ANNENBERG
BROWN UNIVERSITY

EdWorkingPaper No. 22-582

The narrowing gender wage gap among faculty at public universities in the U.S.

Cory Koedel
University of Missouri

Trang Pham
University of Missouri

We study the conditional gender wage gap among faculty at public research universities in the U.S. We begin by using a cross-sectional dataset from 2016 to replicate the long-standing finding in research that conditional on rich controls, female faculty earn less than their male colleagues. Next, we construct a data panel to track the evolution of the wage gap through 2021. We show that the gap is narrowing. It declined by more than 50 percent over the course of our data panel to the point where by 2021, it is no longer detectable at conventional levels of statistical significance.

VERSION: May 2022

Suggested citation: Koedel, Cory, and Trang Pham. (2022). The narrowing gender wage gap among faculty at public universities in the U.S.. (EdWorkingPaper: 22-582). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/rrm3-pp69

The narrowing gender wage gap among faculty at public universities in the U.S.

Cory Koedel, University of Missouri
Trang Pham, University of Missouri

May 2022

We study the conditional gender wage gap among faculty at public research universities in the U.S. We begin by using a cross-sectional dataset from 2016 to replicate the long-standing finding in research that conditional on rich controls, female faculty earn less than their male colleagues. Next, we construct a data panel to track the evolution of the wage gap through 2021. We show that the gap is narrowing. It declined by more than 50 percent over the course of our data panel to the point where by 2021, it is no longer detectable at conventional levels of statistical significance.

1. Introduction

Previous research shows that observed gender differences in fields of study, experience, and research productivity—all of which are the product of many factors—combine to explain a large portion of the gender wage gap among university faculty (Blackaby et al., 2005; Ginther and Hayes, 2003; Li and Koedel, 2017; Porter et al., 2008; Umbach, 2006). However, in contrast to racial/ethnic wage gaps among faculty, which can be explained entirely by observed factors, a non-negligible portion of the gender wage gap remains unexplained even after conditioning on rich observable information.[1] The unexplained gender wage gap is a persistent finding in research on faculty dating back to the earliest available estimates (Barbezat, 1987; Porter et al., 2008).

We study the recent evolution of the unexplained gender wage gap among faculty in the U.S. using a panel dataset covering the academic years 2015-16 through 2020–21 (hereafter we use the spring year to denote the academic year; e.g., 2015-16 as 2016). The baseline sample in 2016 includes just over 3,800 faculty at 40 public research universities. Using this baseline sample, we first reproduce the finding from previous research that conditional on rich controls, there is a non-negligible gender wage gap favoring men. We then use our data panel to show the gap narrowed by more than 50 percent from 2016 to 2021. The gap in 2021 is substantively small—at just over one percent of the average faculty member's salary—and not statistically detectable.

A unique feature of our study is that we construct a true data panel tracking the same faculty over time and across institutions, which allows us to document how faculty who change universities influence the gender wage gap.[2] Focusing on mobility within the U.S. public sector—where we can

---

[1] See Li and Koedel (2017) and Porter et al. (2008) for side-by-side estimates of racial/ethnic and gender wage gaps among faculty.
[2] Two other recent studies use data panels at the individual-institution level but cannot track cross-institution movers (Obloj and Zenger, forthcoming; Baker et al., 2021).

observe post-move wages—we show the magnitude of the gender wage gap is not influenced by faculty movers. This is because (a) the gender gap in wage growth among mobile faculty is modest (although it does favor men) and (b) most faculty do not move. We also consider faculty mobility outside the U.S. public sector. This portion of our analysis is more assumptive because we do not observe post-move wages for those who move to private and foreign universities. However, under reasonable assumptions, we find the gender wage gap in our sample inclusive of these movers has likely narrowed as well.

We test directly for two potential mechanisms that could drive the declining gender wage gap. First, we test whether differences in promotion rates favoring women contribute to the narrowing gap and find no evidence to support this hypothesis. Second, we test for a gender gap in the likelihood of receiving an atypically large raise during the period covered by our data panel. We find that women are much more likely to receive atypically large raises, driven by a gender difference among faculty who remain at their original institutions from 2016 to 2021.

Finally, we close with a brief discussion of possible factors underlying our findings. One potential driver is that women may be benefiting from the recent emphasis on pay equity at universities across the U.S., as exemplified by newly-formed committees and commissions on gender equity such as the Louisiana State University Council on Gender Equity and the Commission on Women and Gender Equity in Academia at the University of Rochester.[3] In addition to impacting the gender gap directly, these equity efforts may also affect the labor market in gender-specific ways, such as by increasing demand for female faculty and female willingness-to-move, both of which would be expected to increase the prevalence of large raises among women (Blackaby, Booth, and

[3] In the case of Rutgers University, New Jersey's recent pay equity law, combined with pressure from the faculty union, has resulted in similar efforts, albeit with controversy (Snyder, 2021).

Frank, 2005; Leslie, Manchester, and Dahm, 2017; Groysberg, Healy, and Lin, forthcoming). Other mechanisms suggested by research—perhaps working in conjunction with the recent push for pay equity in academia—include continued increases in the salience of pay transparency (Baker et al., 2021; Obloj and Zenger, forthcoming), the possibility of gendered changes in how faculty are credited for their work (Hussey, Murray and Stock, 2021; Sarsons, 2017, Sarsons et al., 2020), and changes to tenure-clock policies (Antecol, Bedard, and Stearns, 2018; Manchester, Leslie, and Kramer, 2013). Although we are unable to pinpoint the precise cause(s), our findings suggest the factors that have contributed to the gender wage gap in academia historically are not operating in the same ways contemporarily.

2. Previous Research

The literature on the gender wage gap among faculty in the U.S. is comprised primarily of cross-sectional studies. These studies, which have been conducted at different points in time and using different data sources, can be combined to identify empirical regularities and track trends over time.

Studies using data from the late 1980s through the early 2000s consistently identify an unconditional gender wage gap at research universities of about 20 percent. The unexplained portion of the gap is in the range of 4-6 percent of salaries, or 20-30 percent of the unconditional gap. Most papers covering this period use data from the National Survey of Postsecondary Faculty (NSOPF), which was administered as a repeated cross-section four times beginning in the late 1980s through 2004 (Barbezat and Hughes, 2005; Porter et al., 2008; Toutkoushian, 1998; Toutkoushian and Conley, 2005), although papers that use other data sources reach similar conclusions. For example, Carlin et al. (2013) use administrative data from a single institution in the mid-1990s, and their findings are in alignment with the NSOPF-based studies.

