Interdisciplinary Faculty Hiring

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Abstract

Academic departments reproduce themselves through faculty hiring, but a substantial fraction of hires cross disciplinary boundaries. Whether fields behave as separate labor markets, in which surplus graduates from one field spill into others, or as overlapping regions in a shared topic space, in which faculty flow reciprocally across porous boundaries, has remained an open empirical question. Here we analyze a dataset linking doctoral training, postdoctoral appointments, employment, and publication records for 107,039 U.S. tenure-track faculty across 116 academic fields at 440 PhD-granting institutions from 2011–2023. We find that 37% of faculty are hired into a field different from their PhD, and that these flows follow the pattern of intra-industry trade: import and export rates are strongly and positively correlated, both decrease with field size, and hiring concentrates along topically adjacent boundaries. At the individual level, interdisciplinary hires take an average of 1.8 years longer to secure their positions but are 6.3% more productive in the five years that follow. Tracing research topics through publication embeddings reveals that 77.5% of interdisciplinary hires publish in topics consistent with either their degree or hiring field both before and after the transition, indicating that most boundary crossings are relabelings rather than changes in research topic. Together, these findings reveal a disciplinary landscape poorly described by any taxonomic tree—one in which credentials are selectively fungible across cognitively adjacent fields, and faculty are often relabeled rather than retrained.

1 Introduction

Faculty hiring is the primary mechanism through which academic departments reproduce themselves, and each hire is a high-stakes investment in the future of the department and its field. However, these investments are not confined within disciplinary lines. Some fraction of tenure-track hires are *interdisciplinary hires*—faculty whose terminal degree is in a different field from the one that hires them. The pattern of which fields hire which fields' graduates, and which do not, traces the effective boundaries of knowledge and training across the academy. Because doctoral training imparts the skills, credentials, and methods of a particular field [1, 2], interdisciplinary hires reveal the degree to which doctoral training in one field is fungible in another. Two extremes bound the space: if disciplines were perfectly siloed, interdisciplinary hiring would not exist; if credentials were perfectly fungible, disciplinary boundaries would not matter to hiring. Empirical reality lies somewhere between, and where it lies is an open question.

Most quantitative work on the U.S. tenure-track system has focused on the structure of hiring *within* disciplines, finding steep prestige hierarchies [3, 4], gender and demographic disparities [5, 6], country of training effects [4], and faculty productivity [7, 8]. However, this leaves the structure of hiring *between* disciplines

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less examined at scale. What we know of interdisciplinary hiring comes mostly from older or smaller studies. In 1970s–80s analyses of Dutch academia, about a quarter of physics PhDs took positions outside physics, the natural sciences were net exporters to medicine, and physics, chemistry, law, and economics were the largest exporters overall [9, 10]. More recent studies have examined how interdisciplinarity in doctoral research, variously measured by self-report, dissertation field pairings, or reference-based indices, is rewarded or penalized in early-career outcomes, with findings that vary by field, career stage, definition, and institutional prestige [11–14]. These shed light on whether one's work is interdisciplinary, while our aims here are complementary. We study the interdisciplinarity of the hire, i.e., the transition in which a scholar trained in one field is hired by a department in another, and about the field-to-field structure of such transitions across the academy as a whole.

How, then, should we expect faculty to flow across field boundaries? Two competing pictures predict very different patterns. In one, fields behave as separate labor markets with different levels of supply and demand where surplus graduates from one field spill into neighbors, implying that net exporters should be weak importers. In the other, fields are overlapping regions in a shared space of scholarly topics, with porous boundaries along which faculty cross in both directions, and the same boundary mediates flow either way, implying that fields that export heavily should also import heavily. A priori, it is not clear which picture is more likely to fit the data.

Complicating the picture, interdisciplinary research itself is subject to competing forces. Funding agencies [15], universities [16], and governing bodies [17] have framed interdisciplinary work as a driver of innovation, and interdisciplinary research centers are associated with higher productivity and visibility [18]. At the same time, interdisciplinary grant proposals face lower initial success rates [19], interdisciplinary research has been associated with higher visibility but lower within-career productivity [20], and interdisciplinary papers can experience delayed citation recognition [21]. Whether and how these factors manifest in actual faculty hiring, and at what stage of the training-to-faculty pipeline, remains unclear. Moreover, that pipeline is no longer a single step in many fields with postdoctoral training now the norm in much of the life and physical sciences [22], offering a potential opportunity to retrain or bridge to a new discipline before a tenure-track appointment.

To examine these questions at scale, we assembled a dataset covering the entire U.S. tenure-track system at PhD-granting institutions. We linked a census of tenure-track faculty from 2011–2023 to departmental affiliations at both the terminal degree and the first tenure-track position, and augmented it with postdoctoral appointment data via large-language-model-assisted search over public records, and with high-dimensional publication embeddings that let us represent fields and individual scholars as points and trajectories in a shared topic space. The resulting dataset spans 107,039 faculty in 12,832 departments at 431 PhD-granting U.S. institutions across 116 fields. We use it first to characterize the structural pattern of interdisciplinary hiring across the academy, revealing which fields trade faculty with which others, and what those flows reveal about the fungibility of credentials at field boundaries. We then trace the careers of individuals who cross field boundaries, including their training paths, their productivity after being hired, and the degree to which a field change coincides with a change in research topic.

2 Data

Answering questions about interdisciplinary hiring requires knowing, for each faculty member, both the department that granted their degree and the department that hired them. No single data source provides both. We therefore assembled a dataset combining faculty employment records, dissertation metadata, publication affiliations, and postdoctoral appointment data, linked at the individual level. The result is a directed network of department-to-department faculty hiring flows across 116 fields at 431 U.S. PhD-granting institutions from 2011–2023, augmented with publication embeddings that allow us to measure topical proximity between individuals and disciplines.

2.1 Faculty census

We started with faculty employment records from a census of tenure-track faculty at PhD-granting institutions in the United States from 2011–2023 obtained via a data-use agreement with the Academic Analytics Research Center (AARC). The dataset includes the institution and year of each professor's terminal degree and the institution, department and year of each tenure-track position held during the covered time period. However, the dataset lacked the degree departments, which are the key to identifying interdisciplinary hires.

To fill this gap, we augmented the AARC dataset with each professor's degree department using dissertation data from ProQuest [23], scholar profiles from ORCiD [24], and publication affiliation data from OpenAlex [25]. The resulting data forms a network in which the directed edge bundle A_{ij} represents the number of faculty who received their terminal degree from department i and were hired by department j, resulting in a directed multigraph with 107,039 edges between 12,832 nodes representing the departments at 431 U.S. PhD-granting institutions.

Every department was annotated according to a disciplinary taxonomy of 10 broad "domains" and 116 finer-grained "fields" [4] (Table A1). A key challenge in identifying interdisciplinary hires based on these annotations is multidisciplinarity: 42,318 (39.5%) faculty are affiliated simultaneously with multiple disciplines through either their degree or hiring departments. To disambiguate, we propose two definitions of interdisciplinarity. We define *fully* interdisciplinary hires as faculty hired into a completely new set of disciplines than those they were affiliated with during their degree and *partially* interdisciplinary hires as those that were hired into at least one new discipline. For example, a Computer Science PhD hired into a joint Computer Science and Biology department is partially interdisciplinary, while one hired into a Biology department is fully interdisciplinary. Throughout the rest of the paper, we perform analyses using the fully interdisciplinary definition (Section A6 details robustness checks using the partial interdisciplinarity definition) and focus on faculty who cross field boundaries (*inter-field* hires; see Section A5 for analyses of inter-domain hires). We refer to faculty who are not interdisciplinary hires under these definitions as *within-discipline hires*.

We also obtained postdoctoral appointment data for $n = 27,299$ (25.5%) faculty by querying a large language model with search grounding (Sec 6.6). For each professor, we compiled the number of postdoc positions and the institution, department, and field(s) of all postdoc positions (Sec 6.6).

2.2 Publication data and embeddings

We also constructed an epistemic space using publication embeddings to analyze the interactions of interdisciplinary hiring and research topics [26–29]. We collected as input the titles, abstracts, and publication years of papers in OpenAlex authored by the professors in our dataset, resulting in 22.5M publications authored by 103,666 unique faculty, representing 96.9% of our sample. After filtering, we embedded the resulting as high-dimensional vectors using the SPECTER2 scientific document embedding model [30]. By linking each faculty member to the sequence of embeddings representing their publications, we produced geometric representations of the research trajectories of individual faculty, departments, and entire disciplines. We used distance in this publication embedding space as a measure of topical proximity between disciplines (Section 6.7).

3 The structure of the interdisciplinary faculty labor market

3.1 Rates of import and export across fields

Interdisciplinary hiring is common in the U.S. tenure track with 37% of faculty holding a PhD from a different field than their hiring department. In part, this high frequency is due to the scale of our subdivision of U.S. academia into 116 fields (e.g., Physics, Operations Research, or Comparative Literature), yet even at the coarser level of 10 broad academic domains (e.g., Humanities, Social Sciences, Engineering), 17% of faculty are hired into a different domain than their degree.

However, these single-number summaries obscure enormous variation across the academy. To characterize that variation, we measure each field's directional flows using two rates: the *import rate*, the fraction of faculty a field hires from outside itself, and the *export rate*, the fraction of its now-faculty doctoral trainees who are hired by other fields (Section 6.1). Together, these rates capture both how open a field is to outside credentials and how portable its own credentials are. Because any interdisciplinary hire is simultaneously an export from one field and an import to another, import and export rates are two views of the same underlying flows between fields.

Field import and export rates range from nearly complete openness to complete autarky. For instance, International Affairs imports fully 96% of its faculty, while Nursing exports just 4% of its trainees. That is, among sitting faculty with terminal degrees in Nursing, just 4% are faculty outside of Nursing (Table A2). Even fields considered to be hierarchical and closed, such as Philosophy, Mathematics, and Economics [6, 31, 32], import 23%, 24%, and 22% of their faculty, respectively.

Differing import and export rates imply that some fields are net exporters of faculty while others are net importers, and the magnitudes of these imbalances are often substantial. For instance, although Economics has low rates of both interdisciplinary hiring and placement, it is a net exporter: for every 100 Economics professors, there are about 39 Economics PhDs that are professors in other fields. This surplus is concentrated in exports to the fields of Management, Finance, Business Administration and Public Policy (Fig. 1b). Some fields are even more vigorous exporters on a per capita basis, including Comparative Literature and Educational Psychology, which actually place more of their PhDs into other fields than they themselves hire with net outflows of 130 and 108 PhDs per 100 in-field faculty respectively. In contrast, the fields of Gender Studies, International Affairs, and Computational Biology act as net importers of faculty with net inflows of 56, 75, and 61 per 100 faculty, respectively (Table A2).

3.2 What predicts the volume of hiring between fields?

The wide variation in import and export rates documented above raises a natural question: are these rates related? A simple labor-market account would predict that they are negatively correlated. If a field produces more PhDs than its faculty market can absorb, those surplus trainees are pushed into other fields, yielding high export rates. But the same field, having ample domestic candidates, would have little incentive to hire from outside, yielding low import rates. Under this account, net exporters should be closed to imports.

In fact, we observe the opposite. Import and export rates are strongly positively correlated (Spearman $\rho = 0.88, p < 10^{-6}$; Fig. 2), meaning that fields with high export rates also tend to have high import rates. This correlation is a puzzle under the labor-market account, but it is a natural consequence of a different view. Rather than treating fields as separated markets, consider them as regions in a shared space of scholarly topics, with boundaries where their topics overlap. Under this view, interdisciplinary hiring is flux across those shared boundaries, and import and export rates are two measurements of the same thing—the porosity of each field's boundary, viewed from opposite sides. Fields with more porous boundaries will show elevated rates in both directions, while fields with more rigid boundaries will show low rates in both directions.

This picture makes a prediction: because the boundary of a region scales more slowly than its interior as the region grows, larger fields should exhibit lower rates of interdisciplinary hiring in both directions. The data bear this out. Import and export rates both decrease as discipline size increases ($\rho = -0.38$ for imports and $\rho = -0.37$ for exports, $p < 10^{-4}$ Benjamini-Yekutieli corrected; Fig. 2). For instance, Information Science ($n = 849$) imports and exports at rates of 70% and 57%, compared to 28% and 31% for the much larger field of Computer Science ($n = 4,642$; Table A2).

