Do Elite Universities Overpay Their Faculty?*

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Do elite universities overpay their faculty? Not if you believe the AKM model. However, although the AKM model fits well, it is unlikely to be the right interpretation in this case.

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1 Introduction

This paper measures the relation between faculty salaries (net of faculty quality) and university or college prestige. We find no evidence that more prestigious institutions pay premiums above the competitive salary for the quality of the faculty they hire. Indeed, using an AKM (Abowd et al., 1999) model, we find little evidence of any institution effect on salaries, although salaries are higher in urban areas.

The absence of institution effects in the AKM model is striking. It implies that, aside from random factors, faculty would receive the same salary at any university. We authors find it implausible that Oakland University would be willing to match the salaries Stanford pays its tenure-stream faculty.

We draw on the Survey of Doctorate Recipients (SDR), a panel survey of individuals with U.S. doctorates in fields covered by the National Science Foundation. Thus, our results apply to STEM and the social sciences but not necessarily to the humanities or faculty with professional degrees. We merge the SDR with IPEDS institutional data and rankings of colleges and universities.

We begin by applying a standard AKM model. The variance of the institution fixed effects is as little as .007, depending on the correction, and even lower if we apply the Kline et al. (2020) leave-one-out correction to the narrower connected set their approach requires. When we regress the estimated fixed effects on institution characteristics, the effect of university or college prestige is always small and generally insignificant. We find some evidence that institutions with larger endowments per student pay a modest premium.

We repeat the exercise, replacing the two-step estimation with a single step that includes institution characteristics rather than institution fixed effects. The results are similar, as expected since both approaches provide consistent estimates of the same parameters.

We also examine the correlation between institution prestige (measured by rank) and faculty quality, as measured by the individual fixed effect. The correlation is positive, consistent with our expectations (and probably those of most faculty at research universities).

We briefly discuss how to reconcile the absence of a prestige premium, the positive match between prestige and faculty quality, and our sense that faculty at prestigious institutions would earn less at less prestigious institutions. We develop a toy hedonic model in which faculty transition only among similarly ranked institutions. We conclude with some thoughts about why our results differ from AKM models of the broad labor market.

2 AKM in the Academic Context

AKM uses a standard two-way fixed-effect 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.

The institution fixed effect γ_j captures the tendency of the institution to pay all faculty a different salary than they would receive elsewhere. It may reflect compensating differentials or institutional rents shared with faculty.

The individual fixed effect, α_i, captures whatever factors raise a faculty member's salary relative to other faculty in the same (or similar) institutions. It is typically interpreted as reflecting worker quality or productivity. However, it captures any factor that affects pay, including discrimination or, in our case, differentials across fields. We will largely follow tradition and treat this fixed effect as capturing worker (faculty) quality. However, we note that 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 et al. (2019)).

Well-known problems arise if we treat the variance of estimated γ ($\widehat{\gamma}$) as the variance of γ. We correct this bias using Andrews et al. (2008), Bonhomme et al. (2023), and Kline et al. (2020).

It is evident that (1) makes strong assumptions. First, AKM assumes that mobility is random. (Formally, ε and γ are uncorrelated.) Applied to academia, faculty do not change university 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. Second, the semi-log form is highly restrictive; the institution effect is 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}.

Under these assumptions, the AKM model allows us to answer several questions:

1. How important are firms for determining salaries? (What is the variance of γ?)

2. How important are individual differences for determining salaries? (What is the variance of α?)

3. Do the best workers go to the best (highest salary) firms? (What is the covariance of α and γ in the estimated (and corrected) AKM model?)

Unlike most AKM applications, we can measure firm quality directly. In a two-step model, we first estimate (1), and then regress the estimated institution effects, $\widehat{\gamma}$, on published university rankings and 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 ($\widehat{\gamma}_j = \gamma_j + \nu_j$).

Alternatively, we can estimate (1) and (2) in a single step by substituting for γ_j in (1) to get

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

As Amemiya (1978) shows, if the variance components of (2) and (3) are estimated in the same way, generalized least squares (GLS) estimation of the two equations is numerically identical. However, we will estimate (2) by feasible GLS but only correct the standard errors in (3), thus producing somewhat different results.

3 Data

Our primary data come 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 in natural or social sciences, engineering, or health from a U.S. academic institution. Every 2-3 years, the survey collects salary, employer, and demographic information. It also provides the IPEDS (Integrated Postsecondary Education Data System) code for all US academic employers. Therefore, we can identify the work histories of academics trained and working in the United States.

We use all SDR waves through 2019 beginning with the 1993 major SDR restructuring (1993, 1995, 1997, 1999, 2001, 2003, 2006, 2008, 2010, 2013, 2015, 2017, 2019). The SDR includes most survey participants from previous waves, adds newly granted PhDs (from the NSF's Survey of Earned Doctorates), and drops those who age out. However, in 2015, the SDR created a new larger panel that included only a minority of the original sample. Therefore, most participants have data only before 2015 or from 2015 on.

The SDR response rate among U.S. residents who can be found is high, typically more than 95% of eligible respondents. Considering those who could not be found, are missing a key item, or live abroad to be non-responses lowers the rate to 75%-85%.

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 U.S. 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).

Unfortunately, studying moves using the SDR requires considerable data cleaning, described 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 Boston University faculty member in multiple waves might be miscoded as Boston College faculty for one wave while reporting not changing institutions. Academics know they are different; some data coders did not.

We also drop observations with large one-time salary changes within the same institution *if they are subsequently reversed* (see appendix for details). As shown in Appendix B (Tables B1-B5), 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 supplement the SDR data with the rankings from the *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 use the *US News and World Report USNWR)* Best Colleges rankings (USNWR, 2021a,b,c,d) to impute ranks for institutions without a *THE* rank (see Appendix A).

As is well-known, AKM requires that included institutions be connected directly or indirectly. A and C are indirectly connected if a faculty member moves from university A to university B and another one moves from B to C. We limit ourselves to the largest connected set, 660 institutions. Other connected sets were very small. One-step estimation does not require a connected set, but we use the same data to maintain consistency.

We matched 581 (88% of the total) of the 660 institutions to a *THE* ranking. Of the remaining 79, we imputed a rank for 53 schools ranked in USNWR, using the relation between *USNWR* and *THE* ranks, leaving 26 unranked schools (4% of the total). We define *research universities* as those in the *THE* university rankings or imputed from the *USNWR* National University rankings. This group is broader than R1 institutions. We define *colleges* as those in the *THE* college rankings or imputed from any other *USNWR* ranking. Many *colleges* are not liberal arts colleges but simply institutions not included among the *THE* research universities or *USNWR* National Universities. Within each type of institution, we normalize the best rank to 1 and the worst to 100.[1]

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 Rio Grande. The unranked institutions include Texas A&M at San Antonio, Brigham Young University at Idaho, and the University of Texas at Brownsville.

Our data on institution characteristics come from the IPEDS surveys. We obtain total enrollment, number of faculty, endowment, and dummy variables for large city, urban fringe/mid-sized city/suburb, private institution, and undergraduate-only institution from 2001, 2005, 2012, and 2017. We measure endowment by the average of the beginning and ending values.

Table 1 Panel A shows the frequency of moves. We have 64,014 observations on 26,406 individuals, an average of roughly 2.4 observations each. 1,835, 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 we observe only one move for most movers. We have 2,155 transitions involving

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

660 institutions and 1,835 movers, or 1.2 moves per mover and 3.3 moves per institution. Transitions are highly skewed among institutions, with a minimum of 1 and 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 660 institutions in the connected set, of which 148 are *universities* and 486 *colleges*, with the remaining 26 unranked. They vary dramatically in size and endowment. 40% are private, and 13% serve only undergraduates.

4 Results

4.1 Are institutions important for determining wages? Not really!

We first estimate the AKM model with only individual and institution fixed effects. Table 2 shows the overall variance of log salaries 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., 2018a). Thus, their sum exceeds the total variance.

However, it is well known that we overestimate these variances, especially in situations like ours where many institutions experience little turnover (Andrews et al., 2012; Kline et al., 2020; Bonhomme et al., 2023). While $\widehat{\gamma}$ is a consistent estimate of γ, the *variance* of $\widehat{\gamma}$ is an inconsistent estimate of the variance of γ. For a simple insight into why, consider an extreme case where all the γs are 0 (so $\sigma^2 = 0$) and the $\widehat{\gamma}$s are i.i.d. with variance $\sigma_{\widehat{\gamma}}{}^2$. Then, $\sigma_{\widehat{\gamma}}{}^2$ is completely measurement error. Also, AKM negatively biases the covariance between the two sets of fixed effects: if we overestimate the institution fixed effect, we will (partially) subtract that overestimate from the individual fixed effect, creating a negative correlation between the two sets of fixed effects.[2]

When we use the Andrews et al. (2008) correction,[3] the variance of the individual fixed effects falls to .103 or 73% of the overall salary variance, while the variance of the institution fixed effects is only .013 or 9.2% of the overall variance (Table 2). Thus, institutions account for little of the total variance. This proportion is about half the estimate in Kline et al. (2020) for Northern Italian workers but in line with Bonhomme et al. (2023) for a Swedish sample with little turnover (similar to our sample) when using the Andrews variance correction.

