Do Elite Universities Overpay Their Faculty?*

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No. Elite institutions offer high salaries because they hire the most valued faculty. Moreover, in contrast to the broader labor market, faculty are equally likely to move up and down the prestige ladder, and they increase their salary either way. We speculate that these facts reflect the visible nature of faculty productivity and the sporadic nature of academic job openings.

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1 Introduction

We show that the labor market for tenure-stream (tenured and tenure-track) STEM faculty has several features that differ from the broader labor market. In general labor markets, there is a hierarchy of firms, with some paying more on average than others for seemingly identical workers (Bagger and Lentz, 2019; Moscarini and Postel-Vinay, 2018; Haltiwanger et al., 2018). This hierarchy is identified as firm fixed effects in AKM (Abowd, Kramarz and Margolis, 1999) wage equations that allow worker and firm fixed effects. (See Kline 2024 for a review of studies finding firm effects in the broader labor market.)

In broader labor markets, workers moving to more elite or higher-paying firms see wage increases, mobility is more frequently upward than downward, and downward movement results in losses roughly equal to the gains from upward movement. At least some of these firm effects represent rents – a share of profits or return on capital captured by workers (see Card et al., 2018 for a review)

In academia, there is also a clear hierarchy of universities (measured by rankings and research emphasis). And, as others have found (Ehrenberg, 2003; Bound et al., 2019; Rippner and Toutkoushian, 2015) and we confirm, average salaries are higher at elite universities as measured by their rank or endowment. Faculty salaries and productivity are linked both within and across universities, whether measured by the number of publications, citations, or the h-index.[1]

Yet in some other respects, academia is very different from other labor markets. We show that, in contrast to the broader labor market, tenure-stream STEM faculty moving up and down the hierarchy experience similar wage changes, and movements up and down are approximately equally likely.

[1] Katz (1973); Smith and Choudhry (1978); Hamermesh, Johnson and Weisbrod (1982); Hamermesh and Pfann (2012); Hilmer, Ransom and Hilmer (2015); Ransom, Hilmer and Hilmer (2022); Kwiek (2018); Li and Koedel (2017); Faria and Mixon Jr (2021); Sandnes (2018); MacLeod and Urquiola (2021).

To ascertain whether faculty can capture some of the greater resources at elite institutions and, therefore, receive a premium (or rent) relative to their potential salary elsewhere, we estimate an AKM salary model using longitudinal data on academics in STEM fields. We find that firm effects/rents are small to nonexistent. In contrast to studies of firm fixed effects in the broader labor market, institution fixed effects in academia explain little of the earnings variance, so that prestige or endowment *per se* generates, at most, modest earnings differentials, even between the best and worst-ranked or richest and poorest institutions. Instead, salaries are higher at more elite institutions because they hire more elite and, thus, high-earning faculty. Consequently, when faculty move institutions, their salary change is unrelated to the relative prestige change.

What explains these striking differences between the academic and broader labor markets? First, the absence of university effects on salary may result from nonpecuniary compensation or amenities that increase with eliteness more rapidly in academia than in the broader market. Faculty at elite institutions are likely to have lighter teaching loads, more resources for their research, and better students (Claypool et al., 2017), which could substitute for higher salaries. Still, some authors suggest the opposite. Faculty at elite institutions experience more pressure to publish in more highly ranked journals, face more demanding students, and, if not tenured, must meet higher standards for gaining tenure. They may suffer from comparisons with successful colleagues in their department (Frank, 1985). Ehrenberg, Pieper and Willis (1998) found a compensating differential for a lower tenure probability even within institution-prestige tier.[2] We examine the relation between job satisfaction and institution rank and find no evidence to support the hypothesis that better working conditions explain why prestige rents are absent. Moreover, compensating wage differentials cannot account for the unusual mobility pattern in academia.

[2]They also found that institutions appearing to pay a compensating differential for low tenure rates seemingly pay a premium to their tenured faculty, which requires a more complex explanation.

Alternatively, we may fail to find prestige rents because faculty salaries depend on their outside option and indirectly its prestige, not their current job's, as suggested by the models of Postel-Vinay and Robin (2002), Cahuc, Postel-Vinay and Robin (2006), and Bagger et al. (2014). We follow Di Addario et al. (2023) in testing this explanation by allowing salary to depend on both the current and previous employer (their outside option). The results provide little support for this explanation, which, again, does not predict the unusual mobility patterns observed.

We suggest that the mobility and salary patterns we observe reflect that matching is important, but that jobs at specific university departments are available sporadically, making many initial matches imperfect. Salaries increase as faculty matches improve due to moves up or down the prestige ladder. Moreover, perhaps in contrast with the general labor market, moves mostly do not reflect new information; there is good information about STEM faculty productivity even when individuals first enter the assistant professor market.

2 Data

We combine data from (i) restricted-use faculty job histories for US STEM academics, (ii) publicly available university and college rankings, and (iii) administrative data about higher-education institutions.

Our job-history data comes from the restricted-use version of the Survey of Doctorate Recipients (SDR) from the National Center for Science and Engineering Statistics (NCSES). The SDR is a representative longitudinal panel of doctoral recipients from US academic institutions in natural or social sciences, engineering, or health. The survey collects salary, employer, and demographic information every 2-3 years. It also provides IPEDS (Integrated Postsecondary Education Data System) code for all US academic employers, allowing us to construct a matched employer-employee panel of US academics.

We use all SDR waves from 1993 to 2019. Thanks to the SDR structure, our panel has good longitudinal coverage of existing faculty while incorporating data from newly minted PhDs. The SDR includes most survey participants from previous waves, adds newly granted PhDs (from the National Science Foundation's Survey of Earned Doctorates), and drops those who age out. Its response rate among US residents who can be found is high, typically more than 95% of eligible respondents. Adding those not found, missing a key item, or living abroad to the non-responses lowers the rate to 75%-85%. However, in 2015, the SDR created a new, larger panel that included only a minority of the original sample. Therefore, most participants only have data before 2015 or from 2015 onwards.

We restrict the sample to individuals employed full-time (35 hours/week for at least 40 weeks/year) in a tenure-stream (tenured or tenure-track) position at a US 4-year college or university, university medical school, or university research institute. We exclude 2-year colleges, junior colleges, technical institutes that do not confer regular degrees, and non-educational institutions. We drop observations where respondents were in a post-doctoral position, earned less than the minimum National Institutes of Health post-doctoral stipend ($53,760 in 2020), or worked outside the US (in academia or elsewhere).

Despite the high data quality, studying moves using the SDR requires considerable data cleaning that we describe in detail in Appendix A. There were 1,732 observations where the IPEDS university code changed, yet the respondent reported not changing institutions. These frequently involved two institutions with similar names. Thus, a faculty member who reported working at Boston University in multiple waves might be miscoded as Boston College faculty for one wave despite reporting not changing institutions. Academics know they are different; some data coders did not.

We convert salaries into real 2020 dollars using the CPI for all urban consumers (U.S Bureau of Labor Statistics, 2023). We drop observations with large one-time salary changes within the same institution *that were subsequently reversed* (see appendix for details). As shown in Appendix B (Tables B1-B4), including these observations has little effect on the results. Since these are within a person/university match, dropping them leaves the number of movers and moves unchanged.

We further restrict the job-history sample to observations in the largest connected set of institutions. As is well-known, AKM requires that included institutions be directly or indirectly connected. Institutions A and C are indirectly connected if a faculty member moves from A to B and another moves from B to C. Our largest connected set has 654 institutions. Other connected sets were minimal.

Our college and university rankings come primarily from the mutually exclusive *Times Higher Education* 2017 World University Rankings and the *Wall Street Journal – Times Higher Education* 2017 College Rankings (Times Higher Education, 2017a,b), hereafter *THE* rankings. We matched THE-ranked institutions to their IPEDS codes using their name and location, and applied the procedure described in Appendix A to resolve any ambiguities.

We matched 578 (88% of the total) of the 654 institutions to a *THE* rank. We imputed the ranks of the remaining 76 institutions using data from the *US News and World Report (USNWR)* rankings of best national universities, liberal arts colleges, and regional institutions. We used the overlap between the THE and UNSWR datasets to impute, via a regression, the position of *THE*-unranked schools. Using this procedure, we imputed a rank for 50 schools ranked in USNWR, leaving only 26 unranked schools (4% of the total). We recognize that the prestige of individual departments may not always align with that of the overall institution. As a robustness check, we also present results that restrict the sample to Biological Sciences and Engineering PhDs, the largest PhD fields in the SDR data, and that use both the overall institution ranking and field-specific US News & World Report (USNWR) Best Graduate School rankings (USNWR, 2022, 2024).

We define *research universities* as those in the *THE* university rankings or imputed from the *USNWR* National University rankings. This group encompasses institutions other than R1. We define *colleges* as those in the *THE* college rankings or imputed from other *USNWR* rankings. Many *colleges* are not liberal arts colleges but simply institutions not included among the *THE* research universities or *USNWR* National Universities. Within each institution type, we normalize the best rank to 1 and the worst to 100.[3]

The top-ranked research universities are Stanford, Harvard, Cal Tech, and MIT. The worst-ranked include Western Michigan University, Texas State University, Oakland University, and the University of North Carolina, Wilmington. The top-ranked colleges are Amherst, Williams, Wellesley, and Pomona. The worst-ranked include Grambling State University, Southern University of New Orleans, Georgia Southwestern State University, and the University of the Rio Grande. The unranked institutions include Texas A&M at San Antonio, Brigham Young University at Idaho, and the University of Texas at Brownsville.

From the IPEDS surveys, we obtain total enrollment, number of faculty, endowment (converted to 2020 USD), and dummy variables for large city, urban fringe/mid-sized city/suburb, private institution, and undergraduate-only institution for 2001, 2005, 2012, and 2017.

Table 1 Panel A shows the frequency of moves. We have 63,376 observations on 26,135 individuals, an average of roughly 2.4 observations each. 1,805, or about 7% of individuals, changed institutions at least once. Unsurprisingly, we generally observe movers in more surveys. Movers account for roughly 12% of our observations.

Panel B shows that we observe only one move for most movers. We have 2,114 transitions involving 654 institutions and 1,805 movers, or 1.2 moves per mover and 3.2 moves per institution. Transitions are highly skewed among institutions, ranging from 1 to a maximum of 52.

When surveyed, 45% of faculty observations were full professors and 29% associate professors (see Panel C). A few faculty (1%) report being tenure-stream but hold a title other than assistant, associate, or full professor. About one-third of faculty are female; five-sixths are married when surveyed.

Panel D gives information on the 654 institutions in the connected set, of which 147 are *universities* and 481 *colleges*, with the remaining 26 unranked. They vary dramatically in size and endowment. 40% are private, and 13% serve only undergraduates.

[3]Due to ties, the lowest-ranked college is at the 99^{th} percentile.

3 Faculty Mobility

In this section, we report some basic facts regarding mobility (section 3.1) and associated wage changes among tenure-stream STEM faculty (section 3.2).

3.1 Moves Up and Down are Equally Common; Large Moves are Unusual

Unsurprisingly, and as the top panel of Figure 1 confirms, there is a strong relation between average faculty salary and institution rank. The existence of a hierarchy is not unique to academia. There is strong evidence of a widely shared hierarchy of firms in the general labor market, with upward movements more common than downward, at least for job-to-job transitions (Bagger and Lentz, 2019; Moscarini and Postel-Vinay, 2018; Haltiwanger et al., 2018). Similarly, research using the AKM model finds that firms with a higher firm effect attract and retain more workers (Nimczik, 2020; Bassier, Dube and Naidu, 2022; Sørensen and Vejlin, 2013). If academia were similar to the general labor market, we would expect movements up the prestige ladder to be more common than movements down, despite a significant minority of movements to lower-paying firms (Sorkin, 2018).

Surprisingly, Figure 2 shows that movement up and down the prestige ladder is roughly visually symmetric. Moreover, we cannot reject that the median change in rank among movers is 0, and fail to reject symmetry at conventional levels.[4] To address concerns that moves by untenured faculty are involuntary, we restrict moves to tenured faculty and obtain a similar pattern (see Figure C1).

While movement in either direction is equally likely, moves to proximate institutions are more likely than moves to institutions ranked very differently. In Figure 2's histogram,

[4]We rank log rank changes by their distance from 0 and treat positive and negative changes as separate samples. We then apply the Wilcoxon signed-rank test for two samples and cannot reject that they are the same (p=.52).

roughly one-eighth of moves involve a negligible change in rank. About two-thirds of moves involve an absolute change in log rank of less than 1. A change of 1 in log rank corresponds to movement between roughly the first and third percentile institutions (e.g., Princeton and the University of Pennsylvania) or the 37th and 100th percentiles (roughly between Virginia Tech and Loyola Marymount). Even movement between the 25th and 75th percentiles (e.g., the University of Florida and Kansas State) is somewhat unusual. The transition probability matrix (Appendix Table B5) illustrates the same mobility patterns, while providing details on university-college moves, including similar movements up and down and the prevalence of moves within one's own or neighboring quantiles.[5] Roughly 65% of those starting in universities move within +/- 1 university quintile (or to a more highly ranked college).

3.2 Moves Up and Down Have Similar Wage Changes

In the broader labor market, workers moving from a high to a low-wage firm suffer a wage loss approximately equal to the wage gain for workers moving in the opposite direction (Card, Heining and Kline, 2013; Card et al., 2018; Bonhomme et al., 2023). We do not observe a similar asymmetry with respect to academic institution ranks.

Instead, tenure-stream faculty receive a salary increase of roughly $20-30\%$ when changing institutions, regardless of the direction or magnitude of the prestige change between institutions. (See Appendix Tables B7 and B8) Among those moving between universities, the largest average increase is among those moving within the second-highest quintile, while the lowest is among those moving within the middle quintile. University faculty moving from the top to the fourth quintile gain 18 log points on average, while those moving from the fourth to the top quintile gain 21 log points.

Figure C2 shows a binned scatter plot with quadratic fit of the change in log salary against the change in log rank. It reaches an extreme point near 0 and is symmetric, although 0 is the approximate minimum for movements among colleges and the maximum for universities.

[5]Table B6 shows the transition matrix for tenured faculty only.

The sign of the rank change does not predict the sign of the salary change.

Salaries increase an average of 25 log points when faculty move to a more prestigious university, by 24 log points when they move to a less prestigious one, and by 11 log points when the prestige change is negligible. The corresponding values for colleges are 16, 16, and 14.

