Interdisciplinary Faculty Hiring

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Abstract

The transition from PhD to first tenure-track faculty position is a critical juncture in an academic career, yet little is known about how doctoral training prepares scientists for positions outside their training discipline. While previous studies have characterized the steep hierarchies of prestige and production inequalities reflected by the system of faculty hiring within disciplines, those studies lacked the data to examine how faculty hiring between disciplines, i.e., *interdisciplinary faculty hiring*, shapes the composition of the scientific workforce and whether hiring behaves differently across disciplinary boundaries than within disciplines. We overcome this lack of data with a novel dataset of department-to-department faculty hiring flows in the US, analyzing hiring flows between 440 PhD-granting institutions across 116 academic fields from 2011–2023 augmented with detailed information about postdoctoral studies between PhD and faculty jobs. Here we show that interdisciplinary hiring is common (37% of faculty) but flows through narrow channels shaped by field-specific patterns of credential fungibility and topical similarity. Implications for the careers of individual faculty are mixed: interdisciplinary hires undergo an average of 1.8 years of additional training before securing tenure-track positions, but they are 6.3% more productive once they do. The faculty placements of interdisciplinary hires do not differ clearly in prestige from those of within-discipline hires. Furthermore, interdisciplinary hires are more likely than within-discipline hires to hold postdoc positions before being hired but exhibit substantial heterogeneity in the disciplines of their postdocs, as well as in the trajectory of their research topics between their training and faculty career stages. Our results suggest that the fungibility of credentials is highly field-specific and interacts with research topic alignment in shaping flows of faculty between disciplines. This study provides a high-level view of how the academic labor market responds to the training background and credentials of researchers, with implications for understanding the flow of people and ideas between disciplines. Given the emphasis on interdisciplinary research as a driver of innovation in science, we hope our dataset on interdisciplinary faculty hiring will support initiatives to train interdisciplinary scholars and promote the synthesis of research between fields.

1 Introduction

Faculty hiring is the primary mechanism through which academic departments reproduce themselves, and a department's hiring decisions represent high-stakes investments in the future of their field. However, disciplines are not closed labor markets, with the consequence that some fraction of tenure-track hires hold PhDs or equivalent credentials from other fields, that is, *interdisciplinary hires*. Because doctoral training imparts the skills, credentials, and methods relevant to particular fields [1, 2], interdisciplinary hires reveal the degree to which doctoral training is fungible in another. If disciplines were perfectly siloed, interdisciplinary

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hiring would not exist. If credentials were perfectly fungible, disciplinary boundaries would be irrelevant to hiring. The reality lies somewhere between, and the pattern of which fields accept which fields' graduates (and which do not) maps the effective boundaries of knowledge and training across the academy.

Interdisciplinary hiring patterns map the space of knowledge across scientific disciplines by revealing adjacencies and asymmetries between fields. Topically related fields share research methodologies, norms, venues, and social networks, which facilitates mutual faculty hiring [3], overcoming the barriers of established administrative and cultural boundaries that separate them. For example, a 1983 study on "field mobility" found that 25% of Dutch physics PhDs went on to work in non-physics departments, primarily in medicine, engineering, and mathematics [4]. Disciplines whose trainees are frequently hired into others may produce more generalizable skills or credentials, while those that frequently hire faculty from other disciplines may value skills or credentials that they themselves do not produce in their trainees. Thus net flows of faculty hired from one discipline to another might suggest some imbalance in the fungibility of credentials or in the skills imparted during doctoral training [5]. Such imbalances were documented in flows of researchers between academic fields in 1970s Netherlands [6, 7], in which the natural sciences produced a net outflow of researchers to medical sciences, and the fields of physics, chemistry, law, and economics[1] were the largest exporters of professors.

This paper brings together the literature on field mobility with the study of faculty hiring networks using a dataset of faculty hiring across many disciplines in the U.S. from 2011–2023, enabling us to map hiring in a modern context and at a larger scale while also addressing questions about the implications of interdisciplinary hiring for individual career outcomes. For example, prestige is a key descriptor of academic careers, influencing productivity [9], citations and awards [10], and faculty attrition [11]. While previous studies on faculty hiring networks have found steep and ubiquitous hierarchies of prestige within disciplines [12–16], even studies across many disciplines [17] have omitted interdisciplinary faculty hiring. Given the importance of prestige and the imbalances in flows of faculty hiring between disciplines, it is natural to ask whether or not the placements of interdisciplinary hires follow the same prestige hierarchy as conventional within-discipline hires.

Interdisciplinary hiring sits at the intersection of several forces documented in prior work. Doctoral training produces field-specific skills and credentials whose transferability varies [2, 4], labor markets for faculty positions differ in tightness across fields [18, 19], and funding agencies [20], universities [21], and governing bodies [22] have increasingly emphasized interdisciplinary research as a driver of innovation. Evidence that interdisciplinary research centers are associated with higher productivity, funding, and prominence [21, 23] suggests that the labor market may reward boundary-crossing, but these potential reward coexist with well documented frictions. Disciplinary boundaries reduce the fungibility of credentials and hinder the flow of ideas [24], interdisciplinary grant proposals face lower initial funding rates [25, 26], and interdisciplinary research papers experience delayed recognition [27, 28]. Whether these frictions and incentives manifest in the actual hiring of faculty across disciplinary boundaries remains largely unexamined.

We define interdisciplinary hires as those who take faculty positions in disciplines different from their PhD disciplines, but there is a critical intermediate career stage, post-doctoral (postdoc) training. Postdocs have become a common step between graduating with a PhD and landing a tenure-track position in many fields [18, 29, 30] and may provide important opportunities for interdisciplinary hires to re-train or bridge to new disciplines.

In this paper we address questions about the overall structure of interdisciplinary hiring and the careers of individual interdisciplinary hires using two primary data sources. First, we introduce a novel dataset of

[1]The export dominance of physics and economics is not surprising given the influence of physics throughout science and engineering and the centrality of economic thought in the social sciences [8].

tenure-track faculty at PhD-granting institutions in the U.S. from 2011–2023, including their disciplinary affiliations at the time of their degree, their first tenure-track faculty position, and their postdoc position(s). Second, we add high-dimensional embedding representations of the publications of these faculty, which we aggregate to the discipline level using the affiliations from the data above, yielding an abstract "topic space" in which to compare individuals and disciplines. We characterize the structure of the faculty workforce and labor market by answering:

1. How common is interdisciplinary hiring?
2. What structural patterns govern it, and what do these patterns suggest about fungibility of skills and credentials between disciplines?
3. How is interdisciplinary hiring related to topical proximity between fields?
4. Does the system of interdisciplinary hiring differ from within-discipline hiring in placement prestige patterns?

We examine the career trajectories of individual scholars by answering:

1. Are the career outcomes of interdisciplinary faculty hires different in terms of productivity, training time, or other factors?
2. At what career stage does the interdisciplinary transition occur? Before or after postdoctoral training?
3. Does the research of interdisciplinary hires match their training disciplines or their hiring disciplines?
4. Do interdisciplinary hires change research topics when they cross discipline boundaries?

2 Data

2.1 Faculty census

To identify interdisciplinary faculty hires, we needed to know both the department from which a professor received their terminal degree (degree department) and the department into which they were first hired (hiring department). We started with the latter using a census of tenure-track faculty at 431 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 [31], scholar profiles from ORCiD [32], and publication affiliation data from OpenAlex [33]. 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. While previous faculty hiring network datasets have either focused on disciplines in isolation [15] or on hiring at the institution level [17], the department-level resolution and academia-wide scale of our dataset enabled us to study interdisciplinary hiring at scale.

By linking every professor to their degree and hiring departments, we determined their disciplinary affiliations at these two early-career stages. Every department was annotated according to a disciplinary taxonomy of 10 broad "domains" and 116 finer-grained "fields" [17] (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. Under our definitions, a person who got their PhD from a Computer Science department and was hired into a department affiliated with the fields of Computer Science and Biology is partially but not fully interdisciplinary, while a person who got their PhD from a Computer Science department and was hired into a Biology department is fully and partially interdisciplinary. Throughout the rest of the paper, we perform analyses using the fully interdisciplinary definition (see Section A6 for 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*.

In addition to disciplinary affiliations during the degree and in the first faculty position, we collected the disciplines of postdoc positions for the professors in our sample. We obtained post-doctoral appointment data for $n = 27,299$ (25.5%) faculty in our dataset by querying a large language model with search grounding. For each professor, we compiled the number of postdoc positions and the institution, department, and field(s) of all postdoc positions (Sec 6.6).

Following prior work that estimated institutional prestige from faculty hiring networks [15, 17], we used the SpringRank algorithm [34] to infer prestige values for every department and institution in our sample (see Section 6.3 for details).

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 [24, 35–37]. 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 [38]. 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 (see Section 6.7).

3 The structure of the interdisciplinary faculty labor market

3.1 Heterogeneity, reciprocity, and asymmetry in interdisciplinary hiring

Interdisciplinary hiring is common: 37% of faculty are hired from a different field. This high rate reflects hiring flows between the 116 fields that make up the finest level of our discipline taxonomy, but even at the coarsest level of 10 domains, 17% of faculty are hired into a different domain than their degree. Despite the frequency of interdisciplinary hiring, the large majority of field pairs and almost all department pairs do not exchange meaningful numbers of faculty, so the hiring network is sparse. In fact, when considering only hiring flows that represent non-trivial proportions of each field's total faculty hires, the network becomes highly disconnected (Fig. 1a).