[2]We experimented with letting starting salary depend on the prior and current institutions as in Di Addario et al. (2023), but the resulting sample is small, with few transitions per institution.

[3]Following the notation from Bonhomme et al. (2023), the variance of the estimated fixed effects is:

$$\mathbf{E}(\hat{V}_Q^{FE}) = \gamma' Q \gamma + \mathrm{Trace}[A(A'A)^{-1} Q (A'A)^{-1} A' \Omega(A)] \tag{4}$$

where Q is some matrix that typically depends on A, and $\Omega(A) = Var(\varepsilon|A)$ is the conditional variance of the error term. Using Andrews et al. (2008) simplifies computation by assuming the errors are homoskedastic: $\Omega(A) = \sigma^2 I$. Kline et al. (2020) allows for heteroskedasticity but uses a jackknife, thus restricting estimation to the connected set that remains when any observation is removed.

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 of the individual effects is .128, but the corrected variance is .078 or 56% of the overall salary variance, somewhat smaller than with the uncollapsed spells. The uncorrected variance explained by institution fixed effects (.027) is similar to what we found without collapsing spells. After correction, this variance is negligible, .007 or only 5% of the salary variation, somewhat lower as a proportion of variance than Bonhomme et al. (2023) find for five countries and substantially lower than Kline et al. (2020) report using their own preferred correction. Finally, when we use the Kline et al. (2020) approach (not in table), the sample falls to 441 institutions (143 universities, 284 colleges, 5 unranked), and the corrected variance of the institution effects becomes slightly negative, which is easily shown to be unsurprising when the true variance is small.

We thus conclude that institution effects explain almost none of the variation in faculty salaries. Instead, individual faculty (worker) effects explain most of the variance.

Our uncorrected estimates of the correlation between faculty and institution fixed effects are negative (-.34), as is common in AKM models due to mismeasurement bias (Table 2). Since the individual effects may partially reflect field differentials, we also report recalculated correlations netting out field differences. Clearly, this makes little difference.

The corrected correlation without collapsing is -.39. Andrews et al. similarly find little effect of their variance correction unless they restrict the sample to movers and large firms. The corrected correlation after collapsing is +.05. It is difficult to interpret this small positive correlation given the negligible variance of institution effects.

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

Adding the time-varying faculty characteristics in (1) decreases the unexplained variance from 8.5% to 4.8%. The coefficients (see appendix Table B1) are unsurprising and correspond to past studies of academic salaries. Salaries increase with post-PhD experience, although at a declining rate. Nevertheless, the point estimate of the slope remains 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 assistant professors. Associate professors earn a slight premium (5%) relative to assistant professors. Full professors earn about 15-16% 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. The sole exception is that men, but not women, earn about 1% more if they have teenage children. Prior research suggests that children make women less likely to take tenure-stream jobs (Ginther and Kahn, 2006; Cheng, 2020; Wolfinger et al., 2008; Martinez et al., 2007). However, among women who take tenure-stream STEM jobs, children and marriage are positively associated with women's salary in academia (Kahn and Ginther, 2017), as are men's. For both, the positive association is likely due to selection, which our model captures through the individual fixed effects.

We cannot meaningfully estimate a similar equation of firm fixed effects on time-varying *institution* characteristics (such as rankings) because they change very slowly. When they do change, long and uncertain lags in their impact prevent us from associating salary and institutional changes.

4.3 Institution characteristics have little impact on salaries

Although our estimates show institution effects are nearly absent, we ask whether institution characteristics, particularly institution rank and endowments, explain salaries. Because rank and endowment are very highly correlated, we include rank in Table 3 and endowments in Table 4. We first regress the 660 institutional fixed effects, γ, from our AKM model (small as they are) on institution type and other characteristics, controlling for individual effects as in (2). Columns 1-3 give the results. Then, we include these characteristics directly in the ln salary equation as in (3) (columns 4-6).

Column 1 of Table 3 shows the results of regressing firm effects on institution type and rank. This explains only 2.1% of the variation in institutional effects γ, which is, in turn, only 20% of log(salary) variation (see Table 2). Table 2 also showed that almost 60% of the variance in γ's is measurement error (using Andrews et al.), so 2.1% of the (uncorrected) variance of the γ's corresponds to about 5% of the non-measurement error γ variance.

The point estimates in Table 3, column 1 imply that the most prestigious university (ln rank = 0) pays a 20% premium, and the most prestigious college a 14% premium relative to an unranked institution. Comparing among ranked universities, the most prestigious pay premiums of about 11% relative to the least prestigious ($.023 * \ln(100)$), and similarly for colleges. However, the coefficient on university rank is clearly insignificant, and the coefficient on college rank has a p-value of .06. Jointly, their p-value is .09 (F=2.38). Yet, the joint effect of the four type and rank variables is significant (p=.009) (bottom Table 3).

Column 2 includes urbanicity, which not surprisingly significantly affects salaries. Notably, controlling for urbanicity reduces the already small effect of the two rank variables individually and jointly (F=1.75, p=.17) and reduces the joint significance of the four institution type and rank variables (F=2.18, p=.07). Column 3 adds several additional institutional characteristics, further decreasing the significance of institution type and rank with little effect on the other coefficients.

Columns (4)-(6) show the results using one-step estimates of the determinants of ln salary. The estimated coefficients are generally smaller but more precise. Consequently, we can reject the hypotheses that the research university dummy and university rank do not affect earnings in column (4). The most prestigious university pays about a 13% premium relative to unranked institutions and the least prestigious university. Ranked colleges pay only a tiny premium relative to unranked institutions, and there is no difference between colleges with the best and worst ranks. Moreover, comparing the R-squared of .945 in column (4) with the R-squared of .952 explained by the individual and institution fixed effects and individual time-varying variables (Table B1) demonstrates that the 660 institution dummies add very little to the model's explanatory power. Adding controls for urbanicity (column (5)) and other institution characteristics (column (6)) reduces the magnitude and eliminates the significance of the institution-type dummies and the rank variables.

In Table 4, we redo the estimation of Table 3, replacing the rank of universities and colleges with the (log of) the endowment per student of the institution, which measures the resources available to the institution and the rents it can share. Endowment does have a statistically significant effect. Nevertheless, its impact remains small. 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) in column 1. We have estimated similar models with both endowment *and* rank variables; this lowers the size and significance of both, and the R-squared remains less than 4% with all institutional factors included.

The unimportance of institution is not due to the choice of functional form. The top panel of Figure 1 plots binned institution fixed effects against institution rank separately for universities and colleges and fits quadratic lines. Both plots are somewhat U-shaped. Thus, better ranks are not monotonically better. 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 lower panel of the figure, which shows a definite negative relation between binned average *salary* and institution rank.

Our result is robust to limiting the sample to tenured faculty. For the 449 institutions remaining in the connected set, the effect of institution rank on tenured university faculty is even smaller than on all tenure-stream faculty, while the effect on tenured college faculty flips sign. However, neither of the changes is statistically significant (see Appendix Table B6).

As an additional robustness check, we limited the sample to faculty with PhDs in biological sciences. The connected set falls to 230, making our estimates imprecise. However, the results provide no evidence that salaries increase with prestige (see Appendix Figure D1 and Tables B7 and B8).

Appendix Figures D2 and D3 show that the institution effects figure is robust. In D2, we choose bins to equalize the number of movers across bins. In D3, we combine institutions with adjacent ranks until each institution or pseudo-institution has at least five movers. This primarily affects colleges because most universities are sufficiently large to have enough movers. The resulting patterns are largely unchanged.

We have also estimated simple correlations between the university log-rank and the individual effects, which range from ρ = -.22 to -.26 in the two-step and one-step estimates, respectively (bottom Table 3). Since more prestigious institutions have a lower rank, this indicates a substantial positive relation between institution and individual quality. The correlations with college institution effects are smaller and more dependent on which estimate is used, with ρ = -.09 and -.16 for colleges in the 2-step and 1-step models.

Part of the variation in individual effects may reflect salary differentials across fields. The most prestigious universities may be willing to pay both anthropologists and economists more than they would earn at less prestigious institutions but do not pay anthropologists and economists equally. However, the correlation between university ranks and the individual effects net of field is the same to 2 decimal places; the correlation between college rank and net individual effects is about .01 greater than reported in Table 3.

4.4 Why does institutional affiliation matter so little?

We find the absence of institution effects counterintuitive. Consider the University of Wisconsin, Madison, and the University of Wisconsin, Oshkosh. Both have publicly available salaries. In academic year 2021, the median economics full professor at UWM earned $370,954 compared with the median economics full professor at UWO, who earned $126,193. Imagine the UWM professor with median earnings moving exogenously to UWO and vice versa. What salary do you think they would receive? This exchange is hard to imagine, but our results suggest their salaries would not change since there are no meaningful university effects. We find it unlikely that UWM would hire anyone it was only willing to pay $126,193 as a tenured Professor of Economics. It is equally unlikely that UWO would be willing to hire an economics professor with tenure for almost $100,000 more than it pays its Chancellor. Readers are, of course, free to disagree.

4.4.1 There are no clear patterns in salary changes upon moving

We examined salary changes as people move from and to institutions, by quintile rank of universities and colleges. On average, all transitions raise salaries, which is unsurprising since we expect most people to move to better-paid jobs. However, there are few, if any, other clear patterns.