As in the broader labor market, prior wage changes have little predictive power for the direction of movement. Restrictions on sample sizes prevent us from showing or describing the full set of movements. Still, in Figure C3, we illustrate salary movements over time across quartiles of coworkers' salaries for the six combinations we can report. There is no clear time pattern.

4 No Evidence of a Prestige Rent

In this section, we first review the AKM model and describe how it can be used to study university salary premia and factors affecting these premia (4.1). We then present our AKM estimation results, including the near-absence of institution effects and the limited role of either institution rank or endowment for explaining the small effects we find (4.2). In section 4.3, we reconcile the strong relation between average salary and rank with the absence of institution fixed effects in AKM by showing a notable positive correlation between faculty effects and rank, and then do further robustness checks (4.4). We discuss the impacts of time-varying individual characteristics in section 4.5, and then consider and reject some explanations for our failure to find prestige effects in sections 4.6 and 4.7.

4.1 AKM in the academic context

To address whether tenure-stream faculty at elite institutions receive a premium, we estimate the standard two-way fixed-effects model or AKM (Abowd, Kramarz and Margolis,

1999) model:

$$\ln w_{ijt} = X_{it}\beta + \alpha_i + \gamma_j + \varepsilon_{ijt} \tag{1}$$

where w_{ijt} is annual salary, X_{it} is a vector of time-varying individual characteristics, and ε_{ijt} is an i.i.d. mean-zero error term.[6]

Institution fixed effects, γ_j, capture the tendency of an institution to pay all faculty a different salary than they would receive elsewhere. They may reflect compensating differentials or institutional rents shared with faculty.

Individual fixed effects, α_i, capture whatever factors raise a faculty member's salary relative to other faculty in the same (or similar) institutions. They are typically interpreted as reflecting worker quality or productivity. However, they capture any factor affecting pay, including discrimination or, in our case, differentials across fields. We largely follow tradition and refer to this fixed effect as capturing worker (faculty) quality.[7]

Clearly, (1) makes strong assumptions. First, AKM assumes mobility is random conditional on α and γ. Formally, ε is uncorrelated with these terms (and X_{it}). Applied to academia, faculty do not move because the profession has changed its belief about them or because they are particularly valuable at their new university. Instead, moves reflect changes in personal preferences or other random factors unrelated to a worker's productivity. Second,

[6] In an antecedent to the AKM model, Hamermesh (1989) examined salaries of 100 full professor non-movers in six economics departments in two periods. In a robustness check, he added institution fixed-effects to faculty variables such as experience and citations, and found no significant institution effects and no changes to the coefficients on faculty variables. Similarly, in estimates without institution or faculty fixed effects, Claypool et al. (2017) found that both program rank and individual publications predict political scientists' salaries.

[7] In some models (e.g., Eeckhout and Kircher 2011), skill and wages are negatively related, but low-skill workers suffer more unemployment (see also Abowd, McKinney and Schmutte 2019).

the semi-log form restricts the institution effect to be proportional; a given university pays a constant percentage premium to all faculty it hires, except for the random error term ε_{ijt}. Similarly, an individual earning 20% more than the norm at one university would earn 20% more elsewhere, again, except for ε_{ijt}.

Third, the AKM model puts restrictions on the edge-effects (links) in a graph of connected firms, as discussed in Kline (2024). These restrictions are typically (approximately) satisfied if the wage changes from moving from firm A to B and B to A are approximately equal and opposite in sign. However, the restrictions will also be satisfied, at least asymptotically, if movement from A to B and B to A is equally likely, as we have seen to be true for tenure-stream faculty.[8]

This estimation excludes seniority from the time/varying individual characteristics because the conditions under which the AKM model is consistent when seniority affects salary are highly restrictive.[9]

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[8]We appreciate Pat Kline's assistance on this point. For those readers who, like us, find the discussion in Kline (2024) challenging, we provide the following intuition. Suppose we observe only movements between A and B. Our estimate of the A premium will be

$$\widehat{\gamma}_A = \frac{\Sigma_{B\to A}\Delta \ln w_i - \Sigma_{A\to B}\Delta \ln w_i}{M_{B\to A} + M_{A\to B}},$$

the sum of the wage gains among movers from B to A minus the sum of wage gains among movers from A to B divided by the number of movers. Now, suppose that the wage change is the sum of a true firm A effect, γ_A, and a mover premium, m.

$$\widehat{\gamma}_A = \frac{\Sigma_{B\to A}\left(\gamma_A + m\right) - \Sigma_{A\to B}\left(-\gamma_A + m\right)}{M_{B\to A} + M_{A\to B}}.$$

There are two generic settings in which $\widehat{\gamma}_A = \gamma_A$: if $m = 0$ or $M_{B\to A} = M_{A\to B}$.

[9]The loss of a seniority premium can be viewed as a negative m in footnote 8. By the logic shown there, it would be sufficient if the probabilities of movement from A to B and B

In this paper, we are interested in knowing how university characteristics affect salary, controlling for faculty fixed effects. In contrast with most AKM applications, we can measure university quality directly using rankings. Therefore, after estimating the AKM model, we regress the estimated institution effects, $\widehat{\gamma}$, on published university rank and other measures potentially correlated with university eliteness:

$$\widehat{\gamma}_j = Z_j \Lambda + \eta_j + \nu_j \tag{2}$$

where Z is a vector of university characteristics, η is a random error term, uncorrelated with Z, consisting of unmeasured university characteristics, and ν is measurement error ($\widehat{\gamma}_j = \gamma_j \ + \nu_j$).

We can also incorporate university characteristics in a salary equation by estimating (1) and (2) in a single step by substituting for γ_j in (1) to get

$$\ln w_{ijt} = X_{it}\beta + Z_j \Lambda + \alpha_i + \eta_j + \varepsilon_{ijt}. \tag{3}$$

This single-step model (3), while not technically an AKM model, provides an additional method for measuring the impact of university characteristics on salaries. We can control for seniority when estimating (3), since adding seniority in the single-step approach is not inconsistent with this model. In addition, the one-step method is less computationally demanding, allowing us below to consider an extension where salary also depends on the prior institution. However, as Kline (2024) explains, the two-step approach is likely to be more robust.[10] We will estimate (2) by feasible GLS but only correct the standard errors for

to A were equal at each level of seniority. The necessary condition is somewhat weaker but remains strong.

[10] In the two-step method, the institution dummies capture η as well as $Z_j\Lambda$. Therefore, our estimates of the γs are unbiased even when correlated with η. However, with the one-step

clustering in (3).

4.2 Institution prestige or endowment has little impact on salaries

We first estimate the standard AKM model (1) with individual time-varying characteristics and fixed effects for both individuals and firms. (See Table B9 for the coefficients on individual time-varying characteristics from this estimation.) Table 2 shows that the overall variance of log salaries (which we measure in 2020 USD) is .141; the variance of the individual fixed effects, α, with no correction is .131 (93% of the overall variance). In contrast, the variance of the institution fixed effects γ is .029 (21% of the overall variance), in line with the 20% typically found in AKM models (Card et al., 2018).

The sum of these two variances thus exceeds the total variance. However, as is well known, we overestimate these variances, especially in settings like ours where many institutions experience little turnover (Andrews et al., 2008; Kline, Saggio and Sølvsten, 2020; Kline, 2024; Bonhomme et al., 2023). With the Andrews et al. (2008) correction, the variance of the individual fixed effects falls to .104 or 74% of the overall salary variance, while the variance of the institution fixed effects is only .012 or 8.5% of the overall variance (Table 2). Thus, institutions account for little of the total variance. Collapsing the data to the spell level to reduce measurement error, as in Bonhomme et al. (2023), gives a total variance of ln(salaries) by spell of .140, similar to the overall variance. As Table 2 shows, the uncorrected variance explained by institution fixed effects (.027) is similar to the estimate without collapsing spells, but after correction, this variance is even more negligible, .007 or only 4.3% of the salary variation. Finally, using the Kline, Saggio and Sølvsten (2020) approach (not in table), the sample falls to 398 institutions (141 universities, 247 colleges, 10 unranked),[11] and the

approach, the correlation between γ and η will generally also generate correlation between Z and η conditional on the faculty fixed effects and therefore, bias Λ per the Theil omitted-variable bias formula.

[11] Kline, Saggio and Sølvsten (2020)'s correction requires restricting the sample to the

corrected variance of the institution effects becomes slightly negative, which is unsurprising when the true variance is small.

The AKM analysis closest to ours for the broader labor market comes from Abowd and McKinney (2024) who use the Longitudinal Employer-Household Dynamics data set for the US from 1994 to 2017. In estimates controlling for experience and hours worked, the variance of firm effects ranges from .038 to .061. Kline (2024) summarizes 24 estimates from 13 studies, all using the KSS correction, with estimates ranging from .024 for Veneto, Italy, to .488 in Brazil. All are much larger than our corrected variances of .012 and .007.

Although our estimates show institution effects are nearly absent, we analyze whether institution characteristics, particularly institution rank and endowments, explain these institution effects. Because rank and endowment are highly correlated, we include rank in Table 3 and endowments in Table 4.

We next regress the 654 institution fixed effects, $\widehat{\gamma}_j$, from our AKM model on institution type (research university, college, unranked), type interacted with rank, and further institution characteristics. Columns (1)-(3) of Table 3 give the results. Then, we include these characteristics directly in the log salary equation in the one-step model (3) (columns 4-6), which allows us to control for seniority (along with other time-varying individual characteristics). The coefficients on research university and college represent the pay gap between the most prestigious institutions in each category and unranked institutions. The interaction terms at the top of the table show the effect of rank within institution type. The best rank is log(1) or 0. The worst is log(100) or 4.6.

Column (1) shows only a modest effect of rank on salaries, even without controls for further institution characteristics. The expected salary difference between the most and least prestigious institutions is 14% for universities and 10% for colleges. The salary gap between unranked institutions and the least prestigious universities and colleges is small. The coefficient on university rank falls well short of significance at conventional levels; however,

institions that remain connected when any single mover is excluded from the sample.

the two rank variables are jointly significant at the .06 level, and the four coefficients are jointly significant at the .02 level.

The unimportance of rank is not due to the regression's linearity. Panel (b) of Figure 1 plots binned institution fixed effects (where institutions are weighted by the number of movers in the institution) against institution rank separately for universities and colleges and fits quadratic curves. For universities (shown with diamonds), the gap between the peak (at top ranks) and bottom institutions is noticeable but small (less than ten log points). For colleges (shown with circles), even the difference between the peak and trough is negligible. This differs considerably from the top panel, which shows a strong negative relation between binned *average log salary* and institution rank. The minimal relation between rank and premiums is robust to not weighting by movers and to grouping institutions with few movers but similar rank (Figure C4).

Column (2) in Table 3 adds urbanicity, which, not surprisingly, significantly affects salaries and somewhat reduces the already modest effect of the two rank variables individually and jointly, and even the four institution types and rank variables are jointly significant at only the .1 level. Adding three additional institutional characteristics (log of total enrollment, undergrad, private/public) in column (3) has little effect on the other coefficients but makes the four variables jointly insignificant.[12]

Columns (4)-(6) show that the results using one-step estimates are generally similar or smaller but more precise. The net effect is that the rank effects are less significant for colleges and more significant for universities. Still, with the largest set of controls, the salary gap between the most and least prestigious universities is about 9%. The comparable figure for

[12]Previous research finds that private universities pay more than public ones (Alexander, 2001; Ehrenberg, 2003; Zoghi, 2003; Zhang and Liu, 2010; Curtis and Thornton, 2014; Rippner and Toutkoushian, 2015; Cheslock and Callie, 2015). However, we find a small and insignificant coefficient on private institutions with a confidence interval that rules out a large premium.

colleges is 4%.

In Table 4, we redo the estimation of Table 3, replacing the rank of universities and colleges with the institution's log endowment per student, which captures the institution's resources and the rents it can share. Endowment has a statistically significant but modest effect. Endowment and university type together still explain less than 2% of the variation in university effects (column 1). Moreover, the difference between the largest and smallest endowment per student predicts only a 12% difference in the institution salary effects (γ_j) in column (1).

4.3 More prestigious institutions attract better faculty

To reconcile the two facts that elite schools pay more but do not have higher fixed effects (as shown in the two panels of Figure 1), more prestigious institutions must hire faculty with higher fixed effects. The bottom of Table 3 displays the correlation between individual fixed effects and log rank for each specification. Recall that the best log rank is 0. Therefore, we expect a negative correlation between prestige and individual fixed effects. The estimated correlations range from $-.22$ to $-.28$ for universities and from $-.09$ to $-.17$ for colleges.

The correlations between prestige and individual fixed effects are smaller than we expected. This could reflect large salary differences across fields within institutions that dominate the within-field individual quality differences. We investigated this by regressing the individual effects on PhD field and calculating the residuals. The correlations of these residuals with institution prestige are virtually identical to those reported in Table 3.

4.4 Further robustness checks

Tables B1-B4 replicate Tables 1-4 but keep observations where a faculty member had a large pay increase that was subsequently reversed. The results are virtually indistinguishable from those obtained by dropping these observations.

Our result is robust to limiting the sample to tenured faculty. For the 434 institutions remaining in the connected set, the effects of college and university rank flip sign. However, neither change appears to be statistically significant (see Appendix Table B10).

It is possible that the university fixed effects had little variation or relation to university ranks because universities are not equally elite across all departments. Therefore, we also redid this analysis for the two fields with large enough samples to allow analysis, faculty with PhDs in biological sciences and separately, engineering. In Table B11, we show estimates using the THE rankings (columns 1 and 3) and the field-specific *UNSWR* rankings (columns 2 and 4). In all cases, the estimated effect of rank on salary is small and insignificant. Moreover, for biological sciences, the effect of field-specific rank has the wrong sign. We also plot field-specific institutional fixed effects against field-specific rank for these fields (Appendix Figure C5). Again, these effects are small and, moreover, not monotonic with respect to rank.

4.5 Time-varying individual characteristics: It's mostly rank and experience

In Table B9, we show the effect of the time-varying characteristics using the specification in column (1) of Table 3. The coefficients are unsurprising and correspond to past studies of academic salaries. Salaries increase with post-PhD experience, although at a declining rate, while remaining positive at all experience levels in the data. Academic rank, rather than tenure status, affects salaries. The few tenure-stream lecturers and instructors earn salaries comparable to those of assistant professors. Associate professors earn a slight premium (5%) relative to assistant professors. Full professors earn about 10% more than comparable associate professors. The small "other" group lies between associate and full professors.

