

**Quantifying patterns in faculty mid-career moves in PhD
granting universities in the US**

by

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Thesis directed by Prof. Daniel B. Larremore

Despite numerous enlightening studies of the hiring and retention of academic faculty, relatively little is known about the rates, patterns, and causes of mid-career moves (MCMs). Here, we analyze 10 years (2011-2020) of an annual U.S. faculty census to characterize MCMs. Although MCMs are rare in academia, we find a rich heterogeneity in the annual MCM rate by field and domain. Younger faculty, faculty at elite institutions and rural institutions are at a higher risk of moving, self-hires are at a much lower risk, while we do not find a significant gender effect on MCM risk. MCMs tend to move faculty to institutions that are closer in prestige to their origin institution than we expect, exhibit significant assortativity between public and private institutions and effectively increase the number of self-hires and faculty at private and urban institutions. Faculty experience prestige advantages when they move to their alma mater, to private and urban institutions, while women gain slightly more prestige than men over MCMs. Finally, we find that faculty tend to trade prestige for a promotion when they move, prompting us to develop a utility theory of faculty MCMs. These findings quantify large-scale patterns in faculty MCMs in tenure-track/tenured faculty in PhD granting universities in the US at an unprecedented scale, enriching the grounds for further research to determine causal mechanisms that drive these patterns.

Dedication

To my family, mentors and friends who have molded me into what I am today.

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Chapter 1

Introduction

The distribution of talent and personnel is critical to understanding the academic research and innovation ecosystems. Consequently, numerous studies of the patterns and drivers of faculty hiring [5, 21], promotion [1], and attrition [20, 24, 9, 15, 26, 7, 18] have painted an increasingly detailed and quantitative portrait of entry into and exit from the academic labor market, particularly in the U.S. However, despite the substantial attention paid to the market's inflows and outflows, there is comparatively little quantitative study of mid-career moves in which faculty change positions but remain in the academy.

While the present work focuses on broad-scale quantitative analyses, the study of faculty mid-career moves goes back to a landmark 1958 analysis of faculty vacancies and how they are filled, by Caplow and McGee [4]. They outline a comprehensive discussion about how factors like demand for talent, tenure pressures, productivity, compensation and fit of work environment drive mechanisms that create and fill vacancies in academia. From then on, there have been many faculty turnover studies reasoning out the factors influencing factors influencing faculty's decision to depart their institution of employment, most using survey analysis of intent to leave as a proxy for actual faculty departure.

Broadly, faculty turnover has been studied from the perspective of push (work stress, poor fit) and pull factors (higher salary, prestige, better resources) influencing faculty intent to leave [15], finding that having strong pull factors is not sufficient faculty to initiate departure if faculty are already thriving in their current institution. Among these studies, seniority in faculty and tenure

status, especially in large, wealthy and private institutions, were found to decrease the tendency of faculty to leave an institution [29, 4]. On the contrary, job dissatisfaction and poor fit were found to be strong drivers of faculty turnover [29].

Productive faculty were found to have mixed effects on faculty turnover, with some studies claiming higher rates of turnover for highly productive faculty [18], while others found an insignificant effect of productivity on turnover [29]. Similarly, there have been mixed results about gender influences on faculty departure. Gender influenced faculty intention to leave through job satisfaction, teaching and research productivity, with these influences being different for different fields [26]. In addition to gender, demographic variables like race and perceptions of campus racial climate have been found to influence intent to leave through job satisfaction [11]. However, [29] found gender and demographic effects to be very small. These mixed results might emphasize the need to study mid-career moves in isolation, instead of pooling these transitions with attrition, something that is very common in the faculty turnover literature.

In the past, there have been few studies that looked at faculty mid-career moves more explicitly. In faculty mid-career moves, the destination prestige was found to be highly correlated with the origin prestige of the movers [1] while productivity was found to have a small effect on where faculty go after moving. In addition, among the few large-scale studies of faculty mid-career moves that have been done [7], it was found that tenured faculty at high prestige institutions are at a higher risk of moving. More importantly, this study emphasized the crucial role of compensation in faculty retention rates. Higher levels of compensation were found to increase retention rates for assistant and associate professors but not for full professors.

Many of these studies analyze “moves” in the context of why academics leave their positions (focused on attrition and turnover), but do not often differentiate between mid-career moves and attrition [29, 24, 26]. We therefore have a decent understanding of risk factors for leaving, but little detail on risk factors for within-academy moves, and where people go — thus it is hard to tell what the consequences of MCMs are. Moreover, it was found that although faculty expressed factors like higher salary, better opportunities and prestige as the reasons for their intention to

leave, these hardly ever materialized. Instead, in reality, most faculty that actually left stated poor work environment and fit as the reason for leaving [17]. This finding strongly undercuts previous literature that rely on faculty departure intention to study the factors that influence actual departures. In addition, many of these previous studies have analyzed faculty turnover for a handful of faculty, sometimes at a single institution, restricting us to insights about narrow case studies instead of broader patterns in all of academia.

This study aims to provide a broad and quantitative portrait of mid-career moves within U.S. tenure-track academia through three types of analysis. First, we measure the rates of mid-career moves across career stages and fields, and analyze the individual and institutional covariates that help explain them. Next, we investigate the effects of these moves on the composition and distribution of faculty across the academy, using a network lens to better understand what makes mid-career moves different from random mixing. Finally, we analyze the potential impacts of mid-career moves on faculty careers.

To support our analysis, this study brings to bear a sequence of ten annual censuses of all tenure-track faculty at U.S. PhD-granting institutions. Because these records are collected annually, comparison of adjacent years allows us to identify mid-career moves and analyze them in the context of institutional covariates, including prestige and urban/rural and public/private status, as well as individual covariates, including career age, academic rank, gender, and whether one holds a position at one's doctoral alma mater. And, facilitated by the ten sequential years of data, observations of faculty post-move allow us to develop hypotheses about the consequences of moving for academic careers, including time to promotion and tenure.

Chapter 2

Results

2.1 Mid-career moves: rates and risk factors

Faculty surveys have shed light on the numerous individual-level reasons that drive faculty intentions to move from the bottom up. Our analysis takes a complementary top-down approach by describing mid-career move rates, analyzing how they vary by observable factors, and untangling the predictors of mid-career moves using a statistical model of risk factors.

On average, during our 2011-2020 period of observation, 1.03% of faculty made a mid-career move each year from one tenure-track position at a US PhD-granting institution to another. However, mid-career move rates varied considerably by domain of study. For instance, faculty in Public Administration and Policy (1.51%), Applied Sciences (1.36%) and Education (1.33%) made mid-career moves at higher than average rates, while those in the Humanities (0.73%) and Natural Sciences (0.79%) moved at lower rates (Fig 2.1A). In some cases, these averages hide substantial variation from field to field within the same domain. For instance, annual mid-career move rates in Applied Science fields ranged from 0.62% in Plant Sciences to 1.90% in Accounting, with substantial variability across Natural Science fields (0.45%- 1.50%) and Social Science fields (0.79%- 1.64%). On the other hand, rates are markedly more tightly clustered among the fields of the Humanities, Education, and Engineering (Fig. 2.1A), suggesting that the mechanisms driving mobility depend, in some way, on the domains of scholarship, their cultures, their vacancy rates, or some other correlated factors. Rates by domain and field are provided in Table A.1.

While mobility rates are highly variable across fields, they are even more variable across career