In particular, faculty receive similar increases when moving to a better institution (as they would if elite institutions paid rents) or when moving to a worse institution (as they would if they received a compensating salary differential). At research universities, those exiting jobs in the top or second quintile see the largest gains if they end up in the second quintile. However, those exiting the third quintile institution do best if they end up in the fourth quintile and worst in the third. Those starting in the fourth do slightly better ending up in the second than the fourth but noticeably better than ending in the first or third. If the AKM model is correct, the effects of moving from A to B and B to A should be equal and of opposite sign, net of any mobility premium. Here, salary changes are independent of the direction of movement, consistent with more prestigious institutions not paying rents. See Online Appendix Table B9 for more detail.

4.4.2 Movement among institutions is not random

The thought experiment at the beginning of the subsection is challenging because we rarely observe movements across institutions differing wildly in prestige. Unsurprisingly, faculty tend to move between institutions of similar eliteness even though we probably overstate mobility across prestige levels since the prestige of individual departments can differ from overall institution prestige.

To be consistent, the AKM model requires that mobility be random; the error term must be uncorrelated with the explanatory variables, most notably the individual and faculty fixed effects. Movement is not random, although not necessarily in a manner that challenges the AKM assumptions.

When tenure-stream faculty leave a university in the top quintile, almost half (41%) remain in the top university quintile, 66% within the top two quintiles, and 75% within the top two quintiles of universities *or* colleges. There is only a 2% chance of them moving to a lowest-quintile university and almost no chance of moving to a lowest-quintile college. (Numbers too small to report.)

Similarly, roughly 70% of moves to a top-tier university come from first or second-tier universities, and another 6% from top colleges. The likelihood of moving to the best universities from either the lowest quintile universities, the bottom 2 quintile *colleges*, or unranked institutions is tiny. Admittedly, movements involving the most elite university quintile are somewhat atypical in their degree of insularity. For other quintiles and for colleges, movement to proximate quintiles is more common. Movements originating in the highest quintile universities are also more common than those originating in other quintiles or in colleges. Still, regardless of an academic institution's type and rank, there is limited movement to very different institutions. Roughly 65% of those starting in universities move within +/- 1 university quintile or to a more highly ranked college.

Moreover, there is relatively little movement between universities and colleges. Of those who start and end in universities, the same percentage (31%) go to worse-ranked jobs as go to better-ranked jobs. However, of those who start and end in colleges, far more (38%) go to worse-ranked jobs than better-ranked jobs (30%).

For more detail, see Table B10 in the online appendix. Table B11 shows the results are robust to ranking institutions by coworker salary rather than prestige.

4.4.3 Hedonics may explain wages and mobility

We found a substantial positive correlation between faculty fixed effects and university and, to a lesser extent, college prestige (see the bottom of Table 3). Simultaneously, we find no evidence that prestigious institutions pay salary premiums. Consistent with this, there is considerable mobility between institutions, but moving to a higher-prestige institution does not increase one's salary.

A simple (toy) hedonic model augmented with idiosyncratic tastes fits these results well: There is a continuum of institutions with prestige, p. The salary an institution is willing to pay for a particular match, w_m, depends on the potential faculty member's quality, $q \in Q$ and p:

$$w_m = w_m(q, p),\ \frac{\partial w_m}{\partial q} > 0. \tag{5}$$

We assume that w_m is continuous in p. In addition, for any $p' > p''$, there is a q^* such that

$$w_m(q^*, p') = w_m(q^*, p'') \tag{6}$$

and

$$w_m(q, p') > w_m(q, p'') \Longleftrightarrow q > q^*. \tag{7}$$

This ensures that institutions' willingness-to-pay curves cross exactly once. Under these assumptions, there is a unique p that maximizes an individual's compensation.

To take a simple example, let

$$w_m = -p^2 + pq. \tag{8}$$

Then salary is maximized at $p = .5q$, and $w_m = .25q^2$ at the maximum.

With perfect matching, the observed salary is the upper envelope of the individual institutions' willingness-to-pay curves. While, in the example, each institution's willingness-to-pay is linear, equilibrium salary is convex in worker quality as in Roy (1951).

With perfect matching, we cannot distinguish between individual and worker effects. Either p or q fully explains earnings. Thus, in the above example, the maximizing salary, w_m can also be expressed as $w_m = p^2$.

Now, suppose individuals deviate slightly from their optimal institutions. The effect on their earnings is only second-order since the derivative of earnings with respect to prestige is 0 at the optimum. On the other hand, the difference between the imperfectly matched faculty's q relative to other faculty at that institution is first order. Therefore, individual and not institution effects explain wages.

To see this, consider an individual with $p = p^*$ and, therefore, $q = 2p^*$ at their highest-pay institution. Consider a second institution $p' = p^* + \varepsilon$. The individual earns $-(p'-\varepsilon)^2 + 2(p'-\varepsilon)(p'-\varepsilon)$ when matched to p^*, but only $-p'^2 + 2p'(p'-\varepsilon)$ when imperfectly matched to p'. Taking the difference gives the tiny value ε^2. However, comparing the well-matched individual at p^* with a well-matched individual at p' who earns $-p'^2 + 2p'(p')$, the difference is a larger $2p'\varepsilon$.

Therefore, we do not observe University of Wisconsin economists exchanging campuses because both would take significant salary cuts since they are poor matches at the other institution.

Intuitively, the mismatch between faculty and institution differs little among proximate universities. Neither earns rents because there are similar institutions that would offer faculty essentially the same salary.

Online Appendix C develops this example, setting the variance of log salaries at .14, as in our data. If the highest and lowest quality faculty both matched with the most prestigious institution, a highly improbable event for the latter, the ratio of their earnings would be 11. The example allows for a significant degree of mismatch. For example, the median quality faculty has a 6-7% chance of ending up in each of the top and bottom quintiles. Nevertheless, the variance of the institution effects is trivial.

The SDR data are consistent with our interpretation. Neither the wage change at the time of the move nor one period after shows a clear relation to initial salary. Moreover, faculty who moved between high-rank universities had high salaries both before and after their move (see Figures D4 and D5.

5 Discussion and conclusion: is academia different?

Applying standard AKM techniques to tenure-stream academic jobs to separate the firm (university) and individual (faculty) effects based on the movement of faculty between universities, we find the variation is almost entirely in the individual effects. There is no evidence that prestigious institutions pay their STEM faculty rents, while individual faculty members differ considerably in their salaries even when netting out field effects. Moreover, the individual effects are quite correlated with institution rank. We present a simple model suggesting that if faculty and institutions match optimally, AKM estimation can generate seemingly small institution effects.

How much our results differ from findings for broader labor markets depends somewhat on which study we compare our results with. Finding small to nonexistent establishment effects puts our results at the bottom of the range of estimated effects. We can only speculate as to why our findings for faculty differ from those for the broader labor market. Perhaps the labor markets are simply different.

One major difference is that the measures of faculty success – publications in prestigious journals, citations, appointments to prestigious societies, editorships – are observable to all both inside and outside their institution, and there is general agreement on these as measures of success. This alone might make rents unlikely in academia. In contrast, in the broader labor market, contributions to productivity may be difficult to observe outside the firm, making matching more likely to be imperfect. So, for instance, in a world where information about workers or firms is imperfect, and mobility is random, a worker who works in a firm where their high level of skill is not useful may appear to receive rents when moving to a firm that rewards skill more highly. The same would be true moving in the opposite direction. Or, Bose and Lang (2017) argue that most nonacademic jobs are "guardian" jobs. Consequently, firms with high costs of failures would only hire workers who had demonstrated their competence (although not to researchers) and would pay those workers a premium. Of course, it is also possible that the firm effects in the broader labor market are real; some firms may pay efficiency wages, share rents, or offer compensating wage differentials (Sorkin, 2018).

Nothing in our results allows us to distinguish among these explanations and perhaps others that readers may suggest. However, we believe that our results, while perhaps interesting in their own right, should encourage us to reflect more critically on the interpretation of the AKM model.

References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.

Abowd, J. M., McKinney, K. L., and Schmutte, I. M. (2019). Modeling Endogenous Mobility in Earnings Determination. *Journal of Business and Economic Statistics*, 37(3):405–418.

Amemiya, T. (1978). A Note on a Random Coefficients Model. *International Economic Review*, 19(3):793.

Andrews, M. J., Gill, L., Schank, T., and Upward, R. (2008). High wage workers and low wage firms: Negative assortative matching or limited mobility bias? *Journal of the Royal Statistical Society. Series A: Statistics in Society*, 171(3):673–697.

Andrews, M. J., Gill, L., Schank, T., and Upward, R. (2012). High wage workers match with high wage firms: Clear evidence of the effects of limited mobility bias. *Economics Letters*, 117(3):824–827.

Bonhomme, S., Holzheu, K., Lamadon, T., Manresa, E., Mogstad, M., and Setzler, B. (2023). How Much Should We Trust Estimates of Firm Effects and Worker Sorting? *Journal of Labor Economics*, 41(2):291–322.

Bose, G. and Lang, K. (2017). Monitoring for Worker Quality. *Journal of Labor Economics*, 35(3):755–785.