Several papers that use more recent data replicate earlier estimates of the unconditional and conditional wage gaps, suggesting the gaps have remained stagnant for decades. Li and Koedel (2017), using the same cross-sectional dataset from 2016 we use as the baseline in this paper, estimate unconditional and conditional gender wage gaps of 20 and 4 percent of salaries, respectively. These estimates match older estimates closely. Similarly, articles by Chen and Crown (2019) and Taylor et al. (2020)—who use recent administrative data panels from individual institutions spanning roughly 10 years and ending in 2016 and 2017, respectively (in each case, the institution is a public research university)—also support the stagnation hypothesis. Using data pooled over their panels, both papers report an unconditional gender wage gap of just over 20 percent and find that of the total gap, about a quarter remains unexplained after accounting for observables. Both sets of authors also estimate models that leverage their data panels to allow for changes to the conditional and unconditional gaps over time. Taylor et al. (2020) find no evidence of a trend in the gender wage gap, and Chen and Crown (2019) find that it widened.[4]

While the bulk of the literature indicates large and stagnant gender pay gaps among faculty in the U.S., a recent study by Obloj and Zenger (forthcoming) calls the stagnation narrative into question. These authors construct a data panel of public-university faculty in eight states from 1997-2017 and estimate significant declining trends in the conditional and unconditional gender wage gaps over this period.[5] However, while the declining trends conflict with prior studies, Obloj and Zenger

[4] Although Chen and Crown (2019) acknowledge this result is surprising and may be idiosyncratic to the institution they study.

[5] Baker et al. (2021) conduct a similar panel study in Canada and also find that the unconditional and conditional gender gaps have been narrowing. However, it is challenging to connect the Baker et al. (2021) findings to the U.S. because during years that overlap with the bulk of the above-described literature on U.S. faculty (the 1990s and early 2000s), Baker et al.'s estimates of the gender gaps from Canada are quite different. For example, their estimate of the unconditional gender wage gap never exceeds 20 percent of salaries over their full panel (1990-2018), it falls below 15 percent by the late 1990s, and below 10 percent by 2008. These estimates are well below comparable estimates from the literature on U.S. faculty during the same period.

(forthcoming) estimate wage gaps in the early years of their data panel that are higher than in other studies of U.S. faculty, particularly for the conditional gap.[6] Because their initial estimates of the gaps are so large, it allows them to estimate declining trends but still arrive at gap levels similar to other studies by the mid-2010s. For example, in 2016, the same year used by Li and Koedel (2017), Obloj and Zenger (forthcoming) estimate a somewhat smaller unconditional wage gap—around 16 percent of salaries—and a similar conditional gap—around 4 percent of salaries.

In the context of this ambiguity in the literature, our study makes three contributions. First, we conduct a panel study similar in spirit to Obloj and Zenger (forthcoming), but anchored to the previous literature via the original Li and Koedel (2017) estimates. Second, we construct a true data panel tracking faculty over time, which allows us to document the influence of university movers on the gap, which is not possible in Obloj and Zenger (forthcoming).[7] Third, we extend the literature by providing the most recent evidence on the gender wage gap at U.S. academic institutions to date, through 2021.

3. Data

Our data panel is a direct expansion of the cross-sectional dataset originally used by Li and Koedel (2017). We first summarize their dataset and then describe the panel expansion. The original sample consists of tenured and tenure-track faculty at 40 selective, highly ranked public universities

---

[6] Estimates of the unconditional gap from Obloj and Zenger (forthcoming) prior to 2005 are on the high end of the range of other estimates in the literature, at about 25 percent of salaries. They cannot estimate the conditional gap until 2004, but over the first five years they can estimate this gap (2004-2008), they estimate an average *conditional* gap of roughly 12 percent of salaries, or almost half of the total unconditional gap. It bears mentioning that it is not the first-order objective of Obloj and Zenger (forthcoming) to estimate the gender gaps and their trends *per se*—they are focused on estimating the effect of pay transparency on the gaps, which within the structure of their models can be recovered even if the gap levels they report descriptively are inaccurate.

[7] We are not aware of any panel studies of the gender wage gap that permit an analysis of movers. Obloj and Zenger's (forthcoming) discussion of mobile faculty is not entirely clear. It appears their unique identifiers are at the university-individual level, which does not allow them to track cross-university movers. They also have data on faculty at public universities from just eight states, so if a faculty member moves to a public university outside of these states, or a non-public university, he or she cannot be tracked.

in the 2016 *U.S. News and World Report* rankings. The university list roughly corresponds to the 40 highest-ranked public universities in that year, although several small adjustments to the university sample were made for reasons discussed by Li and Koedel (2017). The focus on public universities was a practical consideration as wages are publicly available.

Faculty were sampled from six academic departments—biology, chemistry, economics, education leadership and policy, English, and sociology—three of which were randomly chosen at each university. Once a department was selected for sampling, all faculty listed on the department website were included in the dataset. In total, the dataset includes just over 3,800 tenured or tenure-track faculty from 120 academic departments at the 40 universities. The data were collected in spring 2016, and Appendix Table A1 lists the universities and departments included.

It may raise concerns about generalizability that only six academic departments are represented in the Li and Koedel (2017) data. The decision to restrict the number of departments was made to improve their ability to model field-specific returns to research productivity, noting that their data collection process was labor intensive and constrained the total sample size (i.e., they traded off a greater breadth of fields for larger field-specific samples). Ultimately, the best evidence in favor of generalizability is that Li and Koedel's (2017) estimates of the conditional and unconditional gender (and racial/ethnic) wage gaps are generally aligned with the larger literature, inclusive of studies that use data from many more fields.