The picture also predicts, rather obviously, that interdisciplinary hiring should naturally be concentrated between fields whose regions in topic space are adjacent. Fields that do not share a topical boundary should exchange few faculty, while topically adjacent fields, which draw on similar skills and methods, should trade reciprocally. Qualitatively, the data support this, as many clusters of similar fields are connected by reciprocal exchanges of faculty. For instance, Physics and Astronomy train sizable fractions of each other's faculty (Fig. 1c), as do Computer Science, Computer Engineering, and Electrical Engineering (Fig. 1d), and Chemistry and Biochemistry. Quantitatively, a gravity model of field-to-field hiring confirms the pattern: a one-standard-deviation increase in publication distance is associated with a 64% reduction in interdisciplinary hiring rates (pseudo-$R^2 = 0.88$, distance term $p < 10^{-6}$; see Section 6.2).

Together, these patterns imply that hiring flows should be concentrated along a small number of shared boundaries between adjacent fields, with most pairs of fields — which are not topically adjacent — exchanging few or no faculty. Indeed, the hiring network is sparse: when considering only hiring flows that represent non-trivial proportions of each field's total faculty hires, the network becomes highly disconnected (Fig. 1a).

This boundary-flux picture treats symmetric exchange as the baseline expectation, which makes the asymmetries observed in practice (e.g., Economics placing heavily into Finance and Management without comparable reciprocation) the more striking feature of the data. The picture also leaves open a question about what an interdisciplinary hiring event represents at the level of individual faculty: When a scholar is relabeled from one field to an adjacent one, do their research topics actually shift, or does the boundary crossing reflect a change of label rather than a change of scholarly trajectory?

3.3 Do interdisciplinary hires change research topics?

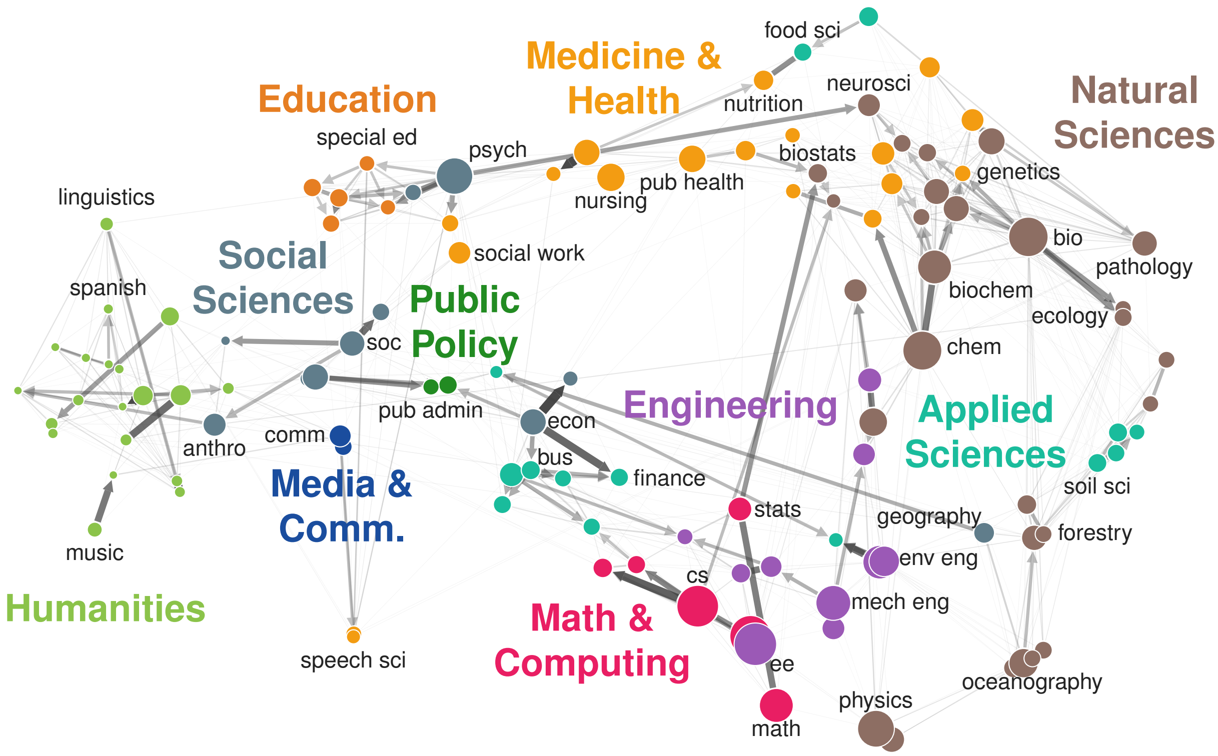
The empirical measurements and geometric interpretation of faculty hiring introduced above raise the possibility that some of those counted as interdisciplinary hires may be *inter*discplinary but not *trans*disciplinary: their scholarship may sit in the overlap region between their doctoral and faculty fields, in which case an observed field change at hiring is merely a relabeling, with no accompanying shift in research topic. On the other hand, the boundary crossing may reflect a real change in what the scholar works on. Distinguishing these possibilities requires tracing individual research trajectories through topic space.

To investigate these possibilities, we compared the topic distributions of each faculty member's publications before and after their first tenure-track hire. For each publication, we computed a local topic distribution by averaging the disciplinary affiliations of its k-nearest neighbors in topic embedding space, then aggregated these across each person's pre-hire and post-hire publications separately (Section 6.7). Comparing these pre-hire and post-hire distributions to the average topic distributions of the corresponding degree and hiring fields yields four categories of interdisciplinary hires and a residual (Table 1). *Label correcters* publish in topics aligned with their hiring field both before and after being hired, suggesting their PhD label was the less-accurate descriptor of their work. *Label adopters* publish in topics aligned with their degree field throughout,

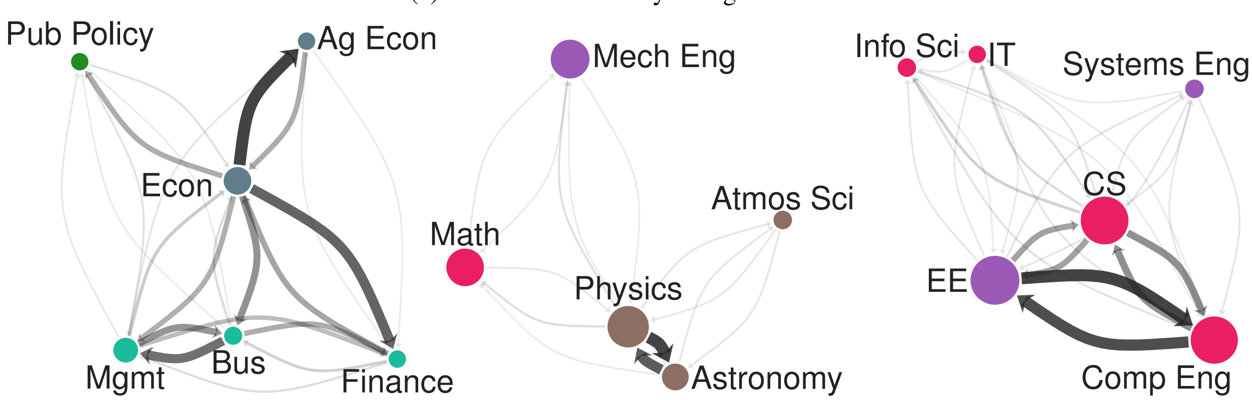
Research topic trajectory	**Pre-hire research**	**Post-hire research**	**Percentage**
Label correcter	Hiring	Hiring	42.9%
Label adopter	Degree	Degree	34.5%
Topic adopter	Degree	Hiring	13.1%
Topic reverter	Hiring	Degree	6.9%
Other	Other	Other	2.5%

Table 1: **Interdisciplinary hiring rarely coincides with changes in research topic.** Categories of interdisciplinary faculty publication topic trajectories. The columns "Pre-hire research" and "Post-hire research" indicate which discipline(s) research papers written before and after being hired are most closely aligned to: degree, hiring, or other disciplines (Section 6.7, and the Percentage column gives the fraction of interdisciplinary hires in each trajectory.

suggesting their hiring label is the less-accurate descriptor. *Topic adopters* and *topic reverters* actually change topics at the time of the field change, moving toward their hiring field or back toward their degree field, respectively. Across academia, the relabeling interpretation dominates: 77.5% of interdisciplinary hires do not change research topics between their PhD and first faculty position. Label correcters are the plurality (42.9%), followed by label adopters (34.5%). Only 20.0% show evidence of actually changing topics at the time of the field change. These proportions vary across disciplines but are broadly consistent across the academy (Fig. A2).



(a) Field-to-field faculty hiring network



(b) Economics neighborhood (c) Physics/Astronomy neighborhood (d) Computer Science neighborhood

Figure 1: **Interdisciplinary hiring flows are shaped by topical adjacency and credential fungibility.** (a) Nodes are academic fields sized by faculty hired and colored by domain. Edges $i \to j$ represent PhDs from field i hired into field j, with widths proportional to the fraction of field j's faculty hired from i; mutual flows are drawn as undirected edges. Node positions reflect a t-SNE embedding of publication space, so that topically similar fields appear nearby. (b–d) Neighborhoods of Economics, Physics/Astronomy, and Computer Science, illustrating asymmetric exports (Economics) and reciprocal exchanges (Physics–Astronomy, Computer Science–Computer Engingeering–Electrical Engineering).

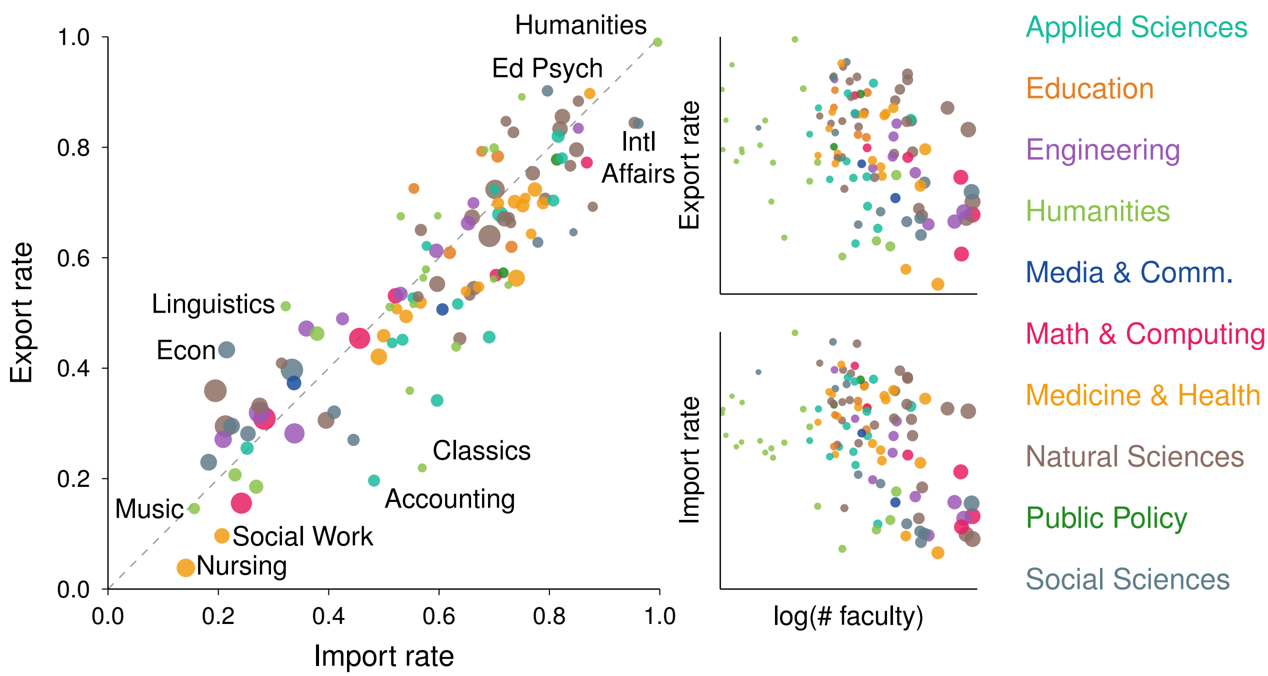


Figure 2: **Interdisciplinary hiring rates are bidirectional and decrease with field size.** Points represent fields with sizes proportional to the number of faculty in each field, and fields are colored by parent domain. The dashed line indicates equal export and import.