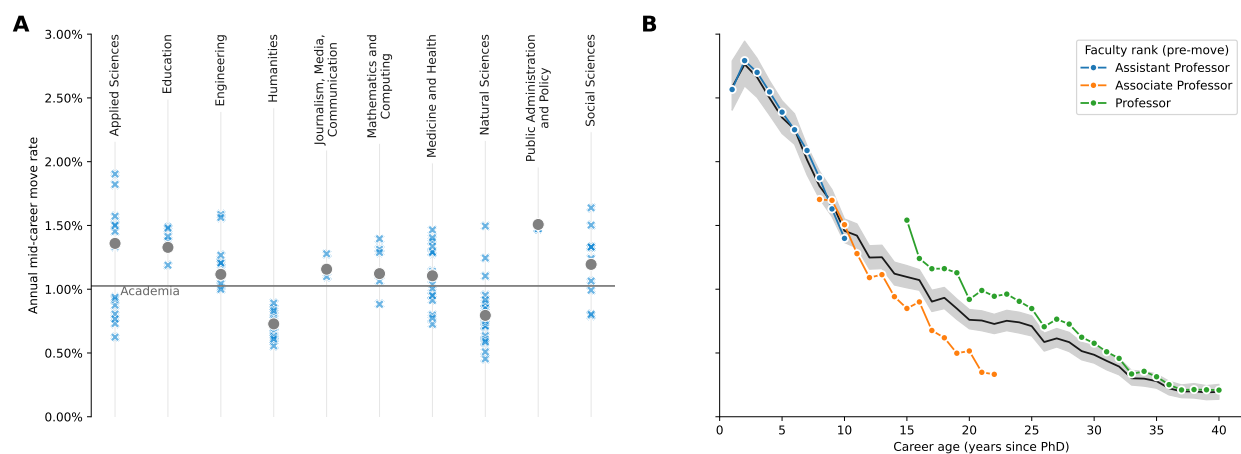


Figure 2.1: Annual mid-career move rates vary substantially by field, career age, and academic rank. **A)** Average annual mid-career move rates (2011-2020) are shown along the vertical axis for Academia (solid gray line), various academic domains (grey circles), and their constituent fields (colored crosses), estimated independently. Corresponding values and standard errors are provided in Table A.1. **B)** The horizontal axis depicts career age while the vertical axis shows the annual mid-career move rate. The black solid line plots the annual mid-career move rate for all faculty at a given career age with the shaded regions around the line showing 95% confidence intervals for the rate estimate. The annual mid-career move rates for individual ranks are shown by the colored lines - for those career ages where the rank makes up at least 30% of the total professoriate.

ages. Mid-career move rates peak 2 years post-PhD at 2.76%, and exceed 2% only in years 1-7, after which they fall to 1.5% by year 10, to 1% by year 16, and 0.5% by year 30 (Fig. 2.1B). These quantitative measurements of realized mid-career moves align well with past survey-based studies of intentions to move which have shown that intentions to leave tend to decrease with career age. This pattern of intent is attributed to sunk cost, satisficing, and risk aversion behaviors [18, 29], the deterrents of accumulated workplace benefits, institutional integration, and social ties which increase the cost of moving [19, 29], and simply fewer opportunities or diminished job attractiveness in the job market [19, 29].

Beyond field, career age, and academic rank, numerous other observable covariates have the potential to influence mid-career move rates. These include factors noted in past survey analyses of intent to move, including whether a university is public vs private [29] or urban vs rural [27] and faculty gender [29, 26, 9]. They also include factors studied in the faculty hiring and attrition literature, including institutional prestige [5, 21] and whether one holds a faculty position at one's doctoral alma mater, a so-called self hire [21]. To investigate these potential risk factors for mid-career moves, we used a logistic regression model on pooled panel data, while controlling for field, academic year, academic rank, and career age (see Methods, Fig. 2.2).

Among the investigated factors, holding a faculty position at one's doctoral alma mater was associated with the largest decrease in mid-career move risk, dropping mid-career move odds by a factor of two, relative to non-self-hires (OR 0.50, $p < 0.001$). On the other hand, mid-career moves were more common among faculty sitting at rural institutions (OR 1.18, $p < 0.001$). The remaining factors—gender, prestige, and public/private status, bear more detailed discussion.

When computed directly from panel data, annual mid-career move rates were 1.13% for women vs 0.95% for men ($p < 0.001$). However, in our logistic regressions, gender retained no association with mid-career move risk ($p = 0.73$). This led us to investigate which covariate(s) could most efficiently explain top-line differences between rates and risk. We found that the association between gender and mid-career move risk became insignificant upon the inclusion of career age as a covariate, leading us to conclude that gender differences in mid-career move rates are likely due

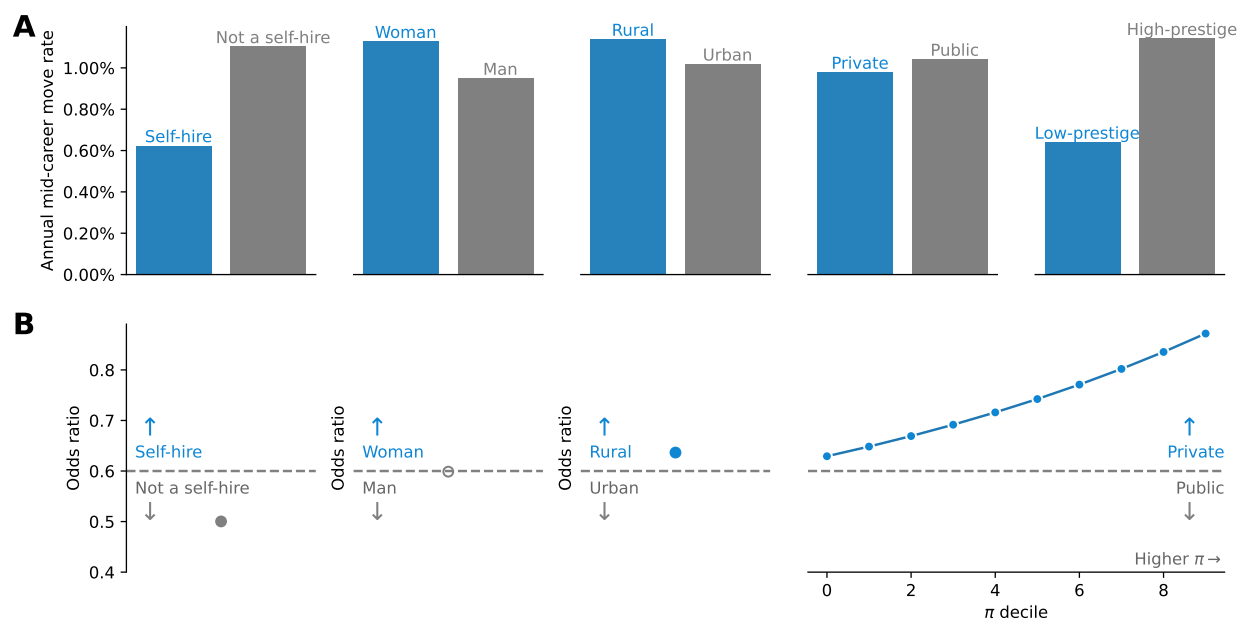


Figure 2.2: **Annual Mid-career move rates and odds ratios by self-hire status, gender, institution locale, institution type and prestige.** **A)** Annual mid-career move rates shown on the vertical axes for different risk factors, without controlling for other risk factors. **B)** Odds ratios shown on the vertical axis for different risk factors from a logistic regression model that predicts whether a faculty makes mid-career moves. Different odds ratios are computed for private against public institutions at different prestige deciles because we interact institution type and prestige in the model. Faculty at rural, public, high-prestige institutions and those that are not self-hires make mid-career moves at a statistically significantly higher annual rate. Women move at a higher rate compared to men, however, this might be because there is a higher fraction of women at lower career ages than that of men (Fig. A.2). Faculty at private institutions, although appearing to have a lower mid-career move rate than those at public institutions, are actually found to have a higher mid-career move rate than public institutions when we control for all risk factors.

to rate variation by career age (Fig. 2.1B) which interacts with the differential gender composition by age (Fig. A.2) owing to demographic turnover [21] and gendered attrition [20].

covariate(s)	coef	std err	p
Self-hire	-0.6902	0.036	$< 10^3$
Prestige (per decile)	0.0534	0.004	$< 10^3$
Private×Prestige (per decile)	0.0803	0.009	$< 10^3$
Female	-0.0058	0.017	0.730
Rural	0.1683	0.034	$< 10^3$
Private	0.1369	0.029	$< 10^3$

Table 2.1: **Analysis of mid-career move risk via logistic regression.** Table shows logistic regression model results for mid-career move risk on pooled panel data. Controls include career age (years since PhD), faculty rank, field, and academic year. Coefficients describe increases in log-odds of making a mid-career move vs the reference class of a non-self-hire man in the top prestige decile at an urban public institution, using prestige reported in Ref. [21]. See methods for the more details.

Higher institutional prestige was associated with increased risk of mid-career moves, but this association was stronger for private vs public institutions: a one-decile increase in prestige increases the odds of a mid-career move by 1.08-fold at private institutions vs 1.05-fold at public institutions ($p < 0.001$). Since mid-career move risks are already higher at private institutions at the bottom of the prestige hierarchy (OR=1.15), mid-career move risks are markedly higher at private institutions at the top (OR 2.36). These interactions emphasize the importance of prestige in shaping the mid-career labor market, and the potential challenges in interpreting public vs private institutional differences in the absence of prestige.

2.2 Nature of mid-career moves and their impact

2.2.1 Flows

While the rates and risk factors investigated in the previous section shed light on who makes mid-career moves, they do little to answer two important questions: what are the net effects of mid-career moves on academia? And what can we reveal about the possible reasons for making moves as revealed by actual moves, but in the absence of survey data?

