Trends in US faculty hiring & retention from 10 years of data:

a study of prestige, diversity & inequality

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University of Colorado **Boulder**

Translator's notes:

any time I say ***I***, I really mean ***we.***

any time I say ***we***, I probably mean:

Nick LaBerge
Computer Science

Katie Spoon
CS & Education

Sam Zhang
Applied Math

Faculty shape the academic ecosystem

- make discoveries [science & scholarship]
- teach courses [education]
- train students [research ecosystem & workforce]
- communicate science [media & public]
- advocate for research priorities [policy]

Research Goal: understand the forces & flows shaping the population of US faculty.

Caplow & McGee, 1958

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The general purpose of the study was to develop a body of systematic knowledge about the academic labor market. We began with the assumption that what "everybody knows" about it would probably turn out to be inaccurate or incomplete. Hence it seemed well to approach the subject as naively as possible, trusting the data to make us more sophisticated.

Review: 😍 😍 😍 😂 🤦

Ten years of comprehensive faculty data

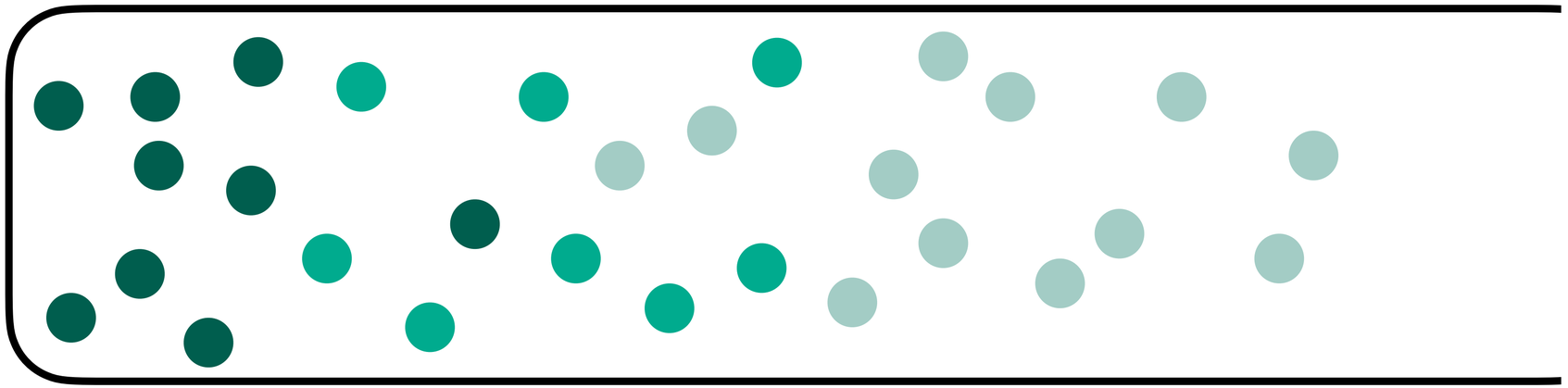
- Complete **tenure-track faculty rosters**
- **10 years** (2011-2020) of rosters, collected annually
- **All PhD-granting US universities**
- All departments, clustered into **107 fields** and **8 domains**
- Each professor's PhD* institution & year

In total: **295,089 faculty** in **10,612 departments** at **368 universities.**

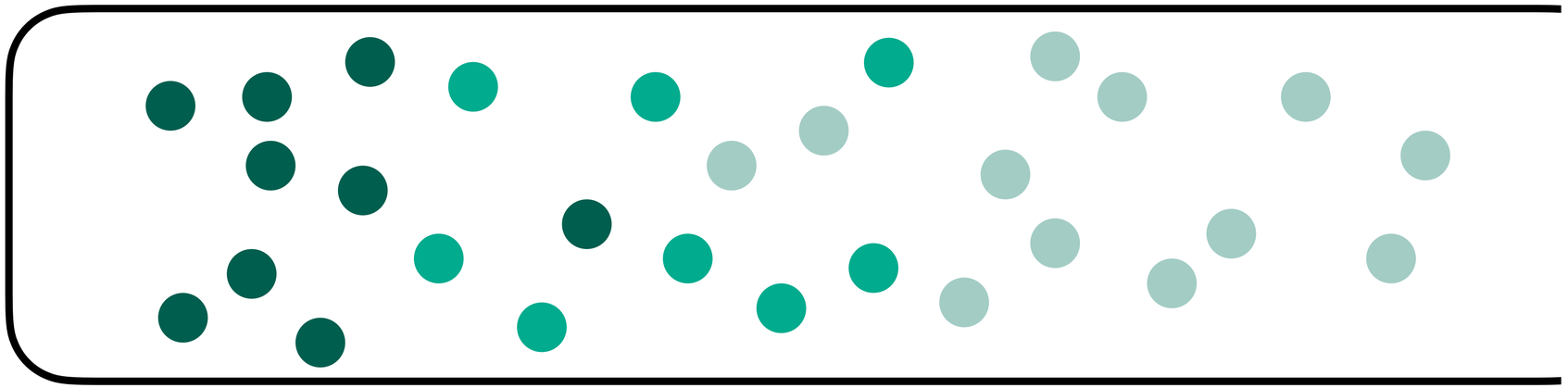
* we treated all doctorates as equivalent

Academic Analytics Research Center

The value of longitudinal data



years since PhD



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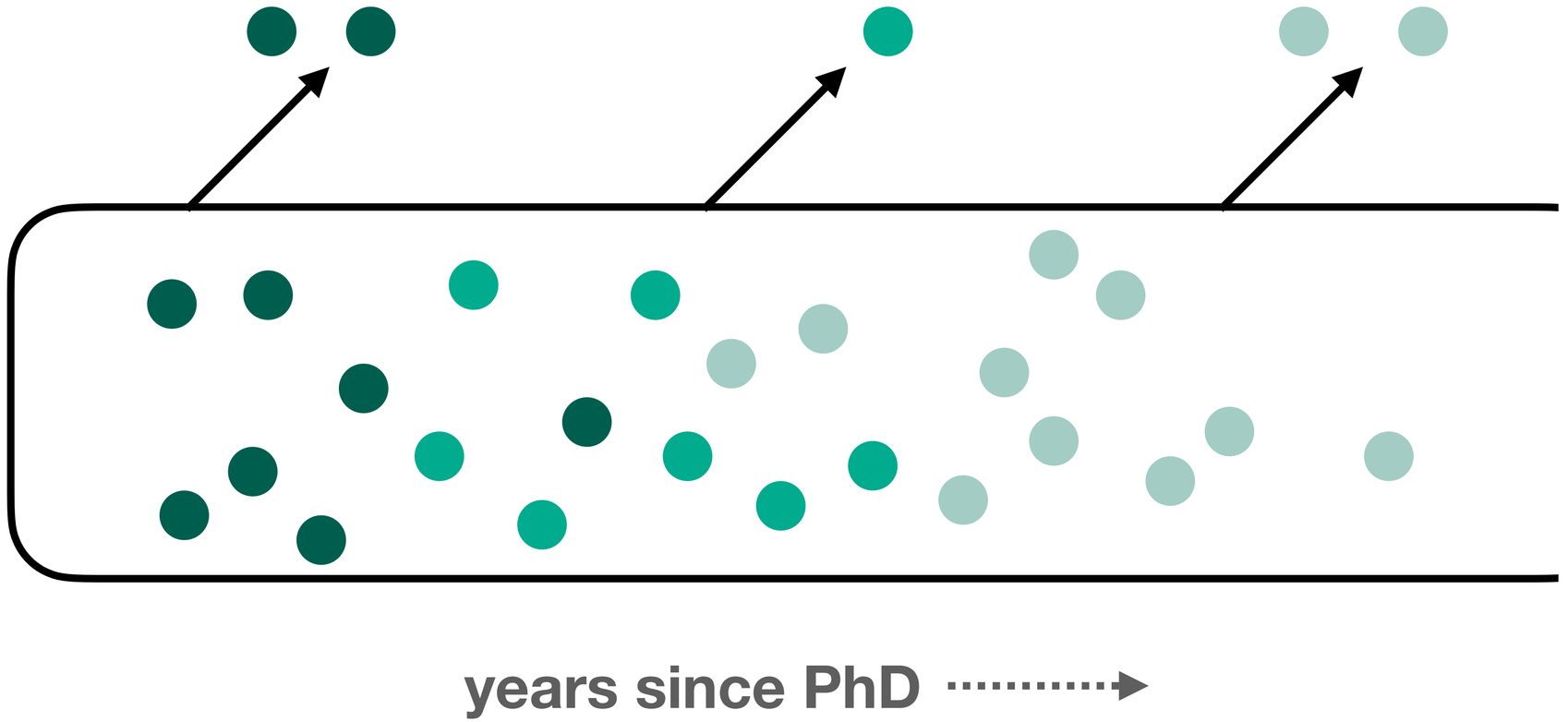
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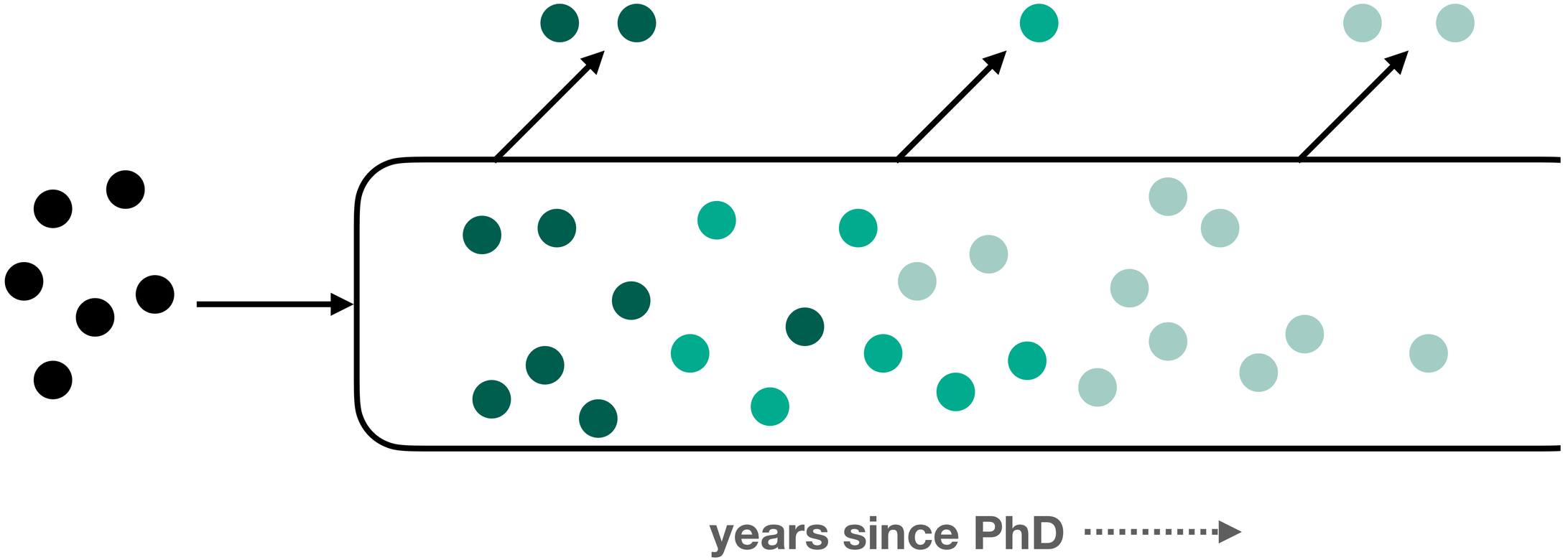
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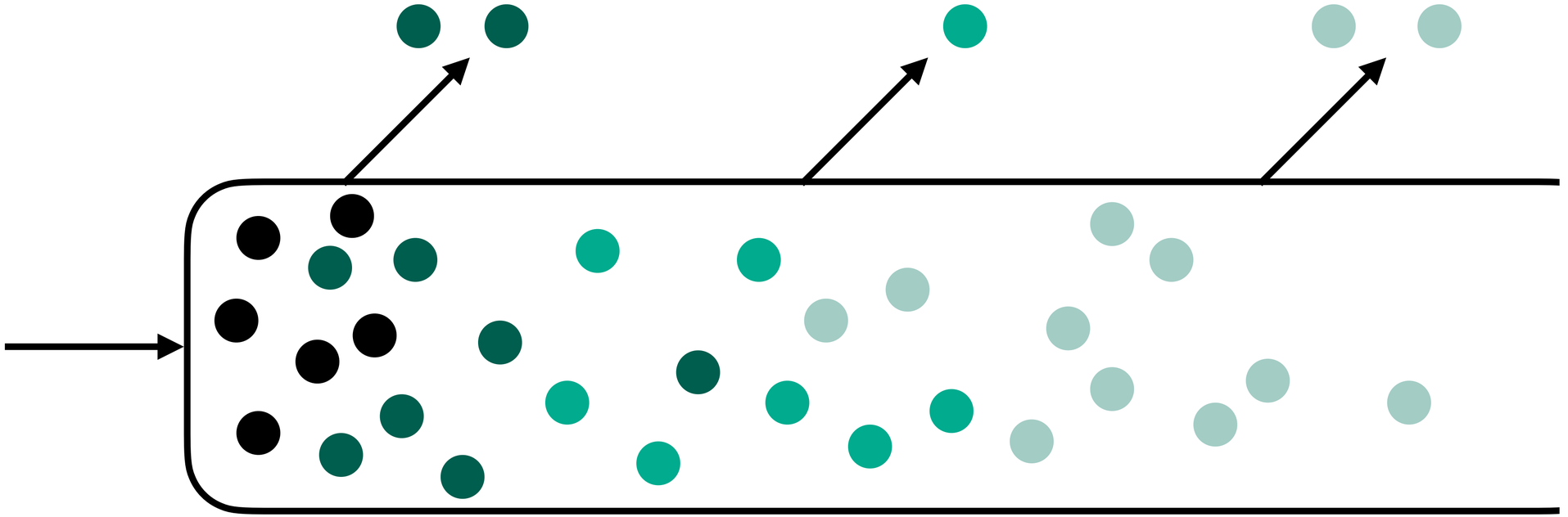

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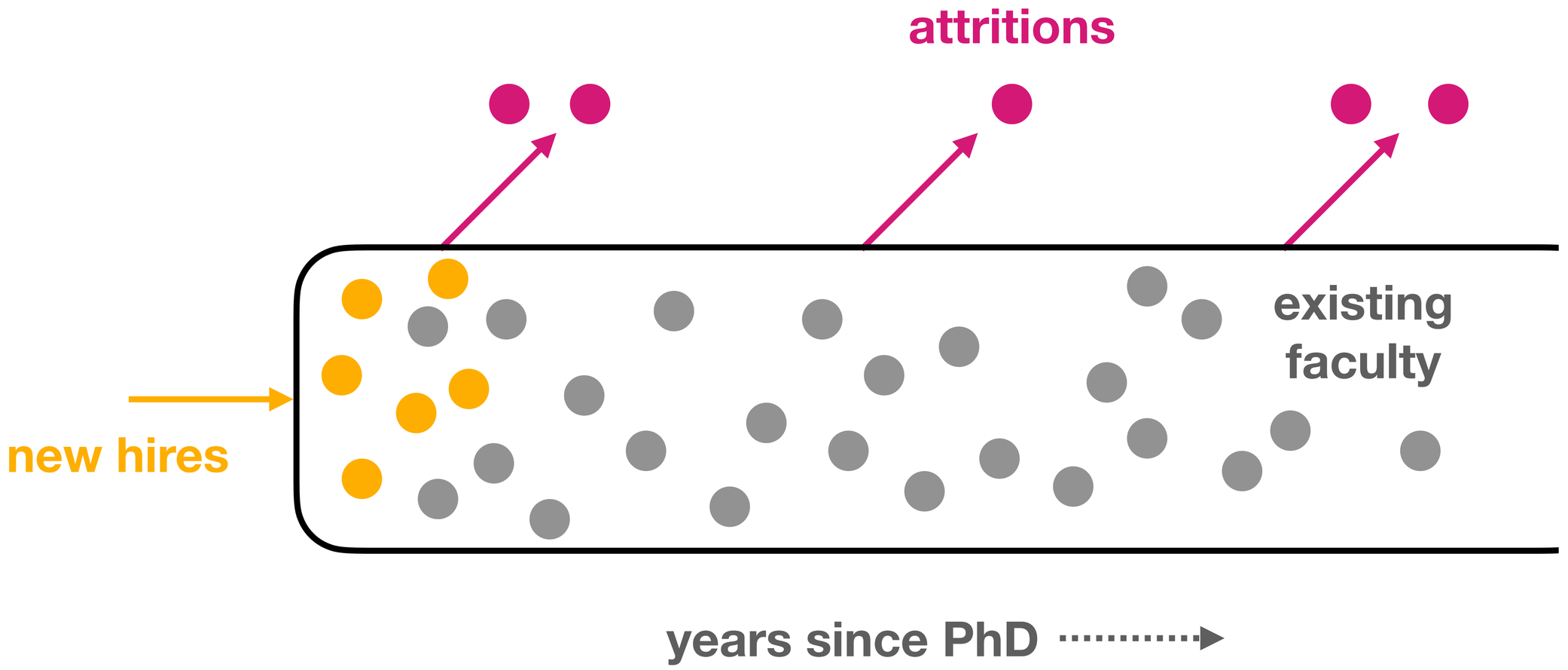
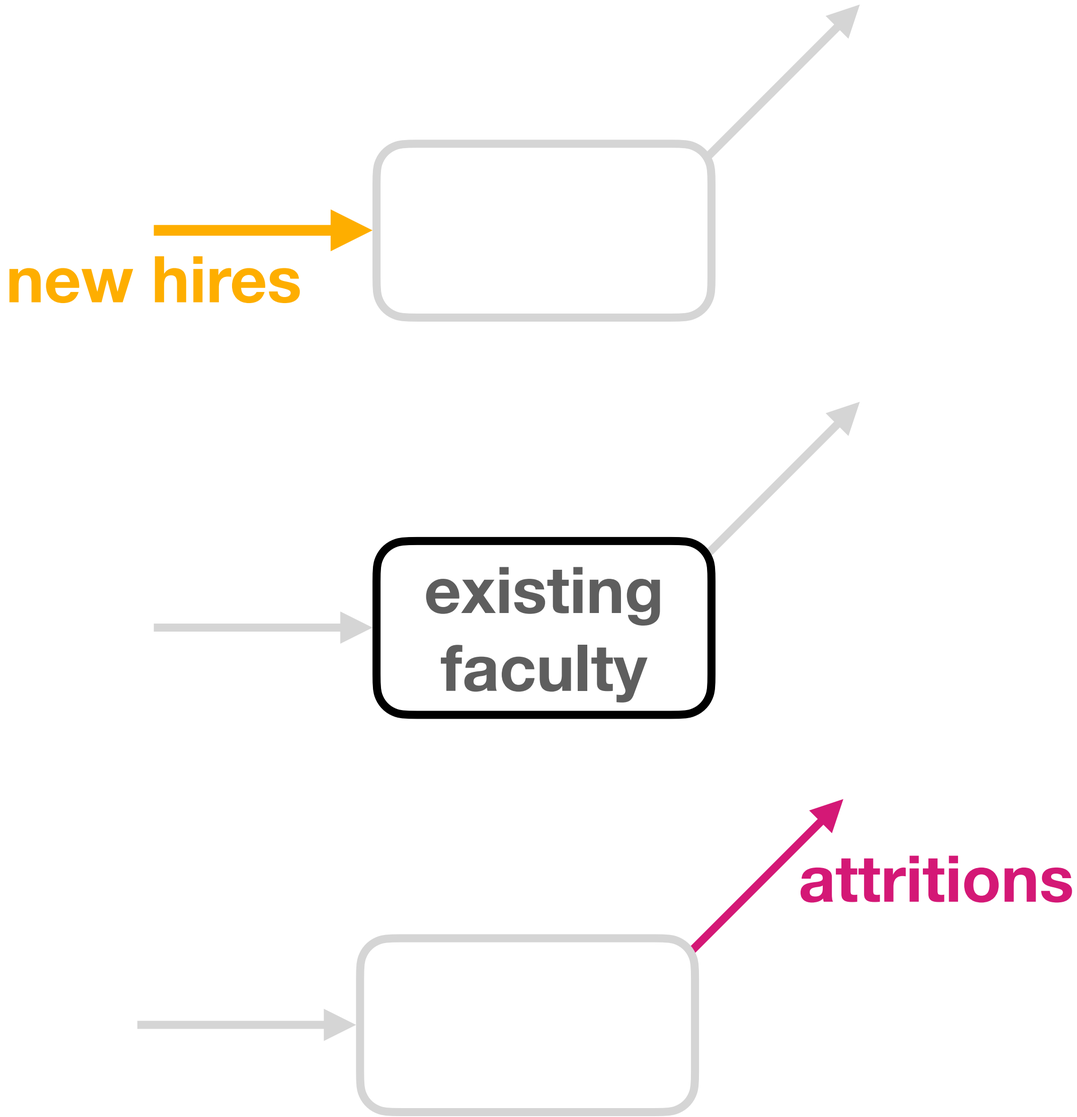