The segmentation of the interdisciplinary faculty hiring market arises from the heterogeneity in prevalence and direction of interdisciplinary hiring across fields. We measure each field's directional rates of interdis-

ciplinary hiring using the *import* and *export* rates, defined as the fraction of faculty hired from other fields and the fraction of PhD graduates placed into other fields, respectively (Section 6.1). These rates range from nearly complete autarky to complete openness: Nursing exports only 4% of its PhDs placed while International Affairs imports 96% of its faculty (Table A2). Even fields considered to be rigidly hierarchical and closed, such as Philosophy, Mathematics, and Economics [8, 39, 40], import 23%, 24%, and 22% of their faculty, respectively.

A natural hypothesis is that topically adjacent fields draw on similar skills and methods, making their credentials mutually fungible. The data support this: many clusters of similar fields are connected by reciprocal exchanges of faculty. Physics and Astronomy contribute sizeable fractions of PhDs to each other's faculty workforce (Fig. 1c), as do Computer Science, Computer Engineering, and Electrical Engineering (Fig. 1d), and Chemistry and Biochemistry. We provide further quantitive backing for this hypothesis in Section 3.2 by fitting a gravity model of field-to-field hiring on topical proximity.

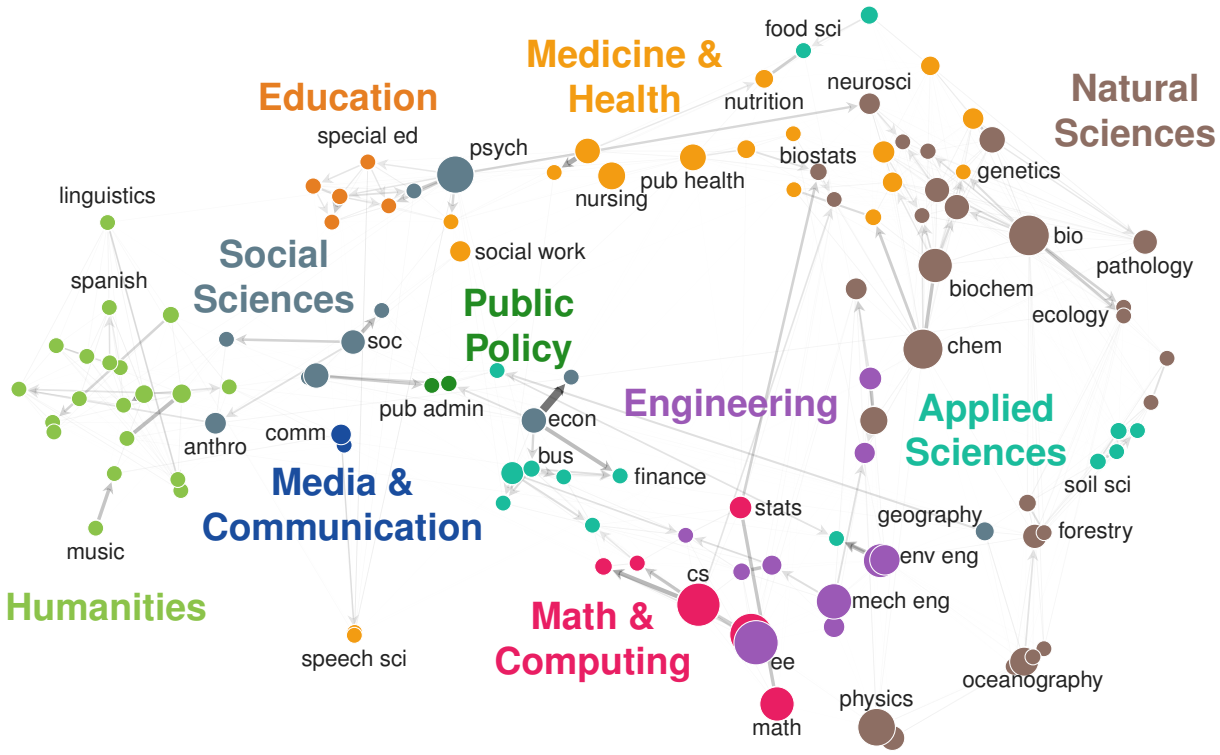
While reciprocal exchanges suggest mutual credential transferability, we also observe strong asymmetries implying that fungibility can be *directional*. A notable example is the field of Economics. Although Economics has low rates of both interdisciplinary hiring and placement, it is a net exporter of faculty: for every 100 Economics professors, there are about 39 Economics PhDs that are professors in other fields. This constitutes a trade surplus concentrated towards the fields of Management, Finance, Business Administration and Public Policy (Fig. 1b). Some fields are even more vigorous exporters. The fields of Comparative Literature and Educational Psychology actually place more faculty outside themselves than they hire, with net outflows of 130 and 108 PhDs per 100 faculty respectively. In contrast, the fields of Gender Studies, International Affairs, and Computational Biology act as net importers of faculty (net inflows of 56, 75, and 61 per 100 faculty, respectively; Table A2). This is perhaps not surprising as this latter set are highly interdisciplinary fields that emerged from the synthesis of multiple disciplines.

In line with previous studies of faculty hiring networks that find high levels of self-hiring [17], we find that 7.4% of faculty are hired into the same department from which they received their degree. But like interdisciplinary hiring, rates of department self-hiring are highly field-dependent, ranging from 34.8% and 21.9% in the fields of Nursing and Epidemiology to 0% and 0.9% in the fields of Gender Studies and Religious Studies (Table A2).

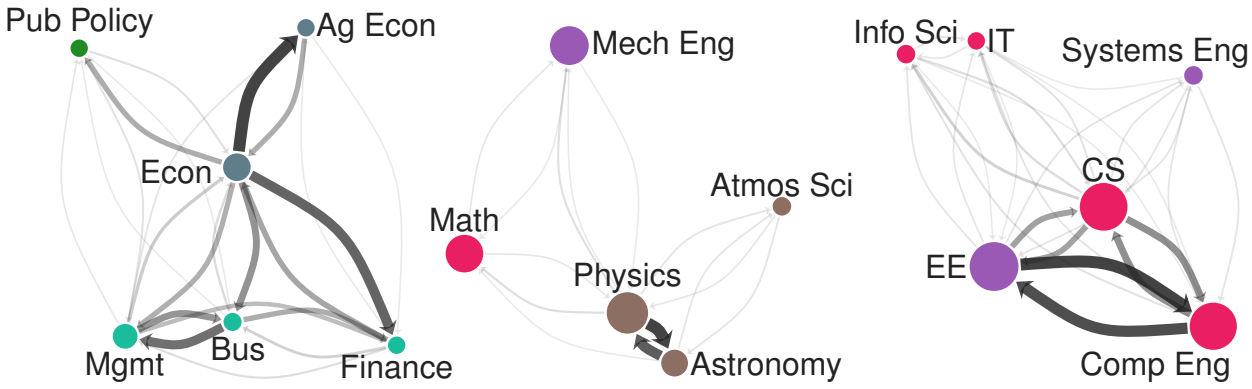
3.2 Interdisciplinary hiring rates decrease with topical distance and field size

Despite the heterogeneity in volume and direction of interdisciplinary hiring between fields, several overarching trends emerge. First, although we documented fields such as Economics that display asymmetric hiring flows with neighboring fields, import and export rates for fields are highly correlated (Spearman $\rho = 0.88, p < 10^{-37}$; Fig. 2). This means that the permeability of field boundaries tends to be bidirectional. Further, import and export rates tend to decrease as discipline size increases ($\rho = -0.38$ for imports and $\rho = -0.37$ for exports, $p < 10^{-4}$ Benjamini-Yekutieli corrected). For example, Computer Science ($n = 4,642$) imports and exports proportionally less than the smaller related field Information Science ($n = 849$), with import and export rates of 28% and 31% versus 70% and 57%, respectively (Table A2).

Interdisciplinary hiring is also positively associated with topical similarity between fields. The mutually and asymmetrically connected field pairs highlighted above are all topically similar. This is reflected in the relative sparsity of long high-volume edges in Fig. 1a, in which node positions reflect the topic embeddings of fields. We fit a gravity model to quantify the dependence of field-to-field hiring on topic distance and found that a one-standard-deviation increase in publication distance is associated with a 64% reduction in interdisciplinary hiring rates between fields (pseudo-$R^2 = 0.88$, distance term $p < 10^{-60}$; see Section 6.2). So, *quantities* of interdisciplinary hiring share common patterns but vary widely between disciplines. We



(a) Field-to-field faculty hiring network



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

Figure 1: **Interdisciplinary hiring flows are driven by topical adjacency, administrative boundaries, and asymmetries in the fungibility of credentials.** (a) Nodes are academic fields and edges $i \to j$ represent professors in field j who received their PhDs in field i. Edge widths are proportional to the fraction of faculty in field j hired from field i: if there this proportional hiring is mutual, we draw an undirected edge. Otherwise, we draw a directed edge with an arrow pointing from the exporting field to the importing field. Node sizes are proportional to the total number of faculty hired in each field and nodes are colored according to their parent domain as shown in the annotations. Node positions are derived from a t-distributed stochastic neighbor embedding of the fields positions in publication embedding space, so that topically similar fields are closer together. (b-d) Selected graph neighborhoods highlighting the asymmetric flows between Economics and its neighbors, and mutual exchanges of faculty between Physics and Astronomy and between Computer Science, Computer Engineering, and Electrical Engineering.