For each university-by-department cell, data were collected for all tenure-track and tenured faculty on demographics, qualifications, research productivity, and salaries. Demographic and qualification data were collected from faculty members' online profiles. The qualification data include each faculty member's rank, years of experience, and their PhD-granting institution. For most faculty, experience is measured from the year the PhD was obtained as reported on faculty websites or CVs. In cases where a faculty member's profile does not indicate the PhD year, experience is measured by the time since the first registered publication, either on the faculty member's website (first choice) or on Scopus© (second choice). Between these sources, experience measures are available for 98 percent of the original cross-sectional sample. The PhD-granting institution was taken from each faculty member's profile and is available for 94 percent of faculty. We divide PhD-granting institutions into four selectivity groups based on their rankings in *U.S. News and World Report*, inclusive of private universities.

The demographic variables—race/ethnicity and gender—were collected using visual inspections of faculty profiles available online. Faculty in the original dataset were grouped into one of five possible racial/ethnic categories—Asian, Black, Hispanic, White, and other/unknown—and one of three gender categories: male, female, and unknown. Li and Koedel (2017) report a high degree of interrater reliability for these variables: 95.5 percent for the race/ethnicity categories and 99.75 percent for the gender categories.[8]

The research productivity measures were taken from externally generated faculty profiles on Scopus©. The dataset includes information on the number of publications, number of citations, and the h-index. For each metric, we standardize productivity within fields as follows:

$$\widetilde{P_{ij}} = \frac{P_{ij} - \overline{P_j}}{\sigma_j}, \tag{1}$$

Where $\widetilde{P_{ij}}$ is the standardized measure for faculty member *i* in field *j*, P_{ij} is the raw measure, and $\overline{P_j}$ and σ_j are the sample average and standard deviation in field *j*, respectively. The standardization procedure yields measures of faculty productivity that are comparable across fields despite

[8] For a deeper conceptual discussion of how the racial/ethnic and gender data were collected, see Laughter (2018) and Li and Koedel (2018).

heterogeneity in the level of measured productivity. Of the three measures, Li and Koedel (2017) report that the h-index is the strongest single predictor of wages.[9]

Wage data for faculty at most public universities are published online with a lag of about one year. Of all tenure-track faculty included on the rosters in the original data collection, wage data were available for 94 percent. The primary reason for missing wage data—and in fact the only reason we can identify given the comprehensive nature of wage reporting for public employees—is that the faculty member is new to the university or was on leave and did not draw a salary. Consistent with this explanation, Li and Koedel (2017) show that being a young professor is by far the strongest predictor of missing wage data in the 2016 sample.

There is also variability across states in how wages are reported. Some states report base salaries, while others report salaries inclusive of supplemental pay (e.g., summer salary from grants). Like Obloj and Zenger (forthcoming), we cannot disentangle the sources of faculty pay and use the data as reported publicly by states. Econometrically, our models include university fixed effects, which subsume state fixed effects and hold reporting conditions within states fixed, although the reporting differences create some ambiguity in interpretation if the gender wage gap differs between base and supplemental pay. Again, we note the broad similarity of the original Li and Koedel (2017) estimates to estimates in previous studies (which use a variety of data sources) as evidence that this reporting issue is unlikely to affect our findings substantively.

To facilitate our current panel study of the gender wage gap, we collected follow-up data in 2021 for each faculty member in the original 2016 dataset. For those who did not leave academia

[9] While all of these research productivity metrics are imperfect (Perry and Reny, 2016), they explain a substantial fraction of faculty wages and the gender wage gap (Li and Koedel, 2017). Unlike most other studies of faculty wage gaps, Li and Koedel (2017) interact the productivity measures with faculty fields in their wage model, which allows for field-specific returns that are important empirically. We take the same approach below.

this was straightforward. Those who left academia either moved to a non-academic position, retired, or passed away.[10] Retirements were confirmed whenever possible by official announcements. In some instances, when a highly senior, tenured faculty member was not found elsewhere online, we assumed they retired. We also searched the internet to find all faculty who left academia and were able to locate all such individuals in their non-academic positions.

Among faculty who remained in academia, we collected updated information about their academic rank and wages. We were able to collect updated wage information for most, but not all, faculty. We summarize wage missingness in the 2021 data as follows. First, about 10.5 percent of the faculty with wage data in 2016 are missing wage data in 2021 for a reason unrelated to job mobility. These are mostly retirees (72 percent, or 7.6 percent of the original sample).[11] Another 6.0 percent of the original sample changed jobs between 2016 and 2021. We recover wages for just over a third of these (about 2.1 percent of the original sample) who moved to another public university, leaving 3.9 percent of the sample with missing 2021 wages due to job mobility. In addition to these faculty with missing data, the wage data suggest a significant measurement problem for another 4.2 percent of faculty, for whom we also treat the 2021 wage data as missing.[12] In total, we were able to recover usable 2021 wages for 81.4 percent of the original sample used by Li and Koedel (2017), as detailed in Table 1.

[10] Thirty faculty members passed away between 2016 and 2021. This number may seem high, but each death was confirmed using external sources. One reason for the seemingly high death rate (close to 1 percent of the baseline sample) is the left-skewed age distribution among faculty. COVID-19 is also responsible for several deaths.

[11] Outside of retirees, there are 110 faculty members in the original sample who did not move and for whom we could find no wage data in 2021. We were unable to identify any common factors among these faculty that might explain why their wage data are missing. Faculty leaves, which are unobserved in our data, likely account for at least some of these instances.

[12] These are faculty with wage decreases of more than 30 percent or wage increases above 100 percent (based on nominal salary growth), which we deem as outside of the bounds of what is realistic. These large changes likely reflect reporting fluctuations due to circumstances such as faculty leaves, partial sabbaticals, and temporary external salary support.

Whether this is a large or small number in absolute terms is in the eye of the beholder, but compared to other faculty panel studies, our sample retention rate is high.[13] The more important question is whether attrition from the panel correlated with gender and wages could confound our analysis of the evolution of the gender wage gap. We devote considerable attention to this possibility below and find no evidence to suggest our findings are confounded by differential sample attrition by gender.

Table 2 provides descriptive statistics for the baseline cross-sectional dataset from 2016, the panel sample with 2021 wages (divided by mobility status), and two data subsamples we use in supplementary models examining gender promotion gaps.

