0

We then repeat this for each of the 4 subgroups: women who left academia, women who retired, men who left academia, and men who retired **(Fig. 4A)**. In order to obtain 95% confidence intervals, we performed a bootstrapping procedure by sampling faculty with replacement (1000 iterations).

Current faculty. We did not ask current faculty to check off which survey items might contribute to hypothetical decisions to leave their jobs, as we thought it would be a cognitively demanding task for current faculty members who have not left a job, as opposed to former faculty, who may still find it challenging, but who are more likely to have already thought about the reasons they left their positions. Instead, current faculty were asked how much impact each broad category (professional, work-life balance, and climate) would have on a potential decision to leave their job ("No impact", "Minor impact", "Moderate impact", "Major impact"). No weighting was implemented for these responses, and we report the fraction of people in each subgroup (women in STEM domains, women in non-STEM domains, men in STEM domains, men in non-STEM domains) who said that category would have a "major impact" if they were to leave their jobs.

C. Supplemental analyses

Faculty who switched institutions vs. faculty who left academia. While our analyses focused primarily on faculty who left academia and retired, switching institutions while remaining in academia is an important, although separate, aspect of retention. We asked faculty who switched institutions ($N = 1,489$) the same questions we asked faculty who left academia and retired, in order to assess whether men and women leave academia or switch institutions for similar or different reasons, and to identify reasons common to both groups. In order to avoid masking interesting patterns, faculty who switched institutions vs faculty who left academia are always visualized separately in our analyses.

Pushes and pulls. Faculty left academia more often due to a push than a pull, while faculty switched institutions more often due to a pull than a push (**Fig. S6**). Furthermore, regardless of whether they switched or left, and among current faculty, women were more likely to report that they did or would leave due to a push than men, and less likely to report that they did or would leave due to a pull than men.

Reasons for leaving. Across nearly all career ages, women select workplace climate as the most prevalent reason for leaving academia, except in the very early career, when work-life balance briefly dominates (**Fig. S7A**). In contrast, men are most likely to leave due to professional reasons in the early-to-mid career, and then select reasons from all categories with roughly equal frequency (**Fig. S7B**). Among faculty who switched institutions, the impact of work-life balance decreases sharply and impacts of professional reasons and workplace climate increase for both men and women throughout their careers, but women are more likely to switch institutions due to workplace climate than men (**Fig. S7C-D**). We note that the underlying data of these career-age plots is smoothed, and consists of relatively small sample sizes.

Among the individual sources of stress within the broad categories, "dysfunctional departmental culture or leadership" was the most common reason among faculty who left academia or switched institutions, regardless of gender, selected by more than half of all respondents (**Fig. S8, Table S28**). Hours worked, low acceptance rates for scholarly work, and difficulties with funding and scholarly productivity were reported more often by faculty who left academia than by those who switched institutions (**Fig. S8**). In contrast, salary and a partner's career were reported more often by faculty who switched institutions than by those who left academia (**Fig. S8**). Discrimination and harassment stressors were selected at far higher rates by women than men, irrespective of having left academia or switched institutions (**Fig. S8**), but still less often than many other sources of stress. The reasons men and women switched institutions were generally more similar than the reasons men and women left academia, which varied considerably (**Table S28**). For example, while women's second most common reason was competition, selected by 41% of women vs. 22% of men, men's second most common reason was difficulties obtaining funding, selected by 43% of men vs. 31% of women (**Fig. S8, Table S28**).

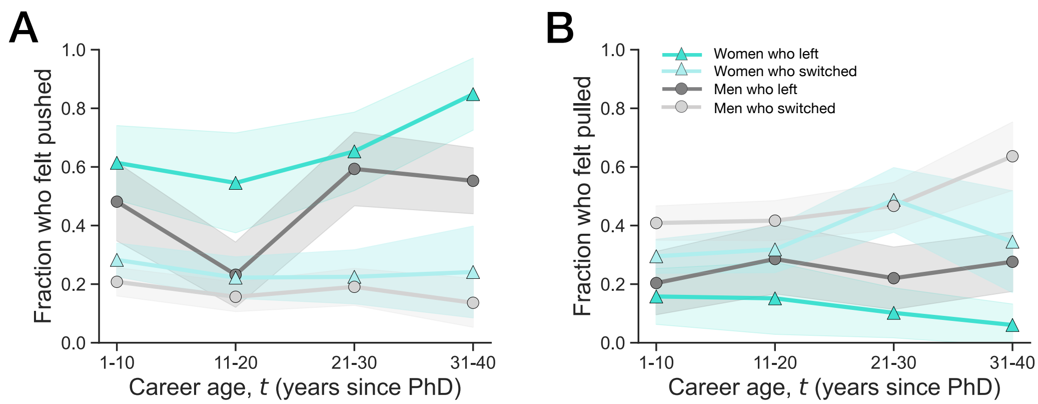

Figure **S6**: **Pushes and pulls for faculty who left academia vs. switched institutions.** The fraction of women and men who left academia and switched institutions due to **(A)** feeling pushed out of their position, or **(B)** feeling pulled towards a better position.