Family composition has little effect on earnings, conditional on rank and experience. Prior research suggests that children make women less likely to hold tenure-stream jobs (Ginther and Kahn, 2006; Cheng, 2020; Wolfinger, Mason and Goulden, 2008; Martinez et al., 2007). However, among women with tenure-stream STEM jobs, children and marriage are positively associated with both women's and men's salaries (Kahn and Ginther, 2017a). The positive association is likely due to selection, which our model captures through the individual fixed effects.

Seniority is theoretically inconsistent with AKM estimation. Therefore, we excluded seniority from the time-varying variables in our two-step estimation shown in Table B9. Using our one-step model, we find a small negative effect of seniority ($-.6\%$ per year of seniority) as shown in Table B12, columns (1)-(3). Negative coefficients on seniority are common in the literature on the academic labor market.[13] For comparison with the prior literature, in Appendix Table B12, columns (4)-(6), we drop the individual fixed effects. This produces a somewhat more negative coefficient on seniority. The most common explanation is *ex post* monopsony (Ransom, 1993; Hallock, 1995).

4.6 Is the absence of institution-effects due to universities matching next best offers?

Most academics expect they can increase their salaries by getting outside offers. Therefore, a model in which the best outside option also influences salaries may be appropriate. Could this explain our inability to find institution effects?

To test this, in Appendix Table B13, we build on Di Addario et al. (2023) and allow the current and previous employer to influence salaries. We re-estimate the one-step model, including institution type and the prior and current institution's rank. This table reports the coefficients on these key parameters. The sample size is much smaller, because we need information on the prior employing institution. Therefore, we can only use movers and then only their observations from the second or later job at which we observe them.

[13]Some of the studies here include Ransom (1993), Barbezat and Hughes (2001), Hallock (1995), Barbezat and Hughes (2001), Brown and Woodbury (1998), Moore, Newman and Terrell (2007), Hilmer, Ransom and Hilmer (2015), Blackaby, Booth and Frank (2005), and Bratsberg, Ragan Jr and Warren (2010).

Ideally, like Di Addario et al. (2023), we would limit our analysis to the initial salary in each job so that the previous job would very likely be the source of the next best offer. Unfortunately, we do not have sufficient data for this approach. Instead, we control for seniority, since those in a job longer have a higher likelihood of having ever received an outside offer.[14]

If faculty capture rents based on their best alternative offer, the coefficients on the rank of their previous institution should be negative. If they can also capture some of the rents from their current institution, the coefficients on the rank of their current institution should also be negative. Only one (rank of prior university) of the four coefficients (prior/current rank x college/university) is statistically significant, and then only at the .06 level. One coefficient (current college rank) has the wrong sign; a second (rank of prior college) only turns negative if we control for other institution characteristics (not shown).

Given the obvious imprecision of our estimates, a generous interpretation might find the marginally significant negative coefficient on the rank of the prior university as some evidence of a second-price effect in which faculty cannot capture current rents. Given the risk of drawing a strong conclusion from one marginally significant effect and the fact that the coefficient on seniority has the wrong sign, we see no real support for this generous interpretation.

Note that our results do not reject the Postel-Vinay and Robin (2002) model. We only rule out that the absence of rents is due to ignoring the effect of prior employer on current salary. If, for example, productivity has an important match-specific component, the model might hold, but the value of the second-best offer might be unrelated to the institution's rank. Moreover, our finding of increased salaries on moving, whether prestige increases or decreases, is consistent with this model.

[14]This would predict a positive coefficient on seniority. Instead, it is negative here (consistent with higher prestige), but as we discussed above, we and many others have found coefficients on seniority, perhaps because of monopsony power.

4.7 Are institution effects absent due to higher nonsalary compensation at elite institutions?

We observe only salaries, but working conditions and other amenities differ among institutions. Moreover, in the broader labor market, amenities and wages are positively correlated (Mas, 2025). Perhaps more elite institutions offer better working conditions, so that looking at salaries alone obscures higher faculty total compensation at elite institutions, as suggested by Claypool et al. (2017).

If jobs at higher-ranked institutions are better, conditional on salary, faculty at such institutions should be more likely to say that they are very satisfied or satisfied with their job. Do they? The SDR asks respondents whether they are very dissatisfied, somewhat dissatisfied, somewhat satisfied, or very satisfied with their job. From this, we construct two alternative job satisfaction dummy variables, one for "very satisfied" and one for very or somewhat satisfied. Following Bond and Lang (2019), we make no claims about average happiness.

To see if faculty at elite institutions are more satisfied with their jobs than would be predicted based on salary alone, we run a similar AKM analysis as we did for ln(salary), replacing log salary with satisfaction as the dependent variable. We add the log of salary as a control variable in both the one- and two-step estimates.

Table B14 shows the impacts of institution characteristics and salary on satisfaction (analogous to Table 3 showing the impacts on salary). None of the institution characteristics' coefficients approaches statistical significance for either satisfaction variable. Moreover, rather than the negative signs on rank consistent with positive amenities at elite universities, many of the signs on the rank variables are positive.

Moreover, the compensating differential explanation is inconsistent with the symmetric mobility pattern we observe. If overall compensation were higher at elite institutions, faculty would generally prefer to move up the prestige ladder. Yet movement up and down the ladder is equally likely, even for tenured faculty whose moves are presumably almost all voluntary.

In sum, it is implausible that our results would differ meaningfully if we could measure the value of amenities. Of course, valuing amenities is particularly problematic in settings such as ours, where workers have very heterogeneous tastes.

5 Discussion: Why is Academic STEM Different?

We find considerable evidence of matching. Better academics, as measured by their fixed effects, are more likely to work at more elite institutions. We also find that mobility is symmetric: movements up and down the prestige scale are equally likely, and, on average, all moves are associated with salary increases.

Separately, each of these facts can be accounted for by many explanations. Collectively, we believe that these findings point us to a model in which the market observes faculty quality even early in careers and where there is an optimal institution match for each level of faculty quality, with the best academics being better matched (more productive or more valued) at more elite institutions and less productive academics better matched at lower-ranked institutions. However, departments hire at irregular intervals, so that the optimal match may not be available when newly minted PhDs enter the academic labor market or faculty search for new jobs.

In contrast, in the standard AKM model, a worker's relative productivity is the same at all firms, and firms' relative pay does not depend on their workers' quality. All workers prefer to work at more productive firms, and all firms prefer more productive workers.[15] Therefore, if most moves are voluntary, moves should be more frequently up than down, which is true in the broader labor market. In AKM, downward moves are either involuntary or to firms whose low pay reflects good working conditions. In either case, the sign of the wage change depends on the direction of the move, unlike what we find for academia.

[15] In this setting, the matching process can generate positive assortative matching even if negative matching would maximize total output (Borovičková and Shimer, 2024).

Outside the AKM model, a reassessment of worker productivity may cause moves. If new information shows a worker is less productive than expected, their job change comes with a wage decrease; if the new information shows they are more productive than expected, their new job pays them more. This, too, does not match the pattern in the academic labor market.

Instead, we suggest that information about academics is very good even when they first enter the tenure-stream market. Our data set includes both natural sciences and social sciences (STEM). It is particularly plausible that information is very good in the natural sciences, where faculty frequently enter tenure-track jobs after an average of 7+ years in graduate school and 4.5 years in post-doctoral fellowships (Kahn and Ginther, 2017b). Even in economics, where, until recently, post-docs were unusual and most new tenure-stream entrants had few if any publications, job market papers and reference letters provide hiring departments with considerable information.

Despite this good information, matches are highly imperfect because most departments have few, if any, openings each year. Moreover, openings are often restricted to narrow fields. Any given university will rarely have an opening in computational biology. At the same time, departments are often keen to fill their positions since unfilled positions at the end of the recruiting season frequently do not carry over to the following year. One study in computer science found that only 2% of computer science searches failed to result in a hire at the top 100 PhD-granting departments, although the failure rate was notably higher at departments not granting PhDs (Wills, 2019). Another (Fox, n.d.) reported an 8% failure rate in ecology. STEM departments apparently avoid failed searches.

So, it seems plausible that STEM faculty are both over- and under-matched. When academics move, they move towards a better-matched institution if a job becomes available. In other words, we suggest that academics do not move because the market has new information about them, but because they were mismatched initially. Each move improves the match and thus increases their salary.[16] Consistent with this interpretation, salary increases are larger when faculty change prestige quintiles, at least within universities.

It seems plausible that a labor market with very visible information about worker quality and limited job openings generates the special aspects we have identified in the academic job market: elite universities attracting the best faculty and paying them salaries comparable to what they would receive at proximate institutions, the predominance of movements to similarly ranked universities, and similar movements up and down the prestige ladder accompanied by positive wage changes.

We do not address how elite universities gain their status. However, departments around the world understand that the way to move up in the rankings is to attract a core of excellent – and expensive – faculty.

[16] If matches were idiosyncratic but still ranked on average as in Borovičková and Shimer (2024), we would still tend to see movement up the eliteness ranking if all workers preferred elite institutions.

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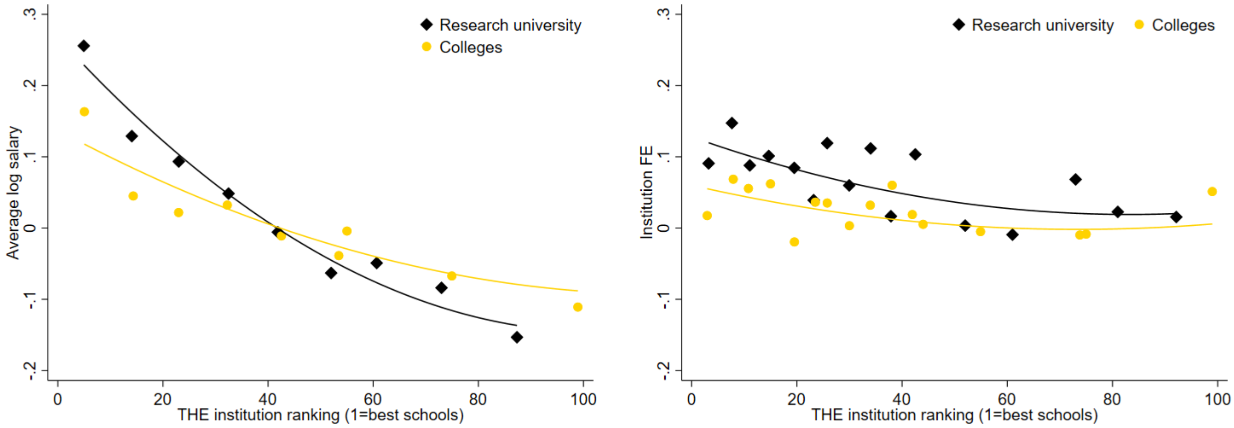
Figure 1: Faculty Log Salary and Institution Rankings

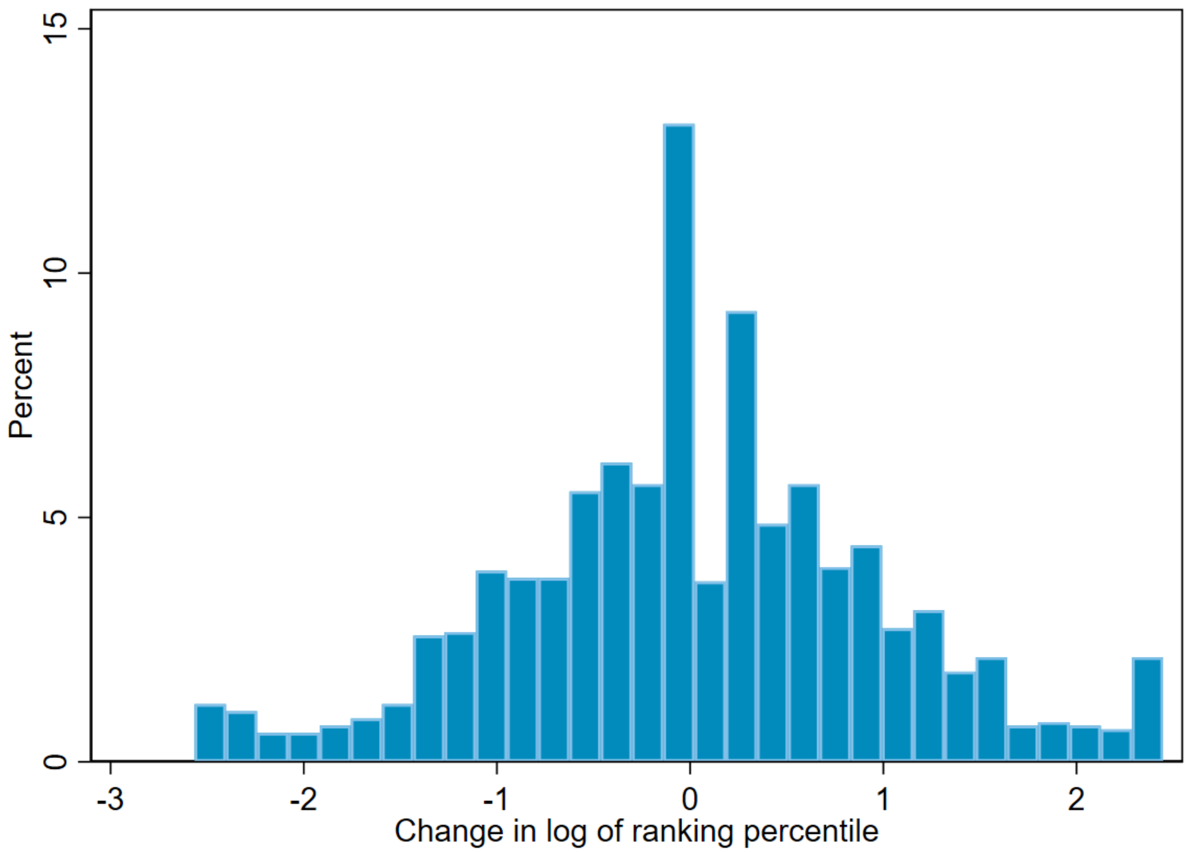
(a) Average salary

(b) Binned Salary Premiums Weighted by the Number of Movers



Notes: The figure shows binned scatter plots relating measures of faculty real pay to institution rankings for research universities and colleges. Panel (a) relates average faculty log salary and institution rankings. Panel (b) relates the estimated pay premiums to rankings, weighted by the number of movers in the institution. All premiums were estimated by regressing ln salary on year, individual and institution fixed effects, years since PhD and its square, academic rank, tenured, female, married, children dummies (<6, 6-11, 12-18, 19+), female $\times$ married, children dummies interacted with female. All faculty salaries are expressed in 2020 USD.