4 Career trajectories of interdisciplinary hires

4.1 Time to first faculty position

Interdisciplinary hires take an average of 1.8 years longer to secure tenure-track positions than their disciplinary peers (7.1 vs. 5.4 years between terminal degree and first tenure-track position; Fig. 3). This difference is directionally consistent across the academy. At the field level interdisciplinary time-to-hire is significantly longer in 38 fields and significantly shorter in none ($p < 0.03$, Benjamini-Yekutieli corrected Mann-Whitney U tests). The pattern holds at the domain level as well, with significantly longer time-to-hire for interdisciplinary hires into 7 of 10 domains ($p < 0.027$), and none significantly shorter. The magnitude varies, with the largest difference in the Medicine and Health domain (+3.2 years), while Applied Sciences shows virtually no difference.

4.2 Postdoctoral training

One might expect that this additional time-to-hire is largely spent in postdoc positions, which have become increasingly common between the PhD and first faculty appointment in many fields [33]. Postdocs are indeed common in our sample overall (60% of faculty held at least one), and interdisciplinary hires hold them at higher rates than within-discipline hires (68% vs. 57%), hold multiple postdocs more often (18% vs. 15%), and spend longer in them on average (3.8 vs. 3.3 years). Postdocs likely do not account for the full 1.8-year gap, however, because the extra training time may also include positions that serve similar career functions without being labeled postdocs, including visiting assistant professorships, research-track appointments in industry, or policy roles.

This aggregate picture masks substantial variation across fields. Postdoc rates range from 2% in Accounting to 95% in Molecular Biology, and across domains from 15% in Journalism to 84% in Natural Sciences. The direction of the interdisciplinary-vs-disciplinary comparison also varies: disciplinary hires are actually *more* likely to hold postdocs in 34 fields, including Physics (90% vs. 77%; Table A3). The aggregate finding therefore reflects a field-weighted average of career pipelines that differ substantially across disciplines.

For those interdisciplinary hires who do take postdoctoral positions, when does the field change happen—in the transition from PhD to postdoc, or from postdoc to faculty position? Comparing the disciplines of postdoc positions to the degree and hiring disciplines lets us locate the transition. Empirically, however, no single paradigm dominates: roughly a third of faculty switch into their hiring field for their postdoc (*interdisciplinary at postdoc*), a quarter use the postdoc as a bridge that partially overlaps both degree and hiring fields (*bridge*), a quarter make the transition between postdoc and first faculty position (*interdisciplinary after postdoc*), and the remaining eighth hold postdocs in a third field entirely (*detour*; Table 2). Even within-discipline hires cross discipline boundaries via a postdoc at non-trivial rates: 13% held postdocs in fields distinct from both their degree and hiring fields (*roundtrip*).

4.3 Post-hire productivity

Inter-field hires publish 6.3% more papers than disciplinary hires in the five years after being hired ($p < 10^{-6}$, Benjamini-Yekutieli corrected Negative Binomial regression). This estimate controls for hiring discipline, gender [5], and hiring institution prestige [8, 34], and for career age at hire—which matters here because interdisciplinary hired tend to be hired later (Section 4.1), and later-career hires are generally more productive in the years following their first appointment. The productivity difference survives these controls (Section 6.4). This productivity advantage is directionally consistent with prior findings that interdisciplinarity *during* doctoral training (as measured from dissertation fields or the discplinary diversity of

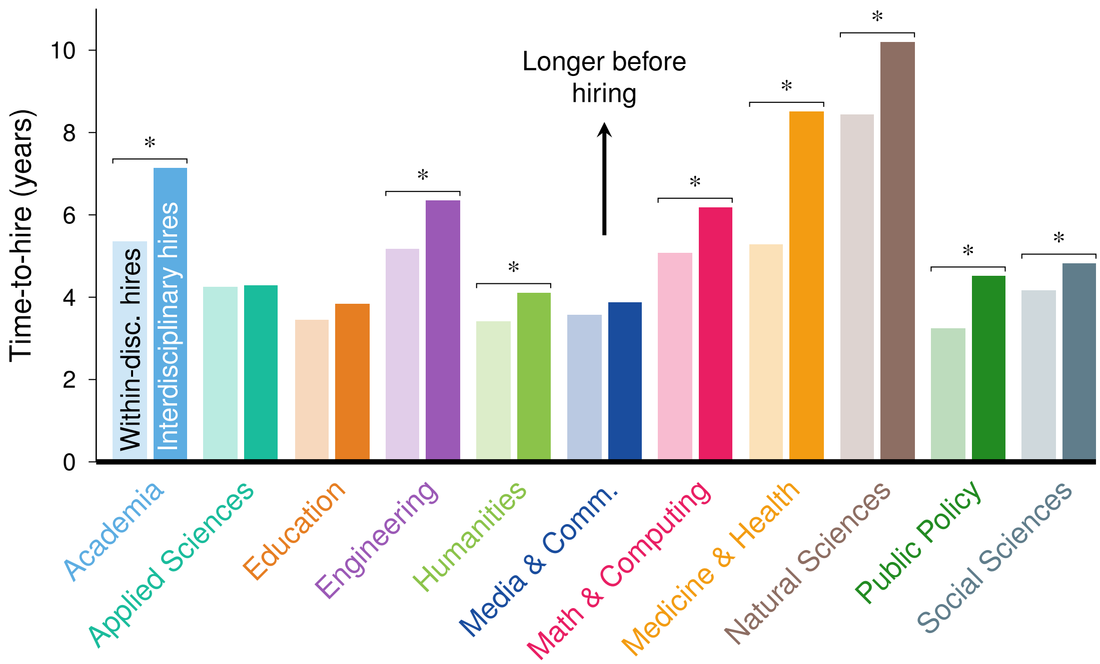


Figure 3: **Interdisciplinary hires take longer to be hired into their first tenure-track positions.** Average time in years between terminal degree and first tenure-track position for within-discipline (light bars, left) and interdisciplinary (dark bars, right) faculty hires across domains and academia overall. Bars are colored according to the domain that faculty are hired into. Stars denote domains with significant differences between disciplinary and interdisciplinary hires (Benjamini-Yekutieli corrected Mann-Whitney U tests).

PhD-era references) predicts higher early-career publication counts [11, 14], though our measure captures interdisciplinarity at the hiring event rather than tin the doctoral research itself.

4.4 Research topic trajectories and individual outcomes

The research-topic trajectories of individual interdisciplinary hires, introduced in Section 3.3, provide a lens on whether the heterogeneity among interdisciplinary hires tracks their career outcomes. Recall that the plurality of interdisciplinary hires (which we termed label correcters and label adopters) do not change research topics between their PhD and faculty careers, while a minority (topic adopters and topic reverters) do.

Post-hire productivity and time-to-hire differ markedly across these categories. Interdisciplinary hires whose research topics remain stable are more productive than the average interdisciplinary hire: label adopters and label correcters publish 22.2% and 17.2% more papers in the five years post-hire than their disciplinary peers ($p < 10^{-6}$, Benjamini-Yekutieli corrected Negative Binomial regression). In contrast, the faculty who do change research topics are less productive than within-discipline hires, writing 2.8% and 4.8% fewer papers for topic adopters and topic reverters, respectively, though these decreases are not significant given the small sample sizes (Table A5).

Time-to-hire shows a milder pattern such that interdisciplinary hires in every trajectory category take longer to be hired than within-discipline peers, but the gap is slightly attenuated for topic reverters (1.1 years) and label adopters (1.7 years; Table A5). Both the trajectory proportions and these outcome differences are stable under alternative definitions of interdisciplinary hiring (Table A4).

Postdoc category	Description	Percentage
Interdisciplinary hires		
Interdisciplinary at postdoc	Already in hiring field before postdoc	34.0%
Bridge	Postdoc fields overlap degree or hiring fields	26.5%
Interdisciplinary after postdoc	Enters hiring field after postdoc	26.5%
Detour	Postdoc in a third field	12.9%
Disciplinary hires		
Singletrack	Degree, postdoc, and hiring all in same field	87.5%
Roundtrip	Postdoc in a different field, returns for hiring	12.5%

Table 2: **No single discipline-crossing paradigm dominates postdoctoral training for interdisciplinary faculty hires.** Postdoc discipline type for interdisciplinary and disciplinary hires. Categories are defined based on overlap between postdoc, degree, and hiring disciplines according to the Description column (Section 6.6). The Percentage column gives the fraction in each category among interdisciplinary and disciplinary hires who had at least one postdoc position.

5 Discussion

Disciplinary boundaries in academia have been shaped by centuries of institutional tradition, yet faculty hiring regularly crosses them, with 37% of U.S. tenure-track hires holding PhDs from a field different than the one they are hired into. The structure of these flows does not match the predictions of a simple labor-market account, in which fields behave as separate markets and interdisciplinary hiring reflects imbalances between them, such that surplus exporters should be closed importers, and vice versa. Instead, we find that a field's import and export rates are strongly positively correlated, that smaller fields exchange faculty in both directions at higher rates than larger ones, and that flow is concentrated between topically adjacent fields. This is the pattern of intra-industry trade [35–37], in which similar regions trade differentiated goods in both directions, and the volume of trade reflects the openness of boundaries rather than asymmetric supply and demand. Viewed through this lens, interdisciplinary hiring is less a leak across disciplinary walls than a signature of the permeability of those walls. Empirically, this permeability varies systematically with field size and topical proximity, and operates on credentials differentiated enough at the individual level that adjacent fields value each other's trainees even when their own supply is adequate.

At the individual level, interdisciplinary hires pay a time cost and accrue a productivity benefit. They take longer to secure tenure-track positions, more often holding postdocs and holding them longer, with no single postdoc paradigm dominating as the mechanism for the field transition. Once hired, they are more productive than their within-discipline peers, though this boost is concentrated among hires whose research topics remain stable across the field change. Individual-level trajectories also suggest that much of what we count as interdisciplinary hiring is a change in disciplinary affiliation rather than a transdisciplinary change in research topic. In other words, faculty are often relabeled rather than retrained.

In many sets of topically similar fields, interdisciplinary hiring is mutual, suggesting that credential transferability flows both ways and tracks cognitive overlap. However, in other cases, asymmetric flows suggest hierarchies between fields, resulting in one-directional credential fungibility. Fields that share unified theoretical foundations may display these hierarchies because their shared theory allows ordering fields by how fundamental they are, e.g. unilateral hiring flows from Psychology to Special Education and Neuroscience, from Biological Sciences to Biomedical Sciences and Cell Biology, and from Economics to Finance and

Business [38] (Fig. A1).

Overall, our results reveal that the disciplinary landscape is poorly described by *any* taxonomic tree. While classifying career moves requires imposing such a taxonomy of disciplines (from broad domains to specific fields), this taxonomy can be misleading: a move from Biological Sciences to Biomedical Sciences appears to span two domains (Natural Sciences to Medicine), yet intuitively it is minor because these fields are closely related. An alternative taxonomy that "fixes" this problem would necessarily induce new ones. The maps of mutual credential exchange via hiring and topical similarity via publication embeddings are therefore more faithful to reality than the imposed taxonomy. The difficulty of cleanly partitioning a continuous similarity structure into discrete categories is a general one [39], not specific to academic disciplines.

What might explain the training and productivity patterns observed at the individual level? The extended training period is consistent with the "burden of knowledge" framing [40, 41]: as science advances and specialization deepens, early-career scientists may train longer and increasingly look outside their training discipline to find tenure-track positions. They may even leverage their external training as a strength [42]. Recent evidence that the productivity of doctoral interdisciplinarity is largest among faculty hired at top-ranked universities, despite those universities' preference for less interdisciplinary candidates [14], suggests this strength can be realized even in settings whose hiring norms do not explicitly reward it. At the same time, outsider contributions to science are often under-recognized [43], raising the possibility that the productivity benefits we observe understate the intellectual contributions of interdisciplinary hires. The productivity and recognition picture is further complicated by compensation: interdisciplinary dissertators in the U.S. have been shown to earn lower first-year post-PhD salaries than their single-discipline peers [12], indicating uneven career rewards to boundary crossing. The productivity boost is harder to pin down. One candidate is that longer pre-hire research periods build momentum that carries into the first years as faculty. Because our model controls for career age at hire, the observed differences cannot be reduced to raw training-time differences. Another candidate involves research strategy. Interdisciplinary hires whose post-hire research matches their training discipline are the most productive of all (Table A5), perhaps because they occupy areas under-exploited by within-discipline hires, acting as vectors for the diffusion of knowledge between fields [44]. The subset who change research topics across the field transition are less productive than their within-discipline peers, consistent with cognitive barriers from learning new skills, methods, and conventions [27] (Table A5). We do not measure whether interdisciplinary hires produce interdisciplinary *research*, so we cannot attribute the productivity pattern directly to the documented costs and benefits of interdisciplinary work [18, 20].