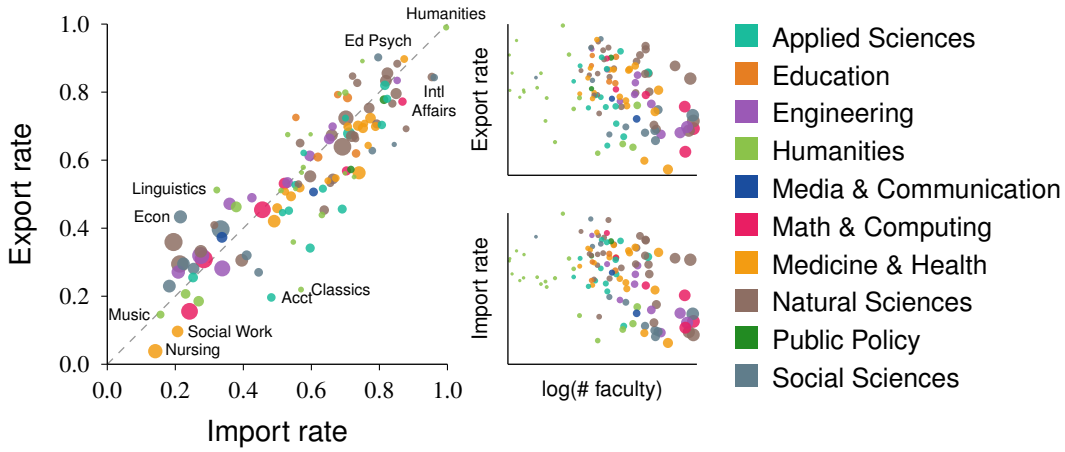


Figure 2: **Interdisciplinary hiring rates are bidirectional and decrease with field size.** Points represent fields with sizes proportional to the number of faculty in each field, and fields are colored by parent domain. The dashed line indicates equal export and import.

next examine differences in the *quality* of the placements of interdisciplinary hires via prestige.

3.3 Interdisciplinary hiring and placement prestige

The prestige of interdisciplinary hires' faculty placements is similar to that of their within-discipline peers. Faculty hiring is defined by universal downward mobility in prestige [15, 17] so that on average faculty are hired into departments with lower prestige than their degree department. However, previous studies of faculty hiring relied on institution-to-institution hiring data and could only measure the prestige of institutions [17]. With our data on department-to-department faculty hiring, we measured and compared prestige values of the 12,832 departments and 431 institutions in our sample separately. Prestige differences are small and switch sign depending on whether we measure department or institution prestige, suggesting that interdisciplinary hires experience no clear placement advantage or disadvantage.

At the department level, interdisciplinary hires experience a significant placement disadvantage, falling further in prestige than within-discipline hires by 3.7 units (Fig. 4). In practice, this difference is equal to 0.24 standard deviations in department prestige, or the difference between the Harvard astronomy department (score 91.62, ranked #10) and the Princeton economics department (score 87.96, ranked #28) on a prestige scale of 0–100 (see Section 6.3). Although this disadvantage holds across all 10 domains, in 18 of 116 fields incoming interdisciplinary hires actually attain more prestigious department placements. The advantage is significant in 5 fields (Statistics, Biochemistry, Anthropology, Chemistry, Sociology; $p < 0.045$, Benjamini-Yekutieli corrected Mann-Whitney U tests). The placement disadvantage is steepest in Epidemiology and Nursing, but notably, these are the two fields with highest levels of department self-hiring. This suggests a potentially confounding effect. Self-hires are by definition within-discipline hires and do not drop in prestige at all, so they inflate the prestige placements of within-discipline hires. After excluding self-hires, the placement disadvantage for interdisciplinary hiring shrinks to 1.4 units.

At the institution level, the effect is reversed, with interdisciplinary hires experiencing a significant placement advantage of 1.1 units (Fig. 4). This advantage spans 4 domains and 41 fields (13 fields significant, $p < 0.043$, Benjamini-Yekutieli corrected Mann-Whitney U tests). The discrepancy between placements measured using institution and department prestige is likely due to field-level hiring patterns, which confound the measurement of department-to-department placement prestige. We have already highlighted how

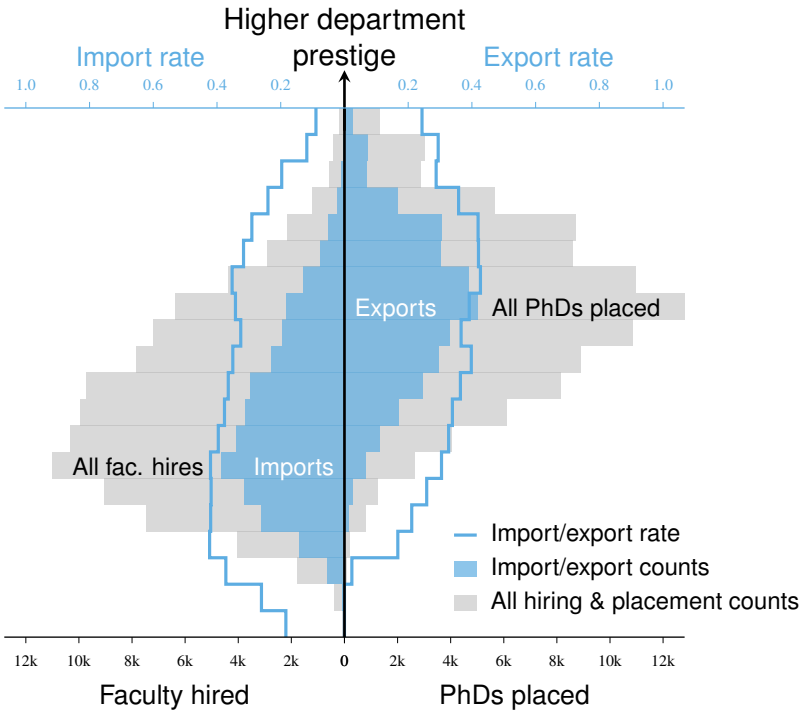


Figure 3: **Import and export rates are unevenly distributed across the prestige hierarchy of departments.** Histograms show counts of total (gray) and interdisciplinary (blue) faculty hiring and placement across department prestige, with interdisciplinary import and export rates overlaid as blue lines. Export rates are highest in departments in the upper half of the prestige hierarchy while import rates are highest in departments in the middle to lower half. If interdisciplinary hires followed the same placement patterns as within-discipline hires, we would expect import and export rates to be constant across prestige.

some fields export faculty to others in asymmetric flows (Section 3.1). These patterns layer a field-level hierarchy onto department prestige: net-exporting fields tend to score higher, as do the smaller feeder fields that place graduates into them (e.g. Astronomy, Evolutionary Biology, Comparative Literature; Figs A1 and A2). As a result, export rates are skewed towards higher-prestige departments while import rates are skewed towards lower-prestige departments (Fig. 3). One way to disentangle department quality from the hierarchy of fields is to return to measuring prestige from institution-to-institution placements.

Regardless of the difference in the direction of department and institution prestige effects for interdisciplinary hires, the magnitudes of both effects are small compared to the typical downward mobility in prestige (-3.7 vs. 17.6 and +1.1 vs. 15.8; difference vs. average drop in department and institution prestige respectively). It is well known that prestige is a key descriptor of faculty careers [9, 10]. Does this lack of a clear difference in placements mean that career outcomes of interdisciplinary hires are indistinguishable from those of within-discipline hires?

4 Interdisciplinary hires train longer, then output more

The early-career outcomes of interdisciplinary hires differ from those of their disciplinary peers in terms of productivity and post-doctoral training time, and these differences are modulated by individual research topic trajectories.

4.1 Increased productivity

Inter-field hires publish 6.3% more papers than disciplinary hires in the five years after hiring, controlled for discipline and other covariates ($p < 10^{-7}$, Benjamini-Yekutieli corrected Negative Binomial regression). Because interdisciplinary hires tend to be hired later in their careers (Section 4.2), their additional training time may partly explain this increased productivity. To control for this and other confounders such as gender [41] and prestige [9, 10], we perform matching and regress on gender, career age (at hire), and hiring institution prestige. The productivity boost we observe is therefore above and beyond what these factors alone explain (see Section 6.4 for regression methods).

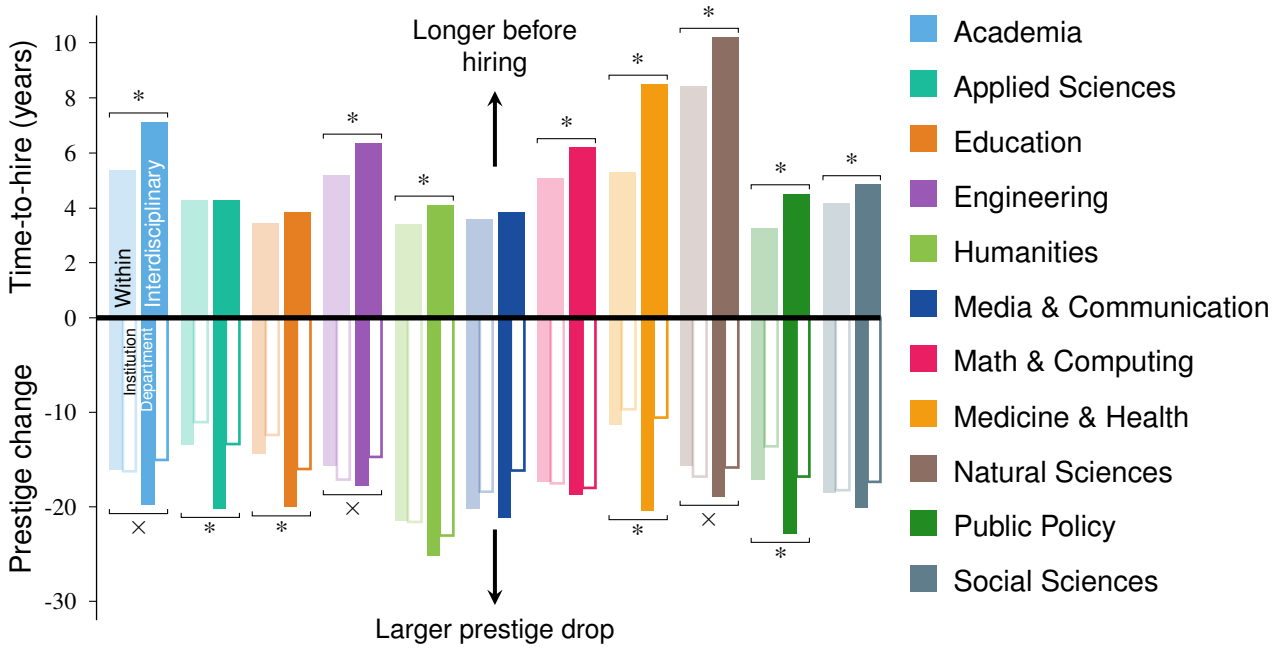


Figure 4: **Interdisciplinary take longer to be hired and do not experience systematic prestige differences.** Top: Average time in years between PhD and first tenure-track position for disciplinary (light bars, left) and interdisciplinary (dark bars, right) faculty hires across domains and academia overall. Bottom: Average prestige change between degree and hiring departments and institutions for disciplinary and interdisciplinary faculty hires, with the same color scheme. Filled bars indicate department prestige change and open bars indicate institution prestige change. Stars denote domains with significant differences between disciplinary and interdisciplinary hires and X's denote domains where department and institution prestige changes differences are significant in opposite directions (Benjamini-Yekutieli corrected Mann-Whitney U tests).