At a high level, the net effect of mid-career moves during 2011-2020 was to move faculty from rural to urban areas, and from public to private institutions. Among the total $N = 20,507$ mid-career moves, 5.6% of mid-career moves were from rural to urban institutions, while 3.8% were from urban to rural (Fig. 2.3B). In other words, for every 10 professors moving away from a rural institution in our data, only about 6.85 professors come back, resulting in a net flow of 363 faculty from urban to rural, effectively reducing the number of faculty at rural institutions. Exchange between public and private institutions was more frequent with 14.3% of mid-career moves from private to public, and 15.2% from public to private (Fig. 2.3A), for a net gain of 175 faculty by private institutions. Among movers, we find an assortativity of 0.225 in the institution type (public, private) of their pre- and post-move affiliations, with faculty in private universities approximately twice as likely to go to another private university than suggested by a null model that rewires mid-career moves, keeping the faculty flows at institutions fixed (Configuration model, see Materials and Methods).

In addition to moving faculty between different institution types and locales, mid-career moves essentially reshuffle faculty within the prestige hierarchy in academia, moving people up and down the hierarchy. We find that mid-career moves induce a near symmetry in flows going up and down the prestige hierarchy with 51.88% faculty moving up and 48.12% moving down, resulting in a net prestige gain of 2.80 positions (Fig. 2.3D). This symmetry is in contrast to the skewed distribution of prestige changes for initial placements, where faculty are placed 18% below their graduate institution on average [21], suggesting that the drivers of prestige change dynamics are possibly different between mid-career moves and initial hires.

Additionally, we find that faculty are much more likely to move to an institution that is closer in prestige to their current institution (under a Mann-Whitney U test, $P < 10^{-5}$) than what is suggested by a null model (Fig. 2.3D) in which mid-career moves are randomly rewired, keeping the flows at individual institutions, and the flows between public/private and urban/rural institutions fixed in expectation (Degree-corrected stochastic block model, see Materials and Methods). On average, faculty see a prestige change of 82 positions in either direction over moves, compared to

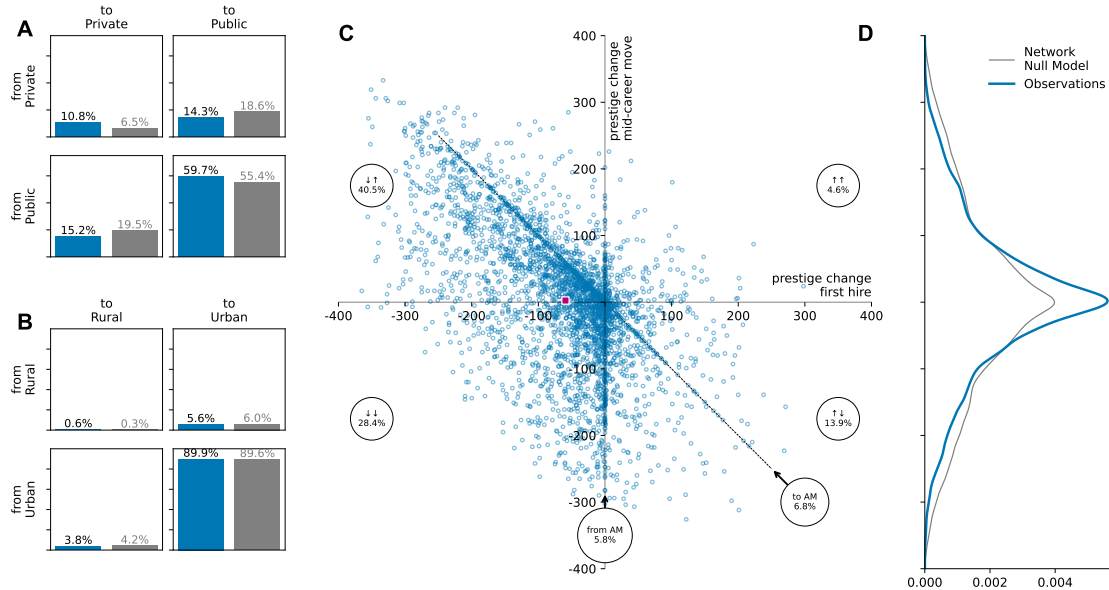


Figure 2.3: **Flows induced by mid-career moves in academia.** **A)** Fraction of moves for each type of public/private transition with the blue bars showing empirical fractions and gray bars showing fractions from a configuration model null model, **B)** same as **A)** but for urban/rural transitions, **C)** Prestige change patterns of mid-career movers showing their initial placement prestige change on the horizontal axis and their mid-career move prestige change on the vertical axis, with the red dot indicating the mean of all points. Self-hires being created ($y = -x$) and destroyed ($x = 0$) stand out as special cases. **D)** Marginal prestige change distribution of mid-career moves, in the data (blue) and a null model (gray). The vertical axis is shared with the vertical axis in **C)**, showing prestige change, with positive values indicating a prestige gain. The horizontal axis shows the density of moves at a particular prestige change.

about 105 positions in the null model. We observe more mid-career moves than we expect from a null model in the prestige change interval ranging from a drop of 67 places to a gain of 90 places.

When we juxtapose the reshuffling of faculty within the prestige hierarchy during mid-career moves against their prestige change during initial placements, we find a rich heterogeneity in the type and frequency of prestige change patterns that we observe, with mid-career moves involving self-hires being special cases (Fig. 2.3C). Most frequent are faculty moving down the prestige hierarchy during their initial placement and going up when they make a mid-career move (down-up), making up 40.51% of our movers. Then we find 28.42% of movers going down-down, 13.93% going up-down and only 4.58% of movers going up-up.

Self-hiring is seen as having a negative impact on the quality of academic research and the spread of ideas [16, 6], while also being associated with higher attrition rates [21]. In light of our study of MCMs, self-hires are interesting because they can be created by a mid-career move (a homecoming MCM) or destroyed by a mid-career move (a leaving-the-nest MCM). In our data, mid-career moves create 1212 self-hires and destroy 988, effectively increasing the number of self-hires in academia, exacerbating academic inbreeding. Although 11% of the initial placements are self-hires [21], only 5.79% of mid-career moves take self-hires away from their alma mater (points on $x = 0$ in Fig. 2.3C), much lesser than we would expect if we assumed mid-career moves affected faculty uniformly at random. This is possibly explained by our earlier observation that self-hire positions have a protective effect against mid-career moves. On the other hand, 6.77% of mid-career moves return faculty back to their alma mater (points on $y = -x$ in Fig. 2.3C), which is much higher than 0.75% in a null model that rewires mid-career moves keeping the inflow and outflow at each institution the same (Configuraiton model, see Materials and Methods). This suggests an additional allure for faculty to join their alma mater — beyond what would be expected from the structure of the mid-career move job market.

2.2.2 Where do faculty go?

The faculty mid-career move job market is a complex system of faculty displacements that results from mutual interactions between the decisions of hiring departments and faculty movers. Previous studies have indicated that factors like prestige, productivity, promotions and academic rank influence changes in faculty affiliation upon moving [1, 4]. Moreover, faculty movement patterns seen earlier between public and private, and urban and rural institutions, suggest they have an influence on where faculty move. In order to understand the influence of these factors on where faculty move while controlling for potential confounding factors, we build a linear regression model that predicts where they move, in terms of displacement along the prestige hierarchy from their current affiliation.

According to our model, moving to one's alma mater increases their prestige by 35.43 ranks and moving away from one's alma mater decreases your prestige by 20.82 ranks (Fig. 2.4). Empirically, we observe identical patterns, with self-hires being created gaining 35.22 places in prestige while those being destroyed losing 41.37 places in prestige. Focusing on self-hires being destroyed, we notice that they experience a shorter drop down the prestige hierarchy compared to an initial hire that is not self-hired, who drops down 76.29 places during their initial placement. This shorter drop in prestige may suggest that faculty are better off being initially hired as self-hires and then moving to another institution as opposed to moving to another institution immediately after they graduate. However, it is important to note that the change in prestige during the initial placement of faculty is driven by different dynamics relative to mid-career moves, making it difficult to draw conclusions from this result.