Card, D., Cardoso, A. R., Heining, J., and Kline, P. (2018a). Firms and Labor Market Inequality: Evidence and Some Theory. *Journal of Labor Economics*, 36(S1):S13–S70.

Card, D., Kluve, J., and Weber, A. (2018b). What works? A meta analysis of recent active labor market program evaluations. *Journal of the European Economic Association*, 16(3):894–931.

Cheng, S. D. (2020). Careers Versus Children: How Childcare Affects the Academic Tenure-Track Gender Gap.

Di Addario, S., Kline, P., Saggio, R., and Sølvsten, M. (2023). It ain't where you're from, it's where you're at: Hiring origins, firm heterogeneity, and wages. *Journal of Econometrics*, 233(2):340–374.

Eeckhout, J. and Kircher, P. (2011). Identifying sorting-In theory. *Review of Economic Studies*, 78(3):872–906.

Ginther, D. and Kahn, S. (2006). Does science promote women? Evidence from academia 1973-2001. In *Science and Engineering Careers in the United States: An Analysis of Markets and Employment*, pages 163–194. Cambridge, MA.

Kahn, S. and Ginther, D. (2017). Women and STEM.

Kline, P., Saggio, R., and Sølvsten, M. (2020). LeaveâOut Estimation of Variance Components. *Econometrica*, 88(5):1859–1898.

Martinez, E. D., Botos, J., Dohoney, K. M., Geiman, T. M., Kolla, S. S., Olivera, A., Qiu, Y., Rayasam, G. V., Stavreva, D. A., and Cohen-Fix, O. (2007). Falling off the academic bandwagon. Women are more likely to quit at the postdoc to principal investigator transition.

National Center for Education Statistics (NCSES) (2023). Integrated Postsecondary Education Data System (IPEDS). Retrieved from https://nces.ed.gov/ipeds/datacenter/DataFiles.aspx?year=-1sid=4dda9a06-7adf-4ad1-9eaa-a07908708f04rtid=7, April 24, 2023.

National Science Foundation, National Center for Science and Engineering Statistics (NCSES) (1993, 1995, 1997, 1999, 2001, 2003, 2006, 2008, 2010, 2013, 2015, 2017, 2019). Survey of Doctorate Recipients.

Roy, A. D. (1951). Some Thoughts on the Distribution of Earnings.

Sorkin, I. (2018). Ranking firms using revealed preference. *Quarterly Journal of Economics*, 133(3):1331–1393.

Times Higher Education (2017a). World University Rankings 2017.

Times Higher Education (2017b). WSJ/THE College Rankings 2017.

U.S Bureau of Labor Statistics (2023). Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL]. retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL, April 24, 2023.

US News & World Report (USNWR) (2021a). Best National University Rankings 2021. Retrieved from https://www.usnews.com/best-colleges/rankings/national-liberal-arts-colleges, May 7, 2021.

US News & World Report (USNWR) (2021b). Best Regional Colleges Rankings 2021. Retrieved from https://www.usnews.com/best-colleges/rankings/regional-colleges, May 7, 2021.

US News & World Report (USNWR) (2021c). Best Regional Universities Rankings 2021. Retrieved from https://www.usnews.com/best-colleges/rankings/regional-universities, May 7, 2021.

US News & World Report (USNWR) (2021d). National Liberal Arts Colleges Rankings 2021. Retrieved from https://www.usnews.com/best-colleges/rankings/national-liberal-arts-colleges, May 7, 2021.

Wolfinger, N. H., Mason, M. A., and Goulden, M. (2008). Problems in the Pipeline: Gender, Marriage, and Fertility in the Ivory Tower. *The Journal of Higher Education*, 79(4):388–405.

Table 1: Summary Statistics

A: Number of movers in the sample

	All	Movers	Share of total
Total observations	64,014	7,973	0.12
Number of people	26,406	1,835	0.07
Average obs./person	2.42	4.34	

B: Number of transitions in the sample

	Total	Min	Max
Transitions	2,155		
Number of movers	1,835		
Number of universities	660		
Transitions per mover	1.17	1	*
Transitions per institution	3.27	1	52

C: Summary statistics: Individuals

Characteristics	N	Mean	Std
Years since Ph.D.	64,014	18.13	10.65
Has tenure	64,014	0.73	0.45
Faculty rank			
Assistant prof.	64,014	0.25	0.43
Associate prof.	64,014	0.29	0.45
Professor	64,014	0.45	0.50
Lecturer	64,014	0.00	0.03
Instructor	64,014	0.00	0.04
Other	64,014	0.01	0.09
Female	64,014	0.32	0.47
Married	64,014	0.83	0.38
Has child under 6	64,014	0.18	0.38
Has child aged 6-11	64,014	0.20	0.40
Has child aged 12-18	64,014	0.20	0.40
Has child aged 19+	64,014	0.10	0.30

D: Summary statistics: University-level characteristics

	Mean	Std	Min	Max
Research universities	48	28	1	99
Colleges	46	25	1	100
Log total enrollment	8.90	1.02	5.79	10.92
Log total endowment ($2020)	18.10	2.10	11.51	24.25
Log endowment/student	9.21	2.09	2.55	14.67
Log faculty size	5.87	1.03	0.81	8.54
Log faculty/student	-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	0.34	0.00	1.00

Note: There are 148 research universities and 486 colleges. 26 institutions are unranked and not classified as colleges or universities. * Suppressed for confidentiality. Exceeds 4.

Table 2: Fixed-effect variance estimates in AKM model

	Uncorrected (1)	**Corrected** Andrews at al. method (2)
A. Individual by year level		
Variance log(*salary*)	0.141	0.141
Variance of Fixed-effects		
Individual	0.131	0.103
Institution	0.029	0.013
Correlation	-0.336	-0.385
Correlation net of field	-0.357	
B. Collapsed at the spell level		
Variance log(salary)	0.140	0.140
Variance of Fixed-effects		
Individual	0.128	0.078
Institution	0.027	0.007
Correlation	-0.311	0.053
Correlation net of field	-0.330	

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 fixed effects?

	Two-Step Estimates			One-Step Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Institution type × log of rank						
Research university	-0.0230	-0.0195	-0.0181	-0.0236	-0.0220	-0.0159
	(0.0209)	(0.0209)	(0.0215)	(0.0097)	(0.0103)	(0.0107)
College	-0.0227	-0.0197	-0.0180	-0.0068	-0.0073	-0.0026
	(0.0120)	(0.0120)	(0.0149)	(0.0095)	(0.0093)	(0.0105)
Institution type (omitted=unranked)						
Research university	0.2010	0.1655	0.1539	0.1263	0.1079	0.0636
	(0.0903)	(0.0910)	(0.0974)	(0.0441)	(0.0461)	(0.0476)
College	0.1426	0.1219	0.1142	0.0333	0.0242	-0.0011
	(0.0640)	(0.0641)	(0.0729)	(0.0410)	(0.0399)	(0.0415)
Institution characteristics						
Large city		0.0755	0.0727		0.0496	0.0433
		(0.0242)	(0.0258)		(0.0151)	(0.0152)
Medium city		0.0275	0.0267		0.0152	0.0131
		(0.0214)	(0.0218)		(0.0126)	(0.0126)
Log of total enrollment			0.0058			0.0148
			(0.0138)			(0.0095)
Undergrad only			0.0089			-0.0148
			(0.0304)			(0.0187)
Private institution			0.0078			0.0340
			(0.0279)			(0.0170)
Joint significance of 2 rank variables						
F statistic	2.383	1.751	0.979	3.047	2.394	1.109
p-value	0.093	0.174	0.376	0.048	0.092	0.331
Joint significance of university type and rank variables						
F statistic	3.441	2.176	1.264	3.662	2.804	0.916
p-value	0.009	0.070	0.283	0.006	0.025	0.454
Correlation between individual fixed-effects and ln(rankings)						
Universities	-0.219	-0.219	-0.219	-0.258	-0.253	-0.253
Colleges	-0.090	-0.090	-0.090	-0.158	-0.153	-0.151
Observations	660	660	660	64,014	64,014	64,014
R^2	0.021	0.035	0.035	0.945	0.946	0.946