attritions
existing
faculty
new hires
years since PhD


attritions
existing faculty
new hires


new hires
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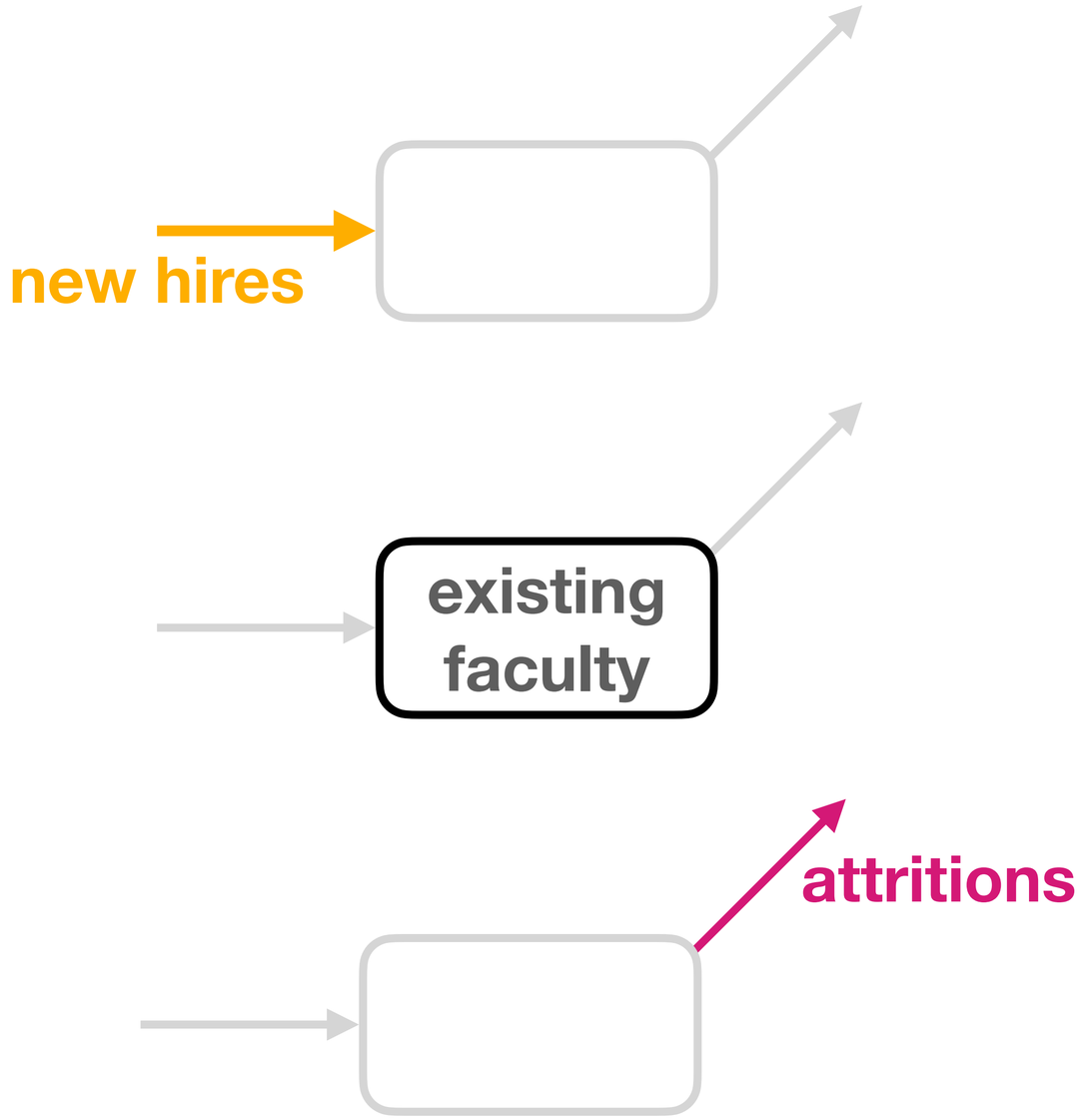


all faculty

We'll use these 4 badges as simple cues as we unpack the patterns highlighted in the this talk.

Does it matter where you trained?

- 11% of US faculty* have non-US doctorates — 123 countries!
  - 2% for Education profs -vs- 19% for Natural Sciences profs

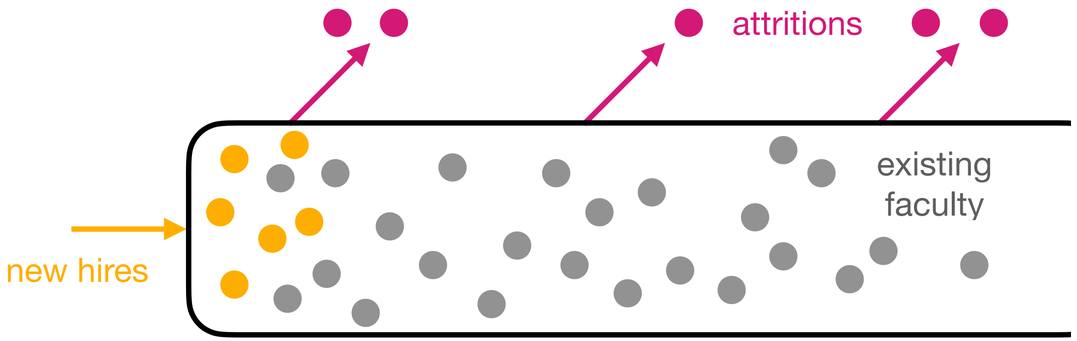
all faculty

Those non-US doctorates?

- 35.5% from Canada & the UK alone.
- 5.4% from Africa and the Americas (minus 🇨🇦, 🇺🇸) combined.

all faculty

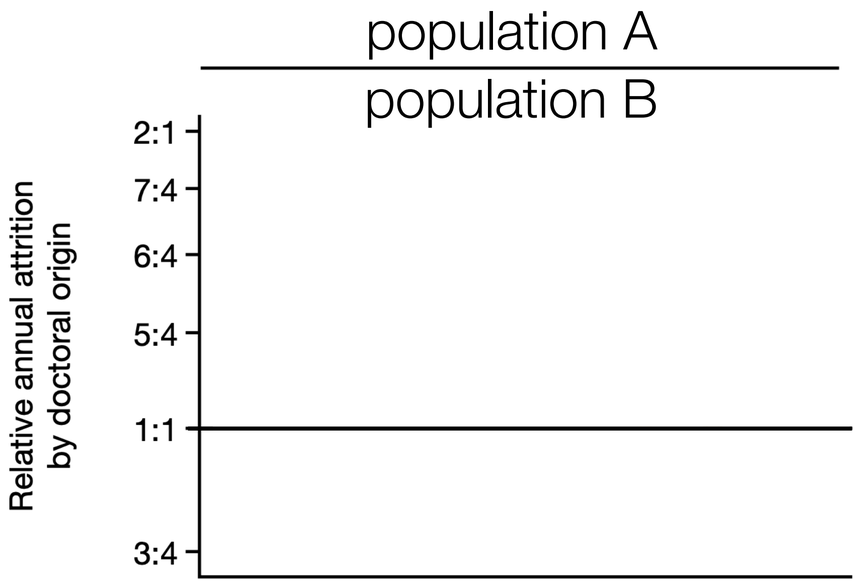
- What are the processes shaping these numbers?



$$\text{risk} = \frac{n \text{ events}}{N \text{ at risk}} = \frac{\bullet\bullet}{\bullet\bullet\bullet\bullet\bullet\bullet\bullet + \bullet\bullet\bullet} = \frac{5}{24+5} \approx 17.2\,\%$$

* tenure-track faculty at PhD-granting US institutions

Does it matter where you trained?



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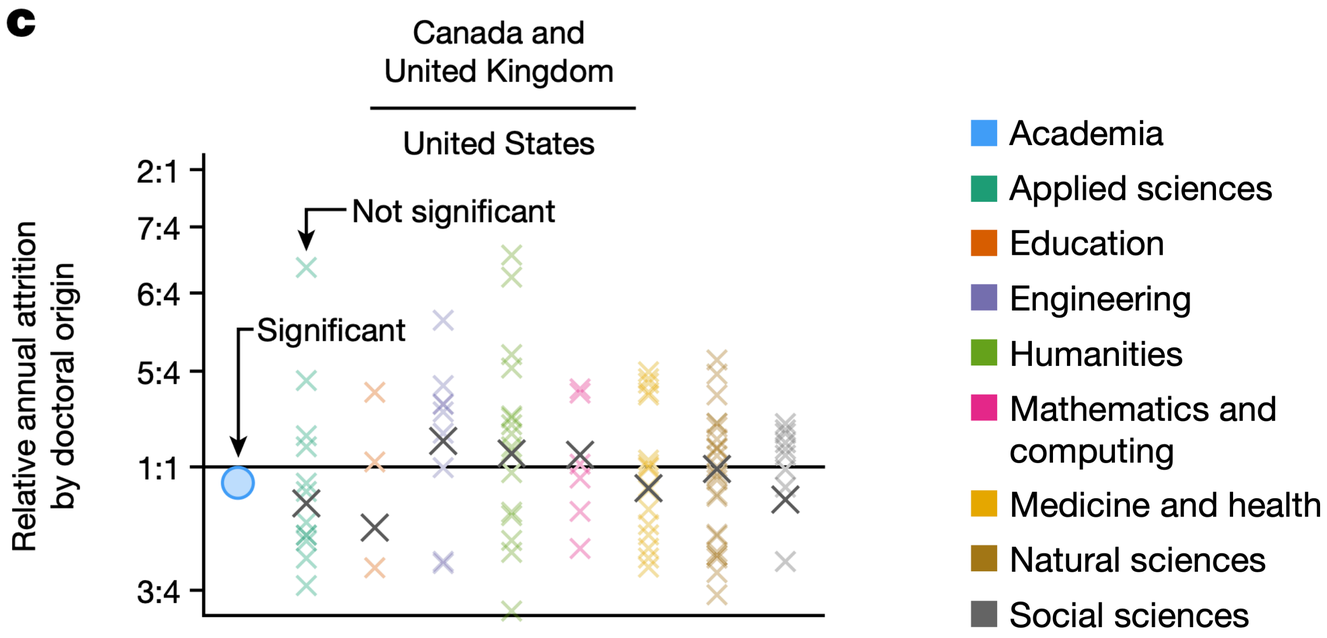
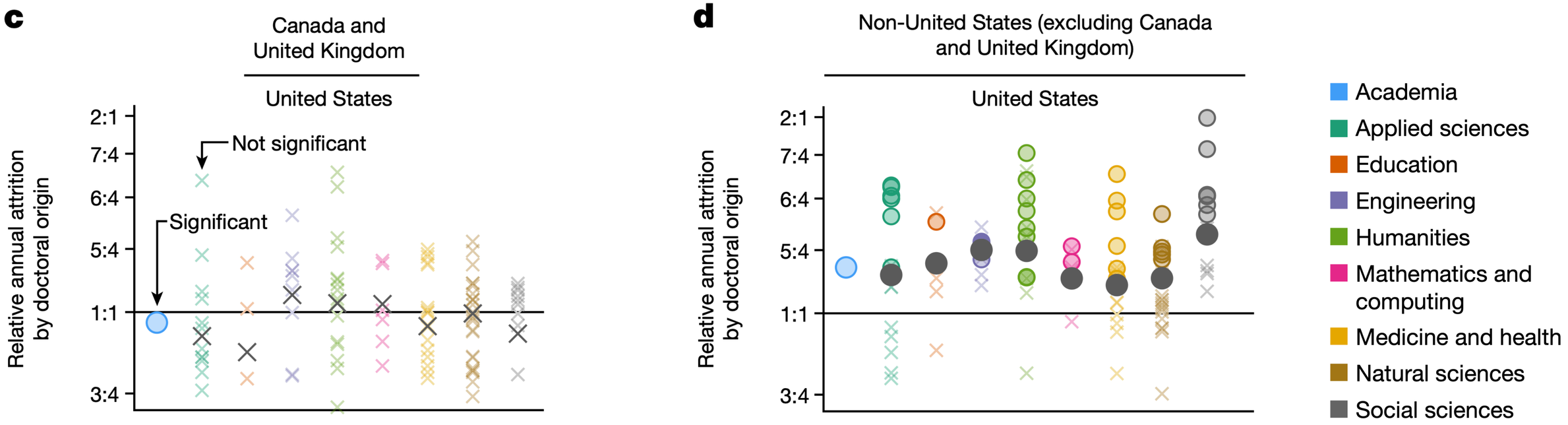


Each colored point is a *field* (107)

Each big grey point is a *domain* (8)

US professors with PhDs from Canada or U.K. are **not** at significantly higher/lower annual risk of attrition, except at the all-of-academia level.

Does it matter where you trained? yes.

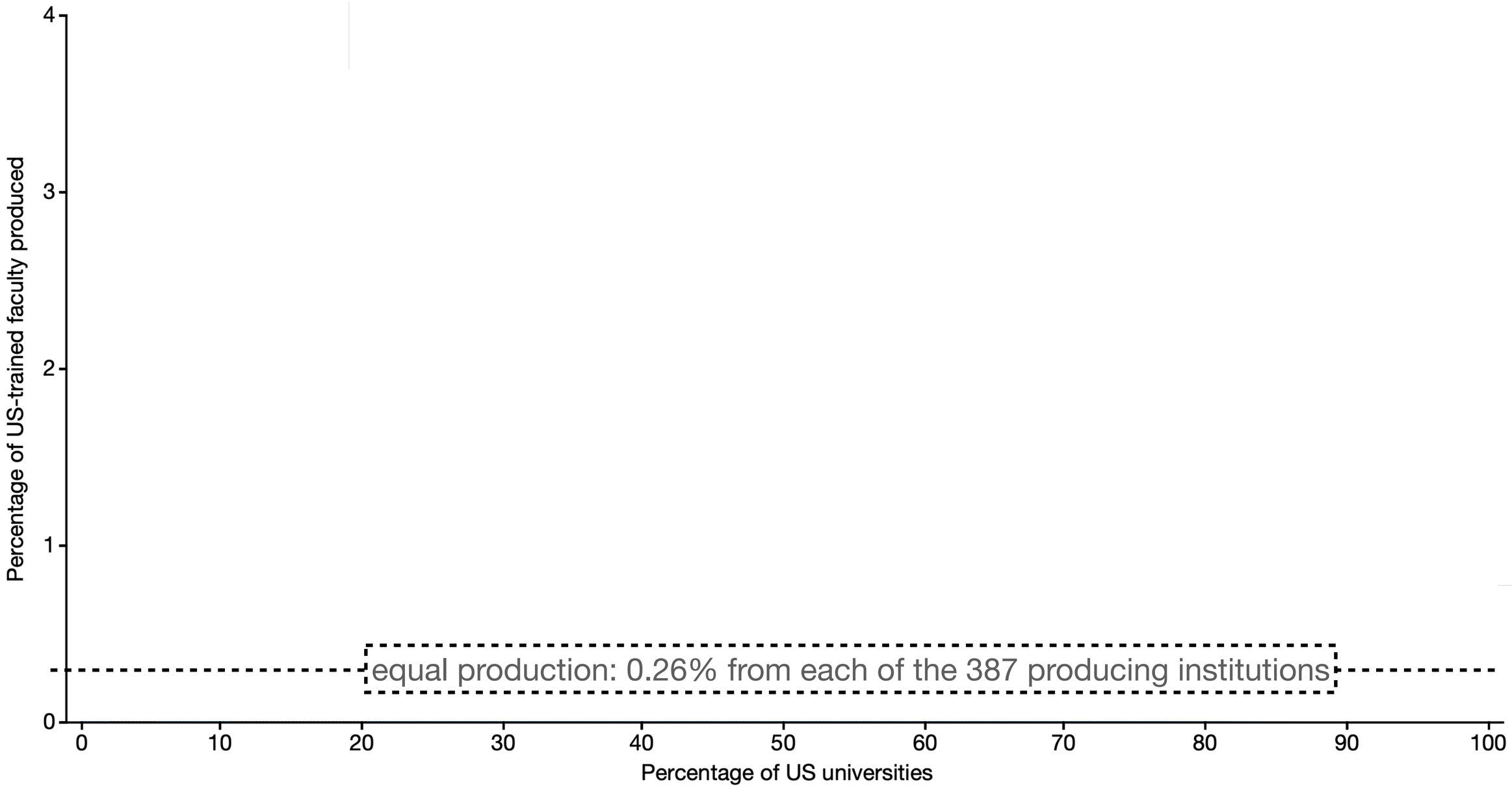


US professors with PhDs from Canada or U.K. are **not** at significantly higher/lower annual risk of attrition, except at the all-of-academia level.