When we control for other factors, faculty moving to private institutions tend to gain more prestige than faculty moving to public institutions. In our model, among faculty moving away from public institutions, faculty moving to private institutions gain 29.32 more places in prestige than faculty moving to public institutions. Among faculty moving away from private institutions, faculty moving to private institutions gain 30.32 more places in prestige than those moving to public

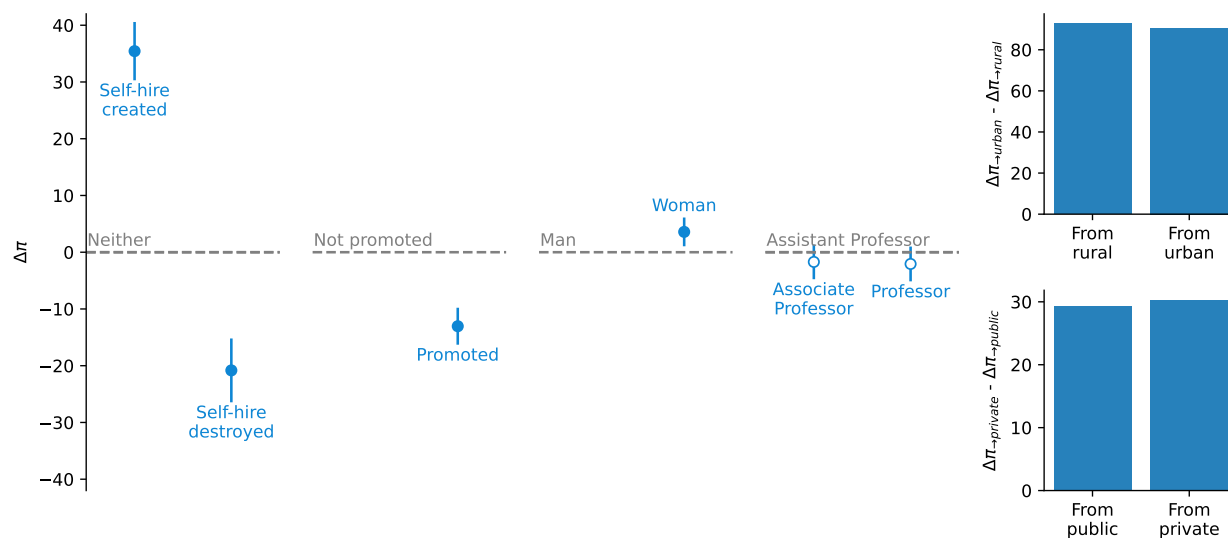


Figure 2.4: **Results of the prestige change linear regression model.** $\Delta\pi$ indicates change in prestige predicted by the model, positive values indicating moves up the prestige hierarchy, error bars indicating 95% confidence intervals on the model parameter estimates. $\Delta\pi_{\rightarrow urban} - \Delta\pi_{\rightarrow rural}$ indicates the prestige advantage/disadvantage of moving to an urban institution, relative to a rural institution, with positive values indicating a relative prestige advantage. $\Delta\pi_{\rightarrow private} - \Delta\pi_{\rightarrow public}$ indicates the same, but for private over public institutions. Self-hires created go up the prestige hierarchy and those destroyed go down. Faculty movers getting promoted go down in prestige relative to non-promotions. Women gain slightly more prestige upon moving than men. There is no significant difference in prestige change between different ranks of the professoriate. Faculty moving to urban and private institutions go up in prestige, irrespective of their origin institution.

institutions (Fig. 2.4). We see a similar effect in urban-rural moves, where faculty going to urban institutions are predicted to gain much more prestige than those moving to rural institutions. Faculty at rural institutions gain 92.82 more places in prestige when they move to an urban institution than if they moved to another rural institution, while faculty at an urban institution moving to an urban institution gain 90.55 more places in prestige than if they moved to a rural institution (Fig. 2.4).

Upon moving, there are no statistically significant differences in the prestige change patterns at different ranks of the professoriate when we control for other factors (Fig. 2.4). However, when we do not control for the origin prestige of movers, we find that assistant professors go up the prestige hierarchy by 8.53 places, associates do not see a significant change and professors go down 4.40 places. Although the patterns of change in prestige at different ranks are very similar across the prestige hierarchy, these apparent differences arise from inequalities in the distribution of movers of different ranks at different parts of the prestige hierarchy. Going a step further, we find that these inequalities in mover densities between ranks is just a consequence of the inequalities in the densities of ranks along the prestige hierarchy for the entire faculty population to begin with (Fig. A.3). In addition, we find that faculty at elite institutions tend to lose prestige upon moving and women tend to gain more prestige than men on average, albeit only slightly, when they make mid-career moves (Fig. 2.4).

In our model, faculty who are promoted over a move tend to lose 13.04 places in prestige compared to those who are not (Fig. 2.4). This finding that faculty making mid-career moves may trade downward prestige mobility for promotion in rank is in agreement with earlier studies of mid-career moves in academia [4]. In our data, we find a trade-off between prestige and promotion (Fig. 2.5 insets) at both the assistant and associate ranks of the professoriate. Among assistant professors, moves with promotions take faculty down by 6.79 places in prestige and moves without take faculty 14.52 places up prestige the prestige hierarchy. We see a bigger effect size among associate professors who move, with promotions dropping faculty 22.04 places down the prestige hierarchy, more than three times the drop of assistant professors getting promoted. Associate

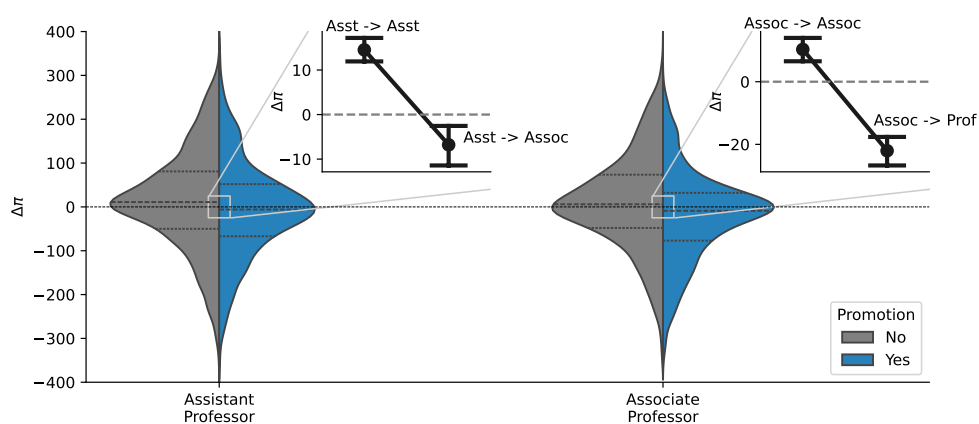


Figure 2.5: **Prestige-promotion trade-off.** Distribution of prestige change for faculty moves with (blue) and without (gray) a promotion, for Assistant Professors and Associate Professors (horizontal axis). The vertical axis indicates the change in prestige, relative to faculty's affiliation before moving, with positive values indicating moves to more elite institutions. The inset plots zoom in on the mean prestige change for faculty moves with and without a promotion, for Assistant Professors (Asst) and Associate Professors (Assoc), showing 95% confidence intervals on the prestige change estimate. The vertical axis indicates the change in prestige, relative to faculty's current affiliation, with positive values indicating moves to elite institutions.

professors go up the prestige hierarchy by 10.31 places if they are not promoted over a mid-career move. However, these average patterns do not represent a typical move for both the promoted and non-promoted groups at both ranks. In both these groups, we have faculty moving almost symmetrically in both directions along the prestige hierarchy, with the differences between them resulting in small but statistically significant effect sizes relative to the size of the prestige hierarchy itself (Fig. 2.5).

2.2.3 Utility

The prestige-promotion trade-off highlights the utility aspect of mid-career moves, where faculty try to increase utility over mid-career moves. Conditioned on a utility increasing move, we expect pairs of utility increasing covariates to be negatively correlated. For instance, we know that an increase in prestige and promotion are both increases in utility. Faculty would be happy to make moves that increase their prestige and grant them a promotion, but if faculty experience a negative or no change in prestige over a mid-career move, they'd want to at least get promoted, and if faculty do not get promoted over a mid-career move, they'd want to at least go up the prestige hierarchy. These tendencies would result in a negative correlation between an increase in prestige and promotion.