4.2 Longer time-to-hire and more postdocs

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; Fig. 4), reflecting extended early-career training periods. We measure this time as the *time-to-hire*, defined as the difference between the year when a professor first enters the tenure track and the year when they received their degree. Like the findings on placement prestige, this effect is field-dependent, but in this case it is nearly universal: inter-field hires have longer average time-to-hire in 99 out of 116 fields. Interdisciplinary time-to-hire is significantly longer in 38 fields and not significantly

shorter in any field ($p < 0.03$, Benjamini-Yekutieli corrected Mann-Whitney U tests). This effect holds in all 10 domains (7 significant; $p < 0.027$). The biggest difference in time-to-hire is in the Medicine and Health domain (+3.2 years), while there is virtually no difference in the Applied Sciences domain. Our results on productivity, prestige, and time-to-hire are robust to alternative definitions of interdisciplinary hiring (see Sections A5 and A6).

One might expect that this additional time-to-hire is largely spent in postdoc positions, especially as it becomes more common for researchers to hold postdocs before securing tenure-track positions [30]. Postdocs are indeed common—60% of faculty in our sample held at least one—and interdisciplinary hires are more likely than within-discipline hires to have held at least one postdoc (68% vs. 57%) and to have held multiple postdocs (18% vs. 15%). Postdocs held by an interdisciplinary hire are also longer on average (3.8 vs. 3.3 years). However, these increased postdoc rates and durations only account for a difference of 0.53 years, leaving most of the 1.8 year difference in time-to-hire between interdisciplinary and disciplinary hires unexplained.

Across domains, postdoc rates range from 15% in Journalism to 84% in Natural Sciences, and across fields rates range from 2% in Accounting to 95% in Molecular Biology. Also, disciplinary hires are actually more likely to have held a postdoc in 34 fields, e.g. in Physics, where 90% of disciplinary hires held postdocs compared to 77% of interdisciplinary hires (Table A3). This variety suggests a diversity of career pipelines both across and within disciplines.

For interdisciplinary hires, postdocs provide an opportunity to fill in the gap between their training disciplines and eventual hiring disciplines. Thus comparing the disciplines of postdoc positions to the degree and hiring disciplines can pinpoint when interdisciplinary hires "jump" between disciplines. No single paradigm dominates: the timing of the interdisciplinary transition is roughly split among before, throughout, and after the postdoc. We define several named categories to capture the possibilities for this timing (Table 1). About a third of faculty make the jump at the start of the postdoc (*interdisciplinary at postdoc*), about a quarter each use the postdoc as a bridge (*bridge*) and make the jump after the postdoc (*interdisciplinary after postdoc*), and only an eighth hold postdocs in unrelated disciplines (*detour*). Even within-discipline faculty hires sometimes cross discipline boundaries via a postdoc: 13% held postdocs in fields distinct from their degree and hiring fields (*roundtrip*).

Table 1: **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 (see Section 6.6). The Percentage column gives the fraction in each category among interdisciplinary and disciplinary hires who had at least one postdoc position.

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: **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.

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%

4.3 Interdisciplinary hiring is primarily a label change

Interdisciplinary hiring represents a disciplinary label change rather than an outright topic shift: 78.3% of interdisciplinary hires do not change research topics when they change fields between their PhD and being hired. We mapped the research topic trajectories of individual faculty before and after they were hired by comparing discipline distributions across the k-nearest neighbors of each publication in topic space, then classified faculty into named categories representing their research trajectories (Table 2; see Section 6.7 for methods). The results show that a plurality (42.4%) of interdisciplinary hires are *label correcters* whose research actually matches their eventual hiring fields, even during their PhD. The next largest category (35.9%) are the *label adopters* whose research matches their degree fields throughout the career. Only 21.7% of interdisciplinary hires showed evidence of changing research topics at the time of their discipline change, either from their degree to hiring disciplines as *topic adopters* or from their hiring back to their degree disciplines as *topic reverters*. The distributions of these categories vary across disciplines, but are generally consistent with the academia-wide proportions (Fig. A3).

Just as topical proximity between fields is associated with interdisciplinary hiring, individual research topic trajectories modulate the productivity and time-to-hire effects discussed above (Table 2). Interdisciplinary hires who do not change their research topic (label adopters and label correcters) are even more productive than the average for interdisciplinary hires, writing 22.2% and 17.2% more papers in the five years post-hire than their disciplinary peers, respectively ($p < 10^{-59}$, Benjamini-Yekutieli corrected Negative Binomial regression). On the other hand, faculty who change research topics (topic adopters and topic reverters), actually write 2.8% and 4.8% fewer papers than within-discipline hires, but these decreases are not significant due to small sample size (Table A5). Interdisciplinary hires in every category experience longer time-to-hire, but the effect is attenuated slightly for topic reverters and label adopters (1.1 and 1.7 years, respectively; Table A5). The distributions of interdisciplinary hires within each category and the modulation of productivity and time-to-hire differences across categories are stable under various alternative definitions of interdisciplinary hiring (Table A4).

5 Discussion

This study provides a comprehensive analysis of interdisciplinary faculty hiring in the United States, linking the aggregate architecture of hiring flows to the career trajectories of scientists who cross disciplinary

boundaries. Despite distinct disciplinary traditions dating back centuries, interdisciplinary hiring is common (37% of faculty) and is structured by both general and field-specific patterns of credential fungibility in which fields produce generalizable training, which value external credentials, and which share mutual hiring, with implications for understanding training effectiveness and labor market structure across disciplines. Also, individuals holding interdisciplinary credentials are selectively valued. While the prestige of their faculty placements is highly field-dependent, in general they are more productive than their disciplinary peers and face extended training periods. Finally, most interdisciplinary hiring represents a change in disciplinary affiliation rather than research topic, suggesting that doctoral training produces skills and credentials that are fungible across related but not distant disciplines.

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 create 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 [3] (Fig. A1).

Although interdisciplinary hires do not systematically differ from their within-discipline peers in prestige of faculty placements, they do enjoy a placement advantage in a handful of fields. Shared theoretical foundations provide a partial explanation for this: For instance, Statistics hires faculty from Mathematics and Physics—two fields with strong fundamental theories—and may reward their credentials with more prestigious placements. However, the mechanisms are unclear in other fields that exhibit placement advantages for interdisciplinary hires, such as Sociology and Anthropology. Overall, our analysis of prestige differences between interdisciplinary and within-discipline hires highlights the complexity of quantifying prestige in the presence of both department quality and field-level prestige hierarchies. We find a qualitative difference in department-level and institution-level placement patterns: more work is required to disentangle these effects.

Patterns in interdisciplinary hiring suggest that the fungibility of credentials is also shaped by disciplinary culture, administrative hiring pipelines, and field maturity. The five fields with the strongest associations with innate talent (Music, Physics, Economics, Philosophy, and Mathematics) [40] all import relatively few faculty. Because of their emphasis on innate ability, these fields may view credentials from other disciplines as less legitimate or indicative of ability, leading to lower rates of interdisciplinary hiring. Other sets of fields exchange more faculty than predicted based on their topical proximity, suggesting the presence of established interdisciplinary hiring pipelines or cognitive similarities not reflected in topic space (e.g. Geography and Urban Planning, Fig. A1). Finally, larger disciplines engage in proportionally less interdisciplinary hiring and placement. The largest fields (Psychology, Chemistry, Physics, Biological Sciences) are also among the oldest and likely have more entrenched internal hiring traditions, suggesting a possible lifecycle in which fields mature and stabilize over time with calcifying boundaries, whereas smaller and newer disciplines hire heavily from the related fields from which they emerged. Although the "age" of an academic field is difficult to determine, future work could attempt to measure this variable and its relationship to interdisciplinary hiring patterns, which would shed light on the dynamics of disciplinary boundaries and the evolution of scientific fields.

Overall, our results reveal that the disciplinary landscape is not neatly hierarchical. Classifying career moves requires imposing a taxonomy of disciplines (from broad domains to specific fields), and 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. The maps of mutual credential exchange via hiring and topical similarity via publication embeddings are therefore more faithful to reality than the imposed taxonomy.

Turning from field-level implications to individual scholarly careers, interdisciplinary hires spend more time in training and are more likely to have held postdoc positions. In the majority of cases, interdisciplinary hires use postdocs as a disciplinary bridge or re-training period to overcome the skill mismatch between their degree and hiring disciplines [42, 43]. But, others use postdocs as further training in their degree fields or in other fields entirely, demonstrating that there are multiple viable career pathways across disciplinary boundaries.