This work is subject to several limitations. First, our analysis is restricted to tenure-track faculty at U.S. PhD-granting institutions from 2011–2023; hiring patterns at liberal arts colleges, teaching-focused institutions, and non-U.S. systems may differ substantially. Second, we rely on departmental affiliation as a proxy for credentials and training. Multidisciplinary departments, administrative housing that does not reflect intellectual identity, and recent renamings all introduce noise that our two definitions of interdisciplinarity only partially address. Third, postdoctoral training data, obtained via language-model search over public records, cover only 26% of our sample, so rates and timing estimates may reflect the coverage of this source rather than underlying differences. Fourth, while our publication embedding space captures topical proximity between fields, it cannot identify individual papers as interdisciplinary. Future work could incorporate citation-based measures of knowledge-base interdisciplinarity [42] or embedding-space methods for identifying interdisciplinary papers [45]. Finally, our results are observational and we cannot distinguish whether interdisciplinary hires are enriched for high-performing researchers able to cross disciplinary boundaries (selection) or whether the trajectory itself contributes to the productivity patterns we observe (treatment).

Our findings have broader significance for the science of science. The selective fungibility of credentials across disciplines reveals fundamental constraints on how knowledge and human capital flow through the academic system. Fields that place graduates successfully into other disciplines likely offer more generalizable training in research methods and communication; those that hire heavily from outside may benefit from investing in bridging programs and mentorship for faculty navigating extended training paths. As funding agencies and universities increasingly emphasize interdisciplinary research, our results provide empirical grounding for policies that support early-career scientists navigating these transitions.

6 Methods

6.1 Discipline-level labor market metrics

We quantify faculty hiring flows at the discipline level using several metrics. The number of faculty exported from discipline j is $\sum_{i \neq j} A_{ji}$, and the number of faculty import to a discipline is $\sum_{i \neq j} A_{ij}$ where A is the adjacency matrix defined in Section 2.1. We define the *export rate* of a discipline j as the fraction of its PhD trainees placed elsewhere:

$$\text{export rate}(j) = \frac{\sum_{i \neq j} A_{ji}}{\sum_i A_{ji}},$$

and similarly, the number of imports (imported faculty) as $\sum_{j \neq i} A_{ji}$ and the *import rate* of a discipline j as the ratio of faculty hired in j from a different discipline to the total number of faculty hired by j:

$$\text{import rate}(j) = \frac{\sum_{i \neq j} A_{ij}}{\sum_i A_{ij}}.$$

We measure the net production of a discipline with the *per capita net export*, defined as the difference between exports and imports divided by the total number of faculty hired in j:

$$\text{per capita net export}(j) = \frac{\text{exports}_j - \text{imports}_j}{\sum_i A_{ij}}$$

This metric indicates whether a discipline is a net producer (> 0) or consumer (< 0) of faculty, and by how much relative to its size.

6.2 Gravity model of field-to-field faculty hiring

We model field-to-field hiring flows using a gravity model adapted from the international trade literature. The model relates weighted hiring flow from degree field i to hiring field j as

$$\begin{aligned} X_{ij} = \exp(&origin_i + dest_j + domainOrigin_i \times border + domainDest_j \times border \\ &+ \beta_1(d_{ij} \times border) + \beta_2 border), \end{aligned}$$

where $border$ is a field border-crossing indicator and d_{ij} is the log cosine distance between publication embedding centroids for fields i and j (Section 6.7). As recommended by practitioners in international trade [46], we include various fixed effects to account for field- and domain-specific characteristics. The terms $origin_i$ and $dest_j$ are origin and destination field fixed effects and the terms $domainOrigin_i$ and $domainDest_j$ are domain fixed effects that are interacted with the border indicator to capture domain-level variation in interdisciplinary hiring. In Section 3.2 we discussed the inverse association between interdisciplinary hiring rates and field size. The field-level fixed effects absorb the effect of field size on hiring without explicitly modeling size.

The data consist of 116 fields with both hiring records and publication embedding centroids, yielding a $116 \times 116 = 13{,}456$ dyad flow matrix including self-flows and zero flows. Each individual hiring event is weighted by $1/(n_{\text{degree fields}} \times n_{\text{hiring fields}})$ to correct for the cross-product expansion of faculty affiliated with multiple fields, ensuring that each person contributes a total weight of one.

We estimate the model using Pseudo-Poisson Maximum Likelihood (PPML), which is consistent for multiplicative gravity models even with heteroskedasticity and zero flows [47]. We apply two-way clustering to the standard errors by origin and destination fields using the Cameron–Gelbach–Miller variance decomposition [48] to adjust for the dependence between dyads sharing the same origin or destination field.

6.3 Prestige

Because institutional prestige is known to be strongly associated with faculty productivity [7, 8, 34], we include hiring institution prestige as a control in our productivity regression (Sec. 6.4). We estimated prestige scores using the SpringRank algorithm [49], which produces continuous scores s_i for every department or institution i based on the structure of faculty placements, with higher scores indicating more prestige. Of the 12,832 departments in the faculty hiring network, 5,397 do not produce any faculty (out-degree 0) and 245 do not hire any faculty (in-degree 0), so the department-to-department network is only weakly connected. To address this, we added regularization $\alpha = 1$, which is equivalent to every entity i hiring once from and placing once into a fictitious entity with prestige score 0. We scaled the resulting scores linearly to the range $[0, 100]$ so that department and institution prestige scores are on the same scale.

6.4 Productivity regression

We quantified faculty productivity via the number of publications produced in the five years after being hired into their first tenure-track position. We filtered publications to those written within five years of hiring to better capture the productivity of faculty during their pre-tenure period, which is more consistent across faculty than later career stages [7]. Similar to the placement time analysis, we excluded all faculty whose first appointment is recorded in 2011, as this is the first year of our dataset. Researcher productivity is known to depend on career age (years since PhD) [7, 50], hiring department prestige [34], and gender [32].

We controlled for these factors using a matched regression approach. First, we performed a coarsened exact matching, matching each interdisciplinary hire to disciplinary hires with the same gender, at least one shared hiring discipline, career age within five years, and normalized hiring department prestige scores within 0.1. This procedure resulted in matches for almost all interdisciplinary and disciplinary faculty, and we performed all subsequent analyses on only faculty hires who were matched (Table A6 and Section A10).

After matching, we fit the following model of productivity on interdisciplinary hire status and other covariates:

$$\begin{aligned} nPapers = \beta_0 + \beta_1 interdisciplinaryHire + \beta_2 timeToHire \\ + \beta_3 hiringInstitutionPrestige + C(gender) + C(hiringDisciplines) + \epsilon, \end{aligned}$$

where $nPapers$ is the (winsorized) number of papers written in the 5 years post-hire, $interdisciplinaryHire$ is an interdisciplinary hire indicator, $timeToHire$ is the (winsorized) time-to-hire, hiringInstitutionPrestige is the scaled prestige score of the hiring institution, $C(gender)$ is a categorical variable for gender and $C(hiringDisciplines)$ is a multi-hot binary vector encoding the hiring disciplines, reflecting differences in publication rates across disciplines. The distribution of 5-year productivity is right-skewed, with a handful of observations exceeding 1000 publications. To reduce the influence of these outliers, we winsorized 1,440 (field-level; 1,676 at the domain level) productivity values outside the 0.025 and 0.975 quantiles. We fit the model using Negative Binomial regression with the method of moments estimator for the dispersion parameter α. We corrected the regression coefficient p-values for multiple comparisons using the Benjamini-Yekutieli procedure. We performed this regression separately at the field and domain levels, and checked robustness to the alternative partial definition of interdisciplinarity (Sections A5 and A6). Finally, we augmented the regression with an additional variable for the number of unique collaborator to test whether the productivity boost for interdisciplinary hires is driven by broader collaboration networks (Section A10).

6.5 Time-to-hire

We defined the *time-to-hire* of a faculty hire as the difference between the year in which they secured their first tenure-track position and the year in which they received their terminal degree. We determined the former as the first year in which they were recorded as faculty in our dataset. Because our dataset only includes tenure-track appointments from 2011 onwards, we excluded all appointments in 2011 because we cannot know whether these reflect the true hiring year or faculty with appointments predating our dataset. This filtering resulted in a sample of 62,404 faculty. Due to noise in the faculty appointments data (e.g. older faculty missing appointments in 2011), we still observed 2,936 (4.7%) faculty with placement times greater than the 0.95 quantile value of 24 years; we winsorized [51] these observations to reduce their influence on the analysis. Then, we compared the distributions of placement times for interdisciplinary and disciplinary hires hired into each field, domain, and academia overall using Mann-Whitney U tests and corrected for multiple comparisons using the Benjamini-Yekutieli procedure.

6.6 Post-doctoral positions

We obtained postdoctoral training information for $n = 27,299$ faculty in our sample by prompting a large language model (LLM) with search grounding. We prompted the LLM to find the department, start and end years, and field for each postdoctoral position held by the individuals in the sample, or report that they did not hold any postdoc positions. We computed the duration of each postdoc to the nearest whole year as the difference between the reported end and start years and the total postdoc duration for each faculty as the sum of the durations of all their postdoc positions (assuming no overlap between postdocs), which allowed us to compare both the rates of postdocs and the average postdoc duration between interdisciplinary and within-discipline hires.

To determine the role of postdoc positions in the disciplinary transitions of interdisciplinary hires, we compared the reported fields of postdoc positions to the degree and hiring disciplines of the faculty who held them. If an individual held multiple discipline affiliations during their postdoc period either via multiple postdocs or multidisciplinary postdocs, we took the union of all postdoc fields as the postdoc discipline set. Based on this comparison, we assigned interdisciplinary hires into one of four postdoc categories:

- **Interdisciplinary at postdoc**: postdoc fields overlap with hiring fields but not degree fields
- **Bridge**: postdoc fields overlap or share an area (Table A1) with at least one of the degree or hiring fields
- **Interdisciplinary after postdoc**: postdoc fields overlap with degree fields but not hiring fields
- **Detour**: no overlap between postdoc fields and either degree or hiring fields

and within-discipline hires into two postdoc categories:

- **Singletrack**: postdoc fields overlap or share an area with at least one of the hiring/degree fields
- **Within-discipline after postdoc**: postdoc fields do not overlap with hiring fields or degree fields.

6.7 Publication embeddings and research topic trajectories

To analyze the research topics of individual faculty and disciplines, we construct a high-dimensional epistemic space using publication embeddings generated by the SPECTER2 scientific document embedding model [30], yielding a 768-dimensional vector for each publication. The input to the embedding model was a set of publications collected from OpenAlex profiles matching faculty in the AARC dataset. We collected only publications (OpenAlex Work objects [25]) of type “article”, “book”, or “book-chapter” and filtered to those whose titles or abstract were at least five words long and contained detectably English text.The post-filtering publication dataset consisted of 22.5M publications representing 103,666 unique AARC faculty authors.

We aggregated publication embeddings at both the faculty and discipline levels by averaging over all embeddings belonging to the relevant unit of analysis. Collecting all embeddings associated with an individual was straightforward via the direct author-to-paper relationship, but to map embeddings to disciplines we applied a two-step aggregation process that accounts for multidisciplinarity and multiple authors. Authors are affiliated with disciplines via their (degree or faculty) departments, and these departments are possibly multi-disciplinary. Thus a single publication may be linked to multiple disciplines by having multiple authors or by authors affiliated with multi-disciplinary departments, or both. We applied a weighted discipline mapping scheme so that each author received equal share and each author’s share was evenly divided among their concurrent disciplinary affiliations (via their department). For example, a paper with three authors with the affiliations

- Computer Science
- Biology, Computer Science
- Mathematics

would receive the following weighted authorship discipline distribution:

- Computer Science: $\frac{1}{3} + \frac{1}{3} \cdot \frac{1}{2} = \frac{1}{2}$
- Biology: $\frac{1}{3} \cdot \frac{1}{2} = \frac{1}{6}$
- Mathematics: $\frac{1}{3}$.

After mapping publication embeddings to disciplines, we computed the embedding centroids for every field for use as input to the gravity model (Section 6.2). We also projected these centroids down to two dimensions using the t-distributed stochastic neighbors embedding method [52] to provide the node positions for Figure 1.