Figure 2: Distribution of Changes in Institution Prestige



Notes: The histogram shows the distribution of changes in the institution's prestige (rank) when faculty change employers. The figure limits the sample to faculty moves within the same institution type (university to university or college to college). Institution ranking expressed in percentiles, with lower values indicating more prestigious institutions.

Table 1: Summary Statistics

A. Number of movers in the sample

	All	Movers	Share of total
Total observations	63,376	7,840	0.12
Number of people	26,135	1,805	0.07
Mean obs. per person	2.42	4.34	

B. Number of transitions in the sample

	Total	Min	Max
Transitions	2,114		
Number of movers	1,805		
Number of universities	654		
Transitions per mover	1.17	1	*
Transitions per university	3.23	1	52

C. Individual characteristics

	N	Mean	SD
Years since Ph.D.	63,376	18.24	10.61
Has tenure	63,376	0.73	0.44
Time in current job	63,376	12.89	10.31
Faculty rank			
Assistant professor	63,376	0.24	0.43
Associate professor	63,376	0.29	0.46
Professor	63,376	0.45	0.50
Lecturer	63,376	0.00	0.03
Instructor	63,376	0.00	0.04
Other	63,376	0.01	0.09
Female	63,376	0.32	0.47
Married	63,376	0.83	0.38

D. University characteristics

	Mean	SD	Min	Max
Research universities	48	28	1	99
Colleges	46	25	1	100
ln(total enrollment)	8.91	1.02	5.79	10.92
ln(total endowment)	18.10	2.10	11.51	24.25
ln(endowment/students)	9.20	2.09	2.55	14.67
ln(faculty size)	5.88	1.03	0.81	8.54
ln(faculty/students)	-3.03	0.46	-5.38	-1.42
Share in large city	0.23	0.42	0.00	1.00
Share in medium city	0.34	0.47	0.00	1.00
Share in small city	0.43	0.50	0.00	1.00
Share private	0.40	0.49	0.00	1.00
Share undergraduate	0.13	0.33	0.00	1.00

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Table 1: continues from previous page

C. Individual characteristics	N	Mean	SD	D. University characteristics	Mean	SD	Min	Max
Has child under 6	63,376	0.18	0.38					
Has child aged 6-11	63,376	0.20	0.40					
Has child aged 12-18	63,376	0.20	0.40					
Has child aged 19+	63,376	0.10	0.30					

Notes: There are 147 research universities and 481 colleges. 26 institutions are unranked and not classified as colleges or universities. * Suppressed for confidentiality. All monetary variables are expressed in 2020 USD.

Table 2: Fixed Effect Variance Estimates in AKM Model

	Uncorrected (1)	Corrected Andrews et al method (2)
Individual by year level		
Variance log(*salary*)	0.141	0.141
Variance of Fixed-effects		
Individual	0.132	0.104
Institution	0.029	0.012
Correlation	-0.334	-0.396
Correlation net of field	-0.356	
Collapsed at the spell level		
Variance log(*salary*)	0.140	0.140
Variance of Fixed-effects		
Individual	0.129	0.080
Institution	0.027	0.006
Correlation	-0.306	0.094
Correlation net of field	-0.326	

Notes: The table shows estimates of the variances of the log salary, the individual and institution fixed effects, and the correlation between institution and individual fixed effects. Column (1) displays uncorrected estimates, while column (2) corrects for limited mobility bias using the method by Andrews et al. (2008). Panel A uses person-year observations, while panel B collapses the dataset at the employment spell level.

Table 3: Do Rankings Increase Institution Premiums?

	Two-step estimates			One-step estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Institution type × log of ranking						
Research university	-0.0307	-0.0273	-0.0269	-0.0248	-0.0237	-0.0186
	(0.0205)	(0.0205)	(0.0211)	(0.0095)	(0.0094)	(0.0097)
Colleges	-0.0227	-0.0201	-0.0213	-0.0111	-0.0119	-0.0077
	(0.0119)	(0.0119)	(0.0148)	(0.0084)	(0.0084)	(0.0096)
Institution type (omitted=unranked)						
Research university	0.2161	0.1841	0.1726	0.1467	0.1326	0.0972
	(0.0884)	(0.0893)	(0.0955)	(0.0445)	(0.0442)	(0.0454)
Colleges	0.1390	0.1210	0.1242	0.0567	0.0510	0.0312
	(0.0631)	(0.0633)	(0.0719)	(0.0385)	(0.0389)	(0.0403)
Institution characteristics						
Large city		0.0666	0.0638		0.0432	0.0379
		(0.0238)	(0.0254)		(0.0137)	(0.0140)
Medium city/suburb		0.0244	0.0240		0.0092	0.0078
		(0.0212)	(0.0215)		(0.0112)	(0.0112)
Log of total enrollment			0.0095			0.0134
			(0.0136)			(0.0085)
Undergrad only			0.0137			-0.0061
			(0.0304)			(0.0190)

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Table 3: continues from previous page

	Two-step estimates			One-step estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Private			0.0014			0.0284
			(0.0275)			(0.0152)
Time in current job				-0.0058	-0.0058	-0.0058
				(0.0003)	(0.0003)	(0.0003)
Joint significance of 2 ranking variables						
F statistic	2.930	2.271	1.649	3.827	3.680	1.915
p-value	0.054	0.104	0.193	0.022	0.026	0.148
Joint significance of institution type and ranking variables						
F statistic	3.235	2.155	1.318	4.860	4.630	1.908
p-value	0.012	0.073	0.262	0.001	0.001	0.107
Correlation between individual fixed effects and log of rankings						
Universities	-0.220	-0.220	-0.220	-0.284	-0.280	-0.280
Colleges	-0.091	-0.091	-0.091	-0.168	-0.163	-0.161
Observations	654	654	654	63,376	63,376	63,376
R^2	0.020	0.031	0.032	0.950	0.950	0.950

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Table 3: continues from previous page

	Two-step estimates			One-step estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Individual-level observations	63,376	63,376	63,376	63,376	63,376	63,376
Number of people	26,135	26,135	26,135	26,135	26,135	26,135
Number of movers	1,805	1,805	1,805	1,805	1,805	1,805

Notes: The table shows estimates from regressions of the institution pay premiums or the log of faculty real salary on institution characteristics. Columns (1) to (3) show two-step estimates. The first step regresses ln salary on individual, institution, and year fixed effects, years since PhD and its square, academic rank, tenured, female, married, number of children dummies (<6, 6-11, 12-18, 19+), female $\times$ married, and interactions between the children dummies and female; the second step (shown) regresses institution fixed effect estimates on institution characteristics using FGLS. One-step estimates –columns (4) to (6)– regress ln salary on individual and year fixed effects, the above time-varying individual characteristics, time in the current job, and the institution characteristics shown, clustering standard errors by institution. Real salaries expressed in 2020 USD. Institution ranking ranges from 1 (best) to 100. Research universities are mainly R1 but include some R2 institutions; colleges include all remaining ranked post-secondary institutions granting four-year degrees; excluded category: unranked. Large, medium, and small cities have populations above 250k, between 100k and 250k, and under 100k, respectively. Standard errors in parentheses.

Table 4: Does Endowment Increase Institution Premiums?

	Two-step estimates			One-step estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(endowment per student)	0.0094	0.0089	0.0149	0.0091	0.0097	0.0093
	(0.0045)	(0.0045)	(0.0069)	(0.0029)	(0.0029)	(0.0039)
Institution type (omitted=unranked)						
Research university	0.0816	0.0619	0.0340	0.0224	0.0099	-0.0037
	(0.0506)	(0.0509)	(0.0566)	(0.0291)	(0.0291)	(0.0302)
Colleges	0.0446	0.0360	0.0305	-0.0044	-0.0147	-0.0151
	(0.0471)	(0.0470)	(0.0478)	(0.0270)	(0.0270)	(0.0268)
Institution characteristics						
Large city		0.0700	0.0705		0.0463	0.0417
		(0.0237)	(0.0256)		(0.0135)	(0.0139)

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Table 4: continues from previous page

	Two-step estimates			One-step estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Medium city/suburb		0.0277	0.0290		0.0102	0.0089
		(0.0210)	(0.0214)		(0.0113)	(0.0113)
Log of total enrollment			0.0139			0.0170
			(0.0134)			(0.0085)
Undergrad only			0.0241			0.0061
			(0.0291)			(0.0190)
Private			-0.0202			0.0164
			(0.0317)			(0.0174)
Time in current job				-0.0058	-0.0058	-0.0058
				(0.0003)	(0.0003)	(0.0003)
Observations	654	654	654	63,376	63,376	63,376
R^2	0.017	0.030	0.034	0.950	0.950	0.950

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Table 4: continues from previous page

	Two-step estimates			One-step estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Individual-level observations	63,376	63,376	63,376	63,376	63,376	63,376
Number of people	26,135	26,135	26,135	26,135	26,135	26,135
Number of movers	1,805	1,805	1,805	1,805	1,805	1,805

Notes: The table shows estimates from regressions of the institution pay premiums or the log of faculty real salary on institution characteristics. Columns (1) to (3) show two-step estimates. The first step regresses ln salary on individual, institution, and year fixed effects, years since PhD and its square, academic rank, tenured, female, married, number of children dummies (<6, 6-11, 12-18, 19+), female $\times$ married, and interactions between the children dummies and female; the second step (shown) regresses institution fixed effect estimates on institution characteristics using FGLS. One-step estimates –columns (4) to (6)– regress ln salary on individual and year fixed effects, the above time-varying individual characteristics, time in the current job, and the institution characteristics shown, clustering standard errors by institution. Real salaries and endowment per student are expressed in 2020 USD. Research universities are mainly R1 but include some R2 institutions; colleges include all remaining ranked post-secondary institutions granting four-year degrees; excluded category: unranked. Large, medium, and small cities have populations above 250k, between 100k and 250k, and under 100k, respectively. Standard errors in parentheses.

A Data

In this paper, we combine data from several sources: (1) individual-level data from the restricted-use version of the Survey of Doctorate Recipients (SDR) from the National Center for Science and Engineering Statistics (NCSES); (2) university and college rankings data from the *Times Higher Education* 2017 World University Rankings, the *Wall Street Journal – Times Higher Education* 2017 College Rankings, and the 2021 *US News and World Report* rankings; and (3) university characteristics from Integrated Postsecondary Education Data System (IPEDS) surveys.

We combine these sources and prepare the dataset in three main steps: (1) build a work history panel for tenure-track faculty, (2) construct a dataset with institution characteristics, and (3) associate each school with a unique ranking. Below, we describe each step in detail.

A1 Building the work history panel

We first combine the information from all the SDR waves available between 1993 and 2017 (inclusive). We restrict the sample to people employed full-time (35 hours/week for at least 40 weeks/year) in a tenure-stream (tenured or tenure-track) position at a US 4-year college or university, medical school attached to a university, or university research institute. We also drop observations where respondents were in a post-doctoral position, earned less than the minimum National Institutes of Health post-doctoral stipend ($53,760 in 2020), or worked outside the US (whether in academia or not). We identify employers using the IPEDS institution code reported by the SDR. We transform all salary figures into 2020 dollars using the yearly CPI for all urban consumers (U.S Bureau of Labor Statistics, 2023). This leaves us with an unbalanced panel tracking the work history of tenure-track faculty across US academic institutions.

A1.1 Determining faculty moves in the SDR

We pay special attention to ensuring that we track faculty moves across academic institutions correctly. The AKM model identifies the pay premiums out of variation coming from people moving across institutions. Thus, it is crucial that we record moves accurately.

We say an academic changed employers whenever we observe a change in the IPEDS code of the current employer, except when these changes result from a leave of absence or a likely coding error. We identify leaves of absence as *temporary moves* out of a primary or home institution. These are moves satisfying three conditions:

(i) we observe the academic in three *consecutive* SDR waves;

(ii) the academic starts in an institution (home) and moves to a *host* institution for one SDR wave;

(iii) to then return to their home institution.

We identify approximately 51 leaves-of-absence in our data. We exclude the host school observation for them, keeping the observations in their home school only.

We also identified and manually corrected moves that were likely the result of a coding error. There were 1,732 observations where the IPEDS university code changed but the respondent reported not changing institutions. These frequently involved two institutions with similar names. Thus, a Boston University faculty member might be miscoded as Boston College faculty for one wave, while reporting not changing institutions. We manually checked these moves and corrected those we deemed to be likely mistakes.

Because we are interested in institution-level premiums, we merged IPEDS codes that identify units of the same university. IPEDS divides some large universities across different codes. For example, ASU-Tempe and ASU-Phoenix have different codes even though they belong to the same institution. We did not count these as moves in our dataset, since all are within ASU. Therefore, we assigned all university units to a single code in such cases. It is possible that we missed some moves in this process, but we wanted to be conservative in what we considered to be moves. Whenever we determined that university campuses were independent of each other, we kept them as separate IPEDS codes. For example, we keep University of Wisconsin-Madison and University of Wisconsin-Oshkosh as separate institutions.

We tried to be as conservative as possible in this process, only combining 42 institution codes into 24 codes. We can provide the list of merged codes upon request.

A2 Salaries

We excluded salary observations featuring very large one-time salary changes that were subsequently reversed *within the same institution*. We identify these outliers as follows:

1. First, we computed the growth in log of real salary adjusted for job experience ($\widetilde{\Delta \ln w_t}$):

$$\Delta \ln \widetilde{w}_t = \Delta \ln w_t - \Delta \ln \widehat{w}_t \tag{A4}$$

   where $\Delta \ln w_t$ is the log change in salary, and $\widehat{\Delta \ln w_t}$ is the expected log salary change due to experience. This expected change comes from a regression of log salary on years of experience and its square:

$$\ln w_t = \alpha_o + \alpha_1 y_t + \alpha_2 y_t^2 + \nu_t$$

   where y_t denote years since Ph.D. Then we define the expected change as:

$$\widehat{\Delta \ln w_t} = \widehat{\alpha}_1 \Delta y_t + \widehat{\alpha}_2 \Delta y_t^2$$

   The expression in A4 measures how much actual salary growth deviates from what we should expect based on the experience profile alone.