After undergoing extended training, interdisciplinary hires publish more papers in their first five years as faculty. However, the subset of interdisciplinary hires who change research topics between their training and placements as professors are actually less productive, suggesting possible cognitive barriers resulting from learning new skills, methods, and conventions [24] (Table A5). We do not measure whether interdisciplinary hires actually produce interdisciplinary research, so we do not know whether the costs and benefits associated with interdisciplinary research are potential mechanisms for either the general productivity increase or the specific productivity decrease [23, 27]. Extended postdoctoral training time is the most likely remaining explanation for the increased productivity: longer pre-hire research periods, especially in postdocs, may provide momentum for higher productivity after hiring. We control for career age and hiring institution prestige, so additional training time alone cannot account for the effect.

Broader collaboration networks offer another possible mechanism, but we find no meaningful difference in the number of unique collaborators for interdisciplinary and within-discipline hires, and the productivity boost survives adding collaborator counts to the regression (Section A10). A more likely confound is selection: underlying individual variation influences productivity, prestige, and the propensity to cross disciplinary boundaries, so interdisciplinary hires may be enriched for high-performing researchers who can successfully navigate between fields. Supporting this interpretation, inter-domain hires, who must overcome even larger barriers between broad domains such as Engineering and Natural Sciences, are more productive still (Section A5).

High rates of interdisciplinary hiring and postdoctoral training reflect the "burden of knowledge" [44, 45] that forces scientists to specialize and often train more as science advances and knowledge accumulates. As disciplinary faculty labor markets saturate, early-career scientists may look outside their training discipline to find coveted tenure-track positions, and they may even leverage their external training as a strength. Interdisciplinary hires whose post-hire research matches their training discipline are even more (Table A5), possibly because they publish in areas under-exploited by within-discipline hires. By bringing their research associated with their training disciplines into new departments, these researchers might also act as vectors for the diffusion of knowledge between fields [46].

In our analyses, we focus on the fungibility of credentials as a key factor shaping interdisciplinary faculty hiring patterns. Our underlying assumption is that the name of the department on a faculty member's CV fully captures these credentials. The addition of publication embeddings allows us to take a more nuanced view by considering research topics as a proxy for skills, knowledge, and credentials. However, the embedding-based topic space we use is limited in that we cannot identify interdisciplinary researchers. Future work could incorporate the citation data that is traditionally used to quantify knowledge-base interdisciplinarity in papers [47] or quantitative methods in embedding space to identify papers that are truly interdisciplinary in topic [48] to measure the extent to which interdisciplinary hires are truly interdisciplinary researchers.

We do not analyze the relationships between interdisciplinary hiring and demographic characteristics such as gender, national origin, or socioeconomic background, nor whether interdisciplinary hires experience differential attrition rates. Attrition rates are higher for women and faculty trained outside the US [17], and women gain additional placement advantage from postdoctoral training [41]. Demographic characterization of the population of interdisciplinary hires would outline additional mechanisms that might contribute to

the observed differences in time-to-hire and productivity and identify the implications of interdisciplinary hiring for the precarity of early-career scientist placements. The extended training periods required for interdisciplinary hires represent additional years of uncertain career prospects, often in poorly compensated postdoctoral positions [18, 30], which may increase attrition rates. At the same time, there is clear demand for interdisciplinary hires in the faculty labor market, and these interdisciplinary hires are more productive after being hired. Thus a better understanding of interdisciplinary hiring pipelines and demographics might reduce faculty attrition and improve the productivity of the scientific workforce.

Our findings have broader significance for the science of science and labor economics. The selective fungibility of credentials across disciplines reveals fundamental constraints on how knowledge and human capital flow through the academic system. Fields that produce graduates who successfully transition to other disciplines may offer more generalizable training in research methods and communication, while fields that rely on external hires could invest in bridging programs or mentorship during extended training periods. 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:

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

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 (see Section 6.7). As recommended by practitioners in international trade [49], 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 [50]. We apply two-way clustering to the standard errors by origin and destination fields using the Cameron–Gelbach–Miller variance decomposition [51] to adjust for the dependence between dyads sharing the same origin or destination field.

6.3 Prestige

We used the SpringRank algorithm [34] to rank every department and institution in our sample according to its faculty placements. SpringRank produces continuous prestige scores s_i for every department or institution i, where higher scores indicate more prestige. The range of the resulting scores depends on the structure of the network and a regularization parameter α. 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.

Faculty hiring is generally hierarchical and production is concentrated in the most prestigious institutions [17], so to measure placement effects we examined the change in prestige between degree and hiring departments. We computed this change for every individual as $s_{hire} - s_{degree}$, the difference between the scaled prestiges of the hiring and degree department or institutions. As noted in Section 3.3, the steep hierarchies of prestige in faculty hiring mean that this change is negative for most faculty (degree department more prestigious than hiring department). However, the extent of the drop in prestige is meaningful: individuals who fall less far down the prestige hierarchy have a placement advantage and those who fall further down have a placement disadvantage. To test whether interdisciplinary faculty hires experience a placement (dis)advantage, we compared the mean prestige changes of interdisciplinary hires to that of disciplinary hires hired into fields, domains, and in academia overall using Mann-Whitney U tests and corrected for multiple comparisons using the Benjamini-Yekutieli procedure [52] (Fig. 4, Table A3). We aggregated into disciplines by taking all faculty hired into that discipline, so our results represent placements for *incoming* faculty rather than outgoing graduates from each discipline. The domain-level statistics we report in Section 3.3 are the means over all inter-field hires hired into fields in the domain, but our results on prestige are robust for interdomain hires and partially interdisciplinary hires (Sections A5 and A6).

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 [53]. 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) [53, 54], hiring department prestige [9], and gender [40].

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:

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

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 [55] 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 [38], 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 [33]) 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 [56] 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 [57]. 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 2 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 2). 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).

7 Acknowledgements

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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 [17]. Each field belongs to exactly one area and domain, but some fields share names with areas (e.g. Biological Sciences and Economics). This occurs when a department cannot be annotated with a more specific field label or a more specific label is not appropriate.

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
	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

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Continuation of Table A1

Domain	Area	Field
	Philosophy	Philosophy
	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

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Continuation of Table A1

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

A2 Full annotated field-to-field hiring network

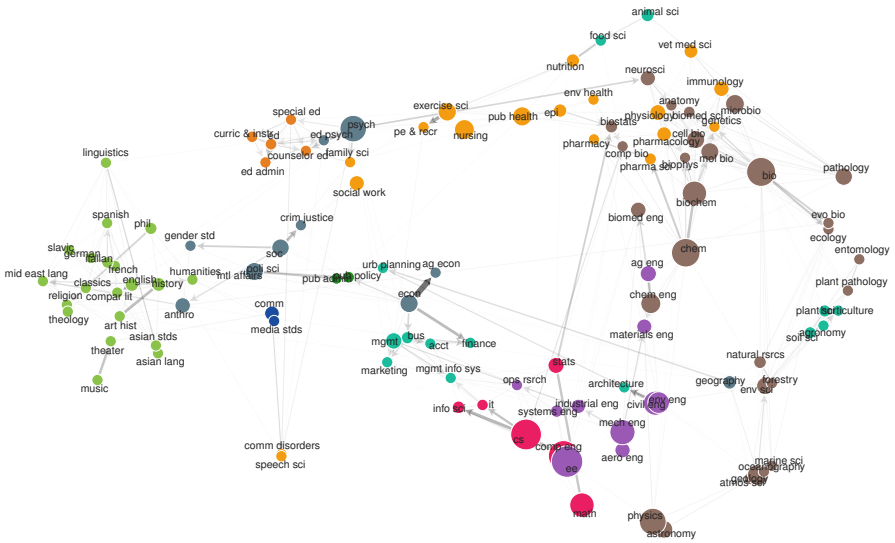


Figure A1: The field-to-field faculty hiring network with all fields annotated. Same encodings as Fig. 1.

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%**

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%

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Continuation of Table A2

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%
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%

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Continuation of Table A2

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%**

In the Section 3.3 of the main text, we described how patterns in the volume of faculty hiring flows between disciplines induces a discipline-level prestige hierarchy in which department in some disciplines tend get higher prestige scores because those disciplines export faculty to other high-prestige disciplines. Within-discipline variation in prestige is larger than the differences in average department prestige between disciplines in most cases, but there is still a clear hierarchy of prestige across disciplines (Fig. A2).