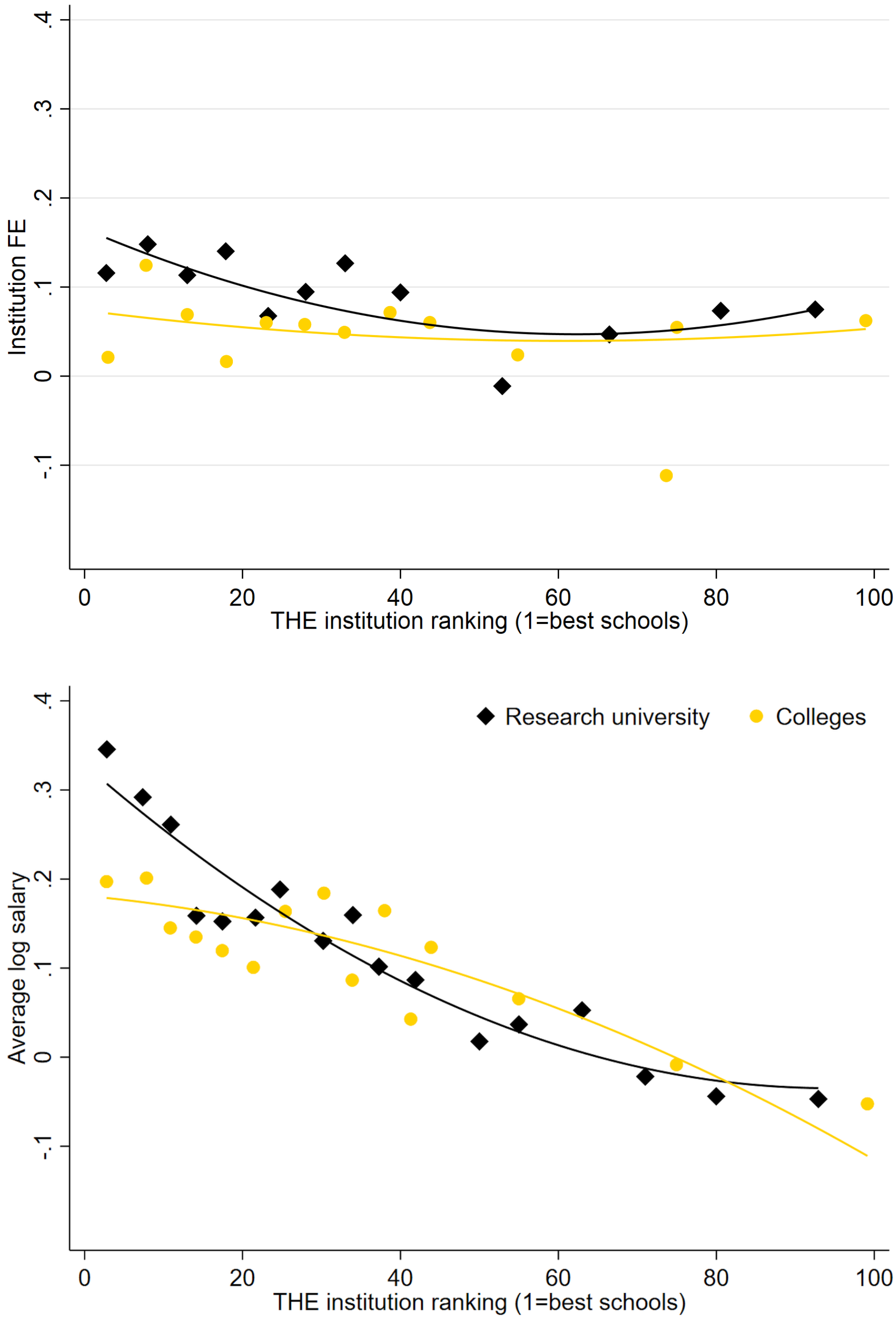
Notes: Standard errors in parenthesis. Institution rank ranges from 1 (best) to 100. Two Step: First step regresses ln salary on individual and instn fixed-effects, years since PhD,academic rank, tenured, female, married, children (<6, 6-11, 12-18, 19+), female*married, female*children; second-step (shown) regresses instn fixed effects on instn the explanatory variables. One-Step regresses ln salary on individual fixed-effects, the above time-varying indiv characteristics, and the institution characteristics shown, clustering standard errors by institution. 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.

Table 4: Does endowment increase institution fixed-effects?

	Two-Step Estimates			**One-Step Estimates**		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(endowment per student)	0.0099	0.0093	0.0134	0.0088	0.0093	0.0080
	(0.0046)	(0.0046)	(0.0070)	(0.0031)	(0.0032)	(0.0042)
Institution type (omitted=unranked)						
Research university	0.0493	0.0292	0.0106	-0.0079	-0.0222	-0.0392
	(0.0451)	(0.0454)	(0.0509)	(0.0257)	(0.0254)	(0.0276)
College	0.0054	-0.0028	-0.0129	-0.0288	-0.0406	-0.0472
	(0.0413)	(0.0412)	(0.0420)	(0.0240)	(0.0236)	(0.0243)
Institution characteristics						
Large city		0.0782	0.0789		0.0524	0.0468
		(0.0240)	(0.0260)		(0.0147)	(0.0150)
Medium city		0.0297	0.0307		0.0160	0.0140
		(0.0212)	(0.0217)		(0.0128)	(0.0127)
Log of total enrollment			0.0093			0.0179
			(0.0136)			(0.0095)
Undergrad only			0.0168			-0.0063
			(0.0292)			(0.0189)
Private institution			-0.0138			0.0217
			(0.0321)			(0.0194)
Observations	660	660	660	64,014	64,014	64,014
R^2	0.020	0.036	0.038	0.945	0.946	0.946

Notes: Institution rank ranges from 1 (best) to 100. Two Step: First step regresses ln salary on individual and instn fixed-effects, years since PhD,academic rank, tenured, female, married, children (<6, 6-11, 12-18, 19+), female*married, female*children; second-step (shown) regresses instn fixed effects on instn the explanatory variables. One-Step regresses ln salary on individual fixed-effects, the above time-varying indiv characteristics, and the institution characteristics shown, clustering standard errors by institution. 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.

Figure 1: Institution prestige predicts average salary but not pay premium



Appendix

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* University and college 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 to a unique ranking. Below we detail the main steps we used to build our final dataset.

A.1 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.

A.1.1 Determining faculty moves in the SDR

We pay special attention to ensuring that we track the moves of faculty 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 correctly.

We say an academic changed employer 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 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 in multiple waves 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 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 wanted to be conservative in what we considered to be moves. Whenever we determined 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.

A.2 Salaries

In addition to excluding observations that we determined to be leaves of absence, we excluded salary observations with 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 the log of salary adjusted for job experience ($\Delta\widetilde{w}_t$):

$$\Delta\widetilde{w}_t = \Delta w_t - \Delta\widehat{w}_t \tag{A9}$$

   where Δw_t is the log change in the individual salary, and $\Delta\widehat{w}_t$ is the expected change in the log salary due to experience. This expected change comes from a regression of log salaries on years of experience, and years of experience squared:

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

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

$$\Delta\widehat{w}_t = \widehat{\alpha}_1 \Delta y_t + \widehat{\alpha}_2 \Delta y_t^2$$

   The expression in A9 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:

$$|\Delta\widetilde{w}_t| = |\Delta w_t - \Delta\widehat{w}_t| > 0.4$$

   We note that 0.4 is a conservative threshold, in the 97^{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 $|\Delta\widetilde{w}_t| > 0.4$, then either w_t or w_{t-1} may be the outlier. We exclude w_t if its distance from any other salary observation for that person is greater than 0.2[4]. That is,

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

5. If $|\Delta\tilde{w}_t| > 0.4$ 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[5].

   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 the do file *"code/build_database/outlier_exclusion_list.do"*

A.3 Building the institution characteristics dataset

All university characteristics other than the rankings are extracted from IPEDS. We use the modules of institution characteristics, fall enrollment, finance, and salaries for the years 2001, 2005, 2012, and 2017. All nominal figures are converted into 2020 dollars using the CPI for all urban consumers. As we say in the paper, we cannot meaningfully add time-varying institution characteristics to our model because they change very slowly, and when they do change, long and uncertain lags in their impact would prevent us from associating salary and institutional changes to salary shifts. 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 a Ph.D. 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. Tables A1 and A2 detail the mapping between both variables.

- **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 of the four survey years.

- **Value of endowment:** IPEDS reports finance information separately for public institutions, private not-for-profit, and private for profit. Our endowment variable corresponds to:

[4] 0.2 is the 90th percentile of the adjusted wage growth.

[5] In later waves, the SDR asked if the person working in an academic institution was (a) a president, provost or chancellor or (b) 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.

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

We use the average of the endowment across the four survey waves.

A.4 University rankings

Our primary sources for the institution rankings are the *Times Higher Education* 2017 World University Rankings, the *Wall Street Journal – Times Higher Education* 2017 College Rankings. The *THE* rankings consist of a list of institution names along with their position in the ranking and the state in which they are located. We linked these rankings to a unique IPEDS code using the institution 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 followed the following rules:

1. Whenever names only differed in the word "college" or "university," we use a Google search and the location information to determine if they were the same institution. For example, if the IPEDS label was "Concordia College" and the *THE* ranking name was "Concordia University". We linked both names if and only if:
   - The institution 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 *THE* rank for "Penn State University" was associated to the IPEDS code for "Penn State University, University-Park."

The procedure above was applied 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 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 581 (88% of the total) of the 660 institutions to a *THE* rank. Of the remaining 79, we imputed a rank for 53 schools ranked in *USNWR*, using the relation between *USNWR* and *THE* ranks (see below). For the 53 institutions matched by this process, we categorized those institutions in the National US News ranking as research universities while the rest we categorized as colleges.

This left 26 unranked schools (4% of the total). These institutions were categorized as **Unranked universities**.

A.5 Imputing the THE ranks

The THE rankings are our primary source of university performance information. However, as we said above, we were unable to match 79 institutions to a THE rank. For 53 of these insitutions, we were able to impute a *THE* rank using U.S. News and World Report (*USNWR*) rankings as follows:

1. First, we merged the *THE* rankings with each of the ten available *US News* ranking lists (national, liberal arts colleges, regional universities, and regional colleges). Merging was done by institution (university or college) name. Names were manually checked to ensure consistency.