US professors with PhDs from non-{US, Canada, UK} **are at significantly higher** annual risk of attrition in 39 fields, 8 domains, and overall.

Where do U.S.-trained profs come from?

all faculty



Where do U.S.-trained profs come from?

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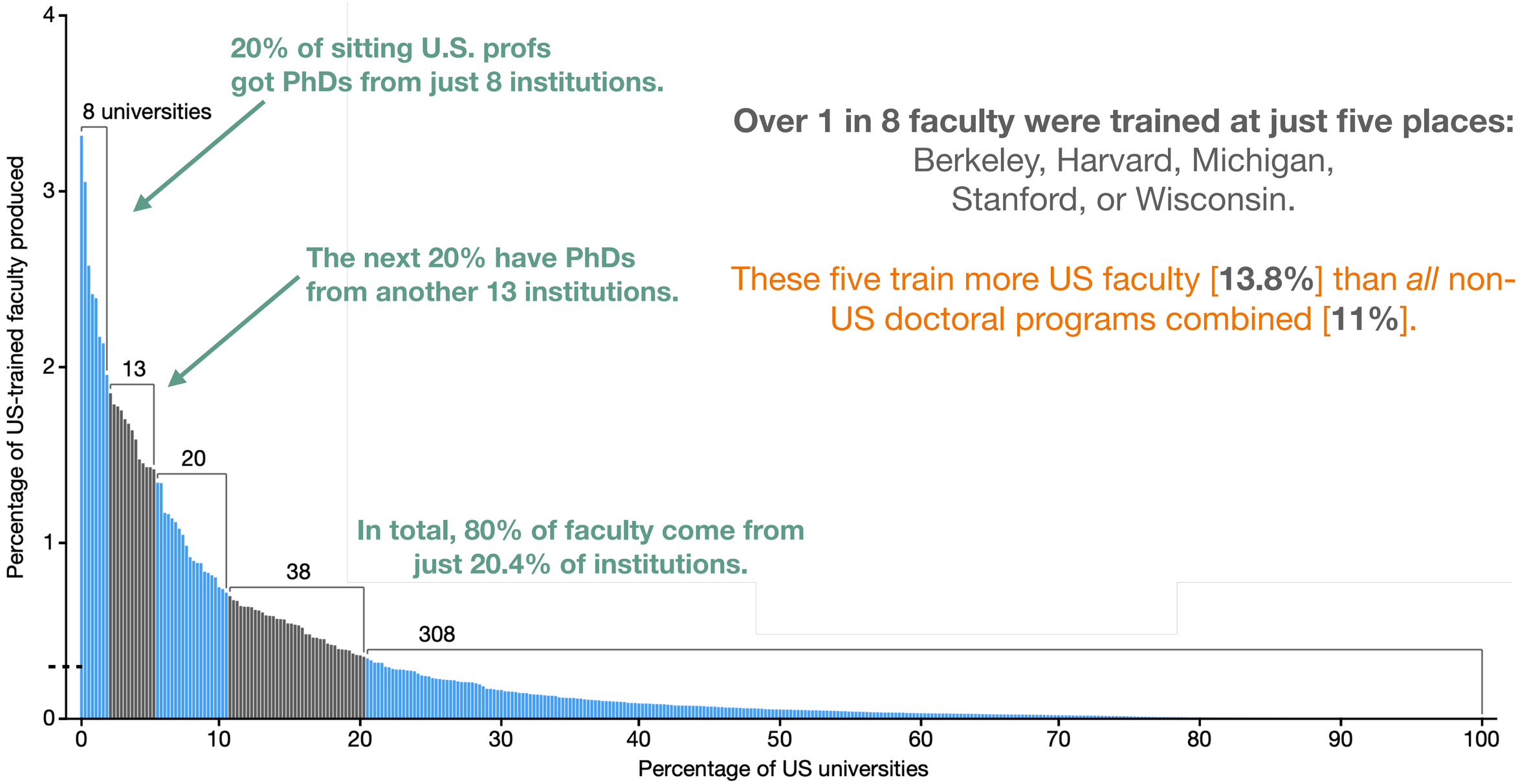
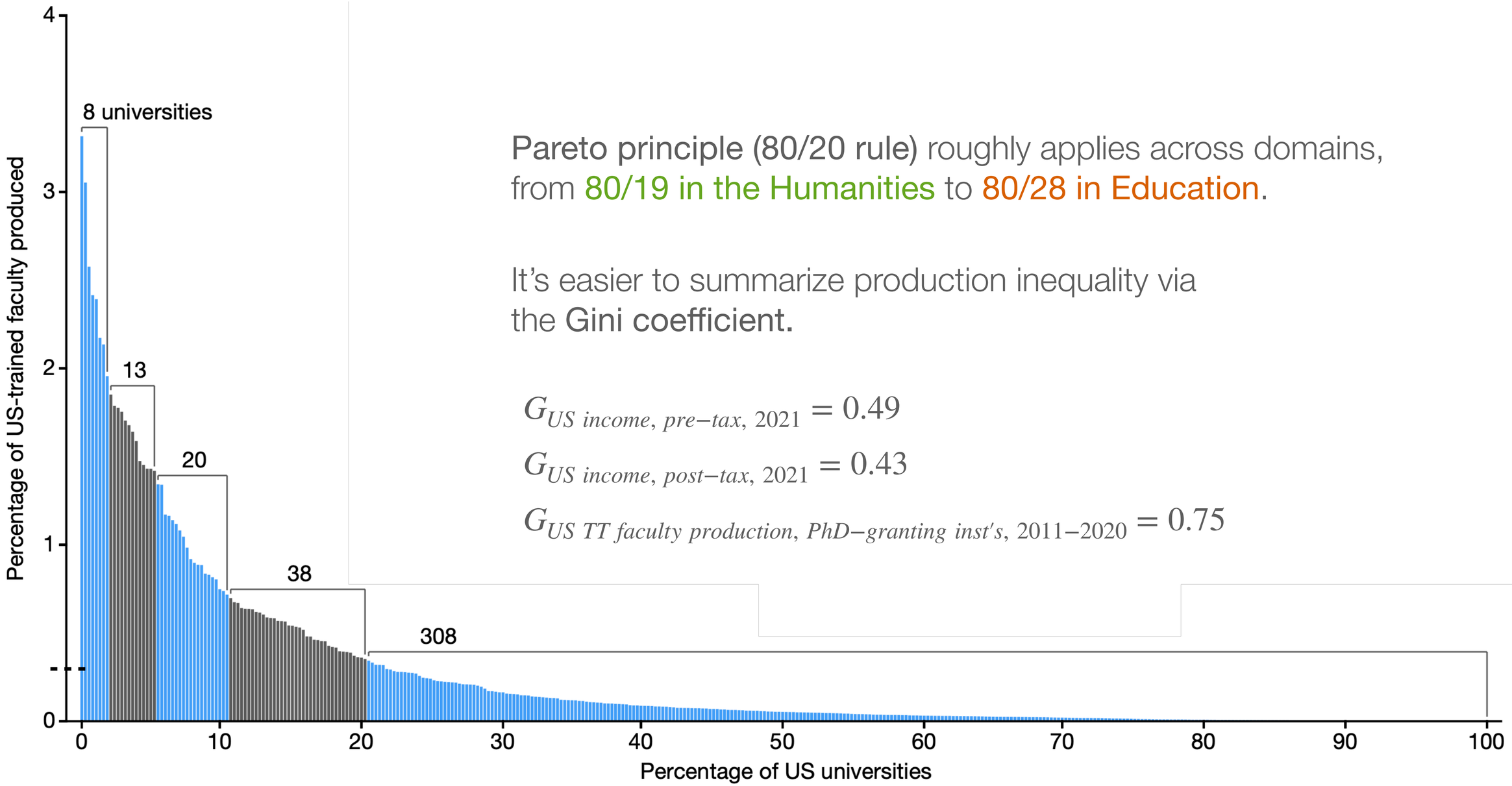


Over 1 in 8 faculty were trained at just five places:
Berkeley, Harvard, Michigan,
Stanford, or Wisconsin.

These five train more US faculty [**13.8%**] than *all* non-US doctoral programs combined [**11%**].

Where do U.S.-trained profs come from?

all faculty



Pareto principle (80/20 rule) roughly applies across domains, from 80/19 in the Humanities to 80/28 in Education.

It's easier to summarize production inequality via the **Gini coefficient.**

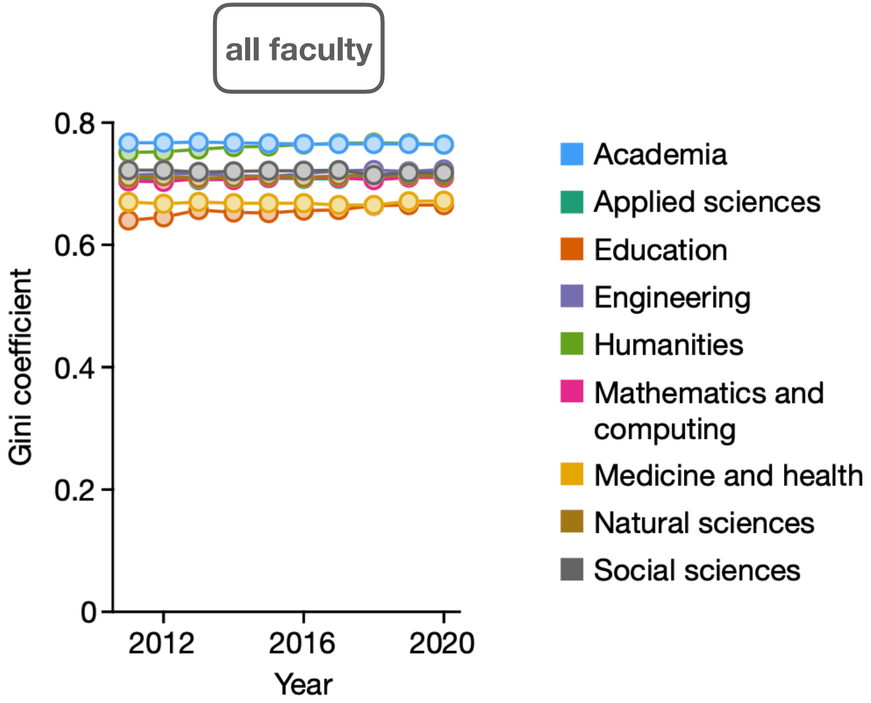
$$G_{US\ income,\ pre-tax,\ 2021} = 0.49$$

$$G_{US\ income,\ post-tax,\ 2021} = 0.43$$

$$G_{US\ TT\ faculty\ production,\ PhD-granting\ inst's,\ 2011-2020} = 0.75$$

https://www.census.gov/library/publications/2022/demo/p60-276.html

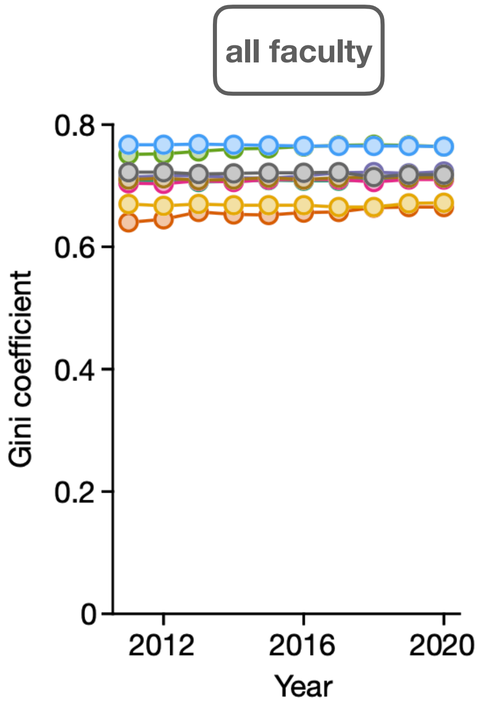
Have inequalities changed over 2011-2020?

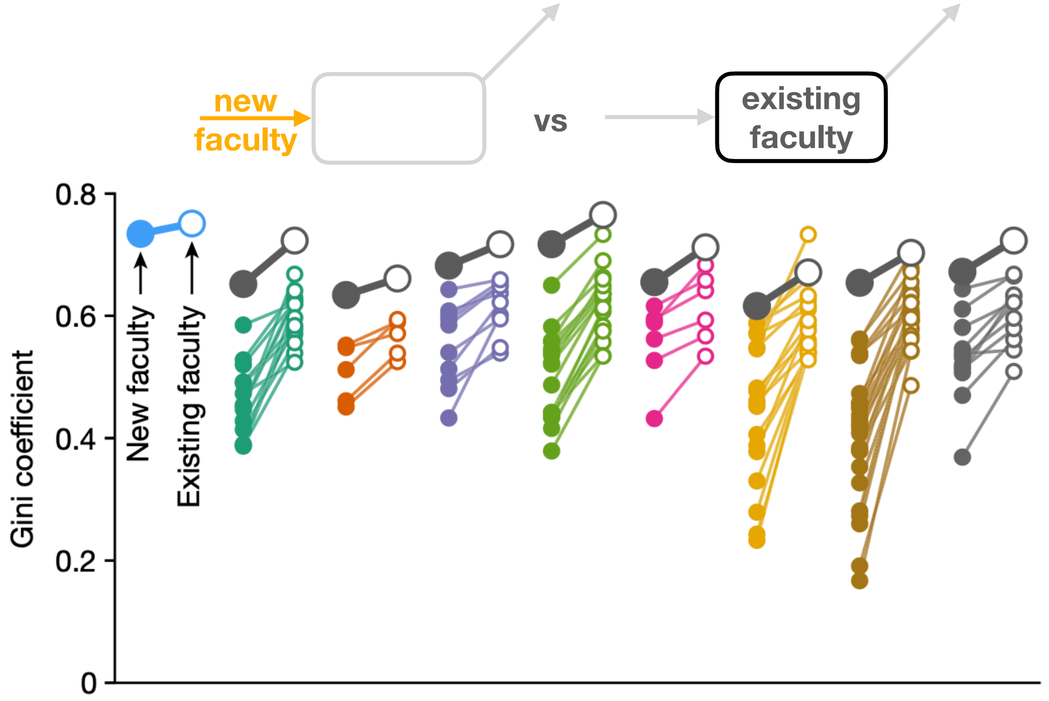


G are all large across domains.

They do not appear to be growing or shrinking over the decade 2011-2020.

Have inequalities changed over 2011-2020?



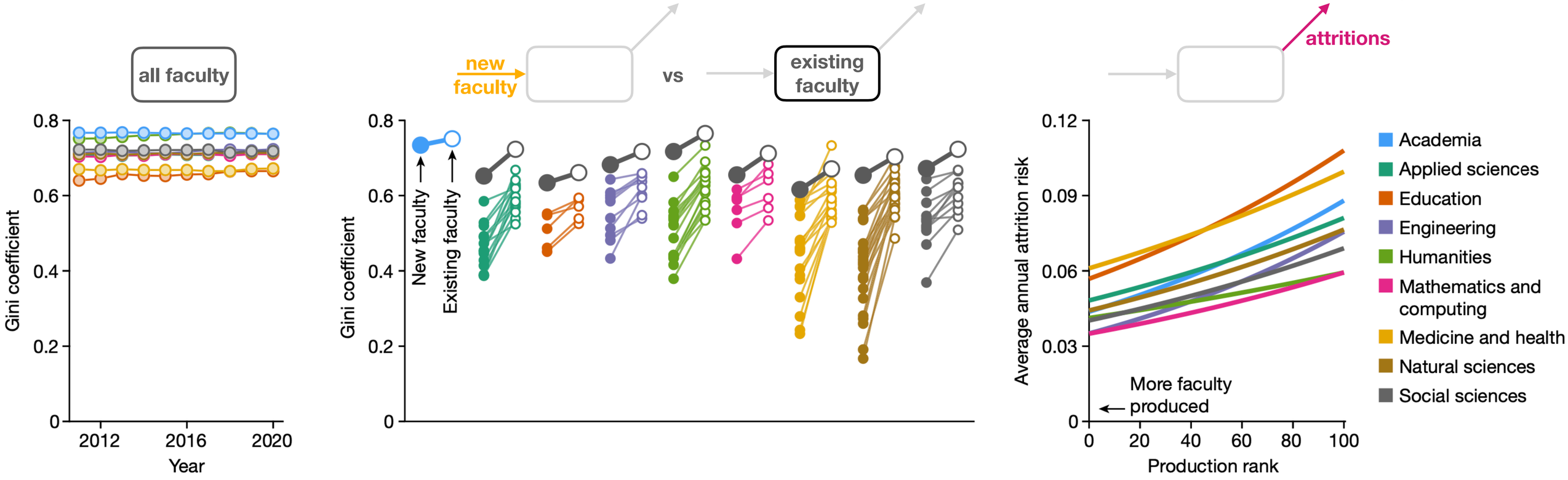


- Academia
- Applied sciences
- Education
- Engineering
- Humanities
- Mathematics and computing
- Medicine and health
- Natural sciences
- Social sciences

In **every** field, domain, and overall, faculty production inequality is **lower for new faculty**, and **higher for sitting faculty**!

What might explain these patterns?