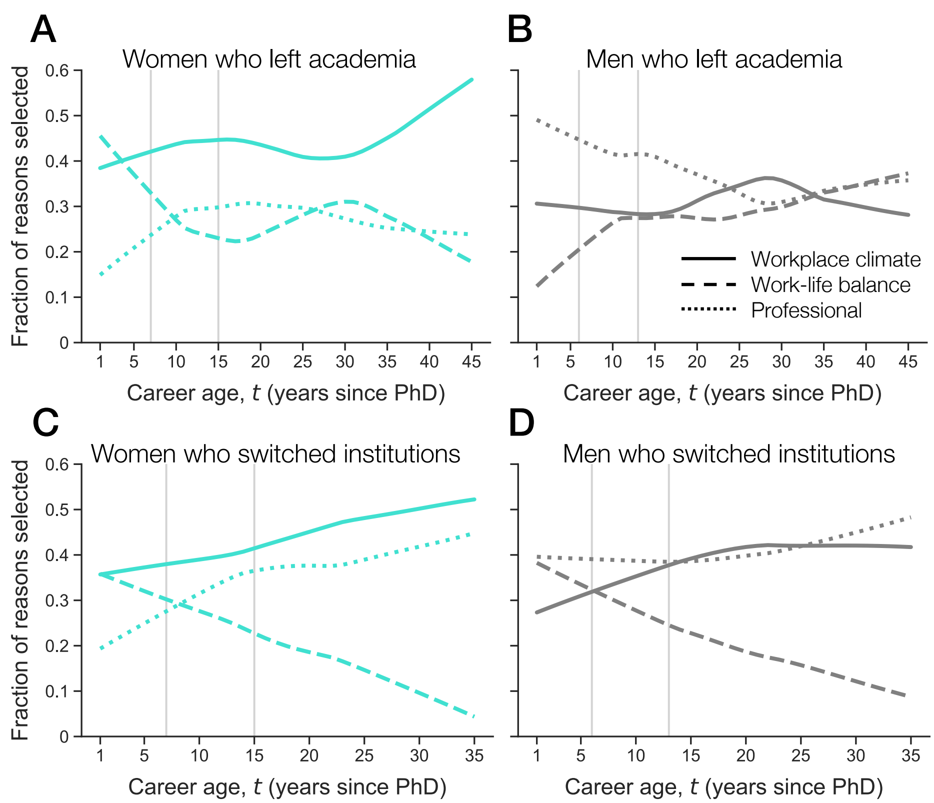

Figure **S7**: **Reasons faculty left academia vs. switched institutions.** Percentage of reasons from each category selected by faculty who **(A-B)** left academia or retired, or **(C-D)** switched institutions, as a function of career age. Vertical lines indicate modal career ages for approximate faculty rank transitions from Fig. 1B. Fractions for each group sum to 1.

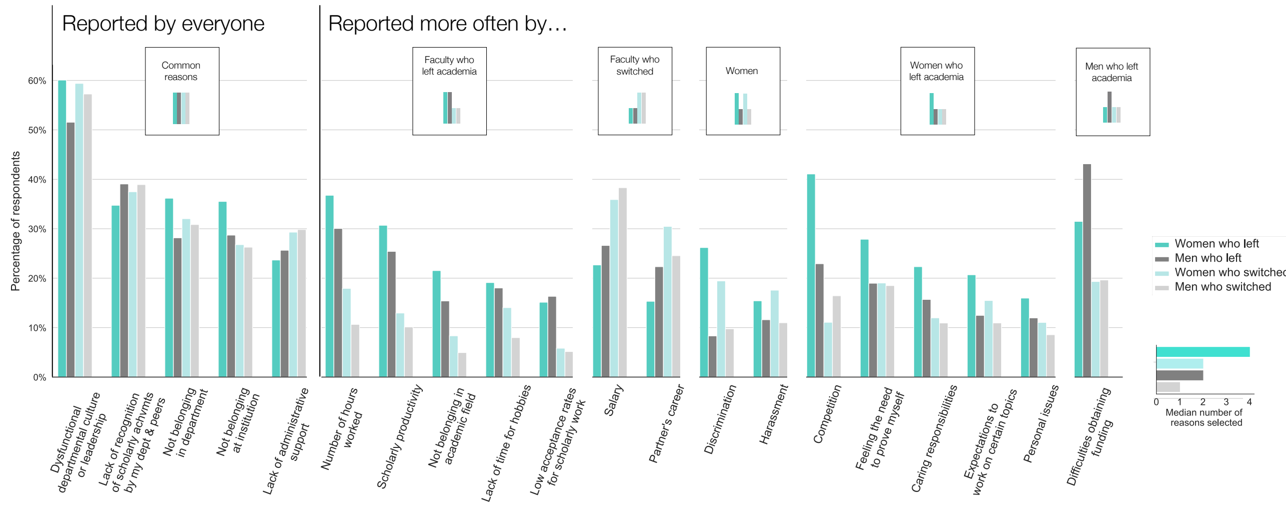

Figure **S8**: **Specific reasons for leaving.** Percentage of faculty who left academia or switched institutions by reasons they reported as contributing to their decision. Respondents could select any number of reasons.

	Left		Switched	
Rank	Women	Men	Women	Men
1	Dept. Dysfunc.	Dept. Dysfunc.	Dept. Dysfunc.	Dept. Dysfunc.
2	Competition	Funding	Recognition	Recognition
3	Hours	Recognition	Salary	Salary
4	Belong, Dept	Hours	Belong, Dept	Belong, Dept
5	Belong, Inst	Belong, Inst	Partner	Admin Support

Table **S28**: The top five reasons women and men left academia and switched institutions. Dept. Dysfunc. = "Dysfunctional departmental culture or leadership", Competition = "The competitive nature of academia", Hours = "Number of hours I worked each week", Belong, Dept = "Feeling like I don't belong in my department", Belong, Inst = "Feeling like I don't belong at my institution", Funding = "Obtaining research funding", Recognition = "Lack of recognition of my scholarly achievements by my department and peers", Partner = "My partner's career constraints, ambitions, location, salary, etc.", Admin Support = "Poor administrative support (e.g., in grant-writing)".

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