4. Methods and Primary Findings

We begin by using the following model to replicate Li and Koedel's (2017) estimate of the conditional gender wage gap using the 2016 cross-sectional dataset:

$$Y_{ijk} = \beta_0 + \mathbf{X}_{ijk}\beta_1 + \mathbf{R}_i\beta_2 + G_i\beta_3 + \delta_j + \theta_k + \eta_{ijk}, \quad (2)$$

where Y_{ijk} is the annual salary for faculty member *i* at university *j* in field k, in 2016 dollars. $\mathbf{X}_{ijk}$ is a vector of faculty qualifications and measures of research productivity, $\mathbf{R}_i$ is a vector of race/ethnicity indicators, G_i is an indicator equal to one if the faculty member is female, δ_j is a university fixed effect, θ_k is a field fixed effect, and η_{ijk} is an idiosyncratic error term. We cluster our standard errors at the university level throughout.[14]

---

[13] Our retention rate is significantly higher than in Ginther and Hayes (2003). It is somewhat lower than in Weisshaar (2017) because Weisshaar (2017) does not collect wage data (ignoring panel attrition due to issues with the wage data, we were able to find virtually every faculty member in the original dataset during our follow-up data collection). Two other recent panel studies—Obloj and Zenger (forthcoming) and Baker et al. (2021)—do not document panel attrition.

[14] Our sample contains 40 universities, which is in the range of concern for the use of typical clustered standard errors (Cameron and Miller, 2015). Given this, we also estimate standard errors using the wild cluster bootstrap, which has better properties in applications with small numbers of clusters. We omit these results for brevity but confirm that none of our findings are sensitive to the clustering approach.

Following Li and Koedel (2017), the *X* vector includes years of experience, the field-normalized h-index from Scopus©, and indicators for the PhD-granting institution's quality. It also includes interactions of the field-normalized h-index and the field indicator variables to allow for differential earnings returns to research productivity across disciplines. For experience, Li and Koedel (2017) use a linear experience control, and we take this approach as well. We use the categories shown in Table 2 to control for the quality of the PhD-granting institution via binned indicator variables.[15] We do not control for rank directly in equation (1) because of gender's potential impact on promotions and the timing of promotions, which can impact wages.

The conditional gender wage gap is captured in equation (2) by the parameter β_3. The first column of Table 3 shows that we exactly replicate the original Li and Koedel (2017) estimate of β_3 —$4,279.70—using the original cross-sectional dataset.[16] This corresponds to 3.6 percent of the average faculty member's salary. As shown in the appendix to Li and Koedel (2017), and verified in our own appendix, this estimate is not meaningfully affected by reasonable modifications to equation (2). For example, it is substantively similar regardless of whether we measure salaries in raw dollars (our main approach) or use the natural log of salaries. It is also similar if we include more information about research productivity (e.g., normalized citation and publication counts, in addition to the h-index) and if we control more flexibly for experience by using experience-year fixed effects instead of the linear experience control. Appendix Tables A2, A3, and A4 confirm the robustness of the conditional gender wage gap to these model adjustments.

---

[15] Also recall that the experience information comes from several different sources in the baseline data file. All of our regressions include indicator variables to identify the source of the experience data, along with a separate indicator for whether experience is missing. Similarly, the model includes an indicator for whether research productivity data are missing and whether the PhD-granting institution is missing.

[16] We drop one observation from their dataset for which gender is unknown, but the coefficient in Table 3 is an exact match to the Li and Koedel (2017) estimate to the hundredth decimal place.

Next, we estimate the gender wage gap for the faculty we track through 2021. We convert all 2021 dollar values to 2016 dollar values so the units are real. We begin with the sample of faculty who did not change academic institutions between 2016 and 2021, who comprise the vast majority of our sample. We incorporate mobile faculty into the analysis below.

First, we re-estimate equation (2) using the same right-hand-side variables from the 2016 data collection but replace the 2016 wage with the 2021 wage on the left-hand side.[17] The results are shown in column (2) of Table 3. We then re-estimate the equation after changing the dependent variable to measure wage growth in percentage terms. In column (3), we measure wage growth from 2016 to 2021 for each faculty member as a percentage of the faculty member's own 2016 salary; that is, the dependent variable is

$$\left\{\frac{Y_{ijk}^{2021} - Y_{ijk}^{2016}}{Y_{ijk}^{2016}}\right\} * 100. \qquad (3)$$

Next, in column (4), we change the dependent variable to measure wage growth as a percentage of the sample average 2016 salary as follows:

$$\left\{\frac{Y_{ijk}^{2021} - Y_{ijk}^{2016}}{\overline{Y}^{2016}}\right\} * 100, \qquad (4)$$

where $\overline{Y}^{2016}$ is the sample average 2016 salary reported in Table 2 for all faculty. The different denominators in equations (3) and (4) result in modest differences in the parameter of interest (on the indicator for being female) because male wages are higher than female wages, on average.

Column (2) of Table 3 shows that the unexplained gender wage gap fell by 60 percent over the period covered by the data panel among faculty who remained at their 2016 institutions, from

[17] The values for most of the independent variables do not change between 2016 and 2021 (e.g., field, demographics, PhD granting institutions) or the change in inconsequential (e.g., experience, since all faculty increment together). The one variable that does change is the h-index. We use the baseline 2016 value because changes in productivity by gender during the period we measure wage growth could be endogenous and using the 2016 values facilitates the cleanest interpretation of our estimates.

over \$4,200 in 2016 to less than \$1,700 in 2021. We use a bootstrap to test the statistical significance of this decline and find that the reduction is significant (p-value < 0.01). The insignificant 2021 estimate of \$1,692 corresponds to 1.2 percent of the sample-average 2021 wage. In columns (3) and (4), we also report statistically significant and economically meaningful differences in real wage growth between men and women during the panel period. Column (3) shows women's salaries grew 2.57 percent faster than men's salaries, on average. The wage-growth gap is smaller when measured against the sample average wage, as expected, in column (4). However, at 2.11 percent, it is still economically meaningful and statistically significant.[18]

In Table 4, we test for heterogeneity between fields that differ by female representation. We combine biology, chemistry, and economics as fields with relatively low female representation and educational leadership and policy, English, and sociology as fields with relatively high female representation. Li and Koedel (2017) show that women account for 18-31 percent of faculty in the low-representation fields and 47-53 percent of faculty in the high-representation fields.