Driver: differential attrition risk by PhD origin

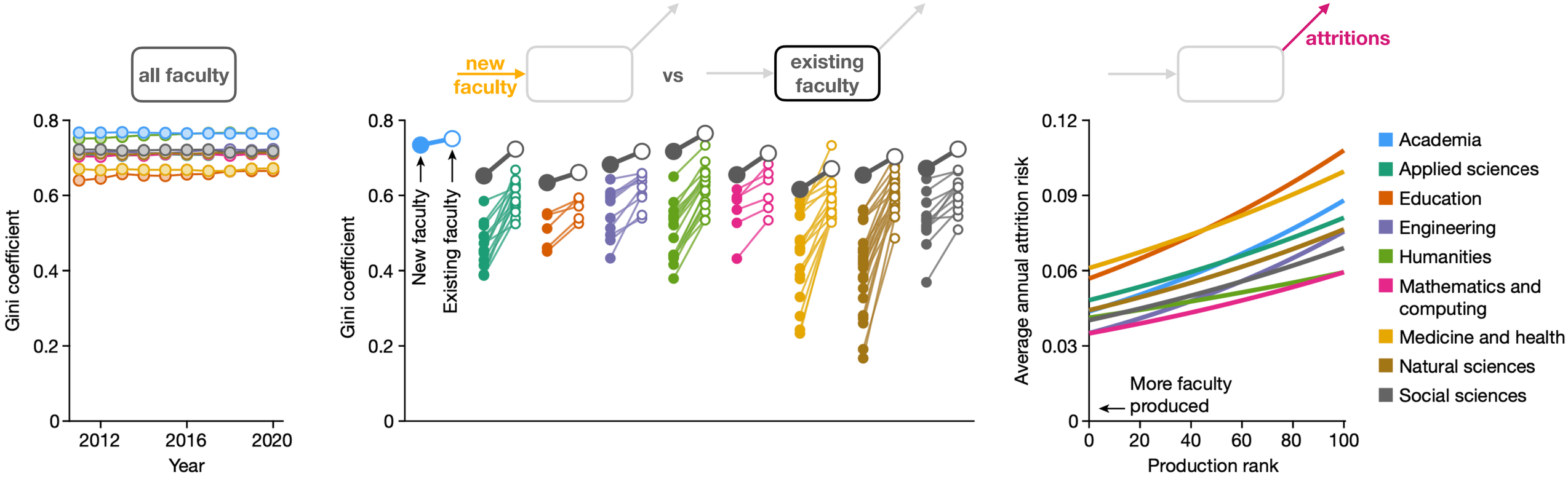


This means that there's **substantial inequality in faculty hiring** and that this inequality is then **exacerbated by attrition**.

Faculty with the "rarest" PhDs show **nearly 2× the attrition rates** of their colleagues with the most common PhDs.

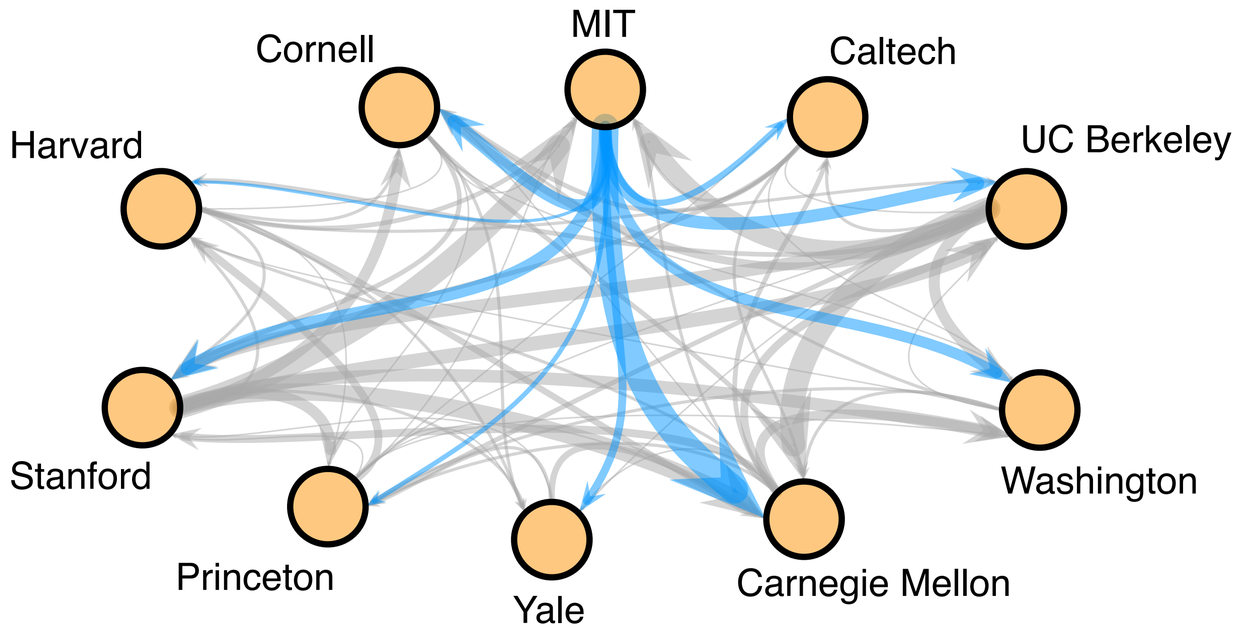
This process makes cohorts less diverse by doctoral origin as they age.

Reflections…



1. Examining just one of these plots by itself might lead us to an **incorrect understanding**.
2. **Longitudinal analyses are critical** to understanding this system — snapshot data won't do.

Faculty hiring networks



Premises:

1. Each hiring committee wants to hire **the best**.*
2. Each hire $u \rightarrow v$ is an endorsement of u by v.
3. Network reveals **collective mutual endorsements**.

* of course “the best” is ill defined! Yet surely no hiring committee is seeking the 65th best of the applicants!

JOB MARKET SIGNALING *

MICHAEL SPENCE

1. Introduction, 355. — 2. Hiring as investment under uncertainty, 356. — 3. Applicant signaling, 358. — 4. Informational feedback and the definition of equilibrium, 359. — 5. Properties of informational equilibria: an example, 361. — 6. The informational impact of indices, 368. — Conclusions, 374.

Spence, 1978 [Nobel 2001 with Akerloff & Stiglitz]

A Status-based Model of Market Competition[1]

Joel M. Podolny
Stanford University

Podolny, 1993

ON THE GRADUATE SCHOOLS OF UNIVERSITY ASTRONOMERS

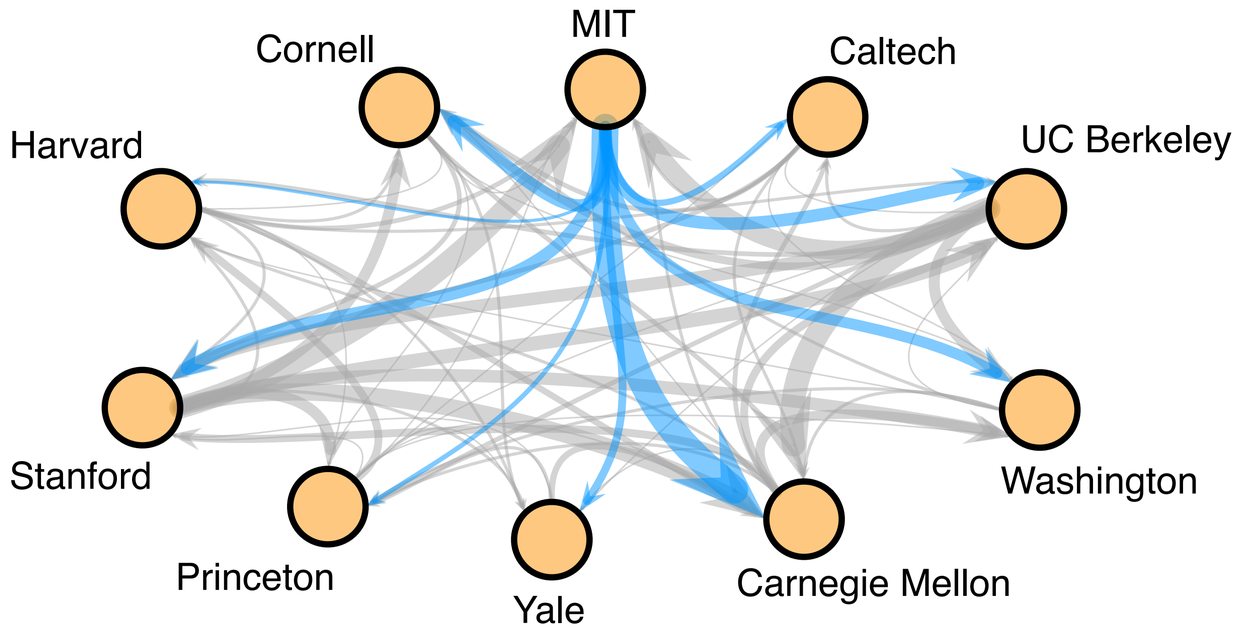
RONALD E. DOMEN
Department of Pathology and Laboratory Medicine, University of South Florida, Tampa, Florida 33612-4799

AND

HARLEY A. THRONSON, JR.
Wyoming Infrared Observatory, University of Wyoming, Laramie, Wyoming 82071

Domen & Thronson, 1988

Faculty hiring networks



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THE *Academic Marketplace*

THEODORE CAPLOW
University of Minnesota

REECE J. McGEE
University of Texas

Caplow & McGee, 1958

"…the present study, which was not originally oriented to prestige as a central variable; our findings, however, forced us to…"

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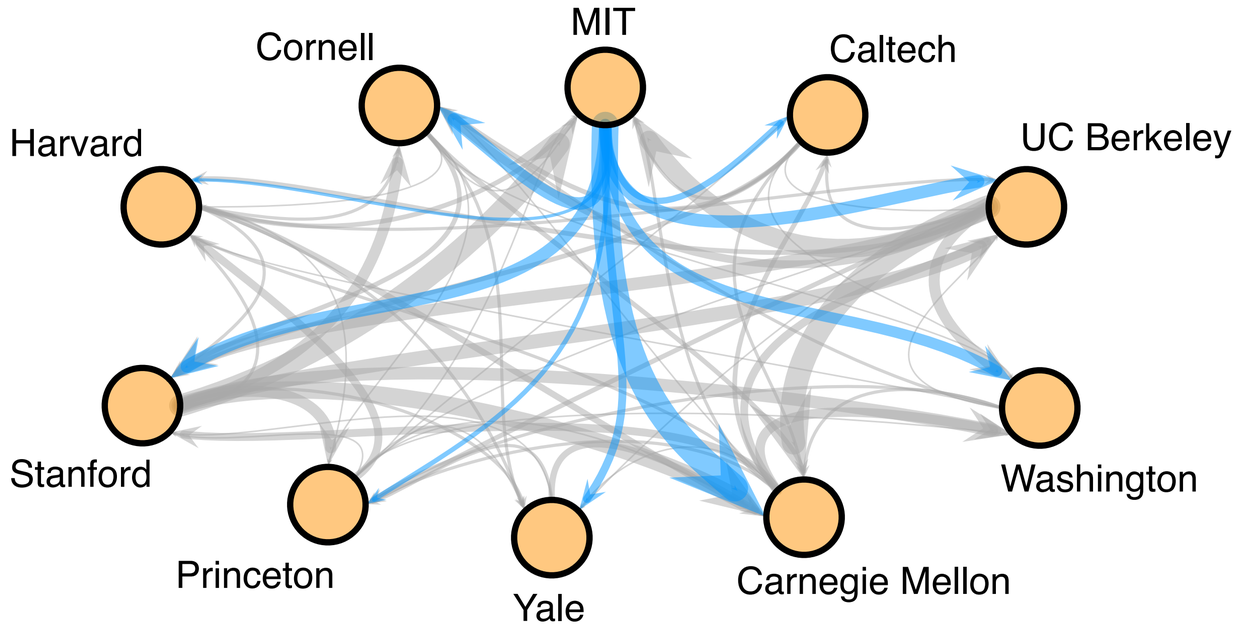
Faculty hiring networks



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A **recursive** notion of prestige:

One becomes prestigious when one is **endorsed by someone prestigious**.

↓

Infer prestige scores directly from the structural patterns in faculty hiring networks.
[SpringRank — cf. RUMs & Discrete Choice]

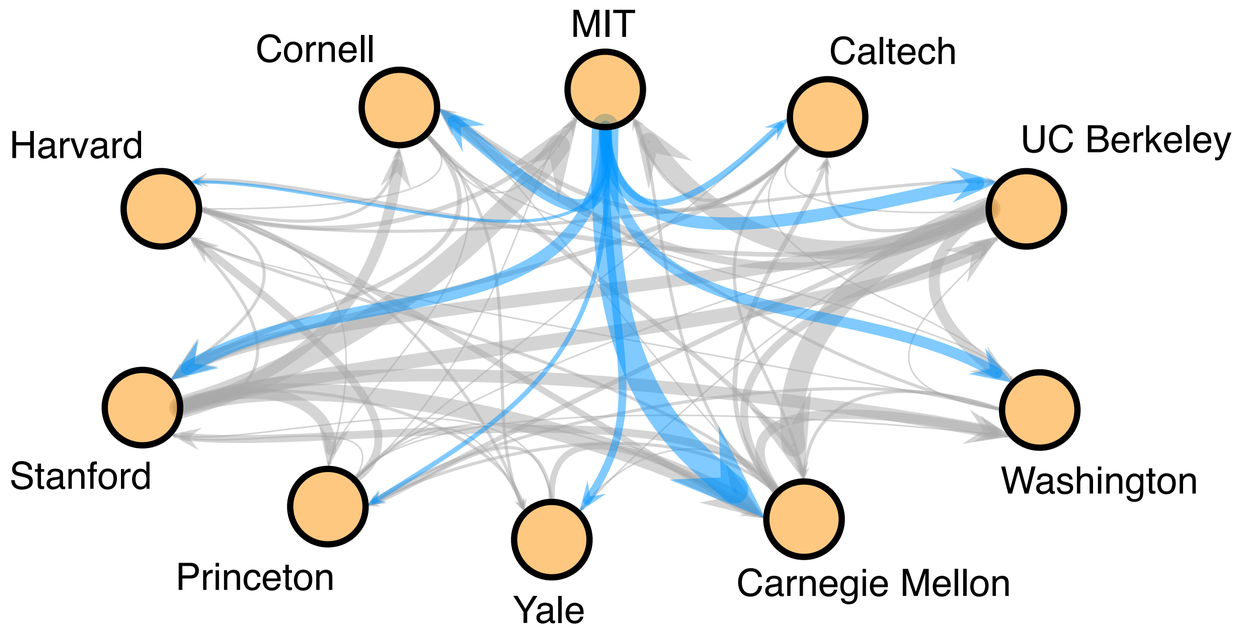
↓

Convert prestige **scores** to **ranks**/percentiles.

Note: to "game" such a ranking, you'd have to **convince departments more prestigious than yours** to hire your graduates!

De Bacco*, Larremore*, Moore. *Science Advances*, 2018.
Clauset, Arbesman, Larremore. *Science Advances*, 2015.

Faculty hiring networks



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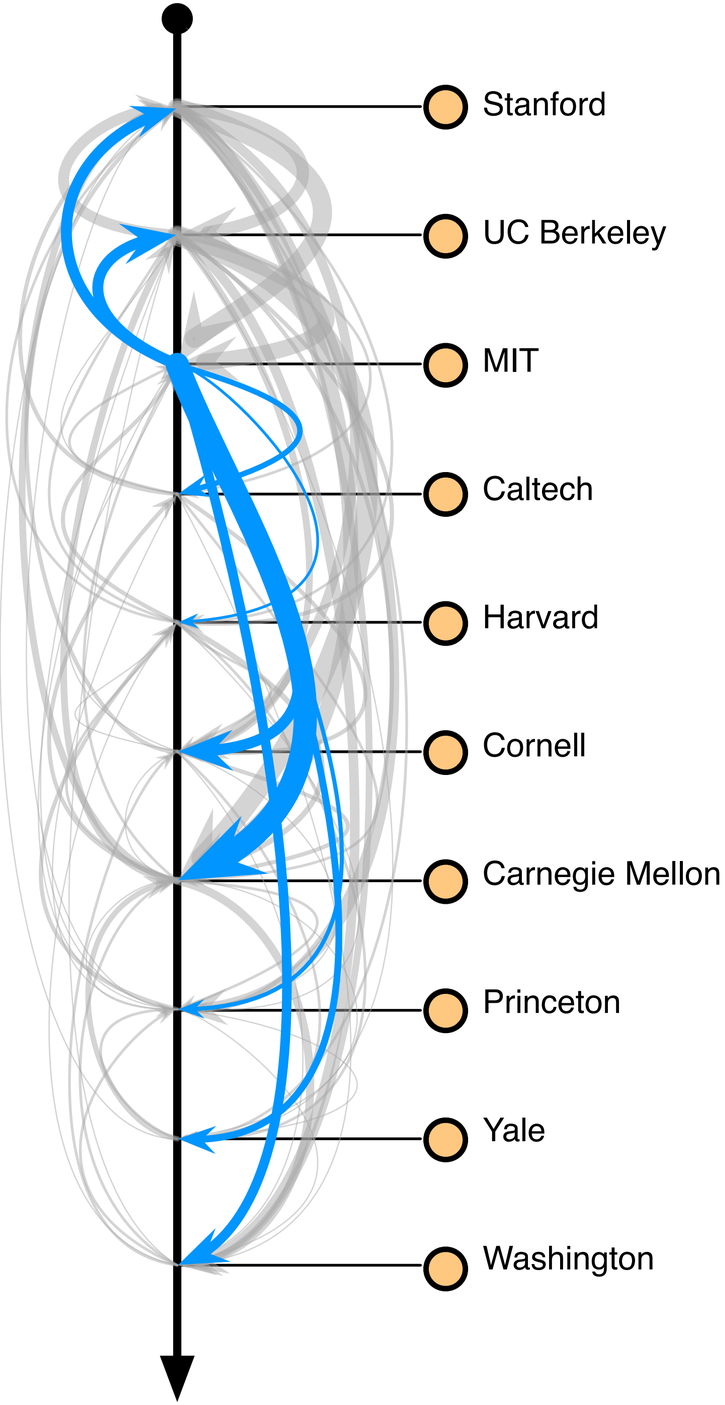