Although centroids are sufficient for capturing the field-level structure of the publication embedding space, we required a more localized approach to characterize individual research topic trajectories in embedding space. The embedding space is high-dimensional and likely features non-convex boundaries between fields. For example, the fields of Statistics and Biostatistics are topically related and are connected by faculty hiring, but their centroids are relatively far apart in embedding space (Fig. 1a). To account for this, we smoothed the publication authorship discipline distributions from the weighted discipline mapping by averaging over each paper’s $k = 50$ nearest neighbors by cosine distance in embedding space, with neighbors identified using the FAISS similarity search method [53]. The resulting smoothed *topic distributions* represent the weighted fraction of a paper’s neighbors in each of the 116 fields (or 10 domains), and capture local information about the structures of fields with no uniformity assumptions. We aggregated by individual and career stage by averaging over the distributions of pre- and post-hire publications separately, yielding pre-hire and post-hire topic distributions for individual faculty.

After aggregating individual's research topic distributions, we classified faculty into the named categories in Table 1 based on the cosine similarity of their pre- and post-hire topic distributions to the average topic distributions for faculty in their degree and hiring disciplines. We first assigned each of the two temporally distinct topic distributions to one of "degree", "hiring", or "other" disciplines using the following procedure:

1. Compute the centroid topic distribution for each hiring discipline by averaging over all faculty hired into that discipline.
2. Compute smoothed pre- and post-hire baseline topic distributions by averaging the cosine similarity between all pre- and post-hire topic distributions to each field centroid. This tells us how similar on average pre-hire and post-hire topic distributions are to each field's average topic distribution.
3. Adjust pre- and post-hire topic distributions by subtracting the corresponding baseline topic distribution to get an excess topic distribution that captures how much more similar the pre- and post-hire topic distributions are to each field than the average pre- and post-hire topic distributions are to that field.
4. If neither degree nor hiring disciplines have positive mass in the resulting excess topic distribution, assign "other."
5. Otherwise, assign whichever category (degree or hiring) contains the field with the maximum excess mass in the excess topic distribution.

The output of these steps was a pair of labels for each interdisciplinary hire indicating whether their pre- and post-hire topic distributions were aligned with their degree discipline, hiring discipline, or other disciplines. Using these labels, we assigned categories for interdisciplinary hires according to the schema

- **Label correcter**: hiring discipline research both pre- and post-hire
- **Label adopter**: degree discipline research both pre- and post-hire
- ***Topic adopter***: degree discipline research pre-hire and hiring discipline research post-hire
- ***Topic reverter***: hiring discipline research pre-hire and degree discipline research post-hire
- **Other**: other discipline research in either pre- or post-hire period

in which only the topic adopter and topic reverter categories (italicized) represent a meaningful change in research topic (we ignore the Other category because a negligible proportion of faculty fall into this category; Table 1). We also performed stratified analyses of prestige, time-to-hire, and productivity differences for each category using the same methods as the main analyses (Section A7).

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A1 Discipline taxonomy: domains, areas, and fields

Table A1: Discipline taxonomy consisting of 116 domains, 28 areas, and 116 fields in increasing order of granularity. Each field belongs to exactly one area and domain.

Domain	**Area**	**Field**
Applied Sciences	Agriculture	Agronomy
		Animal Sciences
		Food Science
		Horticulture
		Plant Sciences
		Soil Science
	Architecture, Design, Planning	Architecture
		Urban and Regional Planning
	Business	Accounting
		Business Administration
		Finance
		Management
		Management Information Systems
		Marketing
Education	Education	Counselor Education
		Curriculum and Instruction
		Education
		Education Administration
		Special Education
Engineering	Engineering	Aerospace Engineering
		Agricultural Engineering
		Civil Engineering
		Electrical Engineering
		Environmental Engineering
		Industrial Engineering
		Materials Engineering
		Mechanical Engineering
		Operations Research
		Systems Engineering
Humanities	Arts	Music
	History	History
	Humanities	Humanities
	Language, Literature, Culture	Art History and Criticism
		Asian Languages
		Asian Studies
		Classics and Classical Languages
		Comparative Literature
		English Language and Literature
		French Language and Literature
		Germanic Languages and Literatures
		Italian Language and Literature
		Near and Middle Eastern Languages and Cultures
		Slavic Languages and Literatures
		Spanish Language and Literature
		Theatre Literature, History and Criticism
	Linguistics	Linguistics
	Philosophy	Philosophy

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Continuation of Table A1

Domain	Area	Field
	Theology and Religion	Religious Studies
		Theological Studies
Journalism, Media, Communication	Journalism, Media, Communication	Communication
		Mass Communications and Media Studies
Mathematics and Computing	Computational Sciences	Computer Engineering
		Computer Science
		Information Science
		Information Technology
	Mathematical Sciences	Mathematics
		Statistics
Medicine and Health	Health	Communication Disorders and Sciences
		Environmental Health Sciences
		Exercise Science, Kinesiology, Rehab, Health
		Health, Physical Education, Recreation
		Human Development and Family Sciences
		Nursing
		Nutrition Sciences
		Public Health
		Social Work
		Speech and Hearing Sciences
	Medical Sciences	Epidemiology
		Genetics
		Immunology
		Pharmaceutical Sciences
		Pharmacology
		Pharmacy
		Physiology
		Veterinary Medical Sciences
Natural Sciences	Biological Sciences	Anatomy
		Biochemistry
		Biological Sciences
		Biomedical Engineering
		Biomedical Sciences
		Biophysics
		Biostatistics
		Cell Biology
		Computational Biology
		Ecology
		Entomology
		Evolutionary Biology
		Microbiology
		Molecular Biology
		Neuroscience
		Pathology
		Plant Pathology
	Chemical Sciences	Chemical Engineering
		Chemistry
	Earth Sciences	Environmental Sciences
		Forestry and Forest Resources
		Geology
		Marine Sciences
		Natural Resources
		Oceanography

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Continuation of Table A1

Domain	Area	Field
	Physical Sciences	Astronomy
		Atmospheric Sciences and Meteorology
		Physics
Public Administration and Policy	Public Administration and Policy	Public Administration
		Public Policy
Social Sciences	Anthropology	Anthropology
	Economics	Agricultural Economics
		Economics
	Gender Studies	Gender Studies
	Geography	Geography
	Political Science	International Affairs
		Political Science
	Psychological Sciences	Educational Psychology
		Psychology
	Sociology	Criminal Justice and Criminology
		Sociology

A2 Full annotated field-to-field hiring network

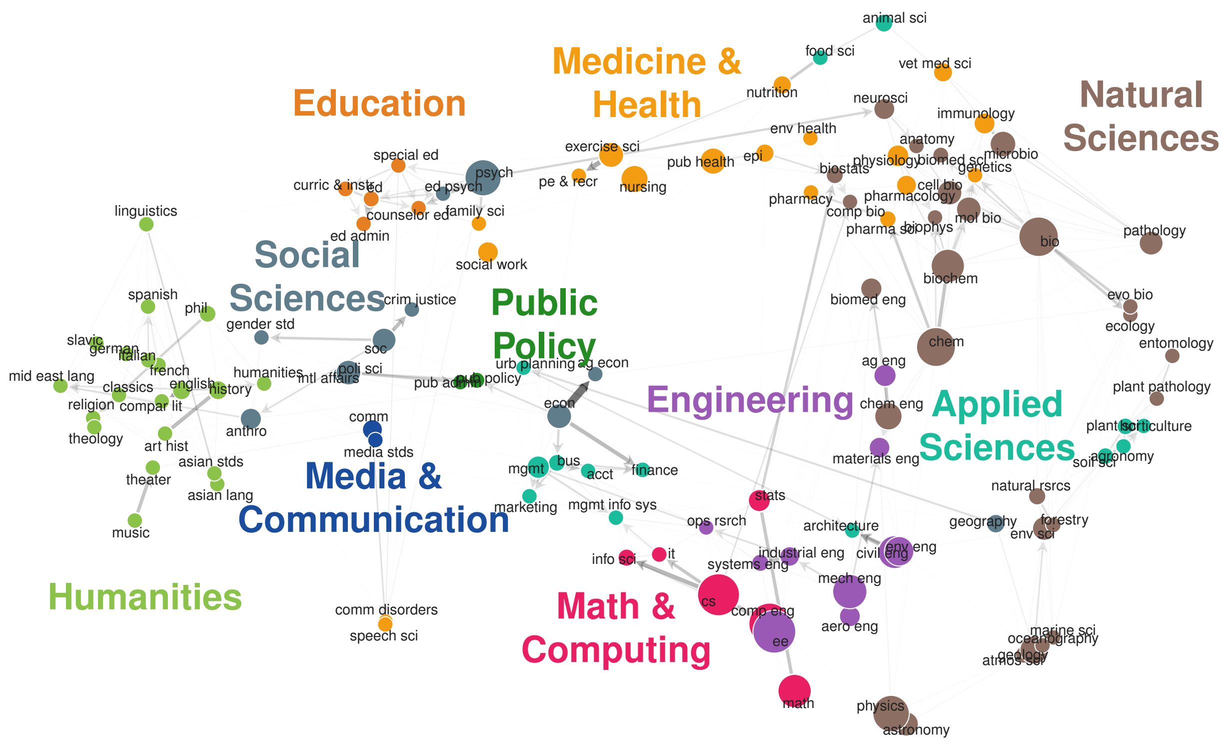

Figure A1: The field-to-field faculty hiring network with all fields annotated. Same encodings as Fig. 1.

A3 Discipline-level faculty hiring statistics

We aggregated the faculty hiring network to the level of fields and domains to compute discipline-level statistics. For each field and domain, we computed the total numbers of faculty placed and hired, the proportion of interdisciplinary hires (import rate) and placements (export rate), the net export per faculty hire, and the proportion of department self-hires (Table A2). The domain-level statistics may differ than the aggregation of the field-level statistics because some departments are affiliated with multiple fields within a domain.

Table A2: Field-level and domain-level faculty hiring statistics. For each of the 10 disciplinary domains, we show inter-field hiring statistics for the constituent fields followed by inter-domain hiring statistics in bold. Statistics include the number of faculty produced (out-degree) and hired (in-degree), import and export rates, net exports per faculty, and the percentage of department self-hires.

APPLIED SCIENCES

Field	Faculty placed	Faculty hired	Import	Export	Net export/fac.	% self-hire
Accounting	453	703	0.48	0.20	-0.36	1.4%
Agronomy	512	541	0.55	0.53	-0.05	19.4%
Animal Sciences	1011	1007	0.25	0.26	0.00	17.0%
Architecture	420	387	0.70	0.72	0.09	4.1%
Business Administration	961	940	0.82	0.82	0.02	2.8%
Finance	480	844	0.69	0.46	-0.43	1.4%
Food Science	578	680	0.53	0.45	-0.15	14.0%
Horticulture	406	464	0.52	0.45	-0.12	13.6%
Management	1544	1714	0.71	0.68	-0.10	1.8%
Management Information Systems	501	621	0.82	0.78	-0.19	1.4%
Marketing	524	855	0.60	0.34	-0.39	1.2%
Plant Sciences	452	695	0.81	0.70	-0.35	8.5%
Soil Science	461	609	0.63	0.52	-0.24	14.3%
Urban and Regional Planning	375	336	0.58	0.62	0.12	5.1%
Applied Sciences	**8279**	**9706**	**0.35**	**0.23**	**-0.15**	**6.5%**

EDUCATION

Field	Faculty placed	Faculty hired	Import	Export	Net export/fac.	% self-hire
Counselor Education	786	505	0.68	0.79	0.56	7.9%
Curriculum and Instruction	816	838	0.62	0.61	-0.03	8.5%
Education	1155	851	0.71	0.78	0.36	7.4%
Education Administration	518	733	0.73	0.62	-0.29	6.7%
Special Education	805	496	0.55	0.73	0.62	13.3%
Education	**4134**	**3726**	**0.30**	**0.37**	**0.11**	**7.8%**

ENGINEERING

Field	Faculty placed	Faculty hired	Import	Export	Net export/fac.	% self-hire
Aerospace Engineering	1291	1279	0.53	0.53	0.01	12.3%
Agricultural Engineering	1405	1365	0.65	0.66	0.03	8.6%
Civil Engineering	2475	2280	0.21	0.27	0.09	8.9%
Electrical Engineering	4305	4038	0.27	0.32	0.07	11.1%
Environmental Engineering	2236	1844	0.36	0.47	0.21	8.9%
Industrial Engineering	1044	927	0.43	0.49	0.13	7.0%
Materials Engineering	1358	1299	0.60	0.61	0.05	7.6%
Mechanical Engineering	3200	3471	0.34	0.28	-0.08	7.6%
Operations Research	447	501	0.85	0.83	-0.11	3.4%
Systems Engineering	784	699	0.66	0.70	0.12	9.6%
Engineering	**15369**	**15429**	**0.23**	**0.23**	**-0.00**	**9.1%**