This analysis is motivated by the hypothesis that field-level gender representation could influence labor market dynamics in gender-specific ways—specifically, women may receive pay premiums in fields in which they are underrepresented. We test for this by adding an interaction between the female indicator variable and an indicator for low-female-representation fields. The dependent variables are as shown in equations (3) and (4), corresponding to the estimates in columns (3) and (4) of Table 3 (note the level effects of low-representation fields are subsumed by the field fixed effects).

---

[18] The magnitudes of these estimates correspond to the total dollar change in the conditional wage gap of about \$2,500. To see this, note from Table 2 that the sample average baseline salary in our data is roughly \$120,000. The estimate in column (4) of Table 3 indicates differential wage growth of 2.1 percent between women and men off of this baseline value, or approximately \$2,500.

The results indicate that women in low-representation fields receive larger raises, but not uniformly. In the model where wage growth is calculated from the individual-level base (as in equation 3), the coefficient on the interaction term is positive but small and insignificant. However, in the model where we use the sample average wage as the base for calculating wage growth (as in equation 4), the interaction coefficient is large and significant. This pattern of results indicates the largest wage increases accrue to women who satisfy the following two conditions: (1) they work in low-representation fields and (2) they had relatively high wages in 2016. The latter condition must be true because the estimated wage increase is higher relative to the sample average baseline wage (column 2) than their own 2016 wages (column 1). This finding is consistent with evidence from Leslie, Manchester, and Dahm (2017), who show that diversity objectives in organizations can generate an earnings premium for "high potential" women.

5. Is the Gender Wage Gap Really Narrowing? Data Issues and Faculty Mobility

In this section, we (a) conduct tests to assess whether our findings could be biased by changes to the composition of faculty in the data panel over time and (b) examine the influence of faculty mobility on the gap. These are related but distinct issues. With the former, the concern is that there could be differential attrition from the data panel by gender correlated with wages. Faculty mobility is one source of attrition—especially mobility outside of the public sector—but there are other sources of attrition as well. Differential attrition by gender correlated with wages could lead us to estimate a narrowing gender wage gap because of changes to the composition of our sample rather than real changes to gender wage dynamics. With regard to faculty mobility specifically, in addition to affecting attrition, mobility can affect the wage gap through gender differences in the earnings returns to mobility (Blackaby, Booth, and Frank, 2005; Groysberg, Healy, and Lin, forthcoming).

First, and most straightforwardly, we conduct a summary test for selection into our panel sample of non-movers with 2021 wage data. To do this, we estimate equation (2) for the 3,019 non-mobile faculty who comprise the panel sample we have analyzed thus far, but model their 2016 wages rather than their 2021 wages. If there is differential attrition from the 2021 sample by gender, and it is correlated with wages, we should expect the 2016 gender wage gap to differ when estimated using the full 2016 cross-section (N = 3,804) versus the panel sample of non-movers (N = 3,019).

Table 5 shows the results. The 2016 wage gap estimated for the panel sample of non-movers is nearly identical to the 2016 wage gap estimated for the full sample—the estimates are about $60 apart and statistically indistinguishable. These results give no indication of problematic attrition from the sample that could lead to bias in our 2021 wage-gap estimate.

To explore the attrition issue further, and as a lead-in to a deeper investigation of faculty mobility, Table 6 provides detailed documentation of the sources of attrition from the data panel by gender. The first row shows that men are 4.4 percentage points more likely to exit the data panel between 2016 and 2021, with the difference concentrated primarily in retirements (which account for 4.0 of the 4.4 percentage-point difference). This is not surprising because male faculty are older and more experienced than female faculty, on average, reflecting their historical overrepresentation in academia (Ceci et al., 2014; Ginther and Hayes, 2003).

A simple way to assess whether the narrowing gender wage gap is due to differential retirement behavior between men and women is to focus on faculty outside of the typical retirement window. In our data, the median 2016 experience level among faculty who retire by 2021 is 38, and experience at the 25th percentile of retirees is 32.[19] In Appendix Table A5 we replicate the results in

[19] Recall that we calculate experience for most faculty as the difference between the current year and the PhD year. This metric does not directly correspond to retirement-eligibility thresholds, which can be institution (or system) specific.

columns (2)-(4) of Table 3, but restrict the sample to faculty with experience at or below 30 in 2016 to reduce the influence of retirees. The findings are similar to our main results, indicating that the narrowing wage gap is not driven by gender differences in retirements.

Outside of retirements, there are no meaningful (or statistically significant) gender differences in the reasons for attrition from the data panel, which is broadly consistent with our overarching test for selective attrition in Table 5. However, faculty mobility can also affect the wage gap through gender differences in post-move wages. That is, although men and women change jobs at roughly equal rates, they could experience different pay changes with their new employers. Given our focus on wage gaps within academia, academic movers are of primary interest.[20]

To gain further insight into the mobility question, in Appendix Table A6 we provide detailed summary statistics broken out by gender for academic movers in the sample. The table shows that of all female academic movers, 58, 33, and 9 percent moved to public, private, and foreign universities, respectively; the comparable numbers for men are 49, 33, and 18 percent. Male movers have much higher pre-move earnings unconditionally, though this is driven by the many descriptive differences between movers by gender (most notably field differences, and to a lesser degree, differences in experience and rank). Movers of both genders to other public U.S. universities—for whom we can track post-move wages—experience substantial wage gains during the panel period. Male movers have earnings that are 53 percent higher post-move, compared to 43 percent for women, on average.

Nonetheless, we use the empirical distribution of observed retirements to identify the range of values of our experience measure during which most retirements occur.

[20] It would also be of interest to track wage changes for women and men who move outside of academia, but this is outside the scope of our study. Non-academic movers are also very small in number.

To assess whether public-university movers influence our conclusions about the evolution of the conditional wage gap, we add them back into the data panel and re-estimate the wage model in equation (2). Column (1) of Table 7 shows that adding these faculty back into our dataset has no substantive impact on our findings—our estimate of the 2021 wage gap is similar to what we show in Table 3 and remains statistically insignificant. This is the product of two factors: (1) although male movers experience higher wage growth than female movers, the gap is modest and (2) most faculty do not move, limiting the influence of movers on the sample-wide gap. We conclude that the gender wage gap has narrowed at public U.S. research universities between 2016 and 2021, and that this is true inclusive of faculty who move within the public sector.