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Faculty hiring networks

low upward mobility

5%↑ Classics
6%↑ Econ, Finance
7%↑ Art History, Stats

⋮

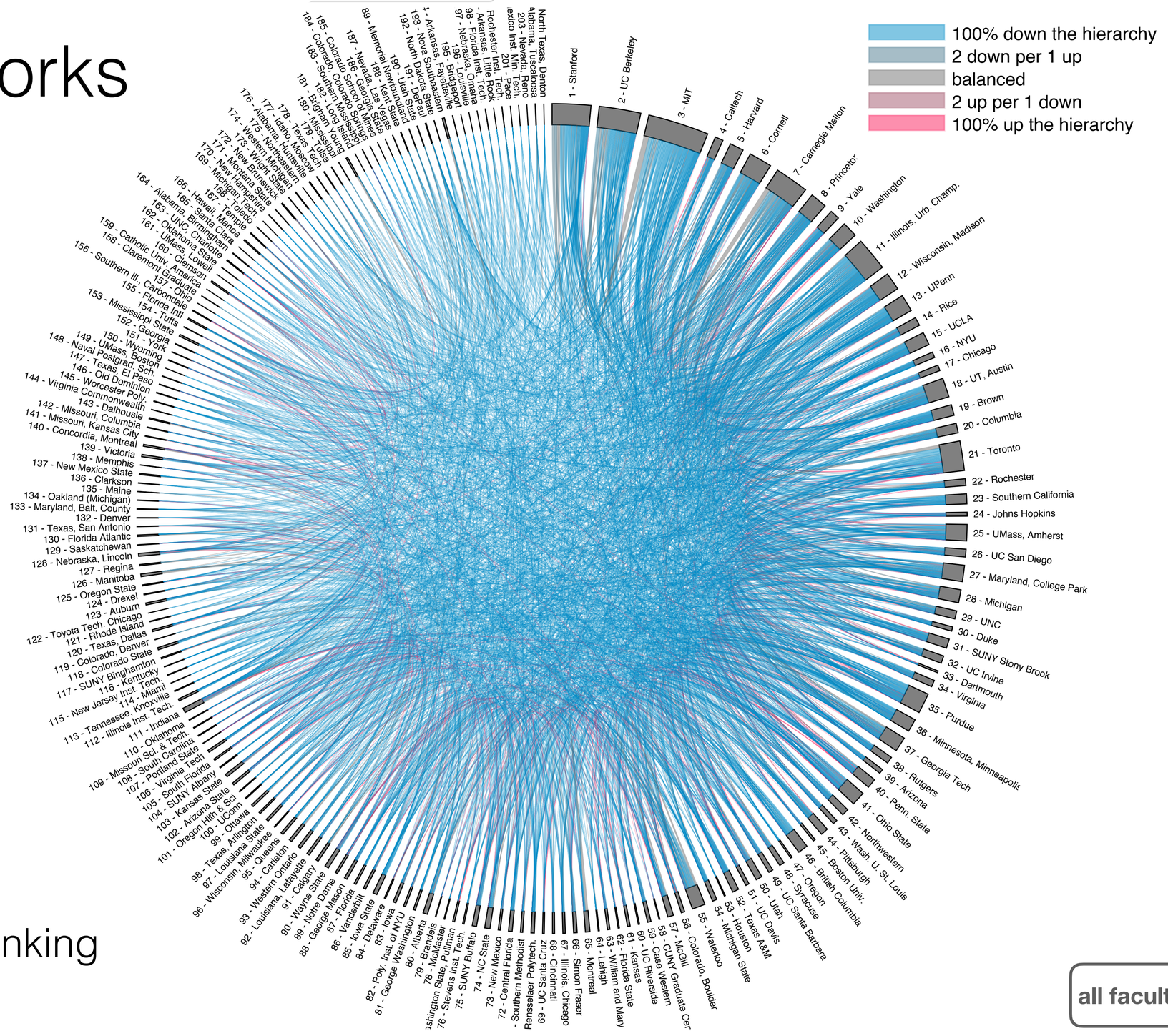
12%↑ CS, Epidemiology

⋮

20%↑ Horticulture
21%↑ Agronomy, Entomology
23%↑ Animal Sci, Pathology

average hire moves down by

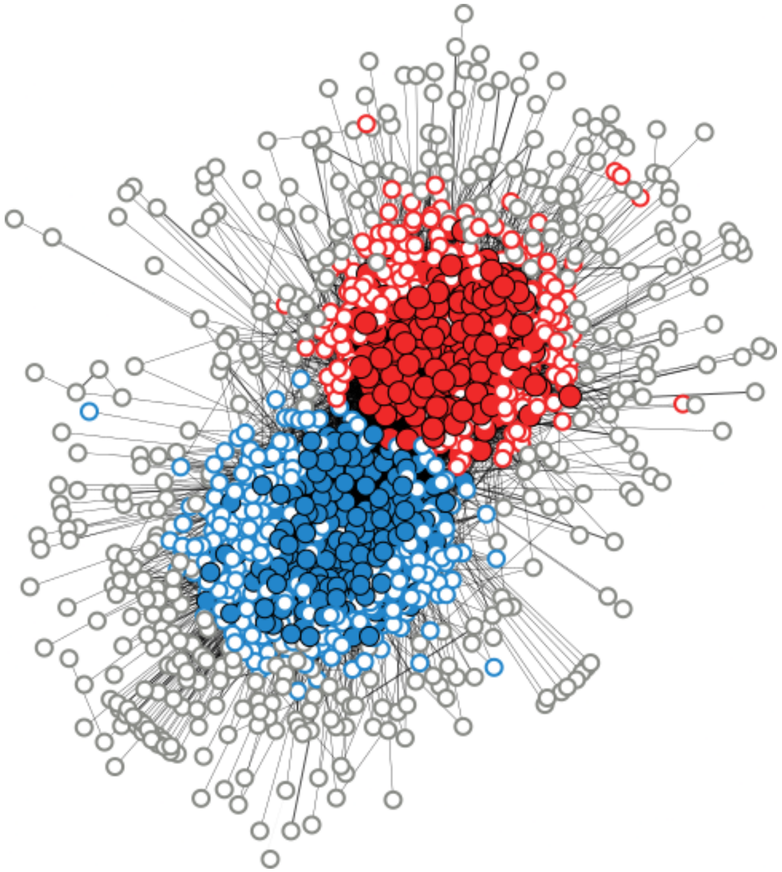
↓28% Econ
↓22% CS
↓14% Agronomy
of each field-specific prestige ranking



Faculty hiring networks — The research agenda

Core & periphery

- **Core** nodes connect to other core nodes directly, or are just a few hops away over the network.
- **Periphery** nodes connect to core nodes, but not to other periphery nodes.
- How many hops to get from one node to each of the others in a network?
  [mean geodesic distance; smaller=closer]



Data: Adamic & Glance, 2005. “Divided They Blog”
Fig: Sadamori Kojaku. https://skojaku.github.io/research/core-periphery-structure/

Faculty hiring networks — The research agenda

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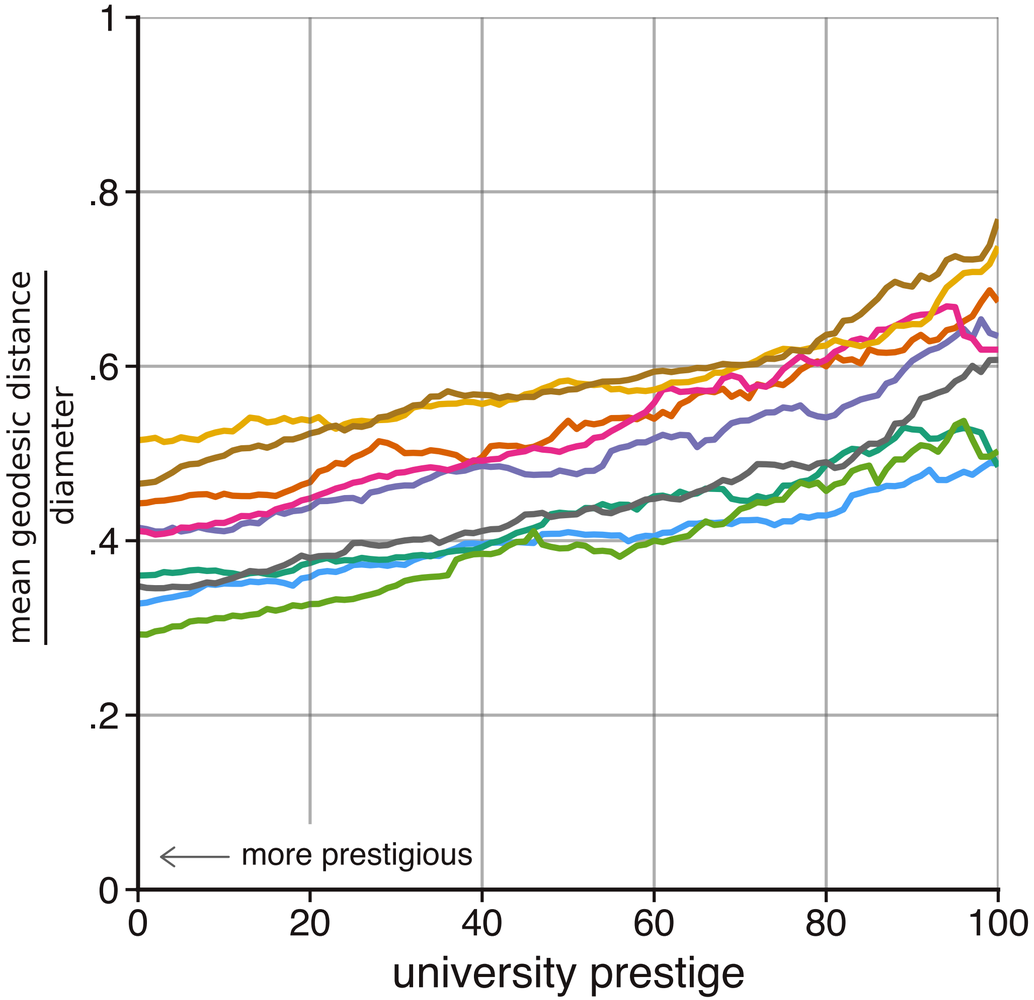


Faculty hiring networks — The research agenda

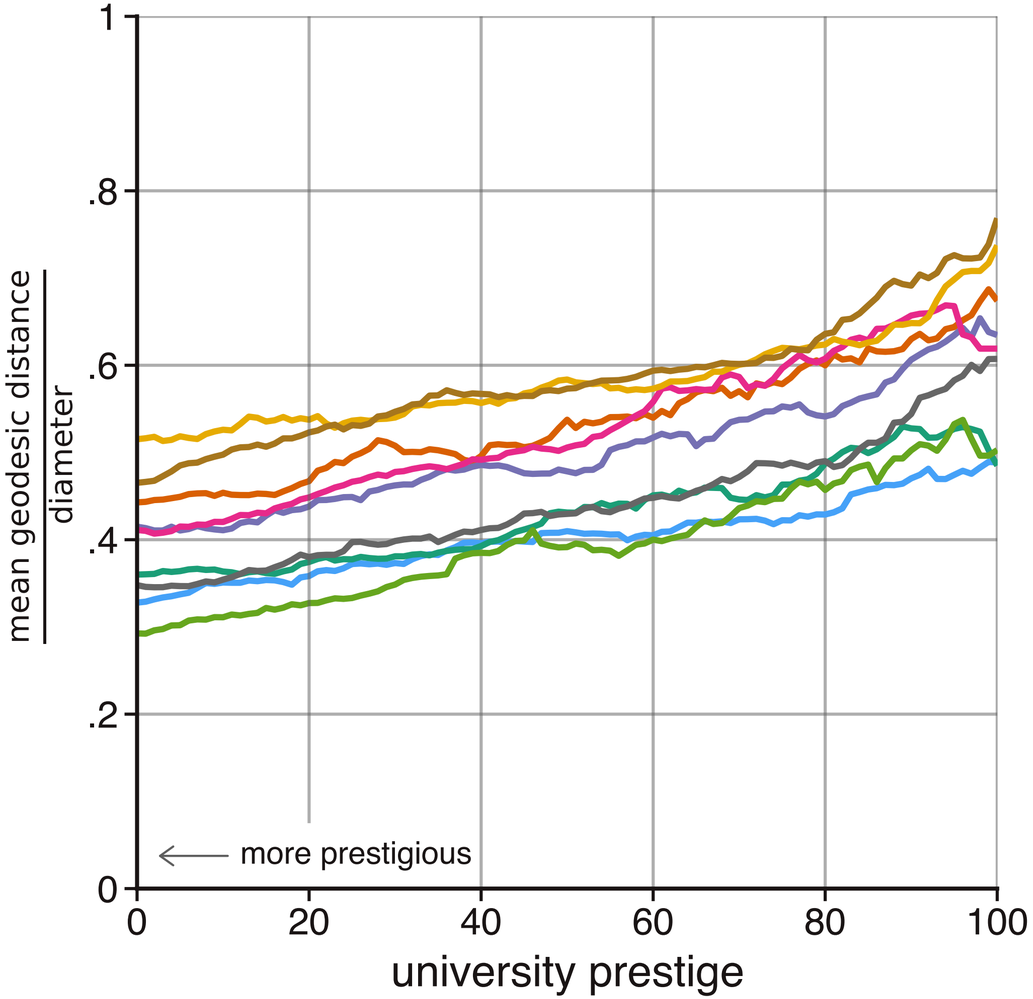
Core & periphery

Prestigious departments sit in the core.

Core departments:
- mutually exchange graduates
- export graduates to periphery departments

Periphery departments:
- import graduates from the core
- rarely export their graduates to other departments

This structure has epistemic & cultural consequences:
- New hires bring their ideas & norms with them.
- Departments in the core: **setting the research agenda** for the broader network.



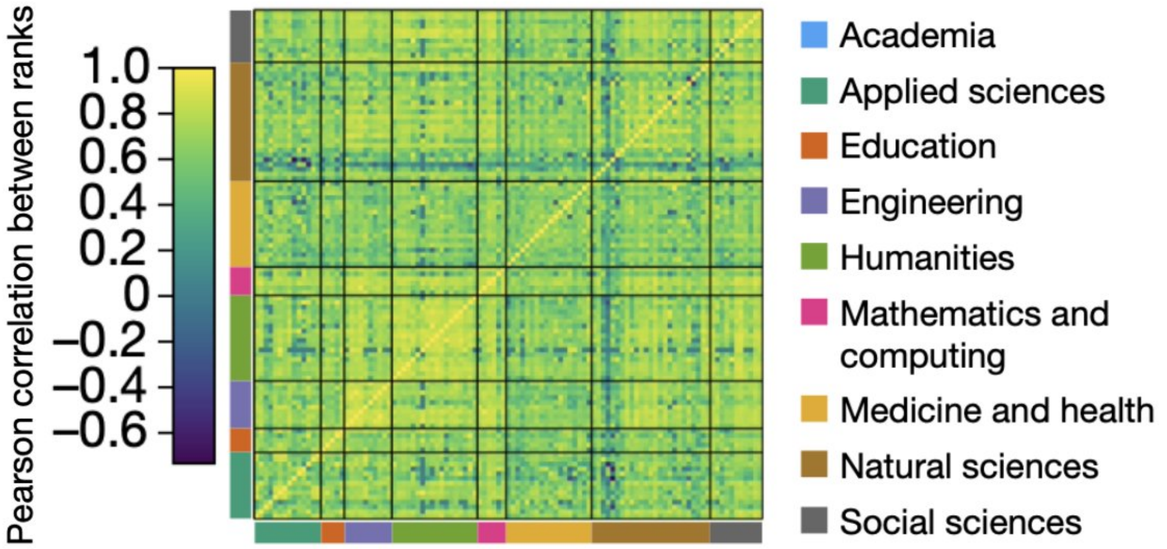
See also: Wellmon & Piper (2017). Morgan, Economou, Way, Clauset (2018).

Institutions are in the core — not just departments

Systematic patterns → ↓

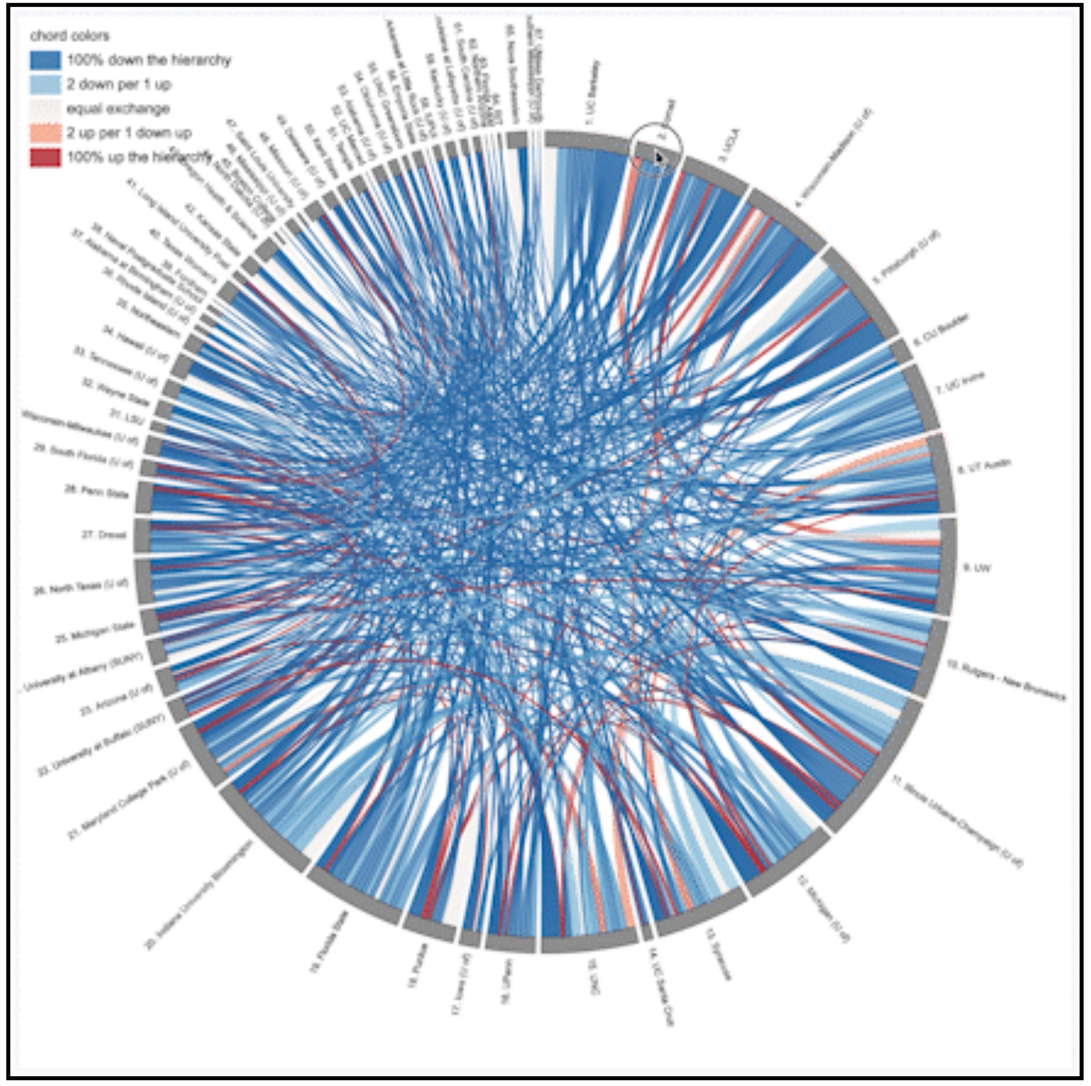
Of the **1070 possible top-10 slots** (107 fields):