2. For universities ranked by both *THE* and *US News*, for each of the 10 lists, we run a separate OLS regression of their position in the *THE* list on their position in the *US News* list:

$$THE\_ranking_i = \alpha + \beta US\_news\_ranking_i + \varepsilon_i \tag{A10}$$

Table A3 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 A10. That is:

$$\widehat{THE}_{\ ranking_i} = \alpha + \widehat{\beta} US\_news\_ranking_i$$

Note that all ten *US News* rankings are mutually exclusive. Therefore, the imputed *THE* position is unique. As we said in the previous section, we treat institutions in the *national US News* ranking as *research universities,* and institutions in all other *US News* rankings (liberal arts colleges, regional universities, and regional colleges) as *colleges.* Table A4 provides a breakdown of the imputed ranks according to the *US News* ranking list we used for the imputation.

Table A1: University location classification

1998 IPEDS locale classification		Recoding used	
Codes	**Labels**	**Codes**	**Labels**
1	Large city	1	Large city
2 3, 4	Mid-size city Urban fringe of large / mid-size city	2	Mid size city / suburb
5, 6, 7 9	Large town, small town, rural Not assigned	3	Small city / rural town

2005-2017 IPEDS locale classification		Recoding used	
Codes	**Labels**	**Codes**	**Labels**
11	Large city	1	Large city
12 21, 22, 23	Mid-size city Suburbs	2	Mid-size city / suburbs
13 31 - 43	Small city Towns, rural	3	Small city / rural town

Table A2: Description of location codes

Location	Description
Large city	Urban area, population above 250k
Mid-size city / suburbs	Urban area, population between 100k and 250k, or suburbs
Small city / rural town	Urban areas with population below 100k, rural areas

Table A3: 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)
r2	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
N	131	151	140	89	108	87	16	20	31	12

Notes: The dependent variable in column (1) is the THE research university ranking. The dependent variables for all the columns is the THE college university ranking.

Table A4: Number of schools imputed by ranking type

Ranking type	**Number of schools**
National rankings	
Universities	7
Liberal arts colleges	13
Regional Universities	
North	5
South	4
West	3
Midwest	7
Regional colleges	
North	4
South	4
West	3
Midwest	3
Total	53

B Tables

Table B1: Effect of time-varying characteristics

	(1) Excluding outliers	(2) Including outliers
Years since PhD	0.0357	0.0374
	(0.0069)	(0.0072)
Years since PhD squared	-0.0002	-0.0003
	(0.0000)	(0.0000)
Is tenured	0.0070	0.0065
	(0.0070)	(0.0087)
Faculty rank (omitted=assistant professor)		
Lecturer	0.0142	-0.0275
	(0.0408)	(0.0775)
Instructor	-0.0071	-0.0039
	(0.0377)	(0.0385)
Associate professor	0.0457	0.0496
	(0.0080)	(0.0100)
Professor	0.1466	0.1596
	(0.0099)	(0.0126)
Other	0.0820	0.0884
	(0.0189)	(0.0212)
Married	0.0062	0.0096
	(0.0058)	(0.0076)
Married × female	-0.0003	0.0012
	(0.0087)	(0.0115)
Children below 6	0.0022	-0.0003
	(0.0041)	(0.0055)
Children below 6 × female	-0.0057	0.0015
	(0.0075)	(0.0088)
Children between 6 and 11	0.0037	0.0022
	(0.0038)	(0.0047)
Children between 6 and 11× female	-0.0096	-0.0093
	(0.0062)	(0.0073)
Children between 12 and 18	0.0101	0.0121
	(0.0036)	(0.0041)
Children between 12 and 18× female	-0.0179	-0.0162
	(0.0066)	(0.0078)
Children between 19+	0.0036	0.0038
	(0.0037)	(0.0044)
Children between 19+× female	-0.0081	-0.0084
	(0.0081)	(0.0097)
Individual FE	✓	✓
Institution FE	✓	✓
Year FE	✓	✓
Observations	64,014	65,365
Number of movers	1,835	1,835
R^2	0.95	0.91

Notes: Standard errors clustered at the institution level in parenthesis. Column (1) uses the full sample. Column (2) excludes extreme within-institution wage changes.

Table B2: Summary statistics including wage outliers

A: Number of movers in the sample	All	Movers	Share of total
Total observations	65,365	8,077	0.12
Number of people	26,662	1,835	0.07
Average obs./person	2.45	4.40	

B: Number of transitions in the sample	Total	Min	Max
Transitions	2,155		
Number of movers	1,835		
Number of universities	660		
Transitions per mover	1.17	1	*
Transitions per institution	3.27	1	52

C: Summary statistics: Individuals

Characteristics	N	Mean	Std
Years since Ph.D.	65,365	18.19	10.66
Has tenure	65,365	0.73	0.45
Faculty rank			
Assistant prof.	65,365	0.25	0.43
Associate prof.	65,365	0.29	0.45
Professor	65,365	0.45	0.50
Lecturer	65,365	0.00	0.03
Instructor	65,365	0.00	0.04
Other	65,365	0.01	0.09
Female	65,365	0.32	0.47
Married	65,365	0.83	0.38
Has child under 6	65,365	0.18	0.38
Has child aged 6-11	65,365	0.20	0.40
Has child aged 12-18	65,365	0.20	0.40
Has child aged 19+	65,365	0.10	0.30

D: Summary statistics: University-level characteristics

	Mean	Std	Min	Max
Research universities	48	28	1	99
Colleges	46	25	1	100
Log total enrollment	8.90	1.02	5.79	10.92
Log total endowment ($2020)	18.10	2.10	11.51	24.25
Log endowment/student	9.21	2.09	2.55	14.67
Log faculty size	5.87	1.03	0.81	8.54
Log faculty/student	-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	0.34	0.00	1.00

Note: There are 148 research universities and 486 colleges. 26 institutions are unranked and not classified as colleges or universities. * Suppressed for confidentiality. Exceeds 4.

Table B3: Fixed-effect variance estimates in AKM model including wage outliers

	Uncorrected	**Corrected** Andrews et al. method
Individual by year level		
Variance log(salary)	0.148	0.148
Variance of Fixed-effects		
Individual	0.139	0.110
Institution	0.029	0.012
Correlation	-0.328	-0.388
Collapsed at the spell level		
Variance log(salary)	0.140	0.140
Variance of Fixed-effects		
Individual	0.129	0.078
Institution	0.028	0.007
Correlation	-0.322	0.021

Table B4: Do ranks increase institution fixed effects (including wage outliers)

	Two-Step Estimates			One-Step Estimates		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Institution type × log of rank						
Research university	-0.0230	-0.0198	-0.0193	-0.0200	-0.0187	-0.0115
	(0.0215)	(0.0215)	(0.0221)	(0.0099)	(0.0105)	(0.0109)
Colleges	-0.0206	-0.0179	-0.0182	-0.0068	-0.0075	-0.0010
	(0.0124)	(0.0124)	(0.0153)	(0.0097)	(0.0096)	(0.0108)
Institution type (omitted=unranked)						
Research university	0.2104	0.1761	0.1666	0.1160	0.1003	0.0516
	(0.0929)	(0.0936)	(0.1001)	(0.0450)	(0.0473)	(0.0489)
Colleges	0.1418	0.1223	0.1227	0.0359	0.0286	-0.0018
	(0.0658)	(0.0659)	(0.0749)	(0.0416)	(0.0406)	(0.0423)
Institution characteristics						
Large city		0.0770	0.0750		0.0492	0.0421
		(0.0248)	(0.0265)		(0.0151)	(0.0151)
Medium city/suburb		0.0236	0.0234		0.0113	0.0096
		(0.0220)	(0.0224)		(0.0126)	(0.0125)
Log of total enrollment			0.0075			0.0168
			(0.0141)			(0.0095)
Undergrad only			0.0132			-0.0094
			(0.0312)			(0.0191)
Private			0.0022			0.0405
			(0.0287)			(0.0173)
Joint significance of 2 rank variables						
F statistic	1.957	1.455	0.976	2.158	1.738	0.557
p-value	0.142	0.234	0.377	0.116	0.177	0.573
Joint significance of university type and rank variables						
F statistic	3.382	2.170	1.318	2.975	2.272	0.531
p-value	0.009	0.071	0.262	0.019	0.060	0.713
Correlation between individual fixed-effects and ln(rankings)						
Universities	-0.216	-0.216	-0.216	-0.255	-0.250	-0.250
Colleges	-0.088	-0.088	-0.088	-0.153	-0.148	-0.144
Observations	660	660	660	65,365	65,365	65,365
R^2	0.020	0.034	0.035	0.906	0.906	0.906

Note: See footnotes Table 3.