With promotion as a known utility increasing change, under our theory, factors negatively associated with a promotion are perceived as an increase in utility. Some of the factors that we want to test the utility of are an increase in prestige, moving to your alma mater, moving to a private institution and moving to an urban institution. To do this, we use a logistic regression model that predicts whether a faculty gets promoted to identify covariate changes that are negatively associated with a promotion. We create different models for assistant and associate professors to account for any differences in utility perception between ranks. For both assistant and associate professors, we find that an increase in prestige is perceived as an increase in utility (Fig. 2.6), but the effect size is very small ($OR \approx 1$ for both assistant and associate professors). On the other hand, for associate professors, moving to one's alma mater is found to be significantly negatively

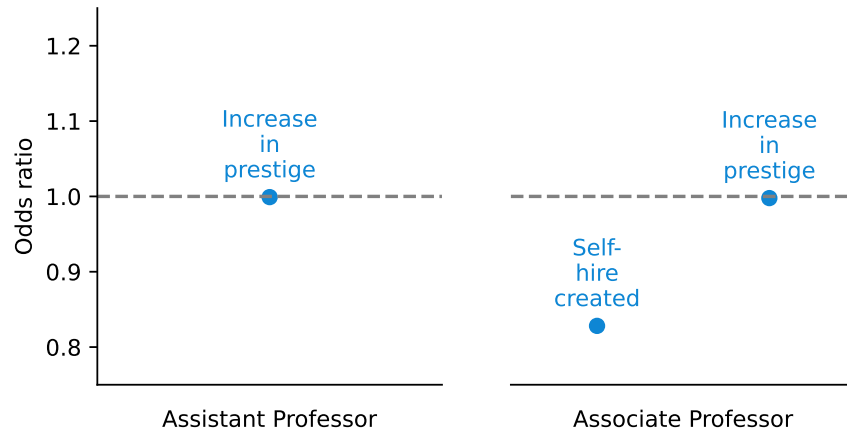


Figure 2.6: **Results of the utility regression model.** Both assistant and associate professors consider an increase in prestige as an increase in utility, with a small but significant effect size ($OR \approx 1$). In addition, associate professors consider going back to their alma mater as an increase in utility. Only significant effects are shown here. The vertical axis shows odds ratios for the utility regression models for each rank (horizontal axis).

correlated with a promotion ($OR=0.83$), suggesting that associate professors may perceive moving to their alma mater as an increase in utility.

Chapter 3

Discussion

From our analysis, we find that although mid-career moves are a rare event, there is a lot of heterogeneity in the risk of faculty making a mid-career move, across many attributes. There is considerable variation in the mid-career move risk of faculty across domains and individual academic fields within those domains, suggesting that the faculty mobility norms might not be the same across all of academia. In the literature, different risk factors were found to influence faculty turnover in different disciplines of academia [25], suggesting disciplinary norms in faculty turnover. Our study is in agreement with these results, finding more explicitly that disciplinary norms could be entrenched in faculty mid-career moves as well, not just all-reason faculty turnover.

Younger faculty are at a much higher risk of moving at every rank of the professoriate, suggesting that younger faculty either tend to have a lower barrier for moving, a higher demand for talent, or they might be forced to move by the ‘up or out’ system that especially exerts pressure on untenured faculty who tend to be young in career age. These findings agree with previous literature that claim that senior faculty tend to be less likely to leave an institution [29, 18, 19].

Career age is measured not only in years, but by academic rank as well, and tenure—typically granted upon promotion from assistant to associate professor—provides a job security that may incentivize moves among those who seek it, or disincentivize moves among those who have it. Even as far back as the 1950s, Caplow and McGee, who analyzed all-cause academic vacancies and how they are filled at 10 U.S. universities, argued that academic rank and tenure would play a role in mobility. They speculated that assistant professors would be the most likely to move, followed

by full professors, while mid-career associate professors would be least likely to move [4]. They reasoned that (i) while all faculty have the potential for elective moves, only assistant professors would be exposed to compulsory moves due to tenure denial, and (ii) that mid-career associate professors would be less attractive than either promising assistant professors or established full professors.

We find these speculations to hold true in our data, but only for career ages that are typical for a rank. For instance, a very young associate professor (at a career age 10) moves at a higher rate than a very old professor (at a career age 30), which disagrees with the speculations of Caplow and McGee. Consequently, we emphasize the importance of looking mid-career move rates of different ranks of the professoriate in the context of their career age to truly appreciate the underlying heterogeneity in faculty's propensity to move at different academic ranks.

Prestige has ubiquitous effects on influencing both the likelihood of faculty to move and where faculty go after moving. High prestige institutions are at an increased risk of losing their faculty to mid-career moves, which could imply that administrators at these institutions should be more meticulous with their institutions' retention policies, to avoid a high rate of turnover. The destination prestige of a mid-career mover is found to be correlated with their origin prestige, so if you are at a high-prestige institution, you tend to be in a high-prestige institution even after moving. This prestige "stickiness" is in agreement with previous studies [1] and may have consequences for the spread of scholarship across academia. By restricting spread of ideas at high prestige institutions to other high prestige institutions only, the research topics that get worked on might be skewed across the prestige hierarchy.

Faculty at public institutions are more likely to move, agreeing with findings from the previous literature that private institutions are better at retaining faculty, specifically tenured faculty [29, 7]. One might reason that the higher compensation offered at private institutions could discourage faculty from making mid-career moves [10]. However, the higher retention rate at private institutions is only apparent because, upon controlling for other factors, we find that private institutions are actually at a higher risk of losing faculty to mid-career moves, with the relative risk only

increasing as we move to more elite institutions. Further analysis, in addition to a mixed-methods approach, seems necessary to determine the reason for this flipping of mid-career move risk when we control for other factors.

In our data, mid-career moves over all 10 years of observation effectively increase the number of faculty at private institutions, however only slightly. This may suggest that faculty have an allure to move to private institutions, possibly due to higher salaries [10] and lower administrative burden. Moreover, the allure for private institutions may be prestige-driven, suggested by our finding that faculty moving to private institutions tend to gain prestige, irrespective of whether they are moving from a public or a private institution. On the other hand, faculty are found to have a predilection to move to universities of similar institution type as their previous institution, with this effect being more profound for private institutions. This signals administrators at public (private) institutions to be more wary of losing their faculty to other public (private) institutions, and to design retention strategies keeping these faculty movement patterns in mind.

Faculty at rural institutions are at a higher risk of moving, with all the mid-career moves in our data inducing a net flux of faculty from rural to urban institutions. These patterns have been observed by [27], whose study is of note because it seems to be the most similar to our study in principle, relative to other relevant pieces of literature. An urban locale may confer several personal benefits upon faculty in terms of better spousal employment, better schools for their children and more access to amenities compared to a rural locale. It may confer professional benefits as well, as faculty moving to urban institutions tend to experience a larger prestige gain relative to those moving to rural institutions, irrespective of whether they are moving from an urban or a rural institution. However, these are only speculations, with some causal analysis required to establish the mechanisms that lead to these patterns.

Self-hires are a unique position in academia because we see peculiar patterns for self-hire positions both in faculty-hiring networks [21] and mid-career moves. Mid-career moves result in a net increase in the number of self-hires, which helps explain why we see so many more self-hires in the extant faculty hiring networks than we might expect. Loads are created during initial hiring,

and even more are added on during MCMs. This goes against what people generally think about self-hires, which is that they are bad and therefore rare. On the contrary, they were shown to be much more common than expected [21], and now help show one additional step that makes them so. Self-hires are also protective, in that self-hires decrease the risk of MCMs, effectively keeping faculty at their alma mater once they move there. With self-hires believed to restrict the spread of ideas and expertise, our result might be a portent for administrators across academia to initiate efforts to preclude academic inbreeding [6].

In our data, self-hires that are created by mid-career moves tend to gain prestige and those destroyed by mid-career moves tend to lose prestige. However, we note that the prestige gain or drop seen when a self-hire gets created or destroyed over a mid-career move is not surprising because we know that production inequalities place most self-hires at the top of the prestige hierarchy. Nevertheless, this pattern could suggest that faculty's allure for a job at their alma mater and their tendency to stay there once they get self-hired might be prestige driven. If you are a self-hire, you did better than we would expect (and better than your graduate cohort) in landing a high[er]-prestige position. So, if you are interested in holding on to prestige (or moving up), a mid-career move is less likely to get you there. On the other hand, if you are not a self-hire, you are likely to be at an institution that is less prestigious than your alma mater. If you want to move up the prestige hierarchy, moving to your alma mater is likely to get you to a more prestigious institution, with this move being potentially easier to make because of existing connections. In addition, self-hires, being at elite institutions, accumulate cumulative resource advantages at these institutions [28, 22], which may lead to benefits beyond just a gain in prestige.

The prestige-promotion trade-off that we notice in mid-career moves hints at a utility theory of what faculty try to optimize over moves. However, we speculate that the trade-off seen at different ranks of the professoriate may be a result of interactions between faculty trying to increase utility over moves and academic departments trying to hire the best talent without destabilizing their existing cohort. Under our utility hypothesis, among faculty that get promoted, we should expect to see a slight drop in prestige, which we do notice for assistant professors that are promoted.

However, for associate professors getting promoted, the drop in prestige is more severe, suggesting the possibility of other dynamics at play. We speculate that this significant drop in prestige for associate professors is driven by poaching and the compression problem.