2. We flag a *within-institution* log salary change as a *potential outlier* if, after adjusting for experience, it is larger than 0.4 in absolute value:

$$\left|\widetilde{\Delta \ln w_t}\right| = |\Delta \ln w_t - \widehat{\Delta \ln w_t}| > 0.4$$

We note that 0.4 is a conservative threshold (97$^{\text{th}}$ percentile of adjusted salary growth).

3. We then focus on the *potential outliers* and exclude observations as follows. We drop all observations from people with only two observations in the dataset and who worked for only one institution. For people having at least three observations and who worked for several institutions, we apply the following procedure:

4. If $\left|\Delta \widetilde{\ln w_t}\right| > 0.4$, then either w_t or w_{t-1} may be the outlier. We exclude w_t if its log distance from any other salary observation for that person is greater than 0.2.[17] That is,

$$\text{Drop } w_t \text{ if } \min_j \{d_j | d_j = |\ln w_j - \ln w_t|\,,\ j \neq t\} > 0.2$$

5. If $|\Delta \widetilde{\ln w_t}| > 0.4$ but its minimum distance is less than 0.2, we apply additional sequential filters –i.e., if an observation survives filter (i) below, then we applied (ii)–:

   i. We excluded all observations where the individual's primary work activities were not teaching or research. These people are likely to be in administrative positions.[18]

   ii. We excluded all salaries that were out of line with the individual's salary trend. This judgment was made on a case-by-case basis. All these modifications were codified into a script.

A3 Building the institution characteristics dataset

We extract all university characteristics other than the position in the rankings from IPEDS. We use the institution characteristics, fall enrollment, finance, and salary modules for the years 2001, 2005, 2012, and 2017. All nominal figures are converted into 2020 dollars using the CPI for all urban consumers (U.S Bureau of Labor Statistics, 2023). We cannot meaningfully add time-varying institution characteristics to our regressions because they change very slowly, and when they do change, long and uncertain lags in their impact would prevent us from associating salary changes with changes in institutional characteristics. Thus, we average all continuous variables across the four survey waves. For all dummy variables, we assign the maximum value across the four years. For example, we classify a university as granting a Ph.D. degree if it ever granted such a degree during any of the four survey waves.

We extract the following variables from IPEDS:

- **University location:** we classify the university's location into small, medium, and large cities. This variable is a recoding of IPEDS' locale variable. Table A1 details the mapping between both variables.

[17] 0.2 is the 90th percentile of the adjusted wage growth.

[18] In later waves, the SDR asked if the person working in an academic institution was (1) a president, provost or chancellor or (2) a dean, department head or department chair. However, this question was not asked in most SDR waves in our study so we do not use it.

- **Private university:** dummy equal to one if the university is private.
- **Undergrad-only:** dummy variable equal to one if the institution only offers undergraduate degrees.
- **Total enrollment:** sum of undergraduate and graduate enrollment for the fall semester averaged over the four survey years.
- **Total faculty:** full-time faculty for the fall semester averaged over the four survey years.
- **Endowment:** IPEDS reports finance information separately for public institutions, private not-for-profit, and private for profit. For each year, endowment variable corresponds to:

  – **Public universities and private non-profits:** we average the value of endowment assets at the beginning and end of the fiscal year.

  – **Private for-profits:** we average the value of equity at the beginning and end of the year.

  We convert the yearly endowment to 2020 USD using the CPI for all urban consumers and average it across the four survey waves.

A4 University rankings

Our primary sources for the institution rankings are the *Times Higher Education* 2017 World University Rankings and the *Wall Street Journal – Times Higher Education* 2017 College Rankings. They consist of a list of institution names along with their ranking position and the state in which they are located. We linked these rankings to a unique IPEDS code using name and location. In most cases, the names in *THE* and IPEDS were similar, and the linkage was straightforward. For the few cases where the linkage was not obvious, we adhered to the following rules:

1. Whenever names only differed in the word "college" or "university," we used a Google search along with the location information to determine if they were the same institution. For example, if the IPEDS label was "Concordia College" and the *THE*-name was "Concordia University". We linked both names if and only if:
   - The institution's state is the same in both datasets.
   - A search for the term "[...] college" gives "[...] university" as the first search result (or vice versa).
2. Different campuses in a university system have different IPEDS codes. Sometimes *THE* provides only one rank for a university system without reference to the campus. In this case, we associated the rank to the flagship campus. For example, the rank for "Penn State University" was assigned to the IPEDS code for "Penn State University, University-Park."

We applied the above procedure to both the *THE* World University and the *WSJ/THE* College rankings. We categorized the institutions matched to the THE World University Rankings as *research universities*. For these institutions, the value of the institution rank is their position in the World University Ranking. The institutions (i) not matched to the World University Ranking but (ii) matched to the College Ranking were categorized as *colleges*. Their *institution rank* is their position in the College Rankings. Note that many institutions in this category are not solely undergraduate institutions.

We matched 578 (88% of the total) of the 654 institutions to a *THE* ranking. For the remaining 76 institutions, we imputed their rank using data from the *US News and World Report (USNWR)* rankings of best national universities, liberal arts colleges, and regional institutions. We took advantage of the overlap between the THE and UNSWR datasets and imputed the position of *THE*-unranked schools using a regression. We imputed a rank for 50 schools ranked in *USNWR*, leaving only 26 unranked schools (4% of the total).

A4.1 Imputing the THE ranks

The THE rankings are our primary source of university performance information. However, we were unable to match 76 institutions to a THE rank. For 50 of these institutions, we imputed their *THE* rank using data from U.S. News and World Report (*USNWR*) rankings, as follows:

1. First, we merged the *THE* rankings with each of the ten available *USNWR* ranking lists by institution name. We use 10 mutually exclusive *USNWR* lists: national universities, liberal arts colleges, four regional university lists, and four regional colleges lists. We checked all name matches manually to ensure consistency.

2. For universities ranked by both *THE* and *USNWR*, we run regressions of the *THE* position on the *USNWR* position. We run a separate regression for each of the 10 *USNWR* lists:

$$THE\ ranking_i = \alpha + \beta USNWR\ \ ranking_i + \varepsilon_i \tag{A5}$$

   Table A2 shows the results of each of these auxiliary regressions.

3. We infer the position in the *THE* rankings for universities unranked by *THE* but ranked by *US News* using the predicted values of the regression in (A5):

$$\widehat{THE\ ranking}_i = \alpha + \widehat{\beta} US\ news\ ranking_i$$

Because all ten *US News* rankings are mutually exclusive, the imputed *THE* position is unique. We treat institutions in the *USNWR National University* ranking as *research universities*, and institutions in all other lists (liberal arts colleges, regional universities, and regional colleges) as *colleges.* The bottom two rows of Table A2 provides a breakdown of the imputed ranks according to the *US News* ranking list we used for the imputation.

Table A1: Institution Location Classification

Original Codes	IPEDS description	Recoding used	Description
A. 2001 IPEDS locale Classification			
1	Large city	Large city	Urban area, population above 250k
2 3, 4	Mid-size city Urban fringe of large / mid-size city	Mid size city / suburb	Urban area, population between 100k and 250, or suburbs
5, 6, 7 9	Large town, small town, rural Not assigned	Small city / rural town	Urban areas with polulation below 100k, rural areas
B. 2005-2017 IPEDS locale Classification			
11	Large city	Large city	Urban area, population above 250k
12 21, 22, 23	Mid-size city Suburbs	Mid-size city / suburbs	Urban area, population between 100k and 250, or suburbs
13 31 - 43	Small city Towns, rural	Small city / rural town	Urban areas with polulation below 100k, rural areas

Notes: The table details the conversion from the origin IPEDS location classification into the location classification we used in the analysis.

Table A2: Ranking Imputation Regressions

	National rankings		Regional universities				Regional colleges			
	(1) National	**(2)** Liberal	**(3)** North	**(4)** South	**(5)** Midwest	**(6)** West	**(7)** North	**(8)** South	**(9)** Midwest	**(10)** West
US News ranking	1.762	3.115	3.101	2.671	2.883	3.872	3.681	1.715	7.927	7.938
	(0.132)	(0.139)	(0.237)	(0.361)	(0.293)	(0.395)	(1.901)	(0.623)	(1.130)	(5.318)
Constant	82.21	-20.90	326.0	550.3	456.5	439.7	624.2	694.0	382.2	585.5
	(17.665)	(15.120)	(21.710)	(24.234)	(23.468)	(25.014)	(50.416)	(23.008)	(37.954)	(68.844)
R^2	0.582	0.771	0.554	0.386	0.477	0.530	0.211	0.296	0.629	0.182
F	179.3	502.0	171.4	54.61	96.79	96.04	3.748	7.571	49.24	2.228
Observations	131	151	140	89	108	87	16	20	31	12
Number of schools imputed	6	12	5	4	3	7	4	3	3	3
Total schools imputed	50									

Notes: The table shows the regressions used to impute *THE*-rank positions to schools ranked by *USNWR* but not by *THE*. Column (1) uses the position in the THE World University ranking as the dependent variable, while columns (2)-(10) use that in *THE/WSJ* college ranking. The imputed position is unique because all the *USNWR* rankings are mutually exclusive. The last two rows show the number of schools imputed with each regression, as well as the total number of schools imputed. We classify schools imputed using column (1) as research universities, and all others as colleges.

B Tables

Table B1: Summary Statistics Including Salary Change Outliers

A. Number of movers in the sample	All	Movers	Share of total	B. Number of transitions in the sample	Total	Min	Max
Total observations	64,721	7,943	0.12	Transitions	2,114		
Number of people	26,392	1,805	0.07	Number of movers	1,805		
Mean obs. per person	2.45	4.40		Number of universities	654		
				Transitions per mover	1.17	1	*
				Transitions per university	3.23	1	52

C. Individual characteristics	N	Mean	SD	D. University characteristics	Mean	SD	Min	Max
Years since Ph.D.	64,721	18.30	10.63	Research universities	48	28	1	99
Has tenure	64,721	0.73	0.44	Colleges	46	25	1	100
Time in current job	64,721	12.91	10.32	Log of total enrollment	8.91	1.02	5.79	10.92
Faculty rank				log(total endowment)	18.10	2.10	11.51	24.25
Assistant professor	64,721	0.24	0.43	log(endowment/students)	9.20	2.09	2.55	14.67
Associate professor	64,721	0.29	0.45	log(faculty size)	5.88	1.03	0.81	8.54
Professor	64,721	0.46	0.50	log(faculty/students)	-3.03	0.46	-5.38	-1.42
Lecturer	64,721	0.00	0.03	Share in large city	0.23	0.42	0.00	1.00
Instructor	64,721	0.00	0.04	Share in medium city	0.34	0.47	0.00	1.00
Other	64,721	0.01	0.09	Share in small city	0.43	0.50	0.00	1.00
Female	64,721	0.32	0.47	Share private	0.40	0.49	0.00	1.00
Married	64,721	0.83	0.38	Share undergraduate	0.13	0.33	0.00	1.00
Has child under 6	64,721	0.18	0.38					
Has child aged 6-11	64,721	0.20	0.40					
Has child aged 12-18	64,721	0.20	0.40					
Has child aged 19+	64,721	0.10	0.30					

Notes: The table shows summary statistics for the sample that includes observations with very large within-institution salary changes. See Appendix A for details. There are 147 research universities and 481 colleges. 26 institutions are unranked and not classified as colleges or universities. * Suppressed for confidentiality. All monetary values are expressed in 2020 USD.

Table B2: Fixed Effect Variance Estimates in AKM Model, Including Salary Changes Outliers

	Uncorrected (1)	Corrected Andrews et al method (2)
Individual by year level		
Variance log(*salary*)	0.148	0.148
Variance of Fixed-effects		
Individual	0.141	0.109
Institution	0.029	0.011
Correlation	-0.326	-0.409
Correlation net of field	-0.356	
Collapsed at the spell level		
Variance log(*salary*)	0.140	0.140
Variance of Fixed-effects		
Individual	0.130	0.078
Institution	0.028	0.006
Correlation	-0.317	0.059
Correlation net of field	-0.326	

Notes: The table reproduces the estimates in Table 2 in the sample that includes observations with large within-institution salary changes that were subsequently reversed. See Appendix A for details. The table shows estimates of the variances of the log salary, the individual and institution fixed effects, and the correlation between institution and individual fixed effects. Column (1) displays uncorrected estimates, while column (2) corrects for limited mobility bias using the method by Andrews et al. (2008). Panel A uses person-year observations, while panel B collapses the dataset at the employment spell level.

Table B3: Do Rankings Increase Institution Premiums? (Including Salary Change Outliers)

	Two-step estimates			One-step estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Institution type × log of ranking						
Research university	-0.0305	-0.0275	-0.0281	-0.0210	-0.0202	-0.0139
	(0.0211)	(0.0211)	(0.0217)	(0.0097)	(0.0096)	(0.0100)
Colleges	-0.0203	-0.0181	-0.0214	-0.0111	-0.0121	-0.0062
	(0.0123)	(0.0123)	(0.0152)	(0.0086)	(0.0086)	(0.0099)
Institution type (omitted=unranked)						
Research university	0.2253	0.1946	0.1849	0.1356	0.1247	0.0848
	(0.0910)	(0.0918)	(0.0982)	(0.0452)	(0.0453)	(0.0468)
Colleges	0.1373	0.1205	0.1321	0.0594	0.0560	0.0311
	(0.0649)	(0.0651)	(0.0740)	(0.0392)	(0.0396)	(0.0410)
Institution characteristics						
Large city		0.0680	0.0658		0.0425	0.0362
		(0.0245)	(0.0261)		(0.0139)	(0.0141)
Medium city/suburb		0.0203	0.0203		0.0046	0.0034
		(0.0218)	(0.0221)		(0.0113)	(0.0112)
Log of total enrollment			0.0113			0.0154
			(0.0140)			(0.0086)
Undergrad only			0.0163			-0.0006
			(0.0312)			(0.0194)
Private			-0.0042			0.0350
			(0.0283)			(0.0155)
Time in current job				-0.0058	-0.0058	-0.0058
				(0.0003)	(0.0003)	(0.0003)
Joint significance of 2 ranking variables						
F statistic	2.427	1.910	1.631	2.840	2.809	1.033
p-value	0.089	0.149	0.197	0.059	0.061	0.356
Joint significance of institution type and ranking variables						
F statistic	3.148	2.123	1.368	4.116	3.931	1.342
p-value	0.014	0.076	0.244	0.003	0.004	0.253
Correlation between individual fixed effects and log of rankings						
Universities	-0.217	-0.217	-0.217	-0.283	-0.279	-0.279
Colleges	-0.088	-0.088	-0.088	-0.163	-0.157	-0.154
Observations	654	654	654	64,721	64,721	64,721
R^2	0.019	0.031	0.033	0.910	0.910	0.910
Individual-level observations	64,721	64,721	64,721	64,721	64,721	64,721
Number of people	26,392	26,392	26,392	26,392	26,392	26,392
Number of movers	1,805	1,805	1,805	1,805	1,805	1,805

Notes: The table reproduces the estimates in Table 3 in the sample that includes observations with large within-institution salary changes that were subsequently reversed. See Appendix A for details. The table shows estimates from regressions of the institution pay premiums or the log of faculty real salary on institution characteristics. Columns (1) to (3) show two-step estimates. The first step regresses ln salary on individual, institution, and year fixed effects, years since PhD and its square, academic rank, tenured, female, married, number of children dummies (<6, 6-11, 12-18, 19+), female × married, and interactions between the children dummies and female; the second step (shown) regresses institution fixed effect estimates on institution characteristics using FGLS. One-step estimates –columns (4) to (6)– regress ln salary on individual and year fixed effects, the above time-varying individual characteristics, time in the current job, and the institution characteristics shown, clustering standard errors by institution. Real salaries expressed in 2020 USD. Institution ranking ranges from 1 (best) to 100. Research universities are mainly R1 but include some R2 institutions; colleges include all remaining ranked post-secondary institutions granting four-year degrees; excluded category: unranked. Large, medium, and small cities have populations above 250k, between 100k and 250k, and under 100k, respectively. Standard errors in parentheses.