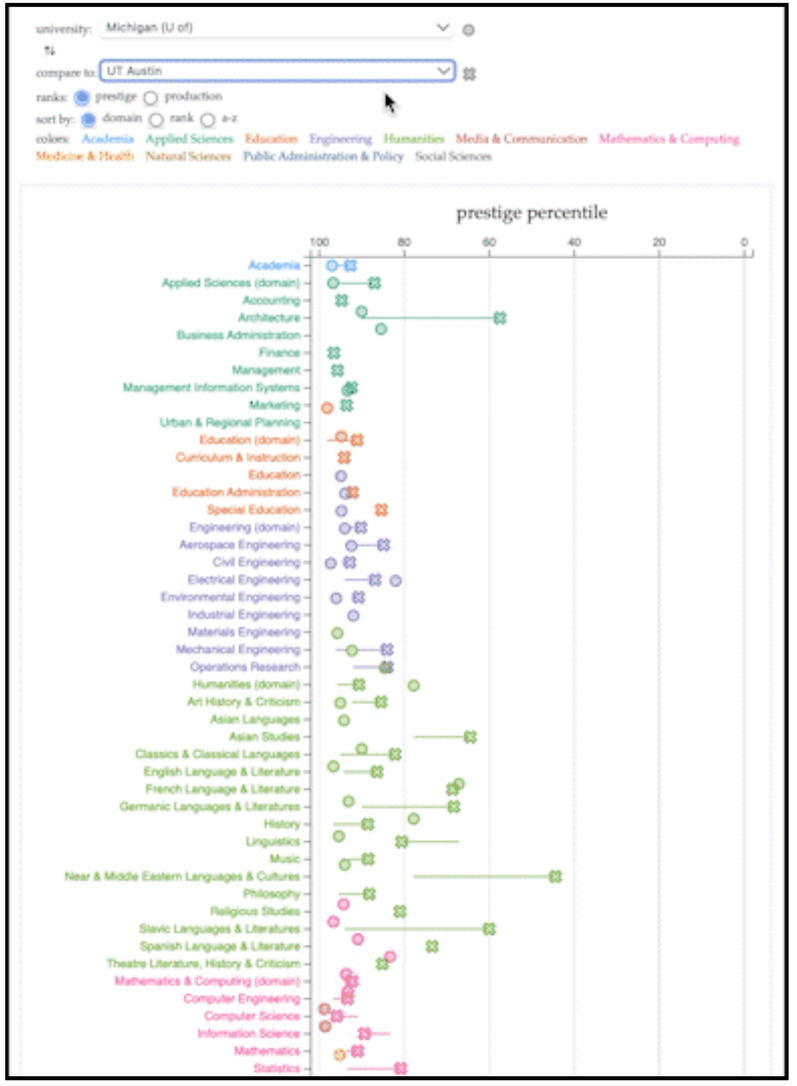
- 248 (23.2%) slots are taken by **just 5 institutions**.
- Full 252 universities (64%) have 0 top-10s.



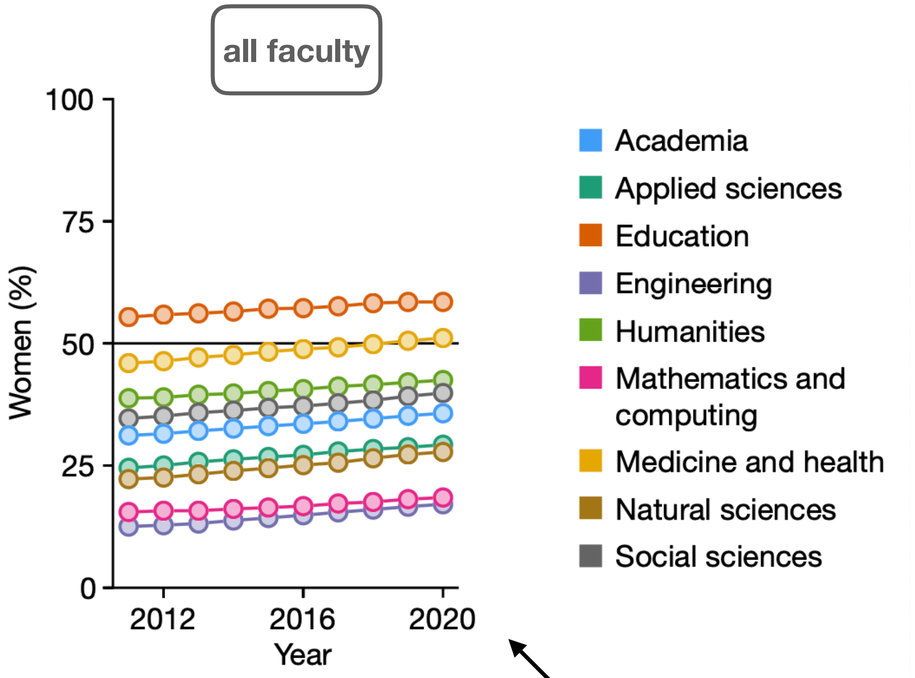
All but 116 (of 12,024) pairwise correlations in this heatmap are positive.
Pathology has the least correlated rankings with any other field.

Explore: Larremore Lab.github.io/**us-faculty**





Women’s representation in the academy

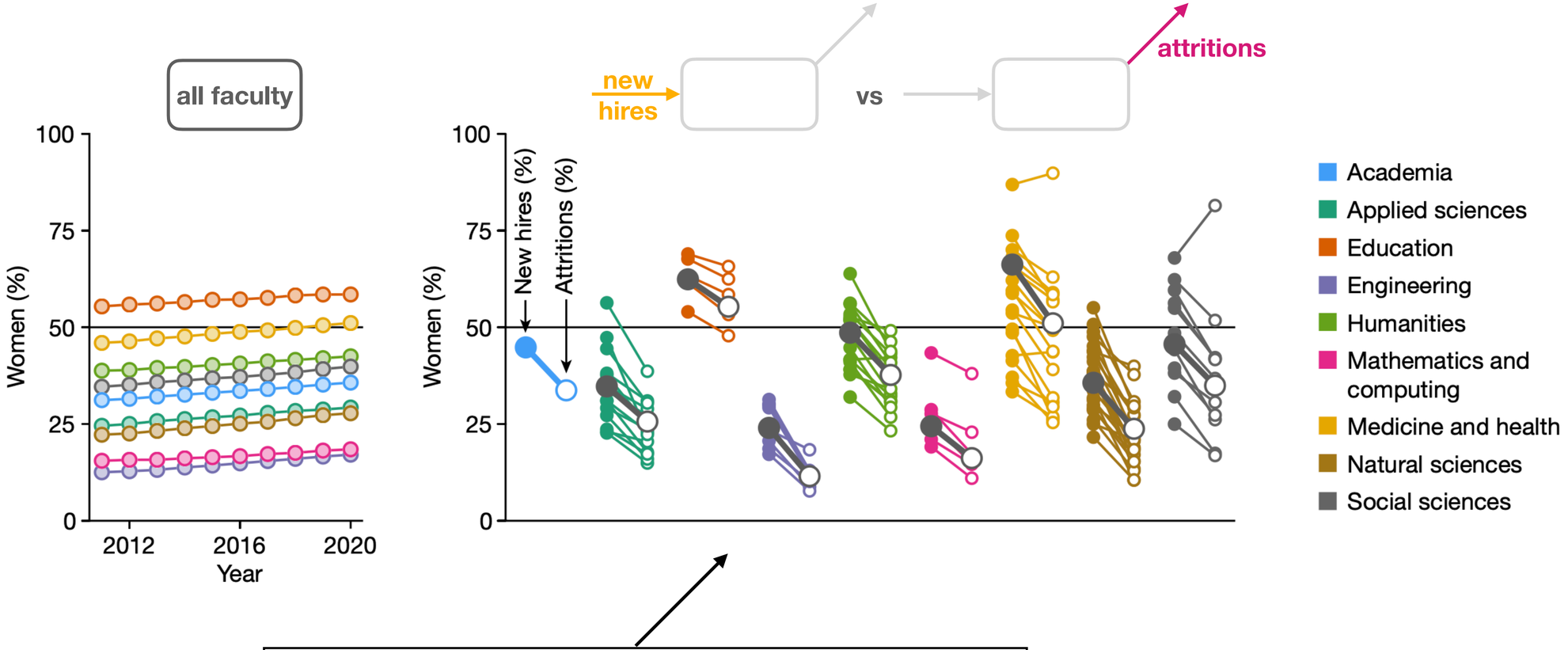


From 2011-2020:

Women’s representation **significantly increased** in academia overall, all 8 domains, and 80/107 fields.

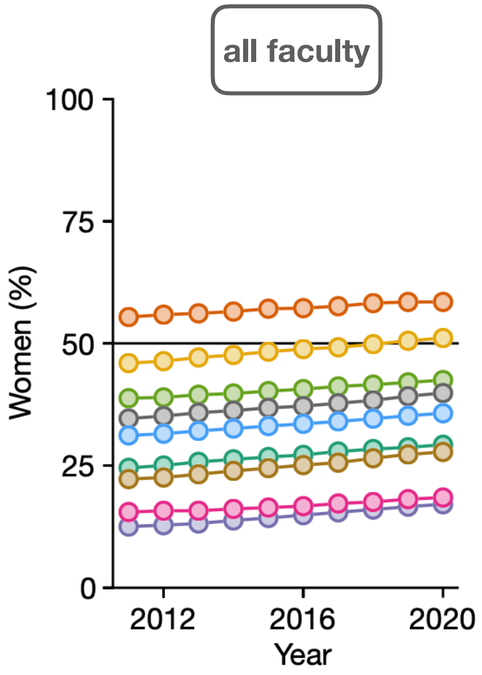
It decreased in only 1 field (nursing).

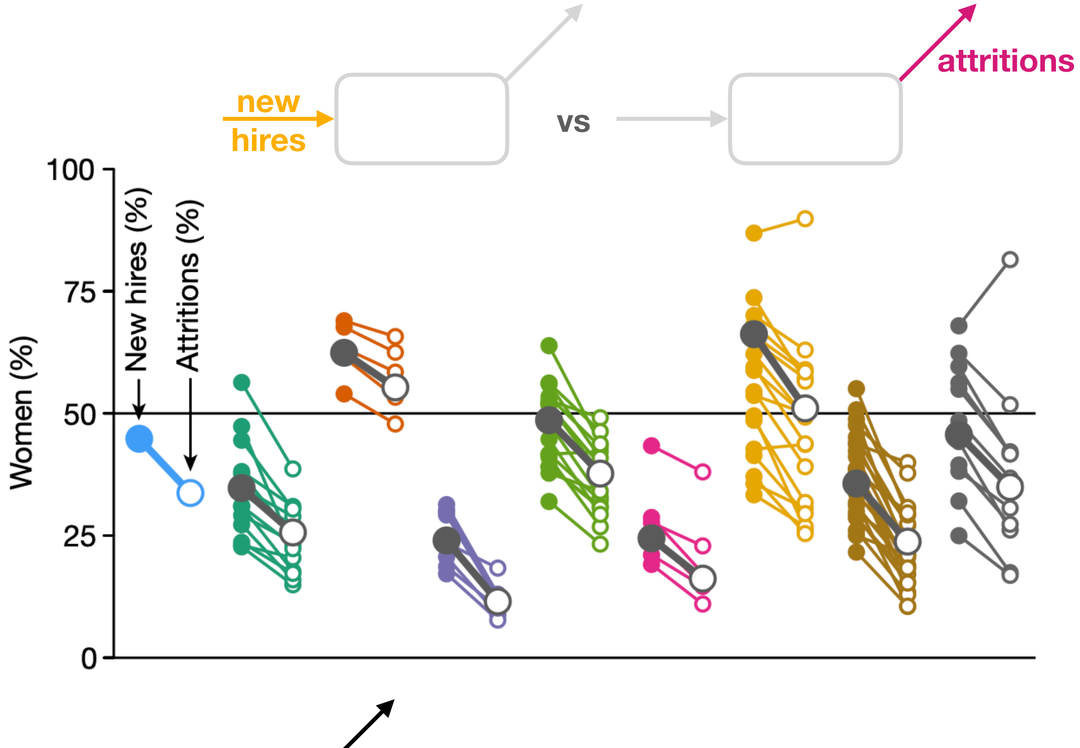
Women’s representation in the academy

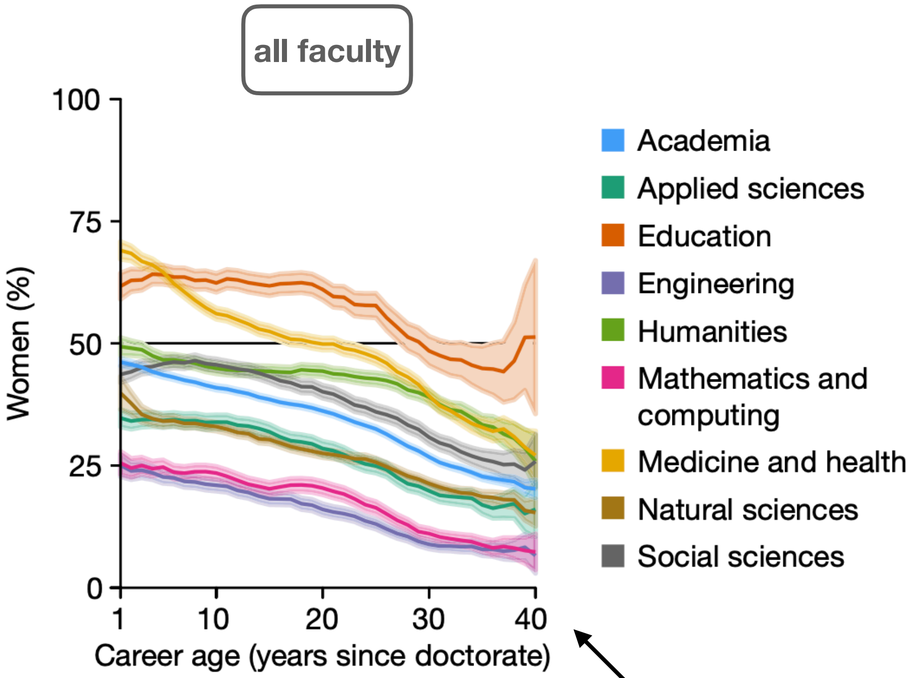


Women’s representation is systematically **higher among new hires** and **lower among attritions** in 103/107 fields.

Women’s representation in the academy



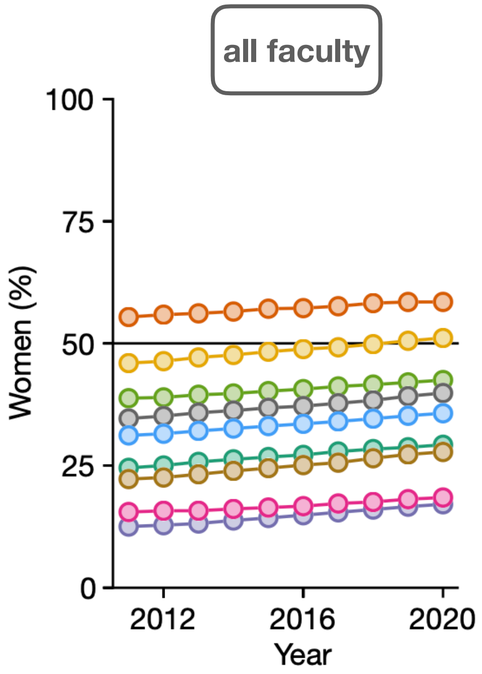


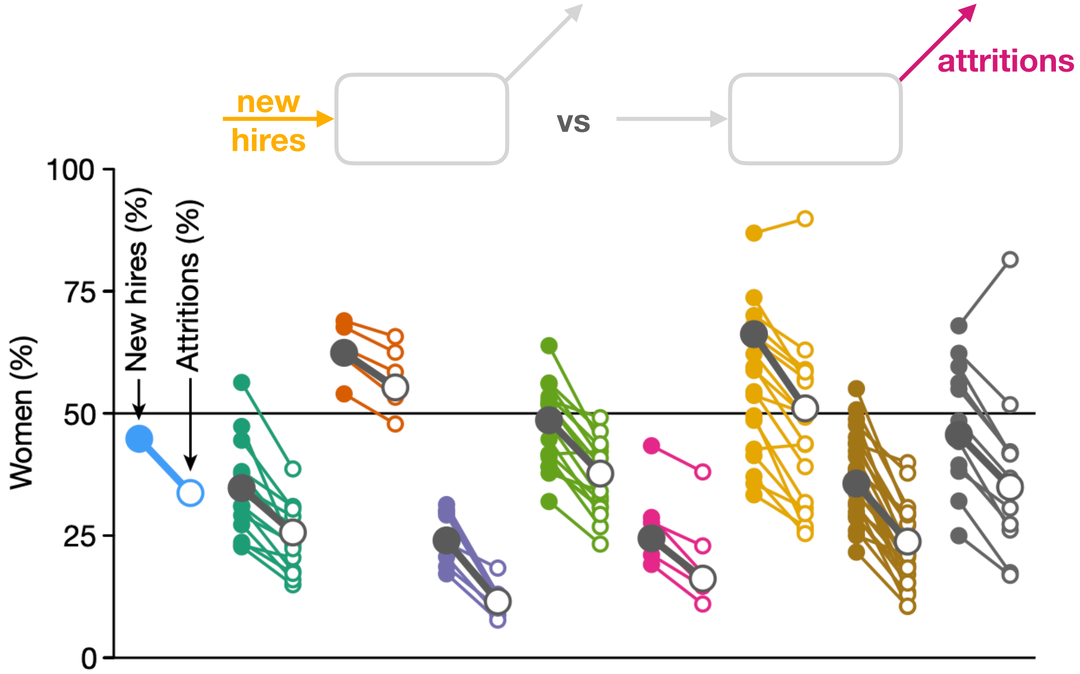


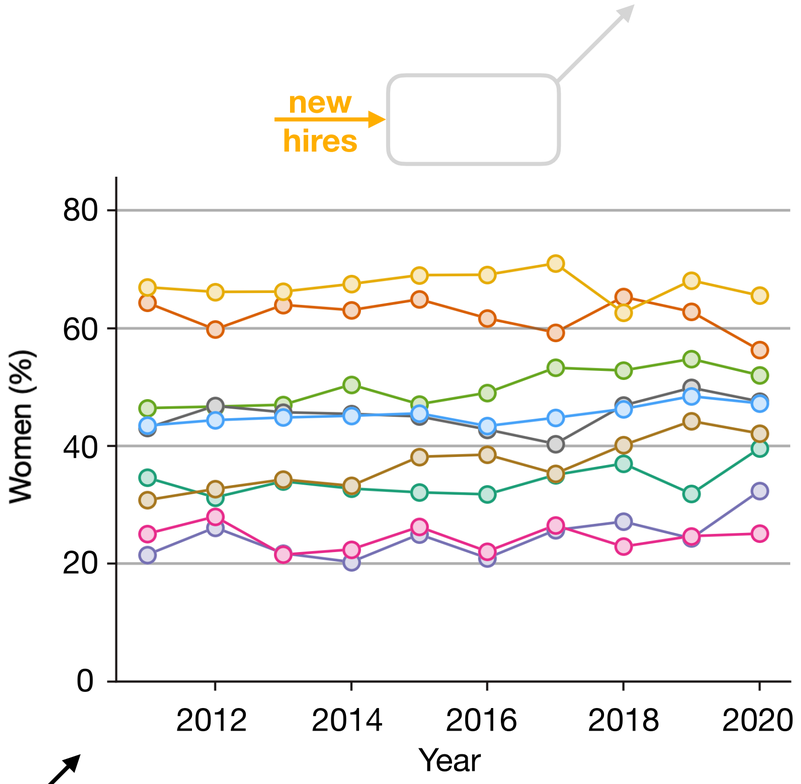
Women’s representation is systematically **higher among new hires** and **lower among attritions** in 103/107 fields.