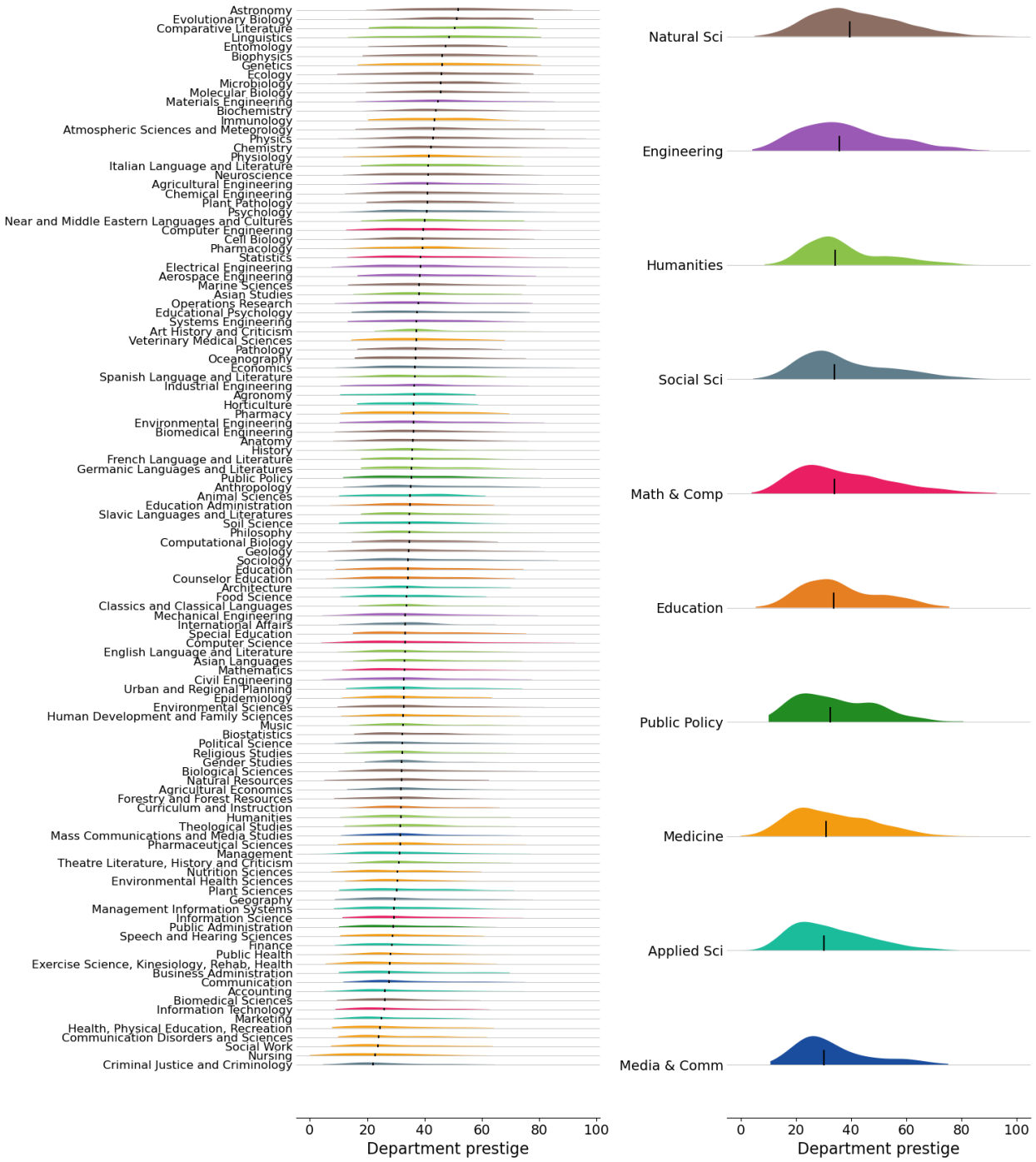


Figure A2: Distribution of department prestige scores for fields (left) and domains (right). The discipline-level prestige hierarchy is induced by the structure of faculty hiring flows between disciplines, with disciplines that export more faculty to other high-prestige disciplines tending to have higher average prestige scores.

A4 Prestige change, 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	**Dept. prestige change**			**Time to hire (yrs)**			**Postdoc rate (%)**		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Accounting	-24.75	-18.80	-21.20	2.88	2.52	2.67	0.0	1.9	1.6
Agronomy	-14.87	-5.96	-9.59	6.26	6.40	6.34	62.9	45.3	52.7
Animal Sciences	-13.38	-6.99	-8.34	6.95	5.83	6.07	63.3	47.0	51.6
Architecture	-21.95	-17.95	-19.47	3.63	2.78	3.10	42.9	28.3	33.8
Business Administration	-18.66	-14.80	-17.77	2.77	2.62	2.74	11.5	11.1	11.4
Finance	-25.58	-21.01	-23.27	3.27	3.91	3.59	9.5	7.2	7.8
Food Science	-17.66	-9.93	-12.68	7.68	5.88	6.52	66.1	59.3	61.5
Horticulture	-14.13	-6.61	-9.69	6.60	6.62	6.61	64.6	32.6	44.0
Management	-22.21	-19.91	-21.35	3.74	3.22	3.55	12.7	7.1	10.4
Management Information Systems	-23.93	-18.57	-22.18	4.58	3.38	4.19	5.7	0.0	3.7
Marketing	-23.66	-18.57	-21.18	3.82	4.63	4.21	3.7	2.9	3.1
Plant Sciences	-17.59	-13.14	-15.87	6.95	6.97	6.95	67.1	50.0	59.7
Soil Science	-17.59	-9.03	-12.73	6.54	6.79	6.69	56.2	49.5	51.8
Urban and Regional Planning	-19.95	-16.88	-18.11	6.32	2.92	4.28	38.7	33.3	35.8
Applied Sciences (avg)	**-20.13**	**-13.45**	**-16.86**	**4.30**	**4.26**	**4.28**	**36.1**	**26.8**	**30.6**
(interdomain)	**-22.39**	**-15.94**	**-17.59**	**4.93**	**4.05**	**4.28**	**43.8**	**30.3**	**32.8**

EDUCATION									
Field	**Dept. prestige change**			**Time to hire (yrs)**			**Postdoc rate (%)**		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Counselor Education	-17.68	-15.25	-16.49	3.39	3.38	3.39	55.5	18.8	44.9
Curriculum and Instruction	-21.52	-14.25	-18.05	3.52	2.73	3.14	12.9	13.2	13.0
Education	-17.16	-14.15	-16.11	4.17	4.00	4.11	36.9	28.6	34.4
Education Administration	-24.46	-15.84	-21.25	3.74	3.23	3.55	11.1	20.8	16.3
Special Education	-15.17	-13.19	-14.02	4.03	4.10	4.07	41.2	21.2	33.9
Education (avg)	**-19.96**	**-14.42**	**-17.67**	**3.84**	**3.44**	**3.67**	**31.5**	**20.5**	**28.5**
(interdomain)	**-19.48**	**-18.05**	**-18.40**	**4.77**	**3.56**	**3.85**	**35.0**	**25.6**	**28.4**

ENGINEERING									
Field	**Dept. prestige change**			**Time to hire (yrs)**			**Postdoc rate (%)**		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Aerospace Engineering	-17.07	-14.81	-15.32	6.29	5.12	5.38	64.4	58.9	60.1
Agricultural Engineering	-17.87	-13.33	-15.05	7.87	4.97	6.07	82.0	65.3	72.7
Civil Engineering	-14.97	-16.76	-16.50	6.01	4.47	4.70	57.5	50.7	52.2
Electrical Engineering	-15.40	-15.14	-15.19	7.21	5.31	5.64	61.1	34.8	40.1
Environmental Engineering	-14.89	-15.78	-15.61	6.48	4.21	4.64	60.5	51.4	53.8
Industrial Engineering	-15.36	-14.79	-14.94	4.54	3.96	4.11	34.9	28.0	30.5

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Continuation of Table A3

Field	Dept. prestige change			Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Materials Engineering	-17.62	-16.21	-16.69	7.50	6.93	7.12	77.0	67.9	71.7
Mechanical Engineering	-19.79	-17.03	-17.68	6.22	5.80	5.90	64.0	53.8	55.9
Operations Research	-22.30	-17.94	-20.92	3.28	2.68	3.09	40.0	18.4	31.6
Systems Engineering	-18.68	-13.35	-15.11	5.43	3.26	3.98	38.1	28.2	31.8
Engineering (avg)	**-17.79**	**-15.61**	**-16.17**	**6.35**	**5.17**	**5.47**	**57.9**	**45.7**	**50.0**
(interdomain)	**-19.29**	**-16.31**	**-16.69**	**7.26**	**5.40**	**5.64**	**65.7**	**50.6**	**52.5**

HUMANITIES

Field	Dept. prestige change			Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Art History and Criticism	-26.01	-27.44	-26.69	3.47	3.67	3.57	34.8	38.9	35.6
Asian Languages	-27.91	-21.27	-24.00	4.51	2.35	3.24	50.0	35.3	40.0
Asian Studies	-27.50	-21.60	-24.00	3.39	2.21	2.69	50.0	42.1	44.4
Classics and Classical Languages	-29.66	-22.66	-26.14	3.03	2.31	2.67	0.0	30.8	28.6
Comparative Literature	-23.12	-17.00	-19.68	2.78	2.71	2.74	37.5	12.5	32.5
English Language and Literature	-24.53	-20.35	-21.22	4.04	3.32	3.47	14.7	25.6	23.8
French Language and Literature	-24.65	-21.18	-22.16	2.95	2.39	2.55	0.0	27.3	21.4
Germanic Languages and Literatures	-30.20	-18.30	-21.81	3.36	3.00	3.11	0.0	75.0	60.0
History	-25.83	-23.49	-24.21	3.91	3.48	3.61	60.8	46.2	52.4
Humanities	-25.26	-26.46	-25.52	5.08	2.16	4.45	50.0	0.0	47.4
Italian Language and Literature	-19.79	-19.72	-19.73	2.08	2.67	2.57	0.0	54.5	40.0
Linguistics	-19.35	-15.25	-16.07	3.85	3.87	3.86	50.0	48.5	49.2
Music	-26.43	-22.43	-22.81	5.11	3.22	3.40	20.0	10.9	11.7
Near and Middle Eastern Languages and Cultures	-25.90	-21.36	-23.48	4.30	3.09	3.65	40.0	66.7	43.5
Philosophy	-25.75	-22.79	-23.13	5.67	4.01	4.20	35.3	33.3	33.7
Religious Studies	-26.01	-26.55	-26.35	4.46	3.41	3.81	11.8	35.7	26.7
Slavic Languages and Literatures	-28.10	-20.41	-23.13	3.96	2.67	3.13	0.0	37.5	33.3
Spanish Language and Literature	-23.77	-19.78	-20.86	2.96	2.61	2.71	20.0	25.0	23.5
Theatre Literature, History and Criticism	-25.52	-23.72	-24.29	4.26	3.20	3.53	20.0	0.0	6.2
Theological Studies	-26.22	-15.46	-20.50	4.50	3.25	3.83	33.3	11.1	20.0
Humanities (avg)	**-25.21**	**-21.46**	**-22.54**	**4.11**	**3.41**	**3.61**	**26.4**	**32.8**	**33.7**
(interdomain)	**-25.01**	**-22.75**	**-22.99**	**4.83**	**3.53**	**3.67**	**52.3**	**32.5**	**35.9**