Table B4: Does Endowment Increase Institution Premiums? (Including Salary Change Outliers)

	Two-step estimates			One-step estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(endowment per student)	0.0089	0.0085	0.0168	0.0090	0.0097	0.0086
	(0.0046)	(0.0046)	(0.0070)	(0.0029)	(0.0030)	(0.0040)
Institution type (omitted=unranked)						
Research university	0.0927	0.0727	0.0371	0.0264	0.0154	0.0047
	(0.0521)	(0.0523)	(0.0581)	(0.0292)	(0.0293)	(0.0305)
Colleges	0.0521	0.0433	0.0360	-0.0009	-0.0097	-0.0077
	(0.0484)	(0.0483)	(0.0491)	(0.0270)	(0.0271)	(0.0267)
Institution characteristics						
Large city		0.0712	0.0736		0.0452	0.0398
		(0.0244)	(0.0263)		(0.0136)	(0.0141)
Medium city/suburb		0.0234	0.0256		0.0050	0.0039
		(0.0216)	(0.0220)		(0.0114)	(0.0113)
Log of total enrollment			0.0158			0.0181
			(0.0138)			(0.0087)
Undergrad only			0.0263			0.0095
			(0.0299)			(0.0190)
Private			-0.0312			0.0218
			(0.0325)			(0.0177)
Time in current job				-0.0058	-0.0058	-0.0058
				(0.0003)	(0.0003)	(0.0003)
Observations	654	654	654	64,721	64,721	64,721
R^2	0.017	0.030	0.036	0.910	0.910	0.910
Individual-level observations	64,721	64,721	64,721	64,721	64,721	64,721
Number of people	26,392	26,392	26,392	26,392	26,392	26,392
Number of movers	1,805	1,805	1,805	1,805	1,805	1,805

Notes: The table reproduces the estimates in Table 4 in the sample that includes observations with large within-institution salary changes that were subsequently reversed. See Appendix A for details. The table shows estimates from regressions of the institution pay premiums or the log of faculty real salary on institution characteristics. Columns (1) to (3) show two-step estimates. The first step regresses ln salary on individual, institution, and year fixed effects, years since PhD and its square, academic rank, tenured, female, married, number of children dummies (<6, 6-11, 12-18, 19+), female × married, and interactions between the children dummies and female; the second step (shown) regresses institution fixed effect estimates on institution characteristics using FGLS. One-step estimates –columns (4) to (6)– regress ln salary on individual and year fixed effects, the above time-varying individual characteristics, time in the current job, and the institution characteristics shown, clustering standard errors by institution. Real salaries and endowment per student are expressed in 2020 USD. Research universities are mainly R1 but include some R2 institutions; colleges include all remaining ranked post-secondary institutions granting four-year degrees; excluded category: unranked. Large, medium, and small cities have populations above 250k, between 100k and 250k, and under 100k, respectively. Standard errors in parentheses.

Table B5: Transition Probability by Ranking Quintile and Institution Type

	Destination									
	Universities					Colleges				
	Best	2	3	4	Worst	Best	2	3	4	Worst
Origin	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Universities										
Best	0.419	0.246	0.089	0.039	0.024	0.047	0.047	0.063	0.024	N.D.
2	0.246	0.199	0.144	0.072	0.039	0.058	0.099	0.077	0.050	N.D.
3	0.149	0.186	0.238	0.071	0.033	0.063	0.078	0.119	0.048	N.D.
4	0.082	0.184	0.082	0.088	0.048	0.054	0.095	0.177	0.116	N.D.
Worst	N.D.	0.159	0.150	0.088	0.115	0.062	0.106	0.150	0.115	N.D.
Colleges										
Best	0.142	0.113	0.092	N.D.	0.043	0.092	0.177	0.191	0.085	N.D.
2	0.062	0.156	0.045	0.036	0.036	0.138	0.205	0.161	0.129	N.D.
3	0.051	0.073	0.117	0.069	0.077	0.062	0.102	0.263	0.150	N.D.
4	N.D.	0.051	0.080	0.087	0.123	0.065	0.167	0.203	0.167	N.D.
Worst	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.

Notes: The table shows the probability of moving across institutions with different prestige levels. The table divides research universities and colleges into ranking quintiles separately by type. Each cell shows the probability of moving from an institution in the indicated origin type and ranking quintile (row heading) to another in the indicated destination type and quintile (column heading). Because movements to unranked institutions are not shown, rows do not sum to 1. Data from cells with fewer than 5 individuals (denoted by N.D.) were suppressed to preserve confidentiality.

Table B6: Transition Probability by Ranking Quartile and Institution Type for Tenured Faculty

	Destination							
	Universities				Colleges			
	Best	2	3	Worst	Best	2	3	Worst
Origin	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Universities								
Best	0.463	0.222	0.108	0.039	0.044	0.049	0.054	N.D.
2	0.270	0.180	0.185	0.069	0.090	0.111	0.069	N.D.
3	0.107	0.123	0.310	0.080	0.080	0.091	0.128	N.D.
Worst	N.D.	0.191	0.090	0.124	0.101	N.D.	0.180	0.112
Colleges								
Best	N.D.	0.151	0.079	N.D.	0.190	0.246	0.111	0.103
2	0.067	N.D.	0.192	0.092	0.092	0.100	0.233	0.158
3	N.D.	N.D.	0.129	0.114	0.100	0.186	0.171	0.214
Worst	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.

Notes: The table shows the probability of moving across institutions with different prestige levels for tenured faculty. The table divides research universities and colleges into ranking quartiles separately by type. Each cell shows the probability of moving from an institution in the indicated origin type and ranking quartile (row heading) to another in the indicated destination type and ranking quartile (column heading). Because movements to unranked institutions are suppressed, rows do not sum to 1. Data from cells with fewer than 5 individuals (denoted by N.D.) were suppressed to preserve confidentiality.

Table B7: Log Salary Changes by Ranking Quintile and Transition Type

	Destination									
	Universities					Colleges				
	Best	2	3	4	Worst	Best	2	3	4	Worst
Origin	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Universities										
Best	0.338	0.372	0.282	0.183	0.186	0.188	0.127	0.031	0.151	N.D.
2	0.332	0.408	0.271	0.182	0.310	0.236	0.103	0.172	0.081	N.D.
3	0.275	0.241	0.089	0.335	0.319	0.340	0.289	0.241	0.025	N.D.
4	0.208	0.349	0.301	0.311	0.357	0.158	0.281	0.183	0.176	N.D.
Worst	N.D.	0.275	0.192	0.119	0.258	0.365	0.289	0.320	0.263	N.D.
Colleges										
Best	0.349	0.253	0.297	N.D.	0.382	0.321	0.301	0.204	0.173	N.D.
2	0.303	0.236	0.401	0.284	0.215	0.194	0.189	0.256	0.179	N.D.
3	0.278	0.245	0.189	0.166	0.143	0.189	0.172	0.211	0.150	N.D.
4	N.D.	0.135	0.251	0.113	0.213	0.495	0.136	0.189	0.198	N.D.
Worst	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.

Notes: The table shows average log changes in real salary associated with moves across institutions with different prestige. The table groups universities and colleges into ranking quintiles separately by type. Each cell shows the average log salary change associated with moves starting in institutions in the indicated origin type and ranking quintile (row heading) and ending in the indicated destination type and quintile (column heading). Table B5 shows the probabilities associated with these moves. Data from cells with fewer than 5 individuals (denoted by N.D.) were suppressed to preserve confidentiality.

Table B8: Log Salary Changes by Ranking Quartile and Transition Type for Tenured Faculty

	Destination							
	Universities				Colleges			
	Best	2	3	Worst	Best	2	3	Worst
Origin	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Universities								
Best	0.264	0.398	0.399	0.085	0.132	0.013	0.096	N.D.
2	0.336	0.430	0.318	0.362	0.255	0.082	0.171	N.D.
3	0.169	0.220	0.118	0.296	0.442	0.210	0.290	N.D.
Worst	N.D.	0.318	0.219	0.303	0.213	N.D.	0.172	0.209
Colleges								
Best	N.D.	0.164	0.369	N.D.	0.241	0.221	0.249	0.151
2	0.211	N.D.	0.149	0.155	0.219	0.097	0.166	0.207
3	N.D.	N.D.	0.223	0.105	0.353	0.188	0.329	0.207
Worst	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.

Notes: The table shows average log changes in real salary associated with moves by tenured faculty across institutions with different prestige. The table groups universities and colleges into quartiles separately by type. Each cell shows the average log salary change associated with moves by tenured faculty starting in institutions in the indicated origin type and ranking quartile (row heading) and ending in the indicated destination type and quartile (column heading). Table B6 shows the probabilities associated with these moves. Data from cells with fewer than 5 individuals (denoted by N.D.) were suppressed to preserve confidentiality.

Table B9: Effect of Time-Varying Variables in AKM

	Excluding outliers (1)	Including outliers (2)
Years since PhD	0.0359	0.0376
	(0.0068)	(0.0072)
Years since PhD squared	-0.0002	-0.0003
	(0.0000)	(0.0000)
Is tenured	0.0073	0.0074
	(0.0070)	(0.0087)
Faculty rank (omitted=assistant professor)		
Lecturer	0.0287	-0.0173
	(0.0281)	(0.0795)
Instructor	-0.0068	-0.0040
	(0.0376)	(0.0384)
Associate professor	0.0453	0.0486
	(0.0080)	(0.0100)
Professor	0.1455	0.1582
	(0.0098)	(0.0125)
Other	0.0803	0.0866
	(0.0189)	(0.0213)
Married	0.0060	0.0093
	(0.0058)	(0.0076)
Married × female	-0.0005	0.0010
	(0.0089)	(0.0117)
Children below 6	0.0021	-0.0004
	(0.0041)	(0.0055)
Children below 6 × female	-0.0054	0.0017
	(0.0075)	(0.0090)
Children between 6 and 11	0.0037	0.0021
	(0.0038)	(0.0047)
Children between 6 and 11× female	-0.0096	-0.0091
	(0.0062)	(0.0074)
Children between 12 and 18	0.0100	0.0120
	(0.0036)	(0.0042)
Children between 12 and 18× female	-0.0190	-0.0170
	(0.0066)	(0.0079)
Children between 19+	0.0038	0.0040
	(0.0037)	(0.0044)
Children between 19+× female	-0.0083	-0.0086
	(0.0081)	(0.0098)
Individual FE	✓	✓
Institution FE	✓	✓
Year FE	✓	✓
Observations	63,376	64,721
Number of people	26,135	26,392
Number of movers	1,805	1,805
R^2	0.95	0.91

Notes: The table shows the results of regressing the log of real faculty salary on time-varying controls, institution, year, and individual fixed effects. Column (1) excludes observations with large within-institution salary changes and is the first step for the estimates shown in columns (1)-(3) of Tables 3-4 and is used for the variance estimates in Table 2. Column (2) includes salary change outliers and corresponds to the first step of columns (1)-(3) in Tables B3-B4 and the variance estimates in Table B2. See Appendix A for details on the outlier definition. Real faculty salaries expressed in 2020 USD. Standard errors clustered at the institution level in parentheses.

Table B10: Pay Premiums and Rankings for Tenured Faculty

	All faculty	Tenured faculty
	(1)	(2)
Institution type × log or ranking		
Research university	-0.0250	0.0003
	(0.0180)	(0.0271)
College	-0.0020	0.0323
	(0.0173)	(0.0254)
Institution type (omitted=unranked)		
Research university	0.1828	0.0930
	(0.0948)	(0.1411)
College	0.0926	-0.0305
	(0.0802)	(0.1177)
Institution characteristics		
Large city	0.0660	0.0554
	(0.0225)	(0.0334)
Medium city	0.0332	0.0616
	(0.0203)	(0.0298)
Log of total enrollment	0.0117	0.0017
	(0.0128)	(0.0188)
Undergrad only	0.0012	0.0217
	(0.0318)	(0.0459)
Private institution	0.0054	0.0327
	(0.0298)	(0.0439)
Joint significance of 2 ranking variables		
F statistic	1.064	0.929
p-value	0.346	0.396
Joint significance of institution type and ranking variables		
F statistic	1.256	0.952
p-value	0.286	0.434
Observations	434	434
R^2	0.066	0.027

Notes: The table shows the relationship between institution pay premiums and institution characteristics. The table restricts the sample to faculty remaining in the largest connected set when limiting the sample to tenured faculty. Column (1) shows results for all faculty in this connected set, while column (2) restricts the sample to tenured faculty. The table shows two-step estimates. The first step regresses the log of real salary on year, individual, and institution fixed effects, years since PhD and its square, academic rank, tenured, female, married, number of children dummies (<6, 6-11, 12-18, 19+), female × married, and interactions between the children dummies and femle; the second step (shown) regresses institution fixed effects on the institution characteristics shown. Institution ranking ranges from 1 (best) to 100. FGLS standard errors in parentheses.