Demographic curves show why: representation slides downward for cohorts hired in the past.

Women's representation in the academy

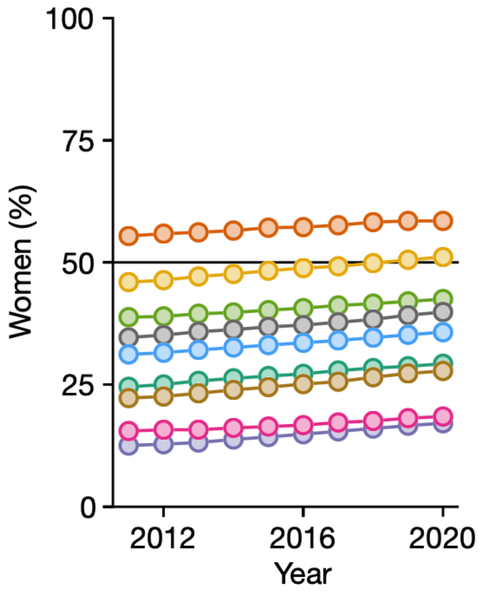


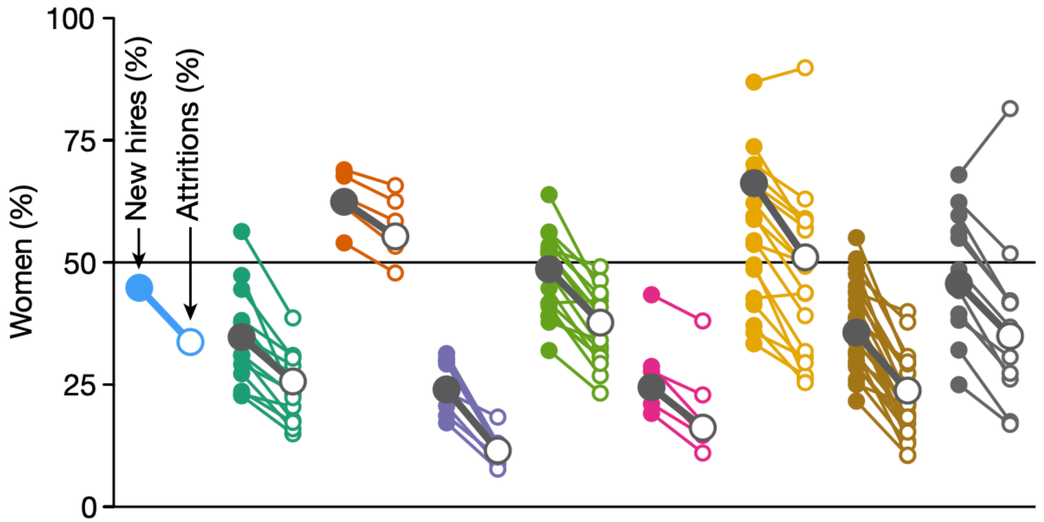


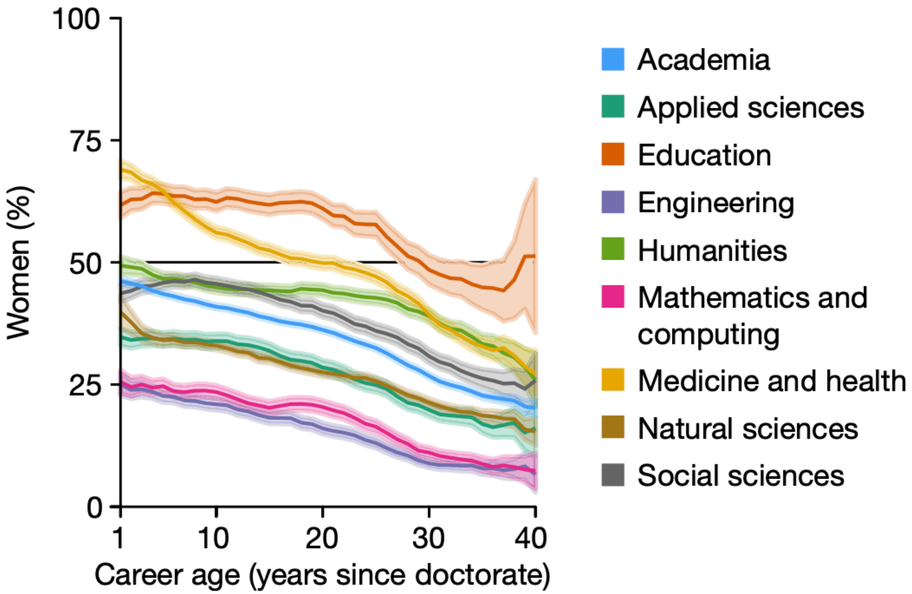


There were **no upward trends** in women's representation **among new faculty** from 2011-2020 in any field.

Women’s representation in the academy



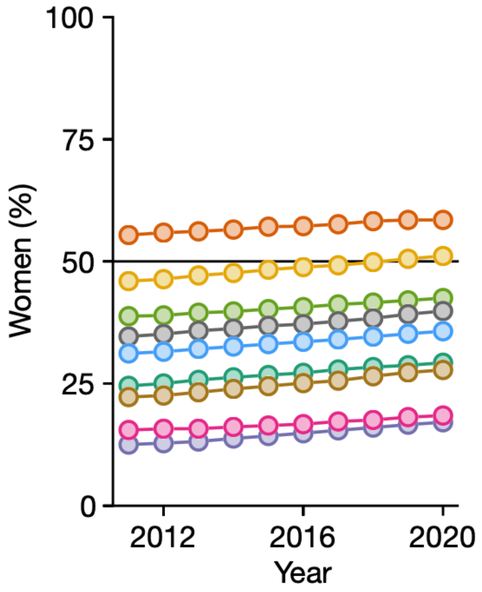


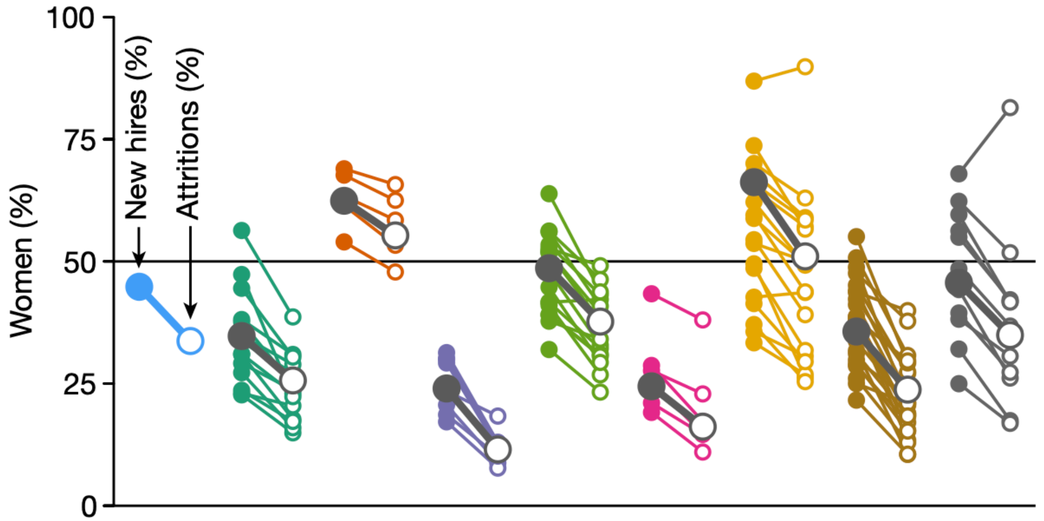


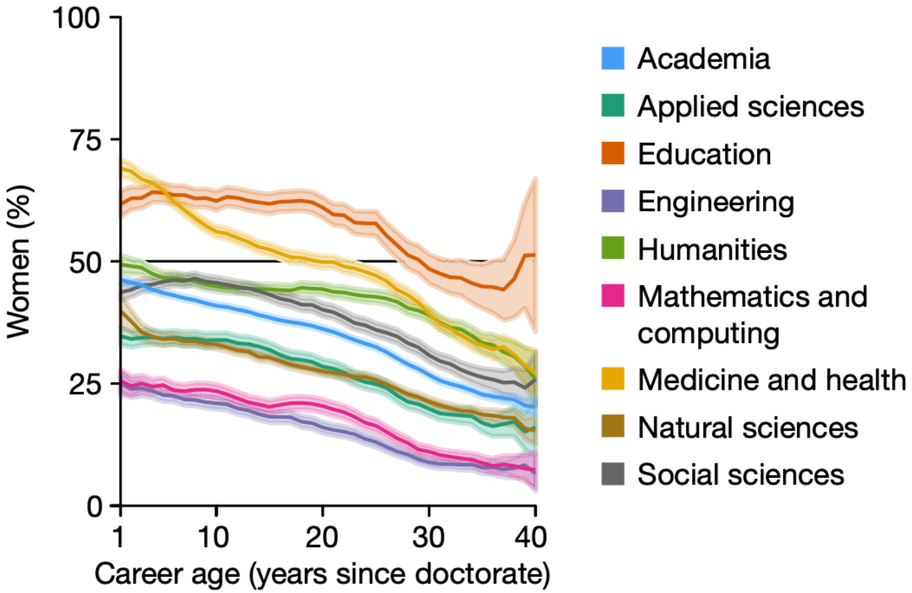
New hires remain predominantly men in 75 of 107 fields, particularly in STEM

There were **no upward trends** in women’s representation **among new faculty** from 2011-2020 in any field.

Without continued efforts toward parity in hiring, the changes in women's overall representation from 2011-2020 will soon plateau.







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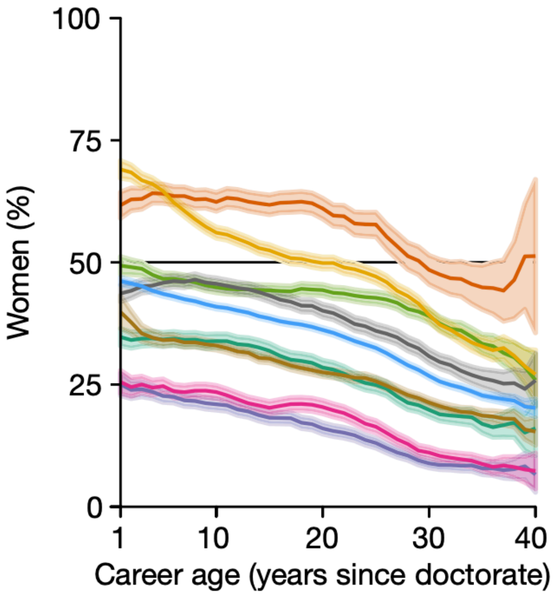
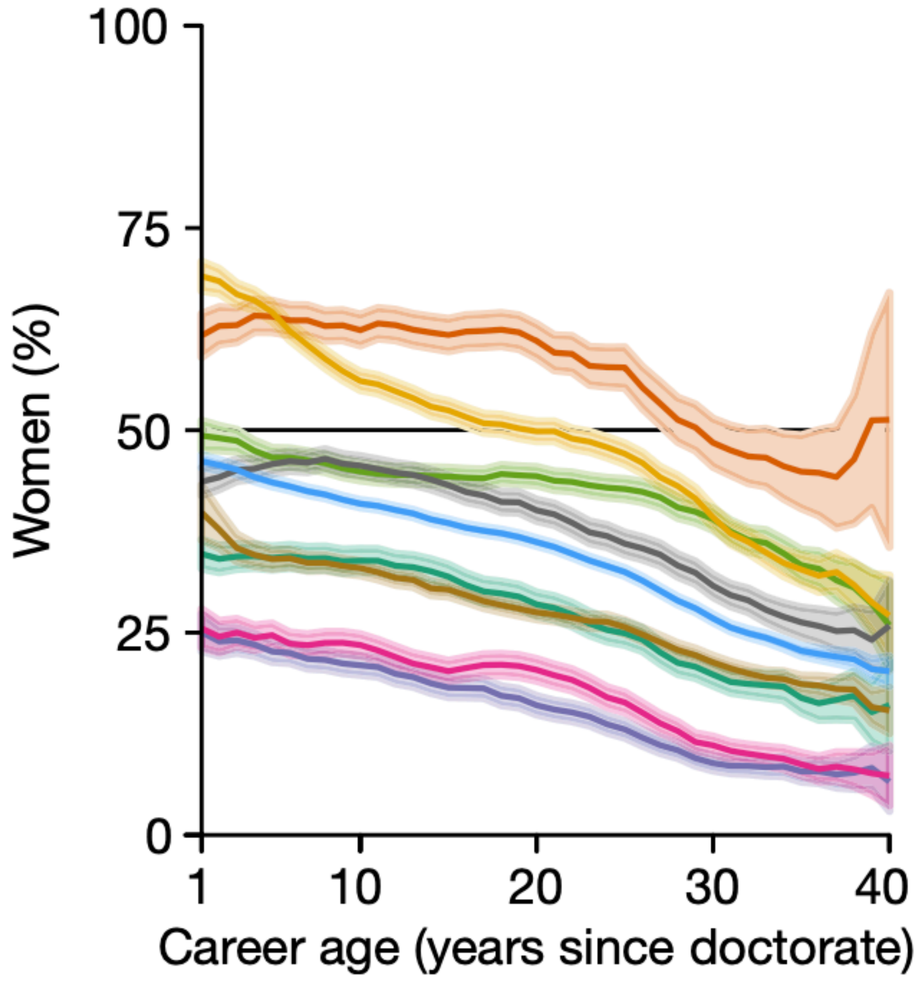

100
75
50
25
0
Women (%)
1
10
20
30
40
Career age (years since doctorate)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Career age (years since doctorate)

Literature: deep, complicated, contradictory

No gendered differences


CULTURE, CLIMATE, AND CONTRIBUTION: Career Satisfaction Among Female Faculty

Louise August*,** and Jean Waltman*

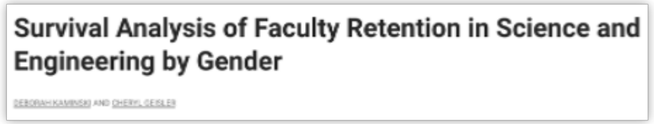
Research in Higher Education (2004)


Women in Academic Science: A Changing Landscape

Stephen J Ceci [1], Donna K Ginther [2], Shulamit Kahn [3], Wendy M Williams [4]

Psych. Science in the Public Interest (2004)

It's complicated…


Survival Analysis of Faculty Retention in Science and Engineering by Gender

DEBORAH KAMINSKI AND CHERYL GESLER

Science (2012)


Retention and promotion of women and underrepresented minority faculty in science and engineering at four large land grant institutions

Marcia Gumpertz, Rallu Durodoye, Emily Griffith, Alyson Wilson

PLOS One (2012)


Women in Academic Economics: Have We Made Progress?