Our study is most informative about the public sector wage gap and given that our baseline sample is comprised of public-sector faculty, this is the most useful parameter we can inform (the public sector gap is also the target parameter in many recent faculty studies—e.g., see Chen and Crown, 2019; Li and Koedel, 2017; Obloj and Zenger, forthcoming; and Taylor et al., 2020). That said, the fact that we also track faculty who exit the public sector allows us to provide at least some insight into how these outside movers are likely to influence the gap.[21] For movers to private and foreign universities, we do not know their post-move wages, but we know who they are, which gives us their weight in the sample, and we know their baseline wages. To estimate their likely impact on the evolution of the gender wage gap in our sample, we use observed moves within the public sector to parameterize their expected returns to mobility. Specifically, we assume a 43 percent earnings

[21] We are not aware of any other multi-institution faculty data panels that have been used to track the gender wage gap, let alone panels that track moves outside of the public sector. Obloj and Zenger (forthcoming) use a data panel based on public university data but cannot track faculty outside of the public sector; moreover, their unique identifiers appear to be at the individual-institution level, so they cannot track mobility even within the public sector (this is also true for Baker et al., 2021, who use similar data in Canada). Other recent panel datasets such as those used by Chen and Crown (2019) and Taylor et al. (2020) allow the researchers to follow individual faculty over time, but both studies use administrative data from just one institution so cannot track leavers.

increase for all female movers and a 53 percent increase for all male movers with unobserved post-move wages.

Using this parameterization, we add all academic movers back into the panel sample and re-estimate equation (2). The results are in Column (2) of Table 7. We estimate the 2021 gender wage gap is about $2,800, or about two percent of the average faculty member's salary. This estimate is still below our estimate from 2016 but implies a lesser reduction of the gender wage gap. This is our best estimate of the gap inclusive of all academic movers in our original sample. If gender differences in the returns to mobility at private and foreign universities are different than in the public sector, the total gap inclusive of all movers could be larger or smaller.

6. Possible Explanations for our Findings

6.1 Gender gaps in promotions

There is a related literature on gender gaps in promotions among U.S. faculty, which is relevant because promotion gaps will likely be reflected in wages. Historically, promotion gaps have favored men, although in more recent studies the evidence on promotion gaps is mixed. There are still some fields in which women are less likely to be promoted than men (most notably, economics), but several recent studies find no evidence of promotion gaps in most fields. In studies that do find promotion gaps, gaps are more common at the associate-to-full level than assistant-to-associate level. An expectation based on the literature is that in our data—i.e., recent data pooled across the six fields originally sampled by Li and Koedel (2017)—promotion gaps should be small-to-null, and if anything, favor men. In the remainder of this section, we test for evidence that promotion gaps have shifted toward favoring women, which could contribute to the narrowing gender wage gap.[22]

[22] This paragraph summarizes a rich literature on gender gaps in promotions. Our summary is based on the following studies: Chen, Kim, and Liu (2022), Durodoye Jr. et al. (2020), Ginther and Hayes (2003), Ginther and Kahn (2006, 2021), Sarsons (2017), and Weisshaar (2017).

We estimate gender promotion gaps separately at the assistant-to-associate and associate-to-full levels. The first model is estimated using only assistant professors from 2016, and the second uses only associate professors from 2016. Each model's structure is the same as equation (2). We use as the dependent variable a binary indicator equal to one if a promotion occurred between 2016 and 2021, and zero otherwise. Faculty who are observed at the rank of assistant professor in 2016 and associate or full professor in 2021, or at the rank of associate professor in 2016 and full professor in 2021, are coded as having been promoted during the panel period. Promotions can occur at the original 2016 university or a new institution. If the individual left academia between 2016 and 2021, or if they are observed at the same or a new university in 2021 at the same rank as in 2016, we code the promotion variable as zero—i.e., a promotion did not occur.

Because the coding of promotions does not require wage data, we estimate the promotion regressions using all assistant and associate professors in the 2016 cross-sectional dataset. In a vacuum, this decision makes the most sense, regardless of the availability of 2021 wage data. However, it raises the possibility that sample composition changes could confound the connection between our promotion and wage models. We address this issue by also estimating a model of associate-to-full promotions using only associate professors in 2016 with observed wages in 2021. We cannot estimate similarly restricted models for assistant professors because their presence in the 2021 wage data is more likely to be affected by the promotion outcome. In other words, tenure denial is one way that a faculty member would exit our data panel.

As a caveat to this analysis, we acknowledge that a non-promotion outcome does not necessarily mean the faculty member failed to be promoted. It may simply be that he or she did not reach their promotion window during the panel period. This should not cause bias in the estimated gender gaps unless men and women are differentially bunched toward or away from their promotion windows, which seems unlikely. Still, to be thorough, we also estimate the promotion models after replacing the linear experience control with experience fixed effects. These exact-experience conditional models are conceptually appealing because they force comparisons to occur only between faculty with the same experience values. However, as a practical matter, our findings are not affected by how we control for experience (see Appendix Table A7).

Columns (1) and (2) of Table 8 report the results from our assistant-to-associate and associate-to-full promotion regressions. Column (3) shows the version of the associate-to-full regression restricted to faculty with 2021 wages. The analytic samples for these regressions are based on 663 assistant professors and 1,111 associate professors (1,004 of whom have 2021 wages) in the original 2016 cross-section, for which summary statistics are reported in Table 2.

None of the estimates in Table 8 indicate statistically significant differences in the conditional likelihood of promotion by gender. The point estimates are also inconsistent in sign between promotion levels. In Appendix Table A8, we further test for heterogeneity in promotion gaps between high- and low-female representation fields and find no evidence of heterogeneity, albeit with the caveat that our promotion models are not well-powered to detect field heterogeneity. Overall, these findings give no indication of differential promotion rates by gender, which we interpret as broadly consistent with other studies using recent data.[23] We conclude that a shift in promotion rates favoring women is not a mechanism by which the gender wage gap is narrowing.