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Continuation of Table A2

HUMANITIES

Field	Faculty placed	Faculty hired	Import	Export	Net export/fac.	% self-hire
Art History and Criticism	452	303	0.70	0.80	0.49	1.3%
Asian Languages	152	151	0.58	0.58	0.01	4.0%
Asian Studies	186	186	0.51	0.51	0.00	5.4%
Classics and Classical Languages	123	223	0.57	0.22	-0.45	2.2%
Comparative Literature	221	96	0.75	0.89	1.30	3.1%
English Language and Literature	1106	1232	0.27	0.19	-0.10	3.0%
French Language and Literature	110	112	0.57	0.56	-0.02	1.8%
Germanic Languages and Literatures	95	103	0.55	0.52	-0.08	1.9%
History	1567	1356	0.38	0.46	0.16	1.2%
Humanities	103	265	1.00	0.99	-0.61	0.0%
Italian Language and Literature	108	87	0.60	0.68	0.24	3.4%
Linguistics	531	382	0.32	0.51	0.39	5.0%
Music	562	569	0.16	0.15	-0.01	4.0%
Near and Middle Eastern Languages and Cultures	127	82	0.68	0.80	0.55	2.4%
Philosophy	957	986	0.23	0.21	-0.03	1.8%
Religious Studies	221	336	0.63	0.44	-0.34	0.9%
Slavic Languages and Literatures	57	83	0.70	0.56	-0.31	2.4%
Spanish Language and Literature	237	164	0.53	0.68	0.45	1.8%
Theatre Literature, History and Criticism	69	113	0.73	0.55	-0.39	5.3%
Theological Studies	128	181	0.55	0.36	-0.29	14.4%
Humanities	**7268**	**7190**	**0.13**	**0.14**	**0.01**	**2.8%**

JOURNALISM, MEDIA, COMMUNICATION

Field	Faculty placed	Faculty hired	Import	Export	Net export/fac.	% self-hire
Communication	1415	1338	0.34	0.37	0.06	2.5%
Mass Communications and Media Studies	620	777	0.61	0.51	-0.20	4.2%
Journalism, Media, Communication	**1839**	**1949**	**0.23**	**0.19**	**-0.06**	**2.9%**

MATHEMATICS AND COMPUTING

Field	Faculty placed	Faculty hired	Import	Export	Net export/fac.	% self-hire
Computer Engineering	3827	3840	0.46	0.45	-0.00	10.2%
Computer Science	4813	4642	0.28	0.31	0.04	6.0%
Information Science	584	849	0.70	0.57	-0.31	4.6%
Information Technology	404	696	0.87	0.77	-0.42	2.9%
Mathematics	3490	3887	0.24	0.16	-0.10	2.8%
Statistics	1670	1635	0.52	0.53	0.02	3.8%
Mathematics and Computing	**13059**	**13032**	**0.16**	**0.17**	**0.00**	**5.9%**

MEDICINE AND HEALTH

Field	Faculty placed	Faculty hired	Import	Export	Net export/fac.	% self-hire
Communication Disorders and Sciences	382	527	0.67	0.55	-0.28	9.1%
Environmental Health Sciences	300	459	0.77	0.64	-0.35	12.2%
Epidemiology	958	1055	0.54	0.49	-0.09	21.9%
Exercise Science, Kinesiology, Rehab, Health	1759	2001	0.49	0.42	-0.12	14.6%
Genetics	692	559	0.87	0.90	0.24	3.9%
Health, Physical Education, Recreation	404	484	0.76	0.71	-0.17	8.5%
Human Development and Family Sciences	716	737	0.71	0.70	-0.03	6.8%
Immunology	1008	1145	0.74	0.70	-0.12	8.1%
Nursing	2373	2657	0.14	0.04	-0.11	34.9%
Nutrition Sciences	834	924	0.57	0.52	-0.10	14.8%
Pharmaceutical Sciences	568	808	0.79	0.70	-0.30	7.8%
Pharmacology	910	1119	0.75	0.69	-0.19	8.8%
Pharmacy	491	508	0.52	0.51	-0.03	19.5%
Physiology	1060	1295	0.77	0.72	-0.18	8.8%
Public Health	1286	2163	0.74	0.56	-0.41	10.4%

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Continuation of Table A2

Social Work	1390	1583	0.21	0.10	-0.12	8.8%
Speech and Hearing Sciences	293	384	0.65	0.54	-0.24	9.6%
Veterinary Medical Sciences	996	1077	0.50	0.46	-0.08	18.1%
Medicine and Health	**16347**	**19652**	**0.38**	**0.25**	**-0.17**	**14.3%**

NATURAL SCIENCES

Field	Faculty placed	Faculty hired	Import	Export	Net export/fac.	% self-hire
Anatomy	454	654	0.84	0.77	-0.31	9.6%
Astronomy	1591	1765	0.60	0.55	-0.10	5.2%
Atmospheric Sciences and Meteorology	915	739	0.57	0.65	0.24	9.2%
Biochemistry	3352	3102	0.70	0.72	0.08	4.7%
Biological Sciences	3710	4336	0.69	0.64	-0.14	3.6%
Biomedical Engineering	969	1309	0.66	0.54	-0.26	9.9%
Biomedical Sciences	212	721	0.95	0.84	-0.71	3.2%
Biophysics	730	576	0.85	0.88	0.27	9.5%
Biostatistics	633	955	0.64	0.45	-0.34	11.0%
Cell Biology	1769	1631	0.82	0.83	0.08	4.9%
Chemical Engineering	2121	1954	0.27	0.33	0.09	5.2%
Chemistry	5832	4640	0.19	0.36	0.26	4.7%
Computational Biology	156	395	0.88	0.69	-0.61	8.1%
Ecology	983	641	0.73	0.83	0.53	3.6%
Entomology	682	588	0.31	0.41	0.16	13.4%
Environmental Sciences	1062	1438	0.85	0.80	-0.26	4.6%
Evolutionary Biology	903	495	0.72	0.85	0.82	3.8%
Forestry and Forest Resources	417	566	0.66	0.53	-0.26	12.5%
Geology	1796	2062	0.40	0.31	-0.13	4.2%
Marine Sciences	473	568	0.73	0.67	-0.17	7.0%
Microbiology	1806	1734	0.66	0.67	0.04	7.7%
Molecular Biology	1988	1626	0.82	0.86	0.22	3.9%
Natural Resources	576	813	0.79	0.71	-0.29	9.5%
Neuroscience	1243	1334	0.77	0.75	-0.07	6.1%
Oceanography	380	474	0.73	0.66	-0.20	8.9%
Pathology	1375	1609	0.72	0.67	-0.15	11.9%
Physics	4680	4194	0.21	0.29	0.12	7.0%
Plant Pathology	489	525	0.56	0.53	-0.07	9.5%
Natural Sciences	**33802**	**32909**	**0.18**	**0.20**	**0.03**	**6.6%**

PUBLIC ADMINISTRATION AND POLICY

Field	Faculty placed	Faculty hired	Import	Export	Net export/fac.	% self-hire
Public Administration	330	497	0.72	0.57	-0.34	3.6%
Public Policy	639	762	0.81	0.78	-0.16	4.3%
Public Administration and Policy	**741**	**984**	**0.74**	**0.65**	**-0.25**	**3.9%**

SOCIAL SCIENCES

Field	Faculty placed	Faculty hired	Import	Export	Net export/fac.	% self-hire
Agricultural Economics	301	507	0.78	0.63	-0.41	4.3%
Anthropology	1670	1608	0.25	0.28	0.04	3.7%
Criminal Justice and Criminology	559	735	0.44	0.27	-0.24	2.6%
Economics	2963	2139	0.22	0.43	0.39	2.3%
Educational Psychology	1267	609	0.80	0.90	1.08	5.6%
Gender Studies	65	147	0.84	0.65	-0.56	0.0%
Geography	915	1054	0.41	0.32	-0.13	5.9%
International Affairs	121	489	0.96	0.84	-0.75	1.6%
Political Science	2146	2022	0.18	0.23	0.06	1.5%
Psychology	5054	4572	0.33	0.40	0.11	4.9%
Sociology	2197	1995	0.22	0.30	0.10	1.9%
Social Sciences	**17770**	**15489**	**0.15**	**0.26**	**0.15**	**3.7%**

A4 Time to hire and postdoc rates by discipline

Table A3: Individual-level statistics by field and domain. Prestige change is the mean change in department SpringRank score between degree and hiring departments. Time to hire is the mean winsorized years between PhD and first tenure-track position. Postdoc rate is the percentage of hires who held a postdoc. Subcolumns are Inter = interdisciplinary hires, Within = within-discipline hires, All = all hires combined. Domain (avg) rows show the average of interfield statistics across fields in the domain. (Interdomain) rows show statistics for interdomain hires.

APPLIED SCIENCES

Field	**Time to hire (yrs)**			**Postdoc rate (%)**		
	Inter	Within	All	Inter	Within	All
Accounting	2.88	2.52	2.67	0.0	1.9	1.6
Agronomy	6.26	6.40	6.34	62.9	45.3	52.7
Animal Sciences	6.95	5.83	6.07	63.3	47.0	51.6
Architecture	3.63	2.78	3.10	42.9	28.3	33.8
Business Administration	2.77	2.62	2.74	11.5	11.1	11.4
Finance	3.27	3.91	3.59	9.5	7.2	7.8
Food Science	7.68	5.88	6.52	66.1	59.3	61.5
Horticulture	6.60	6.62	6.61	64.6	32.6	44.0
Management	3.74	3.22	3.55	12.7	7.1	10.4
Management Information Systems	4.58	3.38	4.19	5.7	0.0	3.7
Marketing	3.82	4.63	4.21	3.7	2.9	3.1
Plant Sciences	6.95	6.97	6.95	67.1	50.0	59.7
Soil Science	6.54	6.79	6.69	56.2	49.5	51.8
Urban and Regional Planning	6.32	2.92	4.28	38.7	33.3	35.8
Applied Sciences (avg)	**4.30**	**4.26**	**4.28**	**36.1**	**26.8**	**30.6**
(interdomain)	**4.93**	**4.05**	**4.28**	**43.8**	**30.3**	**32.8**

EDUCATION

Field	**Time to hire (yrs)**			**Postdoc rate (%)**		
	Inter	Within	All	Inter	Within	All
Counselor Education	3.39	3.38	3.39	55.5	18.8	44.9
Curriculum and Instruction	3.52	2.73	3.14	12.9	13.2	13.0
Education	4.17	4.00	4.11	36.9	28.6	34.4
Education Administration	3.74	3.23	3.55	11.1	20.8	16.3
Special Education	4.03	4.10	4.07	41.2	21.2	33.9
Education (avg)	**3.84**	**3.44**	**3.67**	**31.5**	**20.5**	**28.5**
(interdomain)	**4.77**	**3.56**	**3.85**	**35.0**	**25.6**	**28.4**

ENGINEERING

Field	**Time to hire (yrs)**			**Postdoc rate (%)**		
	Inter	Within	All	Inter	Within	All
Aerospace Engineering	6.29	5.12	5.38	64.4	58.9	60.1
Agricultural Engineering	7.87	4.97	6.07	82.0	65.3	72.7
Civil Engineering	6.01	4.47	4.70	57.5	50.7	52.2
Electrical Engineering	7.21	5.31	5.64	61.1	34.8	40.1
Environmental Engineering	6.48	4.21	4.64	60.5	51.4	53.8
Industrial Engineering	4.54	3.96	4.11	34.9	28.0	30.5

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Continuation of Table A3

Field	Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All
Materials Engineering	7.50	6.93	7.12	77.0	67.9	71.7
Mechanical Engineering	6.22	5.80	5.90	64.0	53.8	55.9
Operations Research	3.28	2.68	3.09	40.0	18.4	31.6
Systems Engineering	5.43	3.26	3.98	38.1	28.2	31.8
Engineering (avg)	**6.35**	**5.17**	**5.47**	**57.9**	**45.7**	**50.0**
(interdomain)	**7.26**	**5.40**	**5.64**	**65.7**	**50.6**	**52.5**