Donna K. Ginther

Shulamit Kahn

American Economic Association (2004)

Yes gendered differences


Trends in the Representation of Women Among US Geoscience Faculty From 1999 to 2020: The Long Road Toward Gender Parity

Meghana Ranganathan, Ellen Lalk, Lyssa M. Freese, Mara A. Freilich, Julia Wilcots, Margaret L. Duffy

American Geophysical Union (2021)


Competing Risks Analysis of Promotion and Attrition in Academic Medicine: A National Study of U.S. Medical School Graduates

Donna B Jeffe [1], Yan Yan, Dorothy A Andriole

Academic Medicine (2019)


Gender Differences in Academic Medicine: Retention, Rank, and Leadership Comparisons From the National Faculty Survey

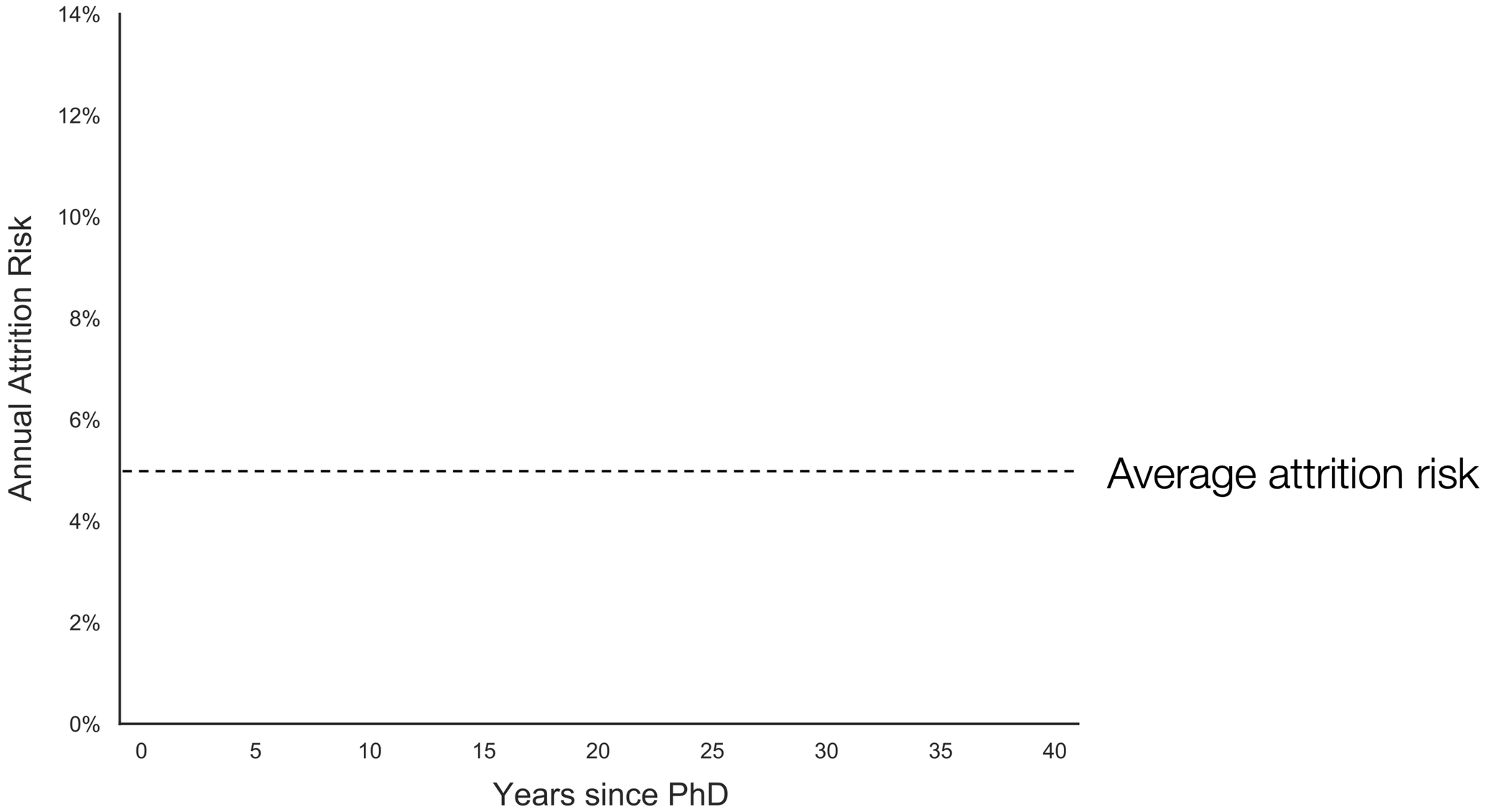
Phyllis L Carr [1], Anita Raj, Samantha E Kaplan, Norma Terrin, Janis L Breeze, Karen M Freund

Academic Medicine (2018)

Why? Some possible limitations:

- Most studies are done at **a single institution or small group of institutions**
- Most studies are done at **a single point in time**
- Most studies are done on **a specific academic field or small group of fields**

Attrition — stratified by career age



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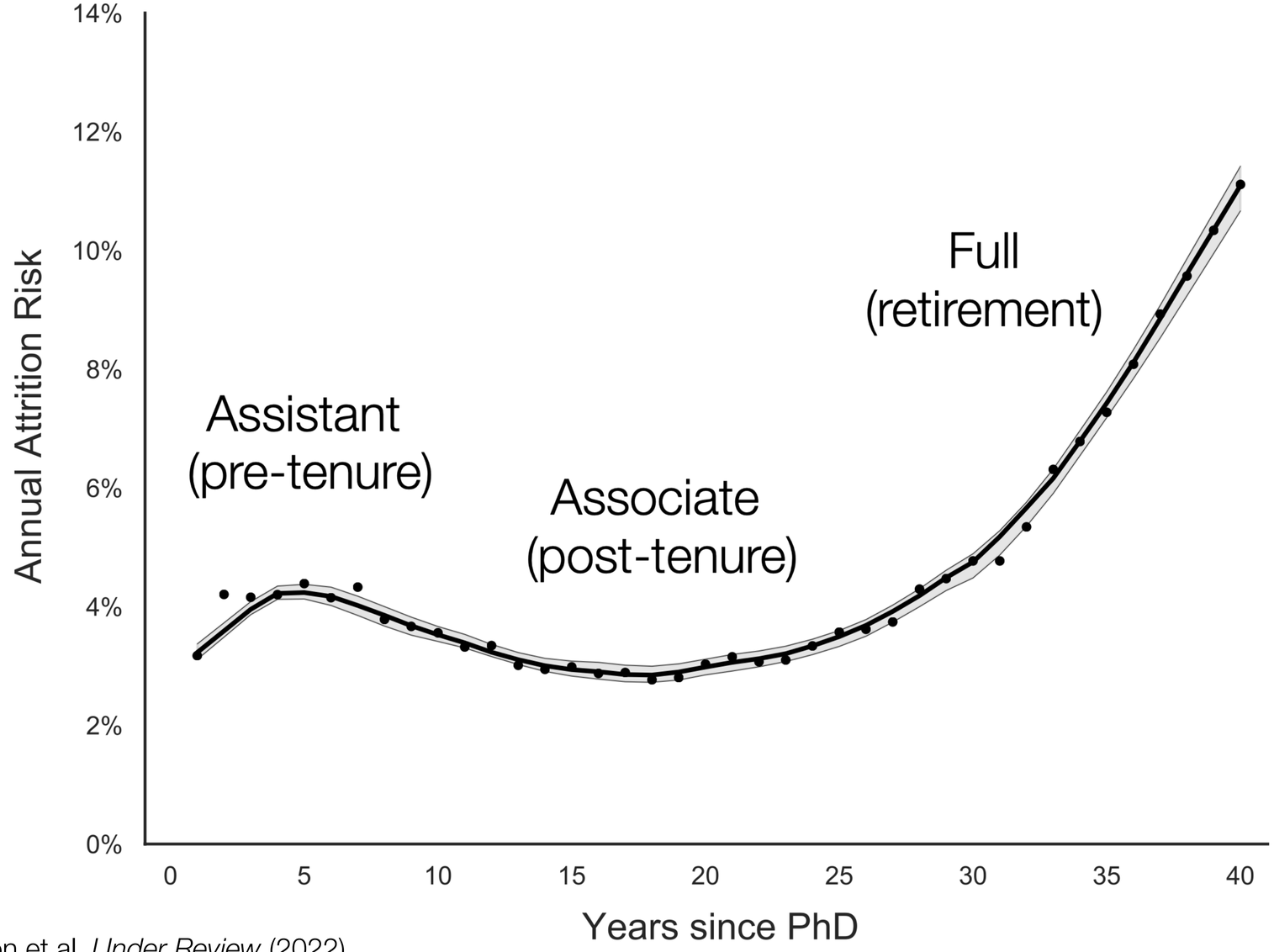
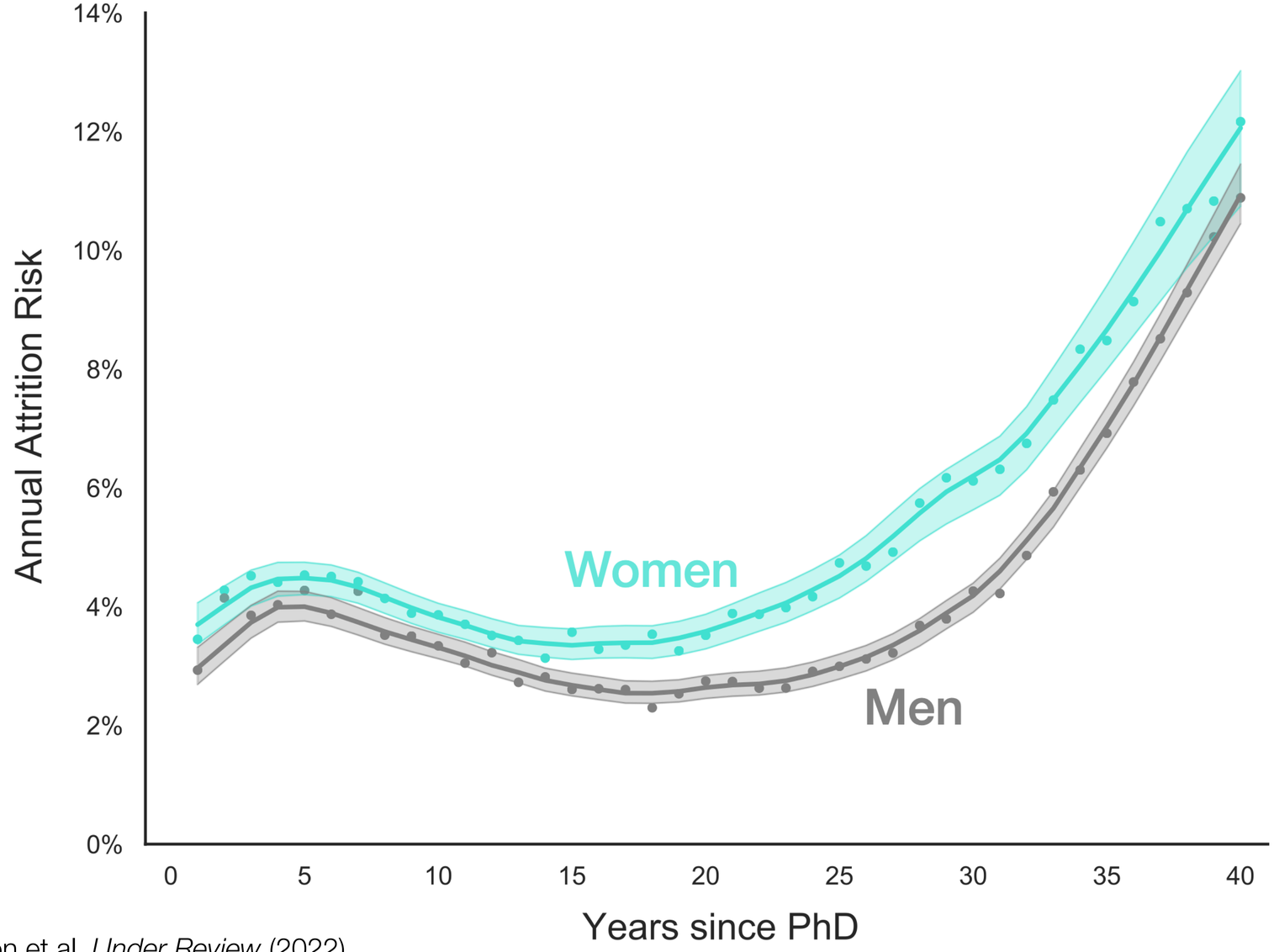


We can clearly see the up-or-out filter of tenure (t=3 to 6), and the gradual onset of retirements from year t=25 onward.

Spoon et al. *Under Review* (2022).

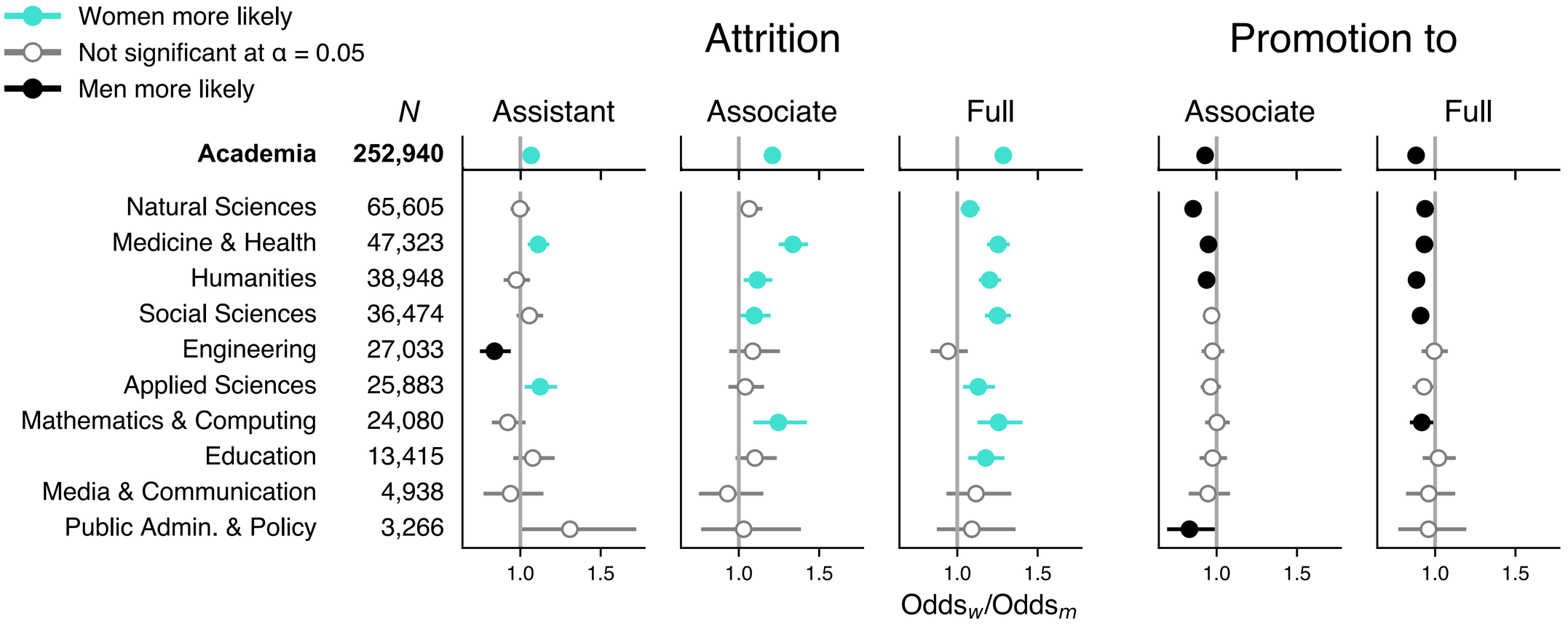
Attrition — stratified by career age & gender



Tenure and retirement persist as patterns, yet **women leave academia at higher per-capita rates for every career age.**

Spoon et al. *Under Review* (2022).

Gender differences in attrition & promotion



Academia-level gendered attrition/promotion patterns hold often [but **not always!**] within domains of study.

Spoon et al. *Under Review* (2022).

Trends in US faculty hiring & retention from 10 years of data: a study of prestige, diversity & inequality

Inequality.

- Most U.S. faculty come from a small number of U.S. institutions. ~80/20
- The hierarchy of prestige is strong; little upward mobility. [5% move “up” in Classics; 6% in Econ.]
- Women’s representation is increasing — but due to efforts of generations past. *Forecasting a slow plateau.*

Attrition.

- Higher attrition rates for those
  - who are self-hires [see paper]
  - trained outside the U.S, U.K., and Canada
  - graduating from less prestigious institutions.
- Substantially higher per-capita annual attrition for women at every career age/stage.
- Inequalities are often instantiated during hiring but exacerbated by attrition.

Methods & Data.

- Longitudinal data provides texture & surprises. Cross-sectional analyses are valuable, but limiting.
- Humans are complex and fascinating, and survey responses are an irreplaceable gift of time. THANK YOU!
- Interdisciplinarity is wonderful: math, complex networks, demography, econometrics, and epidemiology.

Discussion

1. What new data would be most valuable to future work?

   Depth. Self-reported gender/R&E. Undergrad, postdoc, or PhD *department*.
   Breadth. Liberal arts or non-PhD granting institutions; non-tenure track faculty.

2. Is this prestige-oriented system bad? Good? What should change?

   We rely too much on prestige heuristics. Still, those heuristics remain valuable in decision-making under uncertainty and time constraints. Understanding where prestige comes from, and when/how we rely on it will be valuable. Experiments?!

3. What are key weaknesses of this work?

   We observe hiring outcomes, but not key processes. Who applies where? What are the short lists? Who got offers where? Why were some accepted by not others?

4. Can my institution use this work to grow its prestige or prominence?

   Prestige is an emergent consensus. Changing the minds of an entire community is a difficult task. We advocate more attention paid to equity in hiring & retention.

Quantifying hierarchy and dynamics in U.S. faculty hiring and retention

Hunter Wapman, Sam Zhang, Aaron Clauset, Daniel Larremore.
Nature, (2022)

Gender and retention patterns among U.S. faculty

Katie Spoon, Nicholas LaBerge, Hunter Wapman, Sam Zhang, Allison Morgan, Mirta Galesic, Daniel Larremore, Aaron Clauset.
Under Review, (2022)

The Unequal Impact of Parenthood in Academia

Allison Morgan, Samuel Way, Michael Hoefer, Daniel Larremore, Mirta Galesic, Aaron Clauset
Science Advances, (2021)

Socioeconomic Roots of Academic Faculty

Allison Morgan, Nicholas LaBerge, Daniel Larremore, Mirta Galesic, Jennie Brand, Aaron Clauset
Nature Human Behaviour, (2022)

NSF
Alan T. Waterman Award
AFOSR Air Force Office of Scientific Research
Minerva Research Initiative
The Ruth & Sidney Weiss Fund
MIDAS Network
NIH
AARC
University of Colorado Boulder

* Not discussed, but these works are *of a piece*. All work is Open Access.


Erik Johnson


Suchita Lulla


Casey Middleton


Apara Venkateswaran


Aaron Aaeng


Upasana Dutta


Katie Younglove


Kate Bubar


Tzu-Chi Yen


Suyog Soti

Thank you

Larremore Lab.github.io


Sam Zhang


Ian van Buskirk


Katie Spoon


Joanna Mendy


Kate Wootton


Allie Morgan


Nick LaBerge


Aaron Clauset


Hunter Wapman


Maria Martinez


Eun Lee