Table B5: Does endowment increase institution fixed effects? (including wage outliers)

	Two-Step Estimates			**One-Step Estimates**		
	(1)	(2)	(3)	(4)	(5)	(6)
ln (endowment per student)	0.0094	0.0090	0.0154	0.0086	0.0093	0.0072
	(0.0047)	(0.0047)	(0.0071)	(0.0032)	(0.0033)	(0.0043)
Institution type (omitted=unranked)						
Research university	0.1034	0.0807	0.0551	0.0118	-0.0018	-0.0157
	(0.0530)	(0.0532)	(0.0590)	(0.0263)	(0.0265)	(0.0283)
Colleges	0.0549	0.0451	0.0401	-0.0089	-0.0201	-0.0206
	(0.0493)	(0.0491)	(0.0499)	(0.0236)	(0.0236)	(0.0235)
Institution characteristics						
Large city		0.0795	0.0824		0.0517	0.0453
		(0.0247)	(0.0267)		(0.0147)	(0.0150)
Medium city/suburb		0.0257	0.0278		0.0115	0.0098
		(0.0218)	(0.0223)		(0.0127)	(0.0126)
Log of total enrollment			0.0112			0.0189
			(0.0139)			(0.0097)
Undergrad only			0.0207			-0.0029
			(0.0299)			(0.0190)
Private			-0.0253			0.0273
			(0.0330)			(0.0198)
Observations	660	660	660	65,365	65,365	65,365
R^2	0.020	0.036	0.039	0.906	0.906	0.906

Note: See footnotes Table 3.

Table B6: Pay premiums and rankings for tenured faculty

	All faculty **(1)**	**Only tenured faculty** **(2)**
*Institution type * log of rank (low ranks best)*		
Research university	-0.0230	-0.0014
	(0.0187)	(0.0268)
College	0.0012	0.0275
	(0.0174)	(0.0250)
Institution type (omitted=unranked)		
Research university	0.1692	0.0981
	(0.0975)	(0.1398)
College	0.0792	-0.0165
	(0.0808)	(0.1163)
Institution characteristics		
Large city	0.0655	0.0505
	(0.0230)	(0.0332)
Medium city	0.0384	0.0543
	(0.0205)	(0.0295)
Log of total enrollment	0.0118	0.0030
	(0.0130)	(0.0187)
Undergrad only	-0.0015	0.0157
	(0.0313)	(0.0450)
Private institution	0.0112	0.0307
	(0.0303)	(0.0435)
Observations	449	449
R squared	0.055	0.023
Joint significance of 2 rank variables		
F statistic	0.889	0.601
p-value	0.412	0.549
Joint significance of university type and rank variables		
F statistic	0.588	0.416
p-value	0.672	0.797

Notes: Column (1) shows results for the whole sample, while column (2) restricts the sample to tenured faculty only. Standard errors in parenthesis. 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.

Table B7: Institution pay premiums and rankings for faculty in biological sciences

	(1)	(2)	(3)
*Institution type * log of rank (low ranks best)*			
Research university	-0.0374	-0.0373	-0.0177
	(0.0277)	(0.0284)	(0.0310)
College	-0.0933	-0.0913	-0.0550
	(0.0434)	(0.0441)	(0.0498)
Institution type (omitted=unranked)			
Research university	0.1093	0.1024	-0.0118
	(0.1487)	(0.1529)	(0.1823)
College	0.2539	0.2404	0.0866
	(0.1961)	(0.2005)	(0.2307)
Institution characteristics			
Large city		0.0230	0.0070
		(0.0501)	(0.0517)
Medium city		-0.0065	-0.0028
		(0.0494)	(0.0498)
Log of total enrollment			0.0290
			(0.0355)
Undergrad only			0.0354
			(0.1015)
Private institution			0.1023
			(0.0649)
Observations	230	230	230
R^2	0.041	0.043	0.054
Joint significance of 2 rank variables			
F statistic	3.224	2.944	0.672
p-value	0.042	0.055	0.512
Joint significance of university type and rank variables			
F statistic	2.425	2.212	0.701
p-value	0.049	0.069	0.592

Notes: The regression limits the sample to people with a Ph.D. in Biological Sciences. Standard errors in parenthesis. Institution rank ranges from 1 (best) to 100. In one-step estimation, standard errors are clustered by institution. Additional controls include individual fixed-effects, years since PhD,rank(lecturer, instructor, associate, full, other), tenured, female, married, children (¡6, 6-11, 12-18,19+), female*married, female*children. Estimates are obtained by including institution fixed effects and regressing the institution coefficients on the explanatory variables. Research universities are mainly R1 but include some R2 institutions. 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.

Table B8: Summary statistics for faculty in the biological sciences

Observations	12954
Number of people	4906
Number of movers	338
Number of institutions	230
Universities	113
Colleges	110
Unranked	7

Notes: The table shows summary statistics for the connected set that remains invariant after consecutively dropping one observation from the full sample.

Table B9: Salary wage changes by transition type

	Destination										
	Universities					**Colleges**					
	Best	**2**	**3**	**4**	**Worst**	**Best**	**2**	**3**	**4**	**Worst**	**Unranked**
Origin	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Universities											
Best	0.342	0.383	0.281	0.195	0.186	0.189	0.127	0.036	0.099	N.D.	N.D.
2	0.339	0.408	0.284	0.182	0.310	0.245	0.103	0.165	0.077	N.D.	N.D.
3	0.275	0.251	0.089	0.335	0.323	0.340	0.289	0.241	0.077	N.D.	N.D.
4	0.217	0.348	0.297	0.311	0.340	0.158	0.281	0.204	0.178	N.D.	0.120
Worst	N.D.	0.275	0.183	0.119	0.258	0.365	0.289	0.320	0.204	N.D.	N.D.
Colleges											
Best	0.349	0.253	0.297	0.259	0.382	0.311	0.290	0.204	0.173	N.D.	N.D.
2	0.313	0.236	0.400	0.287	0.215	0.195	0.184	0.247	0.176	N.D.	-0.015
3	0.278	0.245	0.201	0.177	0.143	0.189	0.172	0.213	0.150	N.D.	0.174
4	N.D.	0.135	0.251	0.106	0.213	0.495	0.131	0.189	0.198	N.D.	N.D.
Worst	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.
Unranked	N.D.	N.D.	N.D.	0.287	N.D.	N.D.	0.184	0.247	N.D.	N.D.	N.D.

Notes: Data from cells with less than 5 individuals were suppressed to preserve confidentiality. We denote these cells with N.D.

Table B10: Transition probability by ranking quintile and institution type

	Destination										
	Universities					Colleges					
	Best	**2**	**3**	**4**	**Worst**	**Best**	**2**	**3**	**4**	**Worst**	**Unranked**
Origin	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Universities											
Best	0.412	0.247	0.089	0.043	0.023	0.046	0.046	0.064	0.028	N.D.	N.D.
2	0.249	0.195	0.146	0.070	0.041	0.057	0.097	0.078	0.051	N.D.	N.D.
3	0.147	0.191	0.235	0.070	0.033	0.062	0.077	0.118	0.051	N.D.	N.D.
4	0.079	0.178	0.092	0.086	0.053	0.053	0.092	0.178	0.118	N.D.	0.072
Worst	N.D.	0.157	0.148	0.087	0.113	0.061	0.104	0.148	0.122	N.D.	N.D.
Colleges											
Best	0.135	0.108	0.088	0.034	0.041	0.095	0.209	0.182	0.081	N.D.	N.D.
2	0.072	0.158	0.045	0.041	0.036	0.135	0.180	0.167	0.135	N.D.	0.027
3	0.050	0.072	0.119	0.072	0.076	0.061	0.101	0.263	0.151	N.D.	0.032
4	N.D.	0.050	0.078	0.092	0.121	0.064	0.177	0.199	0.163	N.D.	N.D.
Worst	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.
Unranked	N.D.	N.D.	N.D.	0.041	N.D.	N.D.	0.180	0.167	N.D.	N.D.	N.D.

Notes: Data from cells with less than 5 individuals were suppresed to preserve confidentiality. We denote these cells with N.D.

Table B11: Salary wage changes by quintile of coworker salary rank

	Destination				
	Best	**2**	**3**	**4**	**Worst**
Origin	(1)	(2)	(3)	(4)	(5)
Best	0.228	0.228	0.214	0.255	0.265
2	0.300	0.176	0.306	0.324	0.392
3	0.143	0.331	0.235	0.326	0.371
4	N.D.	0.187	0.351	0.186	0.360
Worst	N.D.	N.D.	0.380	0.243	0.290

Notes: We follow Card et al. (2018b) and classify transitions based on coworkers' salary rank. For each worker in each year, we compute the rank of the avarage coworker salary for that year. We then classified transitions using as origin the rank in the year right before the move, and as destination the rank of the first year in the new insitution. Data from cells with less than 5 individuals were suppresed to preserve confidentiality. We denote these cells with N.D.