Poaching is the practice where institutions try to hire faculty from more prestigious institutions by typically offering them attractive salary packages. However, just offering higher salaries would lead to the compression problem [3], where the newly hired associate professor will have a better salary package than that of an existing full professor in the institution, forcing the administration to raise the salaries of their full professors and hence bearing a financial burden on the institution. To alleviate this problem, an institution could attempt to poach faculty from more prestigious institutions by offering higher salaries disguised as a promotion. These practices could be more prevalent at the rank of associate professors because we expect aggressive poaching to target faculty that have a strong reputation, which takes time to build.

Our study, although comprehensive, has some limitations. We are able to identify only mid-career moves within our sample frame, meaning that we may be missing moves within academia but to out-of-sample institutions, like those that do not grant PhDs. Similarly, our analysis only covers the tenured and tenure-track faculty at PhD-granting universities in the US, leaving various sections of the higher-education faculty like non-tenured faculty unrepresented, prompting researchers to expand this research to cover a broader population. We cannot tell the difference between forced moves (failures to get tenure, say), and unforced moves and in general, we cannot tell the difference between pushes and pulls, or from sought-after moves and unprompted offers. In a similar vein, we do not qualitatively study personal (family pressures, spousal employment) and professional factors (salary, workplace stress, lack of fit) leading to the decision to move, which cannot be ignored if we wanted to paint a complete picture of all the influences driving faculty decisions to make a mid-career move.

Our study also lacks analysis of how faculty's productivity affects their risk of moving and where they move to, in addition to productivity being an incentive for faculty to move. Earlier literature has found significant effects of productivity on mid-career move risk and where they go.

Highly productive faculty are more likely to make moves [15, 1]. Compensation has also been previously found to be an important dimension of faculty mid-career move decisions [7]. Our study does not analyze this dimension of faculty mid-career moves, leaving the causal implications of compensation on mid-career move decisions open for further research. In addition to compensation, our research provides a rich basis for further causal exploration of mid-career moves. Why do people make MCMs in the first place? Of course, the difference between forced and elective moves is important, but scholars write more papers when they move to higher prestige institutions [28], due to increased labor resources. For those faculty with the energy and interest in ramping up their scholarly productivity via a mid-career move, this may be one incentive. There are some more questions that remain open for future researchers to tackle. Does a recent promotion tend to protect against a mid-career move? And, how do mid-career moves among Assistant Professors relate to time to tenure? Finally, does the mid-career move network follow a similar core-periphery structure that faculty-hiring networks do?

Chapter 4

Materials and Methods

4.1 Faculty Data Preprocessing

Annual faculty rosters were provided under a data use agreement with the Academic Analytics Research Center (AARC). The AARC had no voice in the research questions, conclusions, or writing of this manuscript. Data were provided as a set of complete, annual tenure-track faculty rosters, for 2011-2020, spanning all US PhD-granting institutions. They included faculty name, department, institution, faculty rank (assistant, associate, or full), year of doctorate or other terminal degree, and a mixture of university-provided and algorithmically identified binary gender annotations. Each department was also annotated with its field (or in some cases, fields, as in a Department of Physics and Astronomy), and each field corresponds to one of ten high-level domains: applied sciences, education, engineering, humanities, journalism/media/communication, mathematics and computing, medicine and health, natural sciences, public administration and policy, and social sciences.

We processed these data in five ways. First, we compared each professor's institution in year t and year $t + 1$ and annotated year t as either a mid-career move or not. Our ten years of data were therefore used to identify nine potential years of mid-career moves. Second, we compared each professor's academic rank in year t and year $t + 1$ and annotated the move or non-move as either a promotion or not. Third, we examined each professor's institution in each year to determine whether the professor's current institution matched their doctoral alma mater, annotating those with a match as a self-hire in that year of observation. Fourth, we defined career age as the number

of years between a professor’s terminal degree and the year of observation, and annotated each observation with a career age. And finally, we annotated each mid-career move by its change in prestige and as $v \rightarrow w$ and $x \rightarrow y$, where $v, w \in \{\text{urban, rural}\}$ and $x, y \in \{\text{public, private}\}$, using the labels described below.

4.2 Urban/Rural and Public/Private Classification

We annotated each institution as either urban or rural, and either public or private, by processing tables from the Integrated Postsecondary Education Data System (IPEDS) at the US National Center for Education Statistics. In IPEDS data, the locale of institutions has been annotated using urban-centric locale codes assigned through a methodology developed by the U.S. Census Bureau’s Population Division. While this classification assigns four different locale types (city, suburbs, town, rural) with further subtypes depending on a locale’s population (large, mid-size, small) and proximity from urbanized areas (fringe, distant, remote), we grouped locales into two broad types to simplify our analysis, mapping both city and suburbs to the label “urban” and both town and rural to the label “rural.”

4.3 Institutional Prestige

We use measures of institutional prestige which come from prior work estimating prestige scores directly from analyzing the structure of faculty hiring networks [21]. Prior to use, we converted scalar-valued prestige scores to ordinal ranks. In calculations, we reverse-coded these ranks to ensure that higher prestige always corresponds to larger rank values, and positive changes in prestige score mean increases in prestige, to avoid confusion in which higher prestige is higher in rank, but numerically lower. For some analyses, we bin institutions into prestige deciles of size $n = 40$ institutions for the top nine deciles, and $n = 32$ institutions for the bottom decile.

4.4 Rate estimation

All mid-career move rates were estimated using independent maximum likelihood estimators on pooled panel data. That is, (i) we estimated the rate of mid-career moves for a particular combination of covariates (e.g. rank and career age) as the number of observed mid-career moves divided by the number of observations matching those covariates, i.e., the number at risk, (ii) each individual is recorded as either a 0 or 1 for mid-career move in each year of observation, and (iii) we did not employ any empirical Bayes or James-Stein type estimation when reporting rates.

4.5 Logistic regression models for risk

To model the influence on various covariates on MCM risk, while controlling for field, academic year, academic rank and career age, we build a logistic regression model that predicts whether a faculty makes a mid-career move based on various risk factors observed prior to the move. In this model, we add interaction terms for career age and academic rank because these covariates are highly correlated and intertwined with each other. We also interact the public/private type of the institution with the prestige of the institution because we found that the mid-career move rate varies differently along the prestige hierarchy for public and private institutions (Fig. A.1). We define the model as follows:

$$\begin{aligned}
\log odds(\text{MCM}) = & \beta_0 + \beta_1(\text{academic year}) + \beta_2(\text{field}) \\
& + \beta_3(\text{rank-assoc}) + \beta_4(\text{rank-full}) + \beta_5(\text{career-age}) \\
& + \beta_6(\text{career age} \times \text{rank-assoc}) + \beta_7(\text{career age} \times \text{rank-full}) \\
& + \beta_8(\text{self-hire status}) \\
& + \beta_9(\text{institution-private}) + \beta_{10}(\text{prestige}) \\
& + \beta_{11}(\text{prestige} \times \text{institution-private}) \\
& + \beta_{12}(\text{institution locale-rural}) \\
& + \beta_{13}(\text{gender-woman})
\end{aligned}$$

In this model, the reference class is a non-self-hire man in the top prestige decile at an urban public institution.

4.6 Null models of the mid-career move network

To test whether the network statistics we observe is a mere consequence of the structure of the mid-career move network, we compare it against the same statistic obtained from a random graph model that preserves the structure of the network while randomizing everything else. Based on our research question, the structure that we would like to preserve could be either the degree structure of the network or the degree and the modular structure of the network. There are random graph models for both these cases, explained below.

4.6.1 Configuration model

In this random graph model, we keep the in-degree and the out-degree of each node in the network fixed, while we randomly rewire edges [8]. From this model, we sample the average value of the statistic of interest observed on this random graph model and compare our empirical value

against this null model average.

4.6.2 Degree-corrected stochastic block model

In this random graph model, in addition to keeping the in-degree and the out-degree of each node in the network fixed, we also fix the inflow and outflow of edges between different modules (communities) of the network and then randomly rewire edges under these constraints [12]. As earlier, we sample the average value of the statistic of interest from this model and compare it against its corresponding empirical value that we observe from the data.