Table B11: Institution Pay Premiums and Rankings by PhD Field

	Biological Sciences		Engineering	
	(1)	(2)	(3)	(4)
Institution type × log of ranking				
Research university	-0.0065		-0.0078	
	(0.0306)		(0.0266)	
College	-0.0521		-0.0240	
	(0.0491)		(0.0407)	
Institution type (omitted=unranked)				
Research university	-0.0691		0.2841	
	(0.1788)		(0.1778)	
College	0.0841		0.2869	
	(0.2265)		(0.2007)	
log of UNSWR field ranking		0.0059		-0.0165
		(0.0206)		(0.0201)
Institution characteristics				
Large city	-0.0115	-0.0084	0.0096	0.0130
	(0.0508)	(0.0459)	(0.0503)	(0.0551)
Medium city	-0.0105	0.0282	0.0992	0.1044
	(0.0493)	(0.0447)	(0.0500)	(0.0530)
Private institution	0.1341	0.1064	-0.0512	0.0603
	(0.0635)	(0.0546)	(0.0607)	(0.0530)
Undergrad only	0.0265		0.0521	
	(0.0987)		(0.1078)	
Log of total enrollment	0.0381	-0.0207	-0.0548	0.0111
	(0.0346)	(0.0385)	(0.0381)	(0.0386)
Joint significance of 2 ranking variables				
F statistic	0.563		0.194	
p-value	0.570		0.824	
Joint significance of institution type and ranking variables				
F statistic	0.520		0.978	
p-value	0.721		0.422	
Observations	224	155	153	113
R^2	0.058	0.063	0.080	0.089

Notes: The table shows estimates of the relationship between institution pay premiums and institution characteristics for faculty with Biological Sciences and Engineering PhDs. The table shows results for two-step estimation when limiting the sample to Biological Sciences PhDs –column (1)-(2) and Engineering PhDs –columns (3)-(4)–. Columns (1) and (3) use the THE rankings as the main regressor, while columns (2) and (4) use the USNWR Departmental Rankings. In the first step, we limit the sample to people with a PhD in Biological Sciences or Engineering and estimate an AKM model controlling for year, individual, and institution fixed effects, and time-varying individual controls. In the second step (shown), we regress the institution fixed effect estimates on the shown institution characteristics using FGLS. Institution ranking ranges from 1 (best) to 100. Research universities are mainly R1 but include some R2 schools. Colleges include all remaining post-secondary institutions granting four-year degrees. Large, medium, and small cities have populations above 250k, between 100k and 250k, and under 100k, respectively. Standard errors in parentheses.

Table B12: Effect of Time-Varying Variables in One-Step Estimation

	(1)	(2)	(3)	(4)	(5)	(6)
Years since PhD	0.0343	0.0343	0.0343	0.0104	0.0102	0.0103
	(0.0067)	(0.0066)	(0.0066)	(0.0009)	(0.0009)	(0.0008)
Years since PhD squared	-0.0002	-0.0002	-0.0002	0.0001	0.0001	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Is tenured	0.0140	0.0141	0.0140	0.0029	0.0058	0.0027
	(0.0072)	(0.0071)	(0.0071)	(0.0080)	(0.0077)	(0.0077)
Time in current job	-0.0058	-0.0058	-0.0058	-0.0106	-0.0106	-0.0105
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)
Faculty rank (omitted=assistant professor)						
Lecturer	0.0699	0.0716	0.0695	-0.0684	-0.0709	-0.0724
	(0.0280)	(0.0286)	(0.0287)	(0.0492)	(0.0483)	(0.0487)
Instructor	-0.0028	-0.0021	-0.0018	-0.1006	-0.1026	-0.1000
	(0.0384)	(0.0383)	(0.0383)	(0.0404)	(0.0419)	(0.0411)
Associate professor	0.0430	0.0428	0.0429	0.1148	0.1135	0.1159
	(0.0080)	(0.0079)	(0.0079)	(0.0076)	(0.0074)	(0.0074)
Professor	0.1460	0.1460	0.1461	0.3653	0.3661	0.3679
	(0.0099)	(0.0098)	(0.0098)	(0.0102)	(0.0101)	(0.0101)
Other	0.0819	0.0822	0.0822	0.0606	0.0634	0.0637
	(0.0197)	(0.0197)	(0.0197)	(0.0303)	(0.0307)	(0.0319)
Married	0.0045	0.0045	0.0045	0.0391	0.0412	0.0404
	(0.0057)	(0.0057)	(0.0057)	(0.0052)	(0.0052)	(0.0052)
Married × female	0.0001	0.0000	-0.0000	-0.0290	-0.0303	-0.0300
	(0.0089)	(0.0090)	(0.0090)	(0.0078)	(0.0077)	(0.0077)
Children below 6	0.0035	0.0035	0.0035	0.0070	0.0071	0.0071
	(0.0041)	(0.0041)	(0.0041)	(0.0048)	(0.0048)	(0.0048)
Children below 6 × female	-0.0074	-0.0079	-0.0080	0.0006	0.0007	0.0017
	(0.0072)	(0.0072)	(0.0072)	(0.0070)	(0.0070)	(0.0069)
Children between 6 and 11	0.0058	0.0058	0.0058	0.0109	0.0106	0.0100
	(0.0037)	(0.0037)	(0.0037)	(0.0041)	(0.0040)	(0.0039)
Children between 6 and 11× female	-0.0123	-0.0126	-0.0126	-0.0058	-0.0048	-0.0037
	(0.0062)	(0.0062)	(0.0062)	(0.0066)	(0.0066)	(0.0065)
Children between 12 and 18	0.0104	0.0105	0.0105	0.0198	0.0206	0.0200
	(0.0033)	(0.0034)	(0.0034)	(0.0043)	(0.0043)	(0.0043)
Children between 12 and 18× female	-0.0175	-0.0174	-0.0174	-0.0126	-0.0138	-0.0124
	(0.0061)	(0.0061)	(0.0061)	(0.0073)	(0.0073)	(0.0072)
Children between 19+	0.0041	0.0041	0.0041	0.0153	0.0141	0.0130
	(0.0036)	(0.0036)	(0.0036)	(0.0053)	(0.0053)	(0.0052)
Children between 19+× female	-0.0087	-0.0091	-0.0090	-0.0060	-0.0083	-0.0048
	(0.0080)	(0.0080)	(0.0080)	(0.0097)	(0.0096)	(0.0095)
Year FE	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓			
Institution type	✓	✓	✓	✓	✓	✓
Institution type × log ranking	✓	✓	✓	✓	✓	✓
Institution location		✓	✓		✓	✓
Log of total enrollment		✓	✓		✓	✓
Undergrad only			✓			✓
Private			✓			✓
Observations	63,376	63,376	63,376	63,376	63,376	63,376
Number of movers	1,805	1,805	1,805	1,805	1,805	1,805
R^2	0.95	0.95	0.95	0.53	0.53	0.54

Notes: The table shows the coefficients on the time-varying controls in regressions of the log of faculty real salary on individual and institution characteristics. Coeffients in columns (1)-(3) correspond to specifications in columns (4)-(6) of Table 3. Columns (4)-(6) use the same specification as columns (1)-(3) but do not control for individual fixed effects. Real salary expressed in 2020 USD. Standard errors clustered at the institution level in parentheses.

Table B13: Effect of Current and Origin Institution Characteristics

	(1)	(2)
Current: log institution type × log of rank		
Research university	-0.0071	-0.0144
	(0.0185)	(0.0276)
College	0.0096	0.0254
	(0.0212)	(0.0349)
Origin: log institution type × log of rank		
Research university		-0.0577
		(0.0300)
College		-0.0310
		(0.0326)
Years in current job	-0.0075	-0.0072
	(0.0014)	(0.0014)
Destination university characteristics		✓
Origin institution characteristics		✓
Observations	4,570	4,570
R^2	0.957	0.959
Within R^2	0.083	0.129

Notes: The table shows the results of regressing the log of faculty salary on current institution type and its interaction with the log of the current employer's rankings, previous institution type, and its interaction with the log of the previous employer's ranking. Other controls include individual fixed effects and time-varying individual characteristics (see Table B9). The regression limits the sample to faculty who moved across institutions at least once, so that we observe the previous employer. When indicated, the regression controls for the following current (origin) institution characteristics: log of total enrollment, city size dummies, and indicators of private and undergraduate-only institution. Standard errors clustered by current institution in parentheses.

Table B14: Do Rankings Increase the Job Satisfaction?

	Very Satisfied		Somewhat satisfied or higher	
	Two-step	One-step	Two-step	One-step
	(1)	(2)	(3)	(4)
Institution type × log of ranking				
Research university	-0.0009	0.0178	-0.0354	-0.0181
	(0.0517)	(0.0215)	(0.0411)	(0.0119)
College	0.0234	-0.0031	-0.0089	0.0029
	(0.0402)	(0.0336)	(0.0323)	(0.0187)
Institution type (omitted=unranked)				
Research university	0.0011	-0.1510	0.2889	0.0687
	(0.2502)	(0.1592)	(0.2011)	(0.0657)
College	-0.1212	-0.0926	0.1376	-0.0015
	(0.2044)	(0.1850)	(0.1657)	(0.0834)
Institution characteristics				
Large city	0.0238	0.0373	0.0069	0.0019
	(0.0658)	(0.0348)	(0.0526)	(0.0199)
Medium city	0.1042	0.0388	0.0008	-0.0088
	(0.0575)	(0.0320)	(0.0463)	(0.0211)
Log of total enrollment	0.0063	0.0349	-0.0107	0.0085
	(0.0388)	(0.0275)	(0.0313)	(0.0136)
Undergrad only	0.0621	0.0800	0.1032	0.0149
	(0.0857)	(0.0728)	(0.0686)	(0.0336)
Private institution	0.0535	0.0189	-0.0550	-0.0399
	(0.0741)	(0.0480)	(0.0596)	(0.0251)
Log of salary		0.2757		0.0868
		(0.0364)		(0.0191)
Time in current job		-0.0017		-0.0008
		(0.0010)		(0.0005)
Observations	475	37,881	475	37,881
R^2	0.012	0.693	0.012	0.645

Notes: The table shows estimates for the relationship between job satisfaction and institution characteristics, after controlling for faculty pay. The dependent variable in columns (1)-(2) is an indicator of being very satisfied with the job, while in columns (3)-(4) is an indicator of being somewhat satisfied or very satisfied with the job. Columns (1) and (3) show two-step estimates. The first step regresses the job satisfaction indicator on log salary, individual, year, and institution fixed effects, years since PhD and its square, academic rank, tenured, female, married, children (<6, 6-11, 12-18, 19+), female × married, and interactions between the number of children and female; the second step (shown) regresses institution fixed effects on institution characteristics using FGLS. One-step estimates –columns (2) and (4)– regress the job satisfaction indicator on year and individual fixed effects, log salary, the above time-varying individual characteristics, time in current job, and the institution characteristics shown, clustering standard errors by institution. Institution rank ranges from 1 (best) to 100. Research universities are mainly R1 but include some R2 institutions; colleges include all remaining ranked post-secondary institutions granting four-year degrees; excluded category: unranked. Large, medium, and small cities have populations above 250k, between 100k and 250k, and under 100k, respectively. Salaries expressed in 2020 USD. Standard errors in parentheses.

Table B15: Log Salary Changes by Quartile of Coworkers' Salaries

	Destination				
	Best	2	3	4	Worst
Origin	(1)	(2)	(3)	(4)	(5)
Best	0.227	0.238	0.211	0.246	0.267
2	0.294	0.189	0.278	0.320	0.388
3	0.143	0.265	0.223	0.357	0.342
4	N.D.	0.218	0.434	0.193	0.351
Worst	N.D.	N.D.	0.310	0.222	0.296

Notes: The table shows the average changes in real log salary associated with moves across institutions with different levels of coworkers' pay. We follow Card et al. (2018) and classify transitions based on coworkers' salary rank. For each worker in each year, we compute the rank of the average coworker salary for that year. We then classified transitions, setting origin rank as the rank quintile in the year right before the move, and as destination rank that of the first year in the new institution. Data from cells with fewer than 5 individuals (denoted by N.D.) were suppressed to preserve confidentiality.

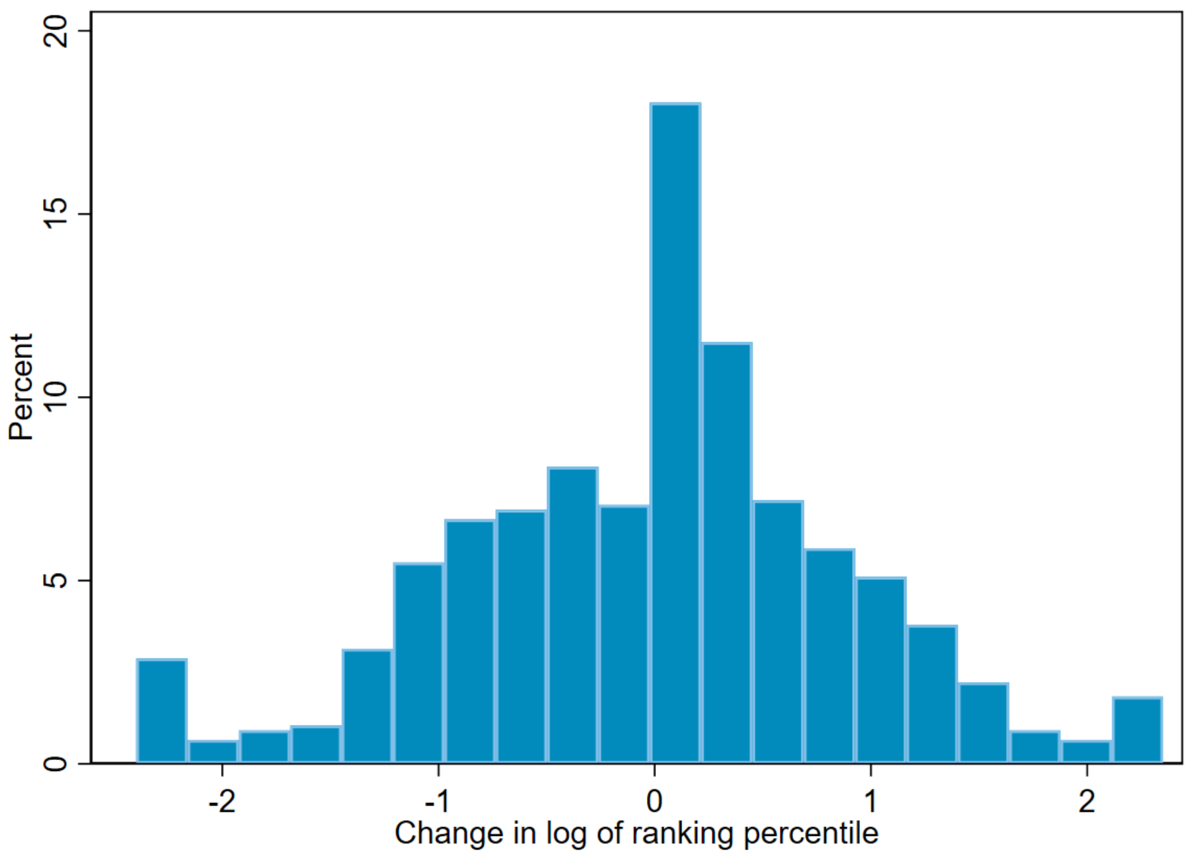
Table B16: Transition Probability by coworkers' salary quintile

	Destination				
Origin	Best (1)	2 (2)	3 (3)	4 (4)	Worst (5)
Best	0.356	0.218	0.176	0.133	0.118
2	0.037	0.360	0.241	0.178	0.183
3	0.021	0.061	0.444	0.292	0.182
4	N.D.	0.033	0.066	0.530	0.357
Worst	N.D.	N.D.	0.033	0.113	0.838

Notes: The table shows transition probability across institutions with different levels of coworkers' pay. We follow Card et al. (2018) and classify transitions based on coworkers' salary rank. For each worker in each year, we compute the rank of the average coworker salary for that year. We then classified transitions, setting origin rank as the rank quintile in the year right before the move, and as destination rank that of the first year in the new institution. Each row sums up to one. Data from cells with fewer than 5 individuals (denoted by N.D.) were suppressed to preserve confidentiality.