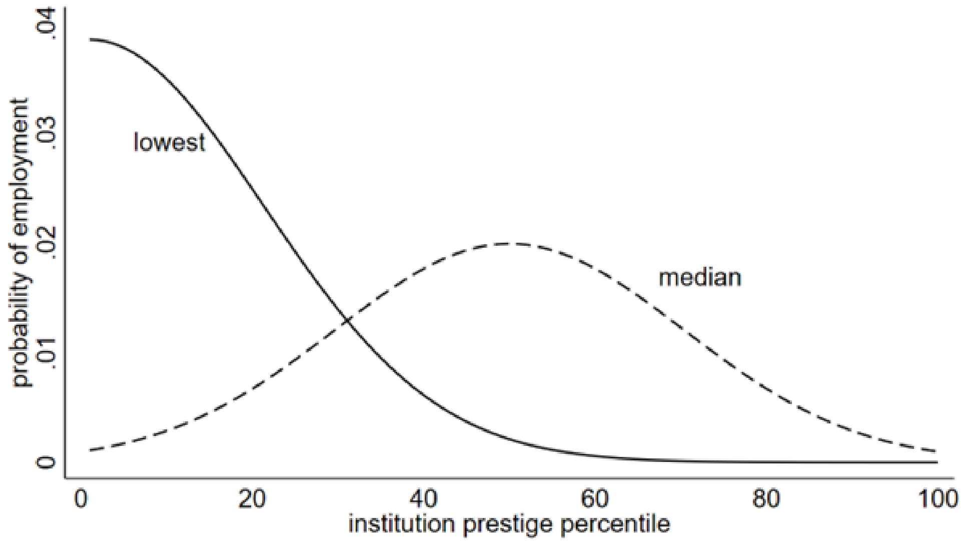
C A simple example

We choose functional forms to generate a realistic example but do not attempt to calibrate the example fully. We have 100 universities with prestige, p, given by $\{.211, .222, .233, \ldots, 1.300\}$. Similarly, we 100 faculty-quality types with quality, q, given by $\{.422, .444, .466, \ldots, 2.600\}$. Universities pay a faculty member $\ln w(p,q) = -p^2 + pq$. These assumptions ensure that each faculty member maximizes their salary by choosing the university with the prestige rank equal to their quality rank. We choose these numbers so that if both are perfectly matched, the highest type earns about five times as much as the lowest type but the highest type would earn about 17 times as much as the lowest type if they were both at the most prestigious university but would only earn about two-thirds more if they were both at the least prestigious. The utility the faculty receives from an appointment at a given university is $u = \ln w + \eta$ where η is type 1 extreme value with scale parameter .1. Then the probability that a worker of quality, q, is in the job with prestige p' is given by

$$P(p', q) = \exp\left(\frac{10 * \ln w(p', q)}{\sum p(10 * \ln w(p, q)}\right)$$

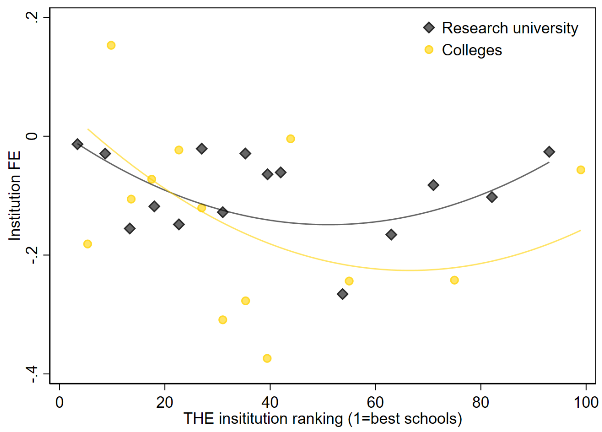
An AKM model on the resulting data fits well in the sense that it explains 99% of the variance. Of course, the example has no idiosyncratic errors, but the ability of the AKM model to fit the data is still striking. Although the university fixed effects are jointly significant, they are relatively unimportant with an uncorrected standard deviation of less than .01. Faculty fixed effects alone explain 83% of the variance. Appendix Figure C1 shows the distribution of the lowest and median quality faculty. Although the lowest quality faculty is most likely matched with the lowest prestige university, they still have a nontrivial chance of ending up in the third quintile. Similarly, the median quality faculty is mostly likely to be matched with the median prestige university but has a nontrivial chance of being in either the top or bottom quintiles. The 10th percentile faculty (not shown) has a 55% chance of being in a bottom quintile university, 35% in the fourth quintile, and 9% in the fifth quintile.

Figure C1: Probability of prestige level: lowest and median quality faculty



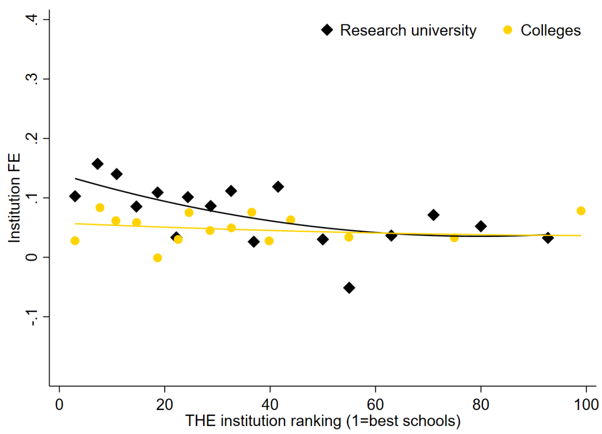
D Figures

Figure D1: Institution premiums and rankings for Biological Sciences PhDs



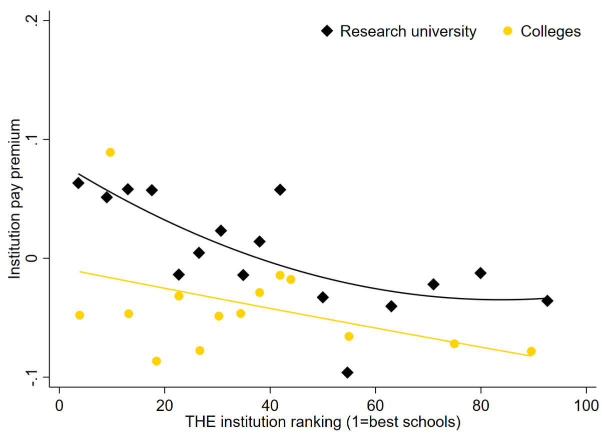
Note: The figure shows the relationship between institution pay premiums and the THE rankings. The premiums are estimated over the sample of faculty with biological sciences PhDs.

Figure D2: Institution premium and institution rankings (weighted by number of movers)



Note: the observations are weighted by the number of movers in the cell. Therefore, each cell accounts for the same number of movers.

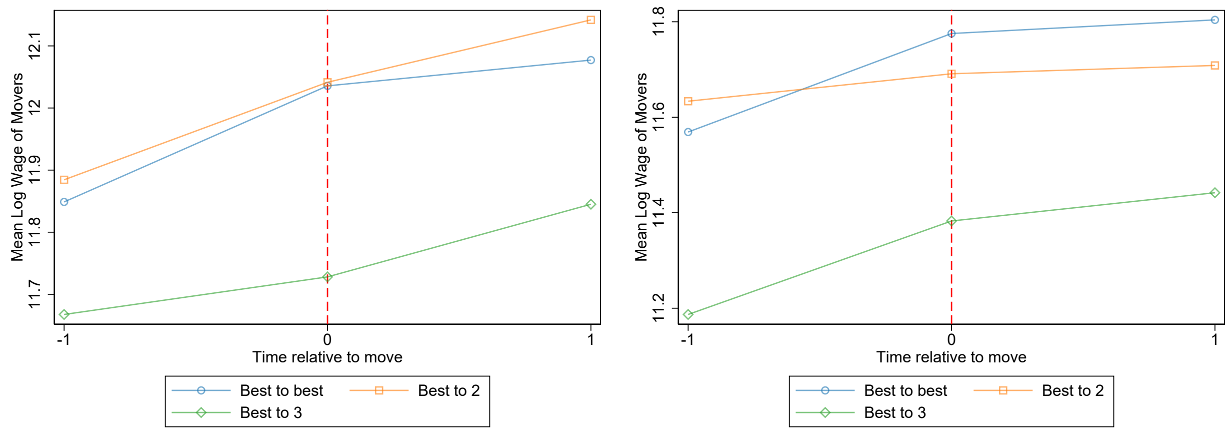
Figure D3: institution premiums and rankings for grouped institutions



Note: the figure shows institution premium estimates for grouped institutions. We group institutions with similar rankings so that each institution "pseudo-institution" has at least five movers.

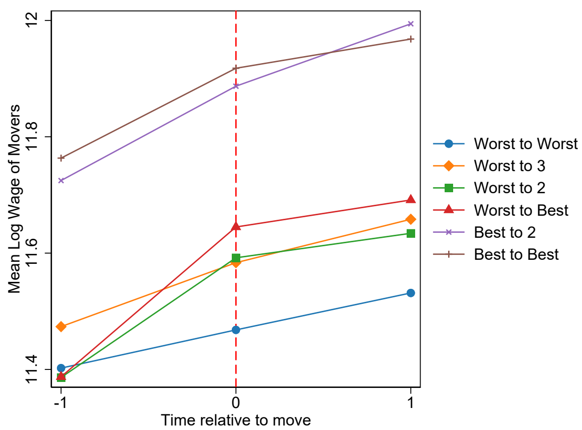
Figure D4: Event studies for moves across quartiles of institution prestige

(a) Universities (b) Colleges



Note: The figure shows the average wages of movers by type of institution and by type of move. Institutions are grouped into quartiles of the THE rankings, and the figure classifies the moves according to the quartiles of origin and destination. We use quartiles rather than quintiles and suppress transitions from best to worst institutions to meet the NCSES privacy requirements.

Figure D5: Event studies for moves across quartiles of coworkers' salaries



Note: The figure shows the average wages of movers by type of institution and by type of move. Institutions are grouped into quartiles of coworkers' salaries, and the figure classifies the moves according to the quartiles of origin and destination. Wages for some transition types were suppressed to meet the NCSES privacy requirements.