4.7 Linear regression models for prestige change

To understand the influences of various covariate changes on where faculty move, we build a linear regression model that infers the influence of these covariate changes on faculty mobility along the prestige hierarchy in terms of the prestige change they experience from their previous affiliation. We model the influences of a self-hire position being attained or lost, a promotion, a change in institution type (public/private) and institution locale (urban/rural) of faculty on their prestige change upon moving while controlling for their origin prestige, gender and academic rank. The regression model is defined as follows:

$$\begin{aligned} \Delta\pi = & \beta_0 + \beta_1(\text{Origin prestige}) + \beta_2(\text{Gender}) + \beta_3(\text{Rank}) \\ & + \beta_4(\text{Self-hire created}) + \beta_5(\text{Self-hire destroyed}) \\ & + \beta_6(\text{Promotion}) \\ & + \beta_7(\text{Private}\rightarrow\text{Private}) + \beta_8(\text{Private}\rightarrow\text{Public}) + \beta_9(\text{Public}\rightarrow\text{Private}) \\ & + \beta_{10}(\text{Urban}\rightarrow\text{Urban}) + \beta_{11}(\text{Urban}\rightarrow\text{Rural}) + \beta_{12}(\text{Rural}\rightarrow\text{Urban}) \end{aligned}$$

In this model, the reference class is a man at the rank of assistant professor who is neither moving away or to his alma mater and does not get promoted over his move. He moves from a public institution to another public institution, and from a rural to a rural institution.

4.8 Logistic regression models for utility

Using promotion as a known increase in utility, we build a logistic regression model to identify the covariate transitions that faculty perceive as utility increases over mid-career moves. To account for differences in utility perceptions between assistant and associate professors, we build two models, one for each rank. The logistic regression model predicts whether faculty get promoted over a mid-career move, using our covariate transitions of interest as predictors, while controlling for origin prestige and faculty gender. We hypothesize that moving to one's alma mater, moving from a public to a private institution and moving from a rural to an urban institution are perceived by faculty as utility increases. As a result, we encode these changes as a 1 in the model, changes in the opposite direction as -1 and a 0 if the covariate does not change. An increase in prestige change is also hypothesized to be an increase in utility and we encode an increase in prestige as a positive prestige change, a decrease being negative. With this encoding, covariate changes associated negatively with promotion are perceived as increases in utility by faculty according to our theory of utility. Here's the model:

$$\begin{aligned}
 \text{logodds(Promotion)} &= \beta_0 + \beta_1(\text{origin prestige}) + \beta_2(\text{gender}) \\
 &+ \beta_3(\Delta\pi) \\
 &+ \beta_4(\text{Public}\rightarrow\text{Private}) \\
 &+ \beta_5(\text{Urban}\rightarrow\text{Rural}) \\
 &+ \beta_5(\text{Self-hire created})
 \end{aligned}$$

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Appendix A

Supplementary Materials

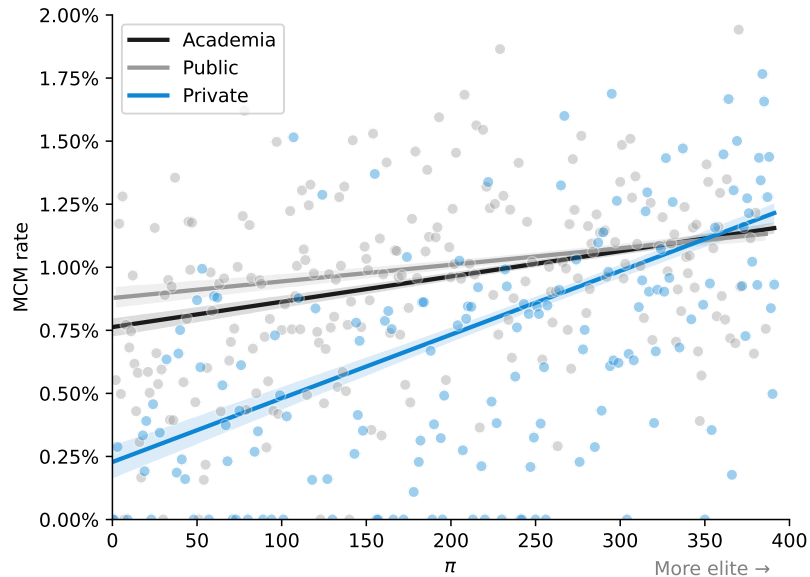


Figure A.1: **Different annual mid-career move rate trends for public and private institutions along the prestige hierarchy.** The horizontal axis shows the prestige of an institution, with larger numbers indicating higher prestige. The vertical axis shows the mid-career move rate. Each scatter point in this plot shows the mid-career move rate at an institution of a given prestige, colored by institution type. A linear regression is fit for all data points (black line), only public (gray line) and only private institutions (blue line), with the errorbars around the best fit lines indicating 95% confidence intervals for the regression estimate.

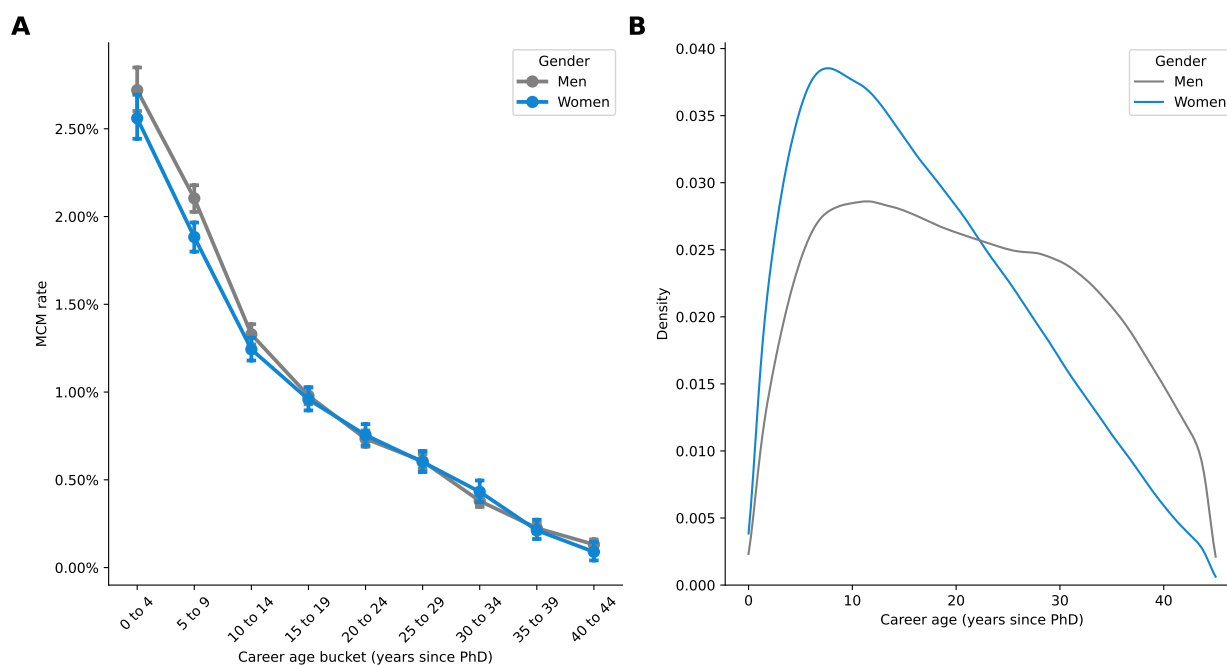


Figure A.2: **Disappearance of gendered effect on mid-career move risk after interacting with career age.** **A)** Career age bucket is shown on the horizontal axis and mid-career move rate is shown on the vertical axis. mid-career move rate is not very different between men and women at most career ages but when we compute the average mid-career move rate for men and women overall, the average is dominated more heavily by the mid-career move rate of younger professors for women than for men, **B)** as women faculty are concentrated in the younger career ages, with the horizontal axis depicting the career age and the vertical axis showing the density of faculty at that career age for that gender. Since faculty at younger career ages make mid-career moves at a higher rate, the mid-career move rate for women gets inflated as an artifact of their distribution across different career ages.