[23] More precisely, this is consistent with recent evidence outside of economics. While economists are included in our dataset, we are not sufficiently powered to conduct field-level tests. What we can say most concretely is the following: if there are promotion gaps among economists in our data, they are not large enough to show up in pooled models of promotions that otherwise match our pooled wage models.

6.2 Gender gaps in large raise events

Next, we test whether male and female faculty differ in their likelihoods of receiving large raises. We hypothesize that women may have been more likely to receive large raises during the panel period for two reasons. First, the emphasis on equity in academia may have empowered female faculty and increased their willingness-to-move. Relatedly, on the demand side, it may have created more outside options for female faculty, especially in fields where women are traditionally underrepresented (e.g., business, economics, and most traditionally-defined STEM fields).

Unconditionally, Table 6 shows that men and women moved at similar rates from 2016 to 2021, on average.[24] Still, even this "null finding" could represent a shift in behavior if men have historically been more likely to move.[25] Moreover, move rates in isolation paint an incomplete picture of *willingness-to-move* because home universities can respond to external offers to retain faculty. Using data on economists from the United Kingdom, Blackaby, Booth, and Frank (2005) show that women have historically received fewer outside offers, but whether this is true in more recent data is uncertain. In summary, push and pull factors may have changed women's willingness and opportunities to move, and correspondingly, their likelihoods of receiving large raises.

The second reason women may be disproportionately likely to receive large raises is a direct consequence of administrator efforts to promote pay equity on university campuses, independent of any gender-based changes in willingness-to-move or outside opportunities. These efforts are exemplified by the formation of committees and commissions on gender equity at many

[24] In an analysis omitted for brevity, we confirm this result holds conditionally as well.

[25] We are not aware of any previous panel data we can use for comparison to confirm or refute this hypothesis empirically (some previous data exist per the above discussion, but none facilitate an appropriate comparison). That said, it seems plausible because men have historically been more likely to be primary earners in their families (Bernard, 1981; Haas 1986), giving them greater flexibility to move for own-career reasons, all else equal (Bielby and Bielby, 1992). In addition, men have a higher proclivity toward negotiation, which may make them more open to moving (Blackaby et al., 2005; Daly and Dee, 2006; Ward, 2001).

institutions—we give several examples in the introduction. Administrator efforts in this regard can be internally driven or a response to external laws and pressure (for an example of the latter, see Snyder, 2021). A report from the Commission on Women and Gender Equity in Academia (2018) at Rochester University provides a general sense of contemporary sentiment in this regard.

Although we lack data to disentangle these underlying mechanisms, we conduct summary tests to determine whether women were more likely to receive large raises during the panel period. We use the specification shown in equation (2) where the dependent variable is a binary indicator for a "large" raise occurring over the panel period. Our preferred definition of a large raise is 30 percent or more (in real dollars). Table 2 shows that among non-mobile faculty, 12 percent received a raise at least this large. We also estimate models where we define a large raise as 20 percent or more (received by 22 percent of non-mobile faculty). We estimate models of large-raise events using the non-mover sample and the sample inclusive of public-university movers for whom post-move wages are observed. Unsurprisingly, large raises are much more common among movers (see Table 2).

Table 9 shows that female faculty disproportionately received large raises during the panel period, driven by raises among non-mobile faculty. In addition to being statistically significant, the gender differences in Table 9 are economically meaningful. For example, using our preferred definition of a large raise of 30 percent or more, non-mobile women were 3.3 percentage points more likely to receive a large raise than non-mobile men, which is 27.5 percent of the sample average rate. Inclusive of mobile faculty, the gender gap in large-raise events attenuates very slightly—to 3.2 percentage points—because more males than females received a large raise as part of a move. However, similarly to above, including movers has a negligible impact on the full-sample estimate. These findings indicate the narrowing of the gender wage gap is driven partly by a higher prevalence of large raise events among female faculty, and non-mobile female faculty in particular.

6.3 Potential Factors Underlying Our Results

The explanations for our findings addressed in the preceding section are best described as mechanical. However, there are a number of deeper factors suggested by previous research that could underlie our findings. These factors are all connected to the greater emphasis on equity in academia in recent years and are either (a) complements to equity-focused policies or (b) ways in which equity-focused policies may be operationalized.

First, a prominent complementary factor is the increased salience of pay transparency at U.S. public universities (Baker et al., 2021; Obloj and Zenger, forthcoming). During the period we study, there were no changes in the legal landscape regarding pay transparency in our sample of universities. In fact, these data have been publicly-available for many years. However, it is possible that with the increased focus on pay equity on university campuses, the salience of publicly-available salary data increased. If pay transparency is indeed a key factor contributing to the narrowing gender wage gap in our data, a testable implication worthy of attention in future research is that there should not be a similar narrowing of the gap at private universities, where there is not pay transparency.

Another possible factor is that women may be receiving more credit for their joint work. Using data on academic economists, Hussey, Murray, and Stock (2021), Sarsons (2017), and Sarsons et al. (2020) show that women receive less credit for coauthored work, especially when their coauthors are men. Related evidence from neuroscience shows that article reference lists include more papers with men as first and last authors—where prominent authors are typically listed—than would be expected if citations were gender neutral (Dworkin et al., 2020). It is speculative to say the gender dynamics of work attribution are changing; but it is possible, and would be consistent with the increased focus on equity at academic institutions.

Finally, it is also possible that changing policies, norms, and perceptions surrounding tenure clock stoppages are contributing to the narrowing gender wage gap. Using data from the late 1990s and early 2000s, Manchester, Leslie, and Kramer (2013) find that faculty who stop the tenure clock for family reasons incur salary penalties relative to those who do not. They further show this cannot be explained by differences in productivity. The increased prevalence of gender-neutral family clock-stopping policies may lead to more equitable salary outcomes as more men take advantage of these policies. The salary penalties may also be declining.[26]

7. Conclusion

We use a recent panel dataset from 2016-2021 to study the evolution of the conditional gender wage gap among faculty at public universities in the U.S. The wage gap declined markedly from 2016 to 2021, falling from 3.6 to 1.2 percent of the average faculty member's salary among those who remained at their original 2016 institutions. Accounting for faculty who moved within the public sector does not change this summary interpretation—inclusive of these mobile faculty, we estimate the 2021 wage gap was only marginally higher, at 1.3 percent of the average faculty member's salary. In addition to these 2021 estimates of the gender wage gap being substantively small, they are statistically indistinguishable from zero.