HUMANITIES

Field	Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All
Art History and Criticism	3.47	3.67	3.57	34.8	38.9	35.6
Asian Languages	4.51	2.35	3.24	50.0	35.3	40.0
Asian Studies	3.39	2.21	2.69	50.0	42.1	44.4
Classics and Classical Languages	3.03	2.31	2.67	0.0	30.8	28.6
Comparative Literature	2.78	2.71	2.74	37.5	12.5	32.5
English Language and Literature	4.04	3.32	3.47	14.7	25.6	23.8
French Language and Literature	2.95	2.39	2.55	0.0	27.3	21.4
Germanic Languages and Literatures	3.36	3.00	3.11	0.0	75.0	60.0
History	3.91	3.48	3.61	60.8	46.2	52.4
Humanities	5.08	2.16	4.45	50.0	0.0	47.4
Italian Language and Literature	2.08	2.67	2.57	0.0	54.5	40.0
Linguistics	3.85	3.87	3.86	50.0	48.5	49.2
Music	5.11	3.22	3.40	20.0	10.9	11.7
Near and Middle Eastern Languages and Cultures	4.30	3.09	3.65	40.0	66.7	43.5
Philosophy	5.67	4.01	4.20	35.3	33.3	33.7
Religious Studies	4.46	3.41	3.81	11.8	35.7	26.7
Slavic Languages and Literatures	3.96	2.67	3.13	0.0	37.5	33.3
Spanish Language and Literature	2.96	2.61	2.71	20.0	25.0	23.5
Theatre Literature, History and Criticism	4.26	3.20	3.53	20.0	0.0	6.2
Theological Studies	4.50	3.25	3.83	33.3	11.1	20.0
Humanities (avg)	**4.11**	**3.41**	**3.61**	**26.4**	**32.8**	**33.7**
(interdomain)	**4.83**	**3.53**	**3.67**	**52.3**	**32.5**	**35.9**

JOURNALISM, MEDIA, COMMUNICATION

Field	Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All
Communication	4.19	3.73	3.85	18.6	12.8	14.6
Mass Communications and Media Studies	3.44	3.11	3.26	16.7	13.1	14.2
Journalism, Media, Communication (avg)	**3.86**	**3.57**	**3.67**	**17.6**	**13.0**	**14.4**
(interdomain)	**4.29**	**3.52**	**3.66**	**19.5**	**13.6**	**14.8**

MATHEMATICS AND COMPUTING

Field	Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All
Computer Engineering	7.18	4.98	5.34	54.0	33.8	37.6
Computer Science	5.95	4.89	5.06	53.8	39.5	42.2
Information Science	6.21	4.18	5.07	26.4	36.5	32.3

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Continuation of Table A3

Field	Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All
Information Technology	5.77	4.21	5.12	14.9	24.3	19.0
Mathematics	6.57	5.87	5.97	68.5	75.9	75.0
Statistics	5.59	4.79	4.95	54.9	52.2	53.3
Mathematics and Computing (avg)	**6.18**	**5.08**	**5.30**	**45.4**	**43.7**	**43.2**
(interdomain)	**6.96**	**5.15**	**5.34**	**55.0**	**51.0**	**51.5**

MEDICINE AND HEALTH

Field	Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All
Communication Disorders and Sciences	4.71	3.94	4.38	34.3	30.2	32.1
Environmental Health Sciences	9.41	5.16	8.11	75.4	58.3	69.1
Epidemiology	8.44	6.28	7.30	69.4	64.7	66.7
Exercise Science, Kinesiology, Rehab, Health	6.50	4.70	5.46	49.7	48.8	49.1
Genetics	10.43	10.10	10.35	92.1	91.1	91.8
Health, Physical Education, Recreation	4.16	3.24	3.77	29.7	32.4	31.1
Human Development and Family Sciences	4.65	3.95	4.40	54.2	41.0	48.3
Immunology	12.63	11.07	11.96	93.9	93.8	93.8
Nursing	7.71	4.51	4.93	50.0	35.9	36.4
Nutrition Sciences	7.59	5.17	6.18	64.4	62.7	63.5
Pharmaceutical Sciences	11.36	8.04	10.36	81.6	65.6	75.3
Pharmacology	12.12	11.18	11.85	84.4	88.3	86.0
Pharmacy	10.06	8.39	9.20	71.2	41.4	55.0
Physiology	11.29	10.80	11.13	88.2	87.4	87.9
Public Health	8.07	5.15	7.10	66.9	55.1	60.6
Social Work	4.70	3.24	3.45	48.3	27.0	29.5
Speech and Hearing Sciences	5.28	3.49	4.49	45.2	48.6	47.1
Veterinary Medical Sciences	9.04	6.42	7.58	76.1	40.0	56.1
Medicine and Health (avg)	**8.51**	**5.27**	**6.81**	**65.3**	**56.2**	**60.0**
(interdomain)	**8.55**	**6.32**	**6.94**	**70.7**	**59.6**	**61.6**

NATURAL SCIENCES

Field	Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All
Anatomy	11.54	9.89	11.03	84.2	83.3	83.8
Astronomy	10.24	9.07	9.20	82.2	88.0	86.8
Atmospheric Sciences and Meteorology	10.59	6.21	7.59	78.7	79.7	79.4
Biochemistry	10.58	10.84	10.74	92.1	92.1	92.1
Biological Sciences	10.66	9.32	10.17	90.0	89.2	89.7
Biomedical Engineering	9.46	6.29	8.00	78.2	74.7	76.2
Biomedical Sciences	12.58	7.80	11.91	83.9	76.9	82.6
Biophysics	10.94	9.38	10.41	94.0	95.9	94.6
Biostatistics	8.28	5.02	6.74	66.2	44.9	54.6
Cell Biology	11.65	10.10	11.17	91.7	93.8	92.3
Chemical Engineering	8.01	6.18	6.55	73.6	64.7	66.6
Chemistry	9.28	9.22	9.23	86.8	89.0	88.3
Computational Biology	9.96	4.72	8.33	73.3	37.5	60.9
Ecology	6.59	6.31	6.46	88.7	91.3	89.5
Entomology	8.00	8.62	8.48	75.3	63.4	67.8
Environmental Sciences	7.94	6.60	7.38	78.0	61.7	70.1

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Continuation of Table A3

Field	Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All
Evolutionary Biology	7.13	6.39	6.77	92.5	83.8	90.1
Forestry and Forest Resources	5.75	5.71	5.74	76.2	40.5	52.9
Geology	8.37	5.81	6.56	75.7	75.7	75.7
Marine Sciences	9.39	7.95	8.72	91.3	88.8	89.9
Microbiology	11.44	10.58	11.06	89.8	90.3	90.1
Molecular Biology	10.90	10.48	10.74	94.5	96.2	95.0
Natural Resources	6.86	5.72	6.50	71.2	55.4	63.6
Neuroscience	12.43	9.22	11.19	88.0	86.8	87.5
Oceanography	11.04	7.00	8.91	86.8	80.7	83.6
Pathology	12.00	10.99	11.67	80.5	58.3	72.4
Physics	9.66	9.85	9.83	77.0	90.5	86.8
Plant Pathology	7.04	7.54	7.36	83.3	70.0	75.3
Natural Sciences (avg)	**10.19**	**8.43**	**9.20**	**83.0**	**76.5**	**79.9**
(interdomain)	**9.48**	**9.12**	**9.16**	**76.8**	**84.5**	**83.3**

PUBLIC ADMINISTRATION AND POLICY

Field	Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All
Public Administration	4.58	3.20	3.97	30.0	11.5	19.6
Public Policy	4.60	3.09	4.09	37.3	27.8	32.4
Public Administration and Policy (avg)	**4.50**	**3.25**	**4.04**	**33.6**	**19.7**	**26.0**
(interdomain)	**4.68**	**3.46**	**4.04**	**32.7**	**31.6**	**32.1**

SOCIAL SCIENCES

Field	Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All
Agricultural Economics	3.25	3.62	3.36	15.2	17.2	16.0
Anthropology	4.87	5.07	5.06	54.1	49.4	50.5
Criminal Justice and Criminology	4.44	3.56	3.78	11.1	13.0	12.6
Economics	3.64	3.15	3.23	32.4	21.8	25.9
Educational Psychology	3.47	3.81	3.58	60.5	37.3	56.8
Gender Studies	5.49	2.87	4.97	33.3	62.5	50.0
Geography	5.84	4.64	4.94	40.7	33.7	35.6
International Affairs	4.74	4.16	4.57	28.6	12.5	17.4
Political Science	3.38	3.03	3.08	33.0	40.4	38.6
Psychology	6.47	5.67	5.90	66.7	65.1	65.7
Sociology	5.10	3.71	3.87	45.7	36.3	38.7
Social Sciences (avg)	**4.83**	**4.16**	**4.33**	**38.3**	**35.4**	**37.1**
(interdomain)	**5.04**	**4.31**	**4.39**	**55.6**	**46.5**	**48.7**

ACADEMIA

Field	Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All
Academia	**7.12**	**5.36**	**6.02**	**52.4**	**47.2**	**50.2**

A5 Interdomain hires

While we focus on faculty hires who cross field boundaries in the main text, our discipline taxonomy also includes 10 broad domains at its coarsest level. Despite the breadth of these domains, 17% of faculty are hired into a different domain than the one in which they were trained. Because every field belongs to exactly one domain, interdomain hires are a strict subset of interfield hires. Like interfield hiring, interdomain hiring is not distributed evenly, but instead concentrated between related fields that happen to be separated by disciplines. The Social Sciences domain exports almost twice as many faculty as it imports (driven largely by the exports of Economics and Psychology), while the opposite is true for the domains of Medicine and Health and Applied Sciences. The top interdomain flows between fields by volume are Electrical Engineering to Computer Engineering, Computer Engineering to Electrical Engineering, and Computer Science to Electrical Engineering. In fact, 22% of interdomain hires hold their degrees in just five fields (Electrical Engineering, Computer Engineering, Psychology, Computer Science, Chemistry).

The individual-level increases in productivity and time-to-hire described for interfield hires in the main text hold for interdomain hires. First, interdomain hires exhibit an even larger productivity boost than interfield hires, authoring 7.7% more publications in the 5 years post-hire compared their within-domain peers ($p < 10^{-6}$, Benjamini-Yekutieli corrected). Second, interdomain hires experience a slightly smaller increase in time-to-hire, taking 1.4 years longer to be hired ($p < 10^{-6}$, Benjamini-Yekutieli corrected). The time-to-hire delay holds in 10 domains and is largest in the Medicine and Health domain (+2.2 years; Table A3).

A6 Robustness to partial definition of interdisciplinarity

In Sec. 2.1, we defined fully interdisciplinary hires as faculty who do not retain any affiliation with their degree disciplines after being hired into a new discipline and partially interdisciplinary hires as faculty who retain at least one affiliation with their degree disciplines after being hired into a new discipline. While the results presented in the main text are for fully interdisciplinary hires, we repeated all analyses using partially interdisciplinary hires to test the robustness of our findings. The results are qualitatively similar to those presented in the main text.

Like fully interdisciplinary hires, partially interdisciplinary hires write more papers post-hire. This productivity boost is actually magified slightly to an increase of 6.7% compared to their within-field peers ($p < 10^{-6}$, Benjamini-Yekutieli corrected). Partially interdisciplinary hires also take longer to be hired, with a time-to-hire increase of 1.6 years that is significant in academia overall and in 68 fields ($p < 0.034$, Benjamini-Yekutieli corrected).

A7 Research topic trajectories: differences in individual outcomes and proportions by discipline and definition

The overall proportions of the five research topic trajectories are generally consistent in each domain and field. Label correcters and label adopters make up the two most common types in all domains and all but a handful of fields, although there is substantial variation in the relative proportions of these two (Fig. A2). The “other” category makes up a tiny proportion of interdisciplinary hires in all domains, with only several Humanities fields having more than 10% in this category.