MEDIA AND COMMUNICATION

Field	Dept. prestige change			Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Communication	-19.19	-20.84	-20.40	4.19	3.73	3.85	18.6	12.8	14.6
Mass Communications and Media Studies	-23.31	-18.92	-20.88	3.44	3.11	3.26	16.7	13.1	14.2
Media and Communication (avg)	**-21.11**	**-20.27**	**-20.56**	**3.86**	**3.57**	**3.67**	**17.6**	**13.0**	**14.4**
(interdomain)	**-20.64**	**-20.61**	**-20.62**	**4.29**	**3.52**	**3.66**	**19.5**	**13.6**	**14.8**

MATHEMATICS AND COMPUTING

Field	Dept. prestige change			Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Computer Engineering	-16.02	-15.14	-15.28	7.18	4.98	5.34	54.0	33.8	37.6
Computer Science	-17.95	-16.87	-17.05	5.95	4.89	5.06	53.8	39.5	42.2

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Continuation of Table A3

Field	Dept. prestige change			Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Information Science	-22.41	-18.69	-20.31	6.21	4.18	5.07	26.4	36.5	32.3
Information Technology	-24.77	-18.46	-22.16	5.77	4.21	5.12	14.9	24.3	19.0
Mathematics	-22.33	-20.34	-20.64	6.57	5.87	5.97	68.5	75.9	75.0
Statistics	-13.85	-19.45	-18.35	5.59	4.79	4.95	54.9	52.2	53.3
Mathematics and Computing (avg)	**-18.75**	**-17.33**	**-17.62**	**6.18**	**5.08**	**5.30**	**45.4**	**43.7**	**43.2**
(interdomain)	**-20.20**	**-17.60**	**-17.88**	**6.96**	**5.15**	**5.34**	**55.0**	**51.0**	**51.5**

MEDICINE AND HEALTH

Field	Dept. prestige change			Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Communication Disorders and Sciences	-22.09	-14.72	-18.88	4.71	3.94	4.38	34.3	30.2	32.1
Environmental Health Sciences	-23.31	-11.72	-19.77	9.41	5.16	8.11	75.4	58.3	69.1
Epidemiology	-21.62	-10.43	-15.71	8.44	6.28	7.30	69.4	64.7	66.7
Exercise Science, Kinesiology, Rehab, Health	-19.56	-12.81	-15.65	6.50	4.70	5.46	49.7	48.8	49.1
Genetics	-15.78	-13.11	-15.12	10.43	10.10	10.35	92.1	91.1	91.8
Health, Physical Education, Recreation	-22.18	-15.33	-19.22	4.16	3.24	3.77	29.7	32.4	31.1
Human Development and Family Sciences	-19.99	-12.74	-17.34	4.65	3.95	4.40	54.2	41.0	48.3
Immunology	-17.95	-9.87	-14.46	12.63	11.07	11.96	93.9	93.8	93.8
Nursing	-20.43	-8.66	-10.20	7.71	4.51	4.93	50.0	35.9	36.4
Nutrition Sciences	-16.84	-9.44	-12.51	7.59	5.17	6.18	64.4	62.7	63.5
Pharmaceutical Sciences	-23.56	-14.05	-20.70	11.36	8.04	10.36	81.6	65.6	75.3
Pharmacology	-18.99	-8.47	-16.00	12.12	11.18	11.85	84.4	88.3	86.0
Pharmacy	-20.25	-9.26	-14.60	10.06	8.39	9.20	71.2	41.4	55.0
Physiology	-18.68	-9.13	-15.65	11.29	10.80	11.13	88.2	87.4	87.9
Public Health	-24.86	-12.65	-20.80	8.07	5.15	7.10	66.9	55.1	60.6
Social Work	-19.20	-16.31	-16.72	4.70	3.24	3.45	48.3	27.0	29.5
Speech and Hearing Sciences	-21.20	-12.57	-17.40	5.28	3.49	4.49	45.2	48.6	47.1
Veterinary Medical Sciences	-17.56	-10.55	-13.66	9.04	6.42	7.58	76.1	40.0	56.1
Medicine and Health (avg)	**-20.39**	**-11.29**	**-15.62**	**8.51**	**5.27**	**6.81**	**65.3**	**56.2**	**60.0**
(interdomain)	**-22.61**	**-13.64**	**-16.15**	**8.55**	**6.32**	**6.94**	**70.7**	**59.6**	**61.6**

NATURAL SCIENCES

Field	Dept. prestige change			Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Anatomy	-21.53	-10.87	-18.24	11.54	9.89	11.03	84.2	83.3	83.8
Astronomy	-18.02	-18.42	-18.37	10.24	9.07	9.20	82.2	88.0	86.8
Atmospheric Sciences and Meteorology	-18.48	-14.82	-15.97	10.59	6.21	7.59	78.7	79.7	79.4
Biochemistry	-14.83	-18.29	-16.93	10.58	10.84	10.74	92.1	92.1	92.1
Biological Sciences	-20.20	-17.05	-19.05	10.66	9.32	10.17	90.0	89.2	89.7
Biomedical Engineering	-21.63	-12.49	-17.43	9.46	6.29	8.00	78.2	74.7	76.2
Biomedical Sciences	-26.75	-16.56	-25.33	12.58	7.80	11.91	83.9	76.9	82.6
Biophysics	-15.14	-10.80	-13.65	10.94	9.38	10.41	94.0	95.9	94.6
Biostatistics	-25.62	-15.53	-20.87	8.28	5.02	6.74	66.2	44.9	54.6
Cell Biology	-19.25	-14.95	-17.92	11.65	10.10	11.17	91.7	93.8	92.3
Chemical Engineering	-18.49	-17.09	-17.38	8.01	6.18	6.55	73.6	64.7	66.6
Chemistry	-15.95	-18.64	-18.21	9.28	9.22	9.23	86.8	89.0	88.3
Computational Biology	-26.15	-16.75	-23.23	9.96	4.72	8.33	73.3	37.5	60.9
Ecology	-12.33	-14.54	-13.36	6.59	6.31	6.46	88.7	91.3	89.5

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Continuation of Table A3

Field	Dept. prestige change			Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Entomology	-9.43	-6.64	-7.28	8.00	8.62	8.48	75.3	63.4	67.8
Environmental Sciences	-21.13	-17.95	-19.79	7.94	6.60	7.38	78.0	61.7	70.1
Evolutionary Biology	-9.48	-12.04	-10.73	7.13	6.39	6.77	92.5	83.8	90.1
Forestry and Forest Resources	-20.30	-8.21	-14.99	5.75	5.71	5.74	76.2	40.5	52.9
Geology	-20.72	-18.88	-19.42	8.37	5.81	6.56	75.7	75.7	75.7
Marine Sciences	-18.99	-16.55	-17.86	9.39	7.95	8.72	91.3	88.8	89.9
Microbiology	-15.34	-9.74	-12.84	11.44	10.58	11.06	89.8	90.3	90.1
Molecular Biology	-15.36	-14.75	-15.13	10.90	10.48	10.74	94.5	96.2	95.0
Natural Resources	-20.72	-8.00	-16.65	6.86	5.72	6.50	71.2	55.4	63.6
Neuroscience	-17.94	-12.13	-15.69	12.43	9.22	11.19	88.0	86.8	87.5
Oceanography	-19.55	-15.89	-17.61	11.04	7.00	8.91	86.8	80.7	83.6
Pathology	-18.09	-7.27	-14.54	12.00	10.99	11.67	80.5	58.3	72.4
Physics	-18.80	-18.16	-18.23	9.66	9.85	9.83	77.0	90.5	86.8
Plant Pathology	-14.29	-12.12	-12.88	7.04	7.54	7.36	83.3	70.0	75.3
Natural Sciences (avg)	**-18.90**	**-15.69**	**-17.09**	**10.19**	**8.43**	**9.20**	**83.0**	**76.5**	**79.9**
(interdomain)	**-18.86**	**-16.86**	**-17.12**	**9.48**	**9.12**	**9.16**	**76.8**	**84.5**	**83.3**

PUBLIC ADMINISTRATION AND POLICY

Field	Dept. prestige change			Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Public Administration	-23.52	-16.46	-20.40	4.58	3.20	3.97	30.0	11.5	19.6
Public Policy	-22.22	-16.48	-20.27	4.60	3.09	4.09	37.3	27.8	32.4
Public Administration and Policy (avg)	**-22.82**	**-17.13**	**-20.71**	**4.50**	**3.25**	**4.04**	**33.6**	**19.7**	**26.0**
(interdomain)	**-22.77**	**-18.61**	**-20.59**	**4.68**	**3.46**	**4.04**	**32.7**	**31.6**	**32.1**