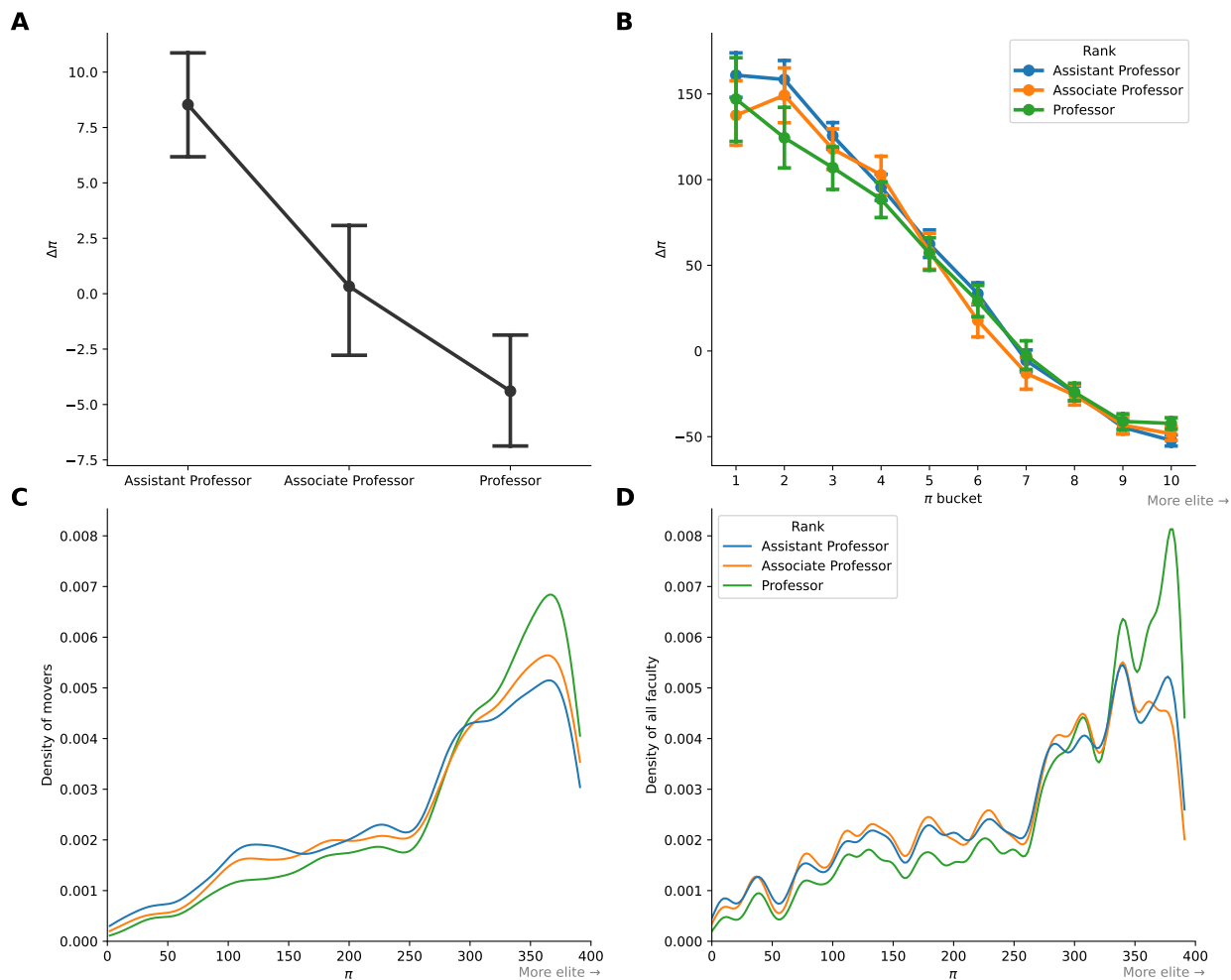


Figure A.3: **Disappearance of rank effect on prestige change upon moving after interacting with origin prestige.** **A)** Average prestige change (vertical axis) for different ranks of the professoriate upon moving, **B)** The prestige change patterns (vertical axis) of different ranks of the professoriate at different parts of the prestige hierarchy. The horizontal axis shows different prestige buckets, larger corresponding to higher prestige, **C)** The density of movers (vertical axis) of each rank across the prestige hierarchy (horizontal axis), computed independently for each rank, **D)** Same as **C)** but for the entire faculty population, not just movers. The density of assistant professors who move is higher than other ranks at the bottom of the hierarchy, and the density of professors is relatively higher at the top. Since faculty at the bottom of the prestige hierarchy typically move up, assistant professors weigh upward moves relatively more heavily than other ranks. Similarly, faculty at the top of the hierarchy tend to go down resulting in professors weighing downward moves more heavily, possibly explaining the prestige change differences we see between ranks when we do not control for prestige. Going a step further, we find that these inequalities in mover densities between ranks is just a consequence of the inequalities in the distribution of ranks along the prestige hierarchy for the entire faculty population to begin with.

Domain/Field	MCM Rate	Domain/Field	MCM Rate
<i>Applied Sciences</i>	1.3657%	<i>Medicine and Health</i>	1.1052%
Horticulture	0.4288%	Genetics	0.5925%
Soil Science	0.6013%	Physiology	0.6876%
Plant Sciences	0.6234%	Immunology	0.7198%
Agronomy	0.6392%	Pharmacy	0.7638%
Animal Sciences	0.9052%	Pharmacology	0.9473%
Architecture	0.9554%	Veterinary Medical Sciences	1.0561%
Food Science	1.1195%	Environmental Health Sciences	1.1048%
Urban and Regional Planning	1.137%	Exercise Science, Kinesiology, Rehab, Health	1.145%
Management Information Systems	1.5377%	Epidemiology	1.1505%
Business Administration	1.5426%	Human Development and Family Sciences	1.1645%
Marketing	1.6494%	Nutrition Sciences	1.1761%
Finance	1.7188%	Health, Physical Education, Recreation	1.1888%
Management	1.7317%	Pharmaceutical Sciences	1.2983%
Accounting	1.9285%	Speech and Hearing Sciences	1.3137%
<i>Education</i>	1.4307%	Public Health	1.3424%
Curriculum and Instruction	1.3024%	Communication Disorders and Sciences	1.3709%
Special Education	1.4869%	Social Work	1.4476%
Education Administration	1.4907%	Nursing	1.5641%
Counselor Education	1.5059%	<i>Natural Sciences</i>	0.7557%
Education	1.6793%	Astronomy	0.4852%
<i>Engineering</i>	1.111%	Physics	0.5219%
Agricultural Engineering	1.0053%	Biophysics	0.5384%
Electrical Engineering	1.012%	Atmospheric Sciences and Meteorology	0.5747%
Materials Engineering	1.0446%	Plant Pathology	0.5763%
Mechanical Engineering	1.1437%	Molecular Biology	0.5906%
Aerospace Engineering	1.1478%	Biochemistry	0.6387%
Civil Engineering	1.1512%	Cell Biology	0.6393%
Environmental Engineering	1.1628%	Entomology	0.6703%
Systems Engineering	1.2472%	Chemistry	0.6789%
Operations Research	1.2991%	Marine Sciences	0.679%
Industrial Engineering	1.4287%	Geology	0.7027%
<i>Humanities</i>	0.7107%	Neuroscience	0.7251%
Comparative Literature	0.5072%	Biological Sciences	0.7588%
Classics and Classical Languages	0.5197%	Microbiology	0.7628%
French Language and Literature	0.5865%	Forestry and Forest Resources	0.8604%
Music	0.6111%	Anatomy	0.8758%
Slavic Languages and Literatures	0.6113%	Natural Resources	0.9045%
Spanish Language and Literature	0.627%	Environmental Sciences	0.9138%
Religious Studies	0.6401%	Pathology	0.9578%
Theatre Literature, History and Criticism	0.6468%	Evolutionary Biology	1.0058%
Theological Studies	0.6528%	Chemical Engineering	1.0157%
English Language and Literature	0.6768%	Ecology	1.0351%
Germanic Languages and Literatures	0.6989%	Biostatistics	1.3321%
Linguistics	0.7139%	Biomedical Engineering	1.418%
Art History and Criticism	0.7201%	<i>Public Administration and Policy</i>	1.6073%
Near and Middle Eastern Languages and Cultures	0.8137%	Public Administration	1.5744%
History	0.8312%	Public Policy	1.6274%
Philosophy	0.8399%	<i>Social Sciences</i>	1.0993%
Asian Languages	0.8838%	Psychology	0.8021%
Asian Studies	0.9633%	Anthropology	0.811%
<i>Journalism, Media, Communication</i>	1.2024%	Geography	0.8806%
Communication	1.18%	International Affairs	1.0735%
Mass Communications and Media Studies	1.2265%	Political Science	1.146%
<i>Mathematics and Computing</i>	1.1086%	Sociology	1.2595%
Mathematics	0.891%	Gender Studies	1.2606%
Statistics	1.0323%	Criminal Justice and Criminology	1.2911%
Computer Engineering	1.1394%	Economics	1.3774%
Computer Science	1.2429%	Agricultural Economics	1.3862%
Information Science	1.3811%	Educational Psychology	1.5649%
Information Technology	1.407%		

Table A.1: **Annual mid-career move rates by domain and field.** The annual mid-career move rate of each domain (italicized) is shown, with the domains sorted lexicographically. For each domain, the constituent fields and their annual mid-career move rates are shown, sorted in ascending order of annual mid-career move rates.