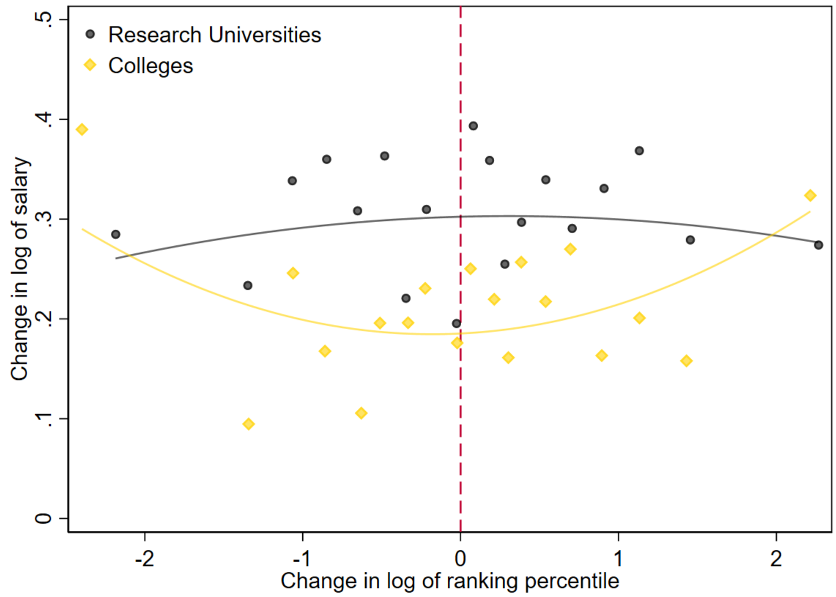
C Figures

Figure C1: Distribution of Changes in Institution Prestige for Tenured Faculty



Notes: The histogram shows the distribution of changes in the institution's prestige (ranking) when tenured faculty change employers. The figure limits the sample to moves within the same institution type (university to university or college to college). Institution ranking expressed in percentiles, with lower values indicating more prestigious institutions.

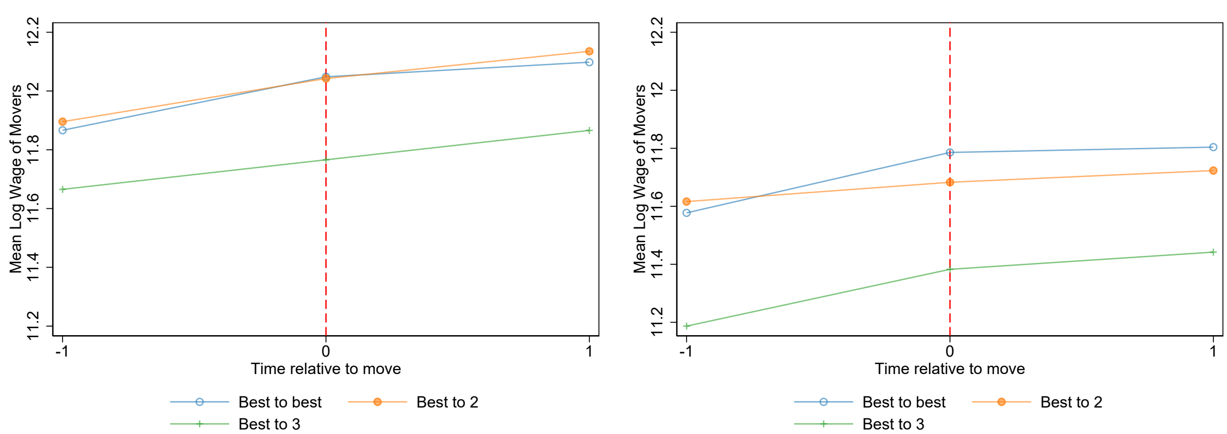
Figure C2: The Relation Between Δ ln Salary and Δ ln Prestige is Symmetric Around 0



Note: The binned scatterplot shows the salary changes associated with changes in institution prestige when faculty switch employers. The figure limits the sample to moves within the same institution type (research university to research university or college to college) and fits a quadratic line separately by institution type. Institution rank is expressed in percentiles, with lower values indicating more prestigious institutions. The NSF longitudinal data and institution ranking underlying the figure are described in detail in the data section.

Figure C3: Event Studies for Moves Across Quartiles of Institution Prestige

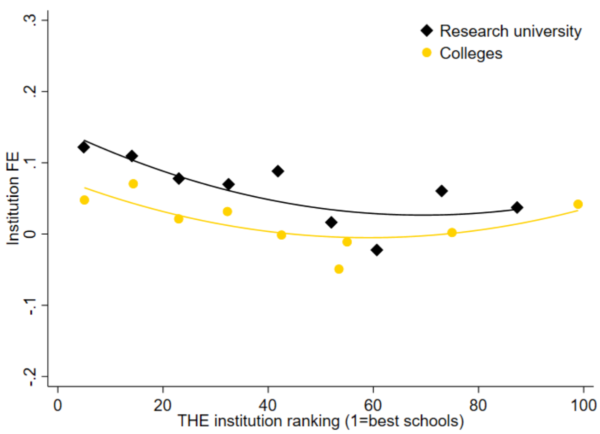
(a) Research universities (b) Colleges



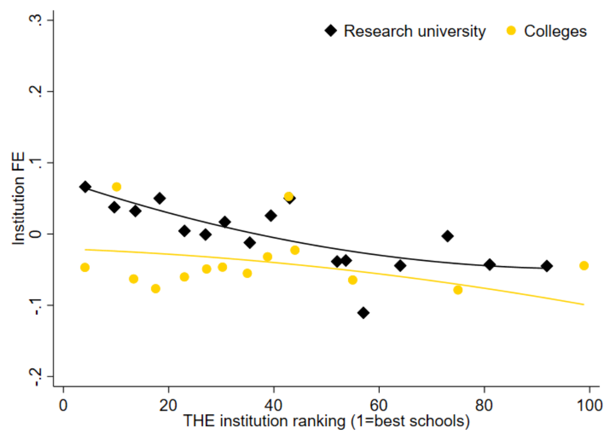
Notes: The figure shows the average log salaries of movers by institution and move types. We grouped institutions into ranking quartiles, and classified moves according to the quartile of the origin and destination institutions. Panel (a) shows faculty moves across research universities, while panel (b) shows moves across colleges. We use quartiles rather than quintiles and suppress transitions with very movers to meet the NCSES privacy requirements.

Figure C4: Relationship Between Institution Pay Premiums and Prestige is Robust

(a) Unweighted



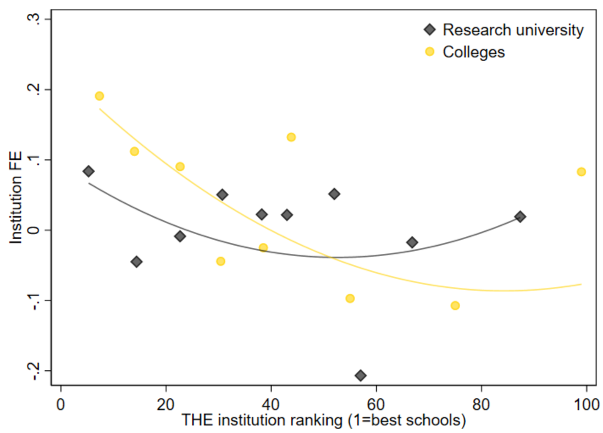
(b) Grouping institutions with few movers



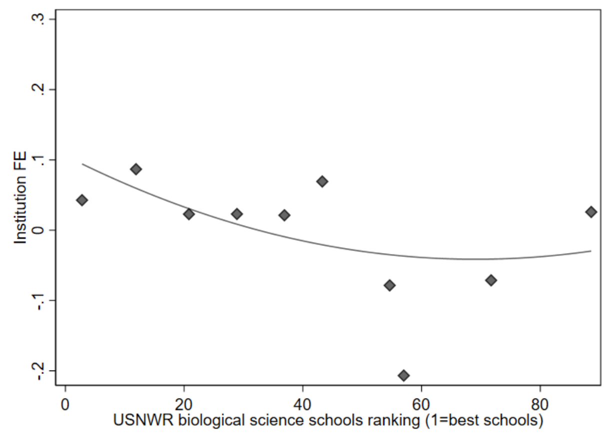
Notes: The binned scatterplots show the relationship between institution pay premiums and prestige for alternative treatments of institutions with few movers. Panel (a) shows the unweighted relationship. Panel (b) relates premiums to rankings for "pseudo-institutions" obtained by grouping similarly ranked institutions to ensure that all the institutions in our sample have at least 5 movers in them. All premiums were estimated by regressing ln salary on year, individual and institution fixed effects, years since PhD and its square, academic rank, tenured, female, married, children (<6, 6-11, 12-18, 19+), female × married, female × children.

Figure C5: Institution Pay Premiums and Rankings for Biological Sciences and Engineering PhDs

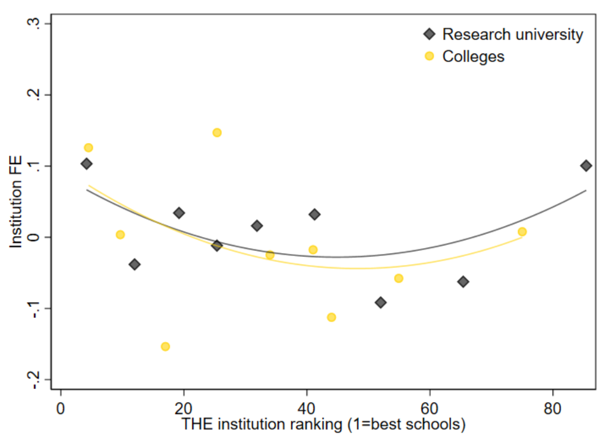
(a) **Biogical Sciences:** THE rankings



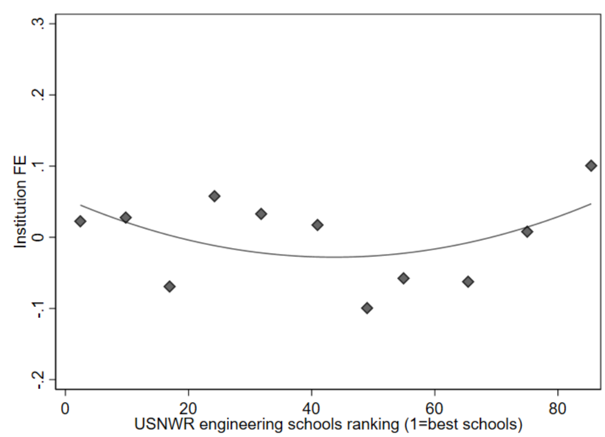
(b) **Biogical Sciences:** Field-specific USNWR ranking



(c) **Engineering:** THE rankings

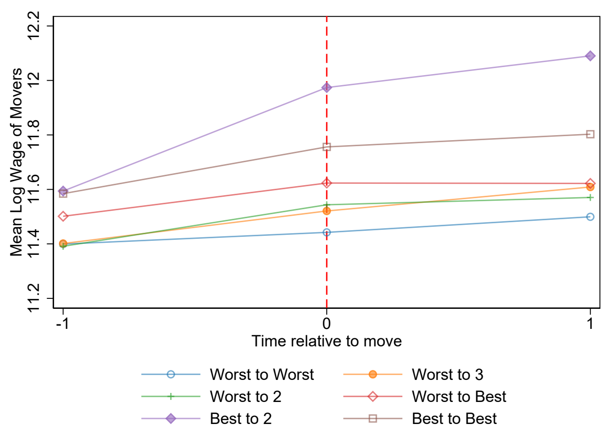


(d) **Engineering:** Field-specific USNWR ranking



Notes: The figure shows the relationship between institution pay premiums and institution prestige (rankings) for PhDs in specific fields. Panels (a) and (b) estimate premiums restricting the sample to faculty with PhDs in Biological Sciences, while panels (c) and (d) limit the sample to faculty with Engineering PhDs. Panels (a) and (c) relate the premiums to the institution's THE rank. Panels (b) and (d) relate the premiums to the UNSWR rankings of Biological Sciences and Engineering Schools, respectively. All premiums were estimated by regressing the log of salary on year, individual and institution fixed effects, years since PhD and its square, academic rank, tenured, female, married, children (<6, 6-11, 12-18, 19+), female $\times$ married, female $\times$ children.

Figure C6: Event Study for Moves Across Quartiles of Coworkers' Salaries



Notes: The figure shows the average log salaries of movers by institution and move types. We grouped institutions into coworkers' salary quartiles and classified the moves according to the quartiles of the origin and destination institutions. We suppressed series for quartiles with very few movers to meet the NCSES privacy requirements.