SOCIAL SCIENCES

Field	Dept. prestige change			Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Agricultural Economics	-26.74	-21.34	-25.18	3.25	3.62	3.36	15.2	17.2	16.0
Anthropology	-14.21	-19.41	-19.00	4.87	5.07	5.06	54.1	49.4	50.5
Criminal Justice and Criminology	-21.45	-21.75	-21.68	4.44	3.56	3.78	11.1	13.0	12.6
Economics	-18.88	-21.27	-20.87	3.64	3.15	3.23	32.4	21.8	25.9
Educational Psychology	-15.98	-13.37	-15.14	3.47	3.81	3.58	60.5	37.3	56.8
Gender Studies	-26.99	-21.11	-25.83	5.49	2.87	4.97	33.3	62.5	50.0
Geography	-17.88	-18.99	-18.71	5.84	4.64	4.94	40.7	33.7	35.6
International Affairs	-29.05	-23.38	-27.35	4.74	4.16	4.57	28.6	12.5	17.4
Political Science	-18.86	-20.39	-20.17	3.38	3.03	3.08	33.0	40.4	38.6
Psychology	-19.06	-15.37	-16.42	6.47	5.67	5.90	66.7	65.1	65.7
Sociology	-16.87	-20.94	-20.46	5.10	3.71	3.87	45.7	36.3	38.7
Social Sciences (avg)	**-20.11**	**-18.48**	**-18.90**	**4.83**	**4.16**	**4.33**	**38.3**	**35.4**	**37.1**
(interdomain)	**-16.62**	**-19.26**	**-18.97**	**5.04**	**4.31**	**4.39**	**55.6**	**46.5**	**48.7**

ACADEMIA

Field	Dept. prestige change			Time to hire (yrs)			Postdoc rate (%)		
	Inter	Within	All	Inter	Within	All	Inter	Within	All
Academia	**-19.74**	**-16.06**	**-17.43**	**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 ($p < 10^{-9}$, Benjamini-Yekutieli corrected). Second, interdomain hires experience a slightly smaller increase in time-to-hire, taking 1.4 years longer to be hired ($p < 10^{-100}$, 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).

Finally, the same inconclusive patterns in prestige change hold for interdomain hires as for interfield hires. Interdomain hires fall further in the prestige of their department placements by 3.4 units compared to within-domain hires. This department placement disadvantage appears in 9 domains and is significant in 8, with a significant placement advantage in only 1 domain ($p < 0.05$, Benjamini-Yekutieli corrected; Table A3). Once again, at the institution level the prestige effect is reversed: interdomain hires place into institutions with 2.8 units higher prestige compared to within-domain hires on average, and this effect is significant in Academia and 5 domains ($p < 0.048$, Benjamini-Yekutieli corrected).

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 ($p < 10^{-7}$, 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).

Despite being even more productive than fully interdisciplinary hires and experiencing a slightly smaller delay in time-to-hire, partially interdisicplinary hires appear to suffer a small but systematic placement disadvantage compared to their within-discipline peers. Unlike fully interdisciplinary hires, who have a placement disadvantage in department prestige but a placement advantage in institution prestige, partially

interdisciplinary hires have a disadvantage in both. They fall further than within-discipline hires by 3.1 units of department prestige and 0.5 units of institution prestige ($p < 10^{-6}$, Benjamini-Yekutieli corrected). More work is needed to understand this difference in institutional prestige between fully and partially interdisciplinary hires, but it seems likely that it is a result of the interaction between the field-level hierarchy superimposed on department prestige (Fig. A2) and multidisciplinary departments. Intuitively, partially interdisciplinary hires are more likely to be hired into multidisciplinary departments, thus making them only partially interdisciplinary because they retain affiliations with their degree fields (e.g. a Computer Science PhD hired into a Computer Science and Engineering department would be partially interdisciplinary, while one hired into a Computer Science department would be fully interdisciplinary).

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. A3). 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-

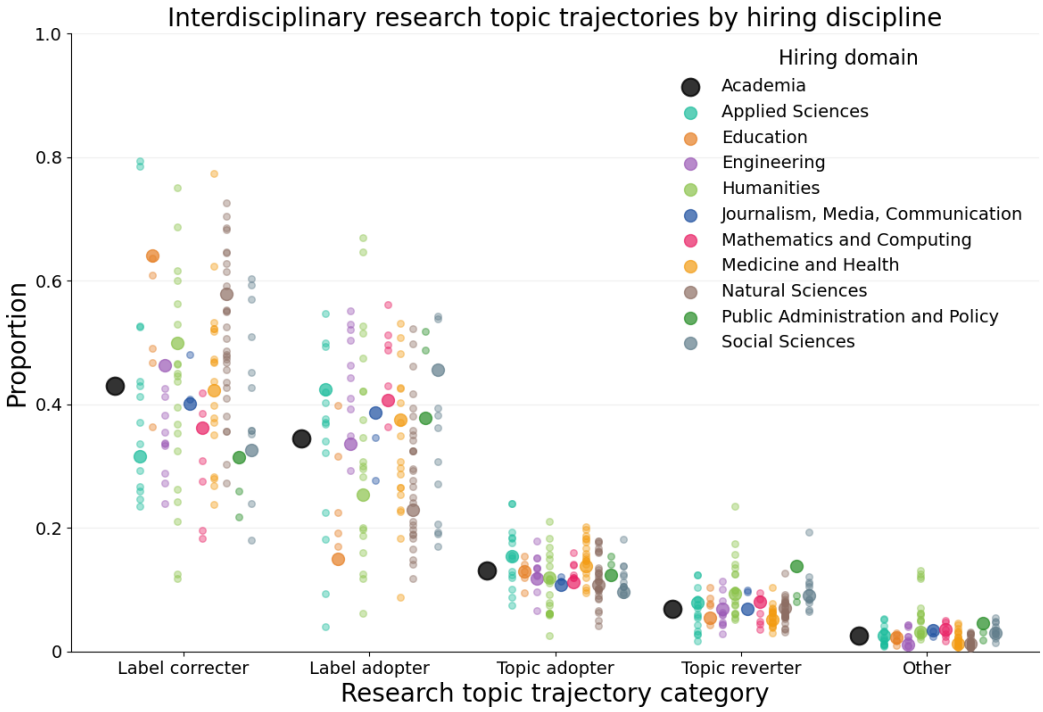


Figure A3: Proportions of interdisciplinary hires in each career class for each domain (large circles), field (small circles), and academia overall (black).

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, time-to-hire, and prestige (Sections 4 and 3.3) 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 and a placement disadvantage in department prestige, but the magnitude of these effects varies between categories. Both label correcters and topic reverters were publishing research consistent with their hiring discipline even before being hired, but whilethe time-to-hire increase and department prestige decrease effects are slightly attenuated for topic reverters, these effects are slightly mangified for label correcters. Faculty in the "other" trajectory type face the largest disadvantages along all three 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**	**+Time-to-hire (years)**	**Δ Dept. prestige change**
Label correcter	7.8%	1.9	−3.9
Label adopter	11.8%	1.2	−3.5
Topic adopter	−11.1%	1.7	−4.6
Topic reverter	−13.0%	1.4	−3.3
Other	−25.4%	2.1	−6.5

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. A4). 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).

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 be-

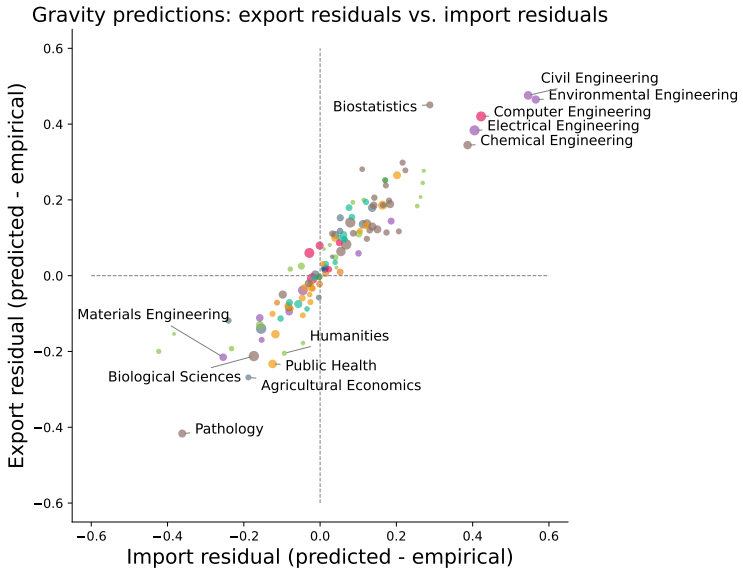


Figure A4: Residuals of the gravity model predictions for field-level export rates vs. residuals for import rates. Circles are fields colored by domain. Labeled fields are those with the six largest and six most negative export residuals.

tween 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. A4). 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).

Discipline	**Interdisc.**	**Interdisciplinary**			**Disciplinary**		
level	**definition**	**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.

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 ($p \approx 0.0$, 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. A5)

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

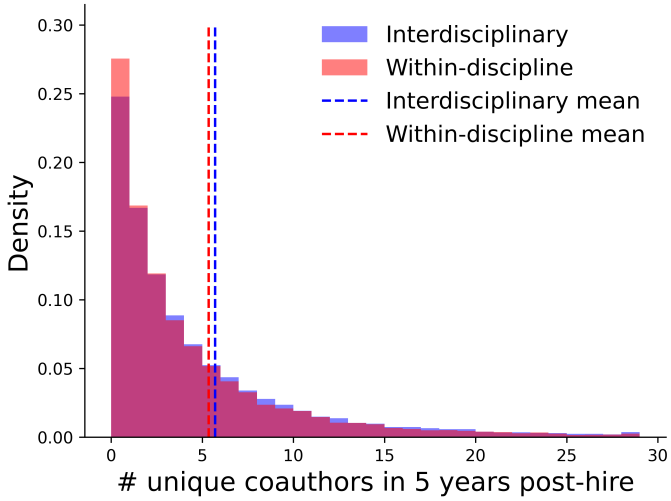


Figure A5: Histogram of the number of unique co-authors in the 5 years post-hire for interdisciplinary (blue) and disciplinary (red) faculty hires. The mean number of co-authors is slightly higher for interdisciplinary hires (5.7 vs. 5.3), but the medians are the same.

significant shift.

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