The consistency above reflects the research topic trajectories of fully interdisciplinary hires only. We also computed proportions in each of the 5 types of trajectories for partially interdisciplinary hires and inter-

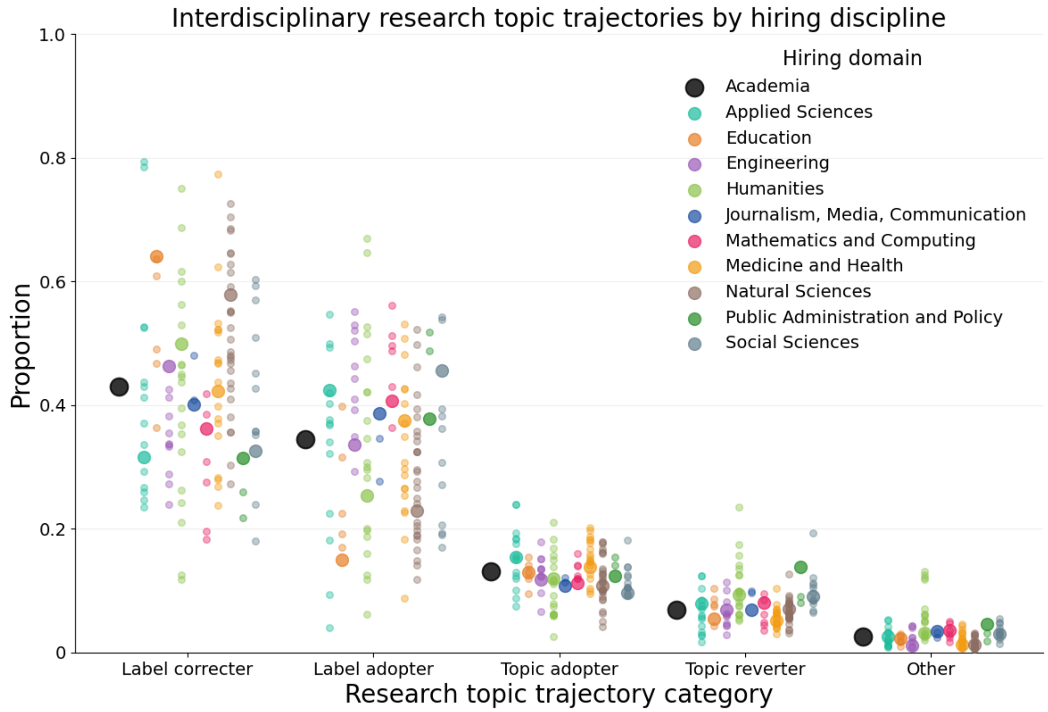

Figure A2: Proportions of interdisciplinary hires in each career class for each domain (large circles), field (small circles), and academia overall (black).

Research topic trajectory	**Partially interdisciplinary hires**		**Fully interdisciplinary hires**	
	Interdomain	Interfield	Interdomain	Interfield
Label correcter	27.0%	28.2%	43.8%	42.9%
Label adopter	58.1%	54.9%	34.7%	34.5%
Topic adopter	8.2%	9.4%	12.3%	13.1%
Topic reverter	4.9%	5.1%	7.1%	6.9%
Other	1.9%	2.4%	2.1%	2.5%

Table A4: Proportions of interdisciplinary hires in each of the five research topic trajectory types for partially and fully interfield and interdomain hires.

domain hires (Table A4). Although proportions are consistent within both levels of fully and partially interdisciplinary hires, partially interdisciplinary hires are enriched for label adopters and depleted for label correcters compared to fully interdisciplinary hires.

Differences in the individual career outcomes of productivity and time-to-hire (Section 4) for interdisciplinary hires in general also hold for each of the five categories, with some exceptions in the productivity effect (Table A5). Label adopters are even more productive then the general population of interdisciplinary hires, while those who change research topics (topic adopters and topic reverters) are actually less productive than within-discipline hires, a reversal of the general productivity effect. All categories experience increased time-to-hire, but the magnitude of this difference varies between categories. Both label correcters and topic reverters were publishing research consistent with their hiring discipline even before being hired, but while the time-to-hire increase is slightly attenuated for topic reverters, this effect is slightly mangified for label correcters. Faculty in the "other" trajectory type face the largest disadvantages along both dimensions.

Table A5: **Research topic trajectories of interdisciplinary hires modulate individual career outcomes.** Differences in individual career outcomes for each of the five research topic trajectory categories compared to within-field faculty hires. The Productivity column indicates the percentage increase in the number of authored publications in the five years post-hire. The Time-to-hire column indicates the difference in mean time-to-hire for interdisciplinary hires in that category compared to within-discipline hires, and the Δ Dept. prestige change column indicates the difference in mean change in department prestige from PhD to first faculty placement for each category.

Research topic trajectory	**Productivity change**	**Time-to-hire increase (years)**
Label correcter	7.8%	1.9
Label adopter	11.8%	1.2
Topic adopter	−11.1%	1.7
Topic reverter	−13.0%	1.4
Other	−25.4%	2.1

A8 Postdoc data collection

We collected data on postdoc positions for the faculty in our dataset by querying a large language model (LLM) with search grounding. For each faculty member, we provided the person's name and additional career information pulled from the AARC faculty census, then instructed the LLM to search the web and find postdoc positions for that person. For each position found, we requested the institution name, department name, lab or group, advisor name(s), start year, end year, and zero or more applicable AARC field labels for our disciplinary analysis. As a quality filter, we also requested the LLM find that person's degree-granting institution and department and the year of their terminal degree, which we validated against the AARC data to ensure that the LLM found the correct person. As another quality check, we instructed the LLM to provide an explanation of its evidence, including links to webpages where it found relevant information. Inspection of the evidence shows that it used predominantly CVs and faculty or lab webpages to produce annotations.

A9 Gravity model of field-to-field hiring

The topic space we construct from publication embeddings appears to be a reasonable proxy of topical similarities between fields. Rates of interdisciplinary hiring predicted by the gravity model reproduce the empirical correlations between import rate, export rate, and size to a first approximation, even with the inclusion of importer and exporter fixed effects to account for discipline-specific patterns, the gravity model predictions exhibit some notable errors (Fig. A3). Several of the field with the largest errors represent possible anomalies in embedding space: the gravity model underestimates the interdisciplinary hiring rates for Pathology because Pathology's embeddings are distant from the embeddings of all of the fields with which Pathology exchanges faculty (Fig. 1a).

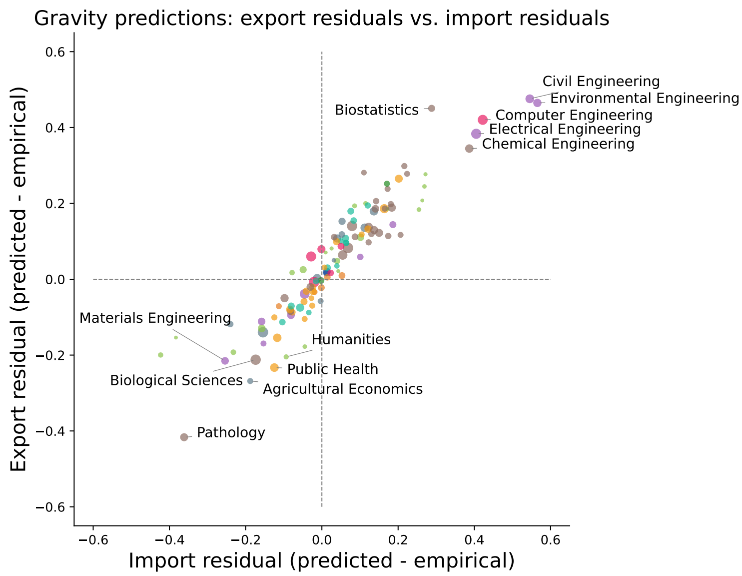

Figure A3: Residuals of the gravity model predictions for field-level export rates vs. residuals for import rates. Circles are fields colored by domain. Labeled fields are those with the six largest and six most negative export residuals.

The gravity model overestimates rates for Civil and Environmental Engineering, the topically closest pair of fields, because the simple linear inclusion of the distance term underfits the complex relationship between topic distance and hiring. This is likely also why the model overestimates interdisciplinary hiring for Computer Engineering and Electrical Engineering, which also have very similar embeddings (Fig. A3). Other errors such as the underestimation for Agricultural Economics and Public Health likely represent the effects of administrative hiring channels unseen by the gravity model, e.g. the Economics to Agricultural Economics pipeline (Fig. 1b).

A10 Productivity analysis robustness

As described in Section 6.4, we performed coarsened exact matching between interdisciplinary and within-discipline faculty hires to control for confounding factors (e.g. gender, career age, training prestige) when comparing their post-hire publication productivity. The table below shows sample sizes and proportions of interdisciplinary and within-discipline hires before matching, after matching, and after filtering for those with publication productivity data. The sums of numbers in the Total column are smaller than our total sample size of $n = 107,039$ faculty because of two filtering steps: First, we filtered to those hired after 2011 to ensure that our estimates of career age and 5-year post-hire productivity were not biased by left-censoring, resulting in $n = 62,404$ faculty for domain-level matching. Second, for field-level analyses we filtered out faculty whose degree or hiring fields were NA, resulting in $n = 55,758$ faculty for field-level matching. Although inter-field hires are matched and have publication data at slightly lower rates than within-field hires, these rates do not differ by more than 5% (Table A6).

After matching, we fit a Negative Binomial regression model as specified in Section 6.4 to estimate the associations between productivity and interdisciplinary hiring and other covariates. As expected, we find that the coefficients for gender, working environment prestige (measured as hiring institution prestige), and career age (measured as time-to-hire) are all significant (Table A7).

Discipline level	Interdisc. definition	Interdisciplinary			Disciplinary		
		Total	Matched (%)	w/ pub. data (%)	Total	Matched (%)	w/ pub. data (%)
Field	Full	20943	19631 (94%)	18720 (89%)	34815	33521 (96%)	31695 (91%)
Field	Partial	27725	25593 (92%)	24363 (88%)	28033	27192 (97%)	25699 (92%)
Domain	Full	11017	10955 (99%)	10373 (94%)	51387	51085 (99%)	48251 (94%)
Domain	Partial	15133	15059 (100%)	14344 (95%)	47271	47101 (100%)	44392 (94%)

Table A6: Sample sizes for interdisciplinary and disciplinary faculty hires before and after matching and filtering for publication data. We performed matching for every combination of discipline levels (field and domain) and definitions of interdisciplinarity (full and partial). Table shows counts, with percentages of the total in each category in parentheses.

Coefficient	Incidence rate ratio (IRR)	p-value (BY-corrected)
Intercept	11.081	$< 10^{-6}$
Gender man (vs. woman)	1.281	$< 10^{-6}$
Gender unknown (vs. woman)	1.708	$< 10^{-6}$
Interdisciplinary hire	1.063	$< 10^{-6}$
Time-to-hire	1.002	0.116
Hiring institution prestige	2.314	$< 10^{-6}$

Table A7: Coefficients and adjusted p-values for the regression of post-hire productivity on interdisciplinary hiring status and covariates. We report the incidence rate ratio (IRR), or the multiplicative increase in the 5-year post-hire publication count for a one unit increase in the covariate, and the Benjamini-Yekutieli corrected p-value for each covariate.

Another possible confounder for productivity is the number of coauthors. To test whether the productivity boost for interdisciplinary hires is explained by differences in the number of collaborators, we performed an additional regression, including the number of unique co-authors in the 5 years post-hire as a covariate. Faculty with more unique coauthors do tend to be more productive. Each additional coauthor is associated with a 5.1% increase in productivity ($p < 10^{-6}$, Benjamini-Yekutieli corrected). With the addition of this effect, the productivity boost for interdisciplinary hires shrinks to 4.5%, but is still significant ($p < 10^{-4}$, Benjamini-Yekutieli corrected). Thus we conclude that the productivity boost for interdisciplinary hires is not entirely explained by differences in the number of collaborators. This is likely because the difference in number of unique coauthors is marginal, with an average of 5.7 for interdisciplinary hires and 5.3 for disciplinary hires in the 5 years post-hire (Fig. A4).

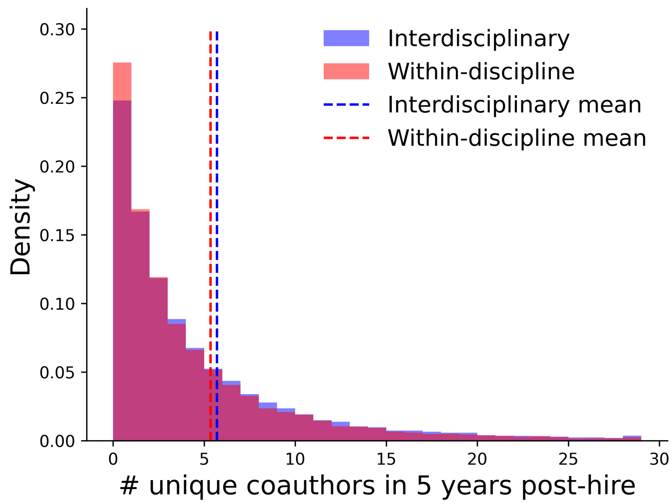

Figure A4: Histogram of the number of unique co-authors in the 5 years post-hire for interdisciplinary (blue) and disciplinary (red) faculty hires. The mean number of co-authors is slightly higher for interdisciplinary hires (5.7 vs. 5.3), but the medians are the same.

A11 Gender of interdisciplinary hires

In our sample of faculty, women comprise 31% of interdisciplinary hires and 29.9% of within-discipline hires, an enrichment of +1.2 percentage points ($\chi^2 = 14.40, p < 10^{-3}$, Chi-squared test), a small but significant shift.

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