Although we cannot resolve the discrepancy in the extant literature about whether our findings reflect a continuation of a declining trend in the gap (as implied by Obloj and Zenger, forthcoming) or a sharp departure from decades of stagnation (as implied by compiling evidence from numerous cross-sectional studies such as Barbezat and Hughes, 2005; Carlin, 2013; Chen and Crown, 2019; Li and Koedel, 2017; Porter et al., 2008; Taylor et al., 2020; Toutkoushian, 1998; and

[26] Women do not benefit from gender-neutral clock-stopping policies in terms of tenure rates (Antecol, Bedard, and Stearns, 2018), although this does not preclude these policies—or changes in how they are perceived—from leading to more equitable pay.

Toutkoushian and Conley, 2005), we provide some clarity by anchoring our panel analysis to the bulk of the previous literature via our replication of the original Li and Koedel (2017) estimates. Although the trend in the gap—or lack thereof—prior to 2016 remains uncertain, we show that between 2016 and 2021 the gap meaningfully declined, at least among faculty at public universities.

We are limited in our ability to test for the factors that drive our findings, but we show female faculty were disproportionately likely to receive large raises during the period covered by our data panel. In terms of deeper mechanisms, we hypothesize our findings may be the result of the shifting culture in academia emphasizing pay equity. This shift could be directly impacting women through explicit equity-targeted initiatives and/or by influencing the dynamics of the faculty labor market in ways that favor female faculty (also see Leslie, Manchester, and Dahm, 2017). The focus on pay equity may also be complemented by other equity improving policies identified in previous research, such as pay transparency in the public sector, among others.

We conclude by noting two caveats to our findings, which stem from the fact that our sample is restricted to faculty working at selective public research universities in the U.S. in 2016. First, it is not obvious how our findings will generalize to faculty in other postsecondary settings. Second, while tracking the same faculty over time is beneficial because it allows us to clearly assess the evolution of the gender wage gap in a fixed sample, our analysis is necessarily restricted to incumbent faculty in 2016. As a result, we do not observe any potential gender differences in wage offers at entry. Previous evidence on the gender wage gap at entry is mixed, with findings ranging from a modest gap favoring men (4-7 percent; see Toumanoff, 2005) to an insignificant gap (Porter et al., 2008). It would be interesting to see if the narrowing gap among incumbent faculty we document here is accompanied by changes the gap among new entrants, which we leave to future research.

BIBLIOGRAPHY

Antecol, H., Bedard, K., and Stearns, J. (2018). Equal but inequitable: Who benefits from gender-neutral tenure clock stopping policies. *American Economic Review* 108(9), 2420-41.

Baker, M., Halberstam, Y., Kroft, K., Mas, A., and Messacar, D. (2021). Pay transparency and the gender gap. NBER Working Paper No. 25834. Cambridge, MA: National Bureau of Economic Research.

Barbezat, D.A. (1987). Salary differentials by sex in the academic labor market. *Journal of Human Resources* 22(3), 422–428.

Barbezat, D. A., & Hughes, J. W. (2001). The effect of job mobility on academic salaries. *Contemporary Economic Policy*, 19(4), 409–423.

Barbezat, D. A., & Hughes, J. W. (2005). Salary structure effects and the gender pay gap in academia. *Research in Higher Education*, 46(6), 621–640.

Bernard, J. (1981). The good-provider role: Its rise and fall. *American Psychologist*, 36(1), 1.

Bielby, W. T., & Bielby, D. D. (1992). I will follow him: Family ties, gender-role beliefs, and reluctance to relocate for a better job. *American Journal of Sociology*, 97(5), 1241–1267.

Blackaby, D., Booth A. L., Frank J. (2005). Outside offers and the gender pay gap: Empirical evidence from the UK academic labour market. *The Economic Journal,* 115 (February), F81–F107.

Cameron, A.C., & Miller, D.L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources* 50(2), 317–372.

Carlin, P. S., Kidd, M. P., Rooney, P. M., & Denton, B. (2013). Academic wage structure by gender: The roles of peer review, performance, and market forces. *Southern Economic Journal*, *80*(1), 127-146.

Ceci, S. J., Ginther, D. K., Kahn, S., & Williams, W. M. (2014). Women in academic science: A changing landscape. *Psychological Science in the Public Interest,* 15(3) 75–141.

Chen, J. J., & Crown, D. (2019). The gender pay gap in Academia: Evidence from the Ohio State University. *American Journal of Agricultural Economics*, 101(5), 1337–1352.

Chen, J., Kim, M., and Liu, Q. (2022). Gender gap in tenure and promotion: Evidence from the economics Ph.D. class of 2008. *Southern Economic Journal* 88(4), 1277-1312.

Commission on Women and Gender Equity in Academia. (2018). Preliminary report. Rochester, NY: University of Rochester.

Daly, C. J., & Dee, J. R. (2006). Greener pastures: Faculty turnover intent in urban public universities. *The Journal of Higher Education*, 77(5), 776–803.

Durodoye Jr., R., Gumpertz, M., Wilson, A., Griffith, E., & Ahmad, S. (2020). Tenure and promotion outcomes at four large land grant universities: Examining the role of gender, race, and academic discipline. *Research in Higher Education,* 61, 628–651.

Dworkin, J.D., Linn, K.A., Teich, E.G., Zurn, P., Shinohara, R.T., and Bassett, D.S. (2020). The extent and drivers of gender imbalance in neuroscience reference lists. *Nature Neuroscience* 23, 918-926.

Ginther, D. K. (2001). Does science discriminate against women? Evidence from academia, 1973–1997. Federal Reserve Bank of Atlanta Working paper 2001–02.

Ginther, D. K., & Hayes, K. J. (2003). Gender differences in salary and promotion for faculty in the humanities 1977–95. *Journal of Human Resources*, 38(1), 34–73.

Ginther, D.K., and Kahn, S. (2006). Does science promote women? Evidence from academia 1973–2001. NBER Working Paper No. 12691.

Ginther, D.K., & Kahn, S. (2021). Women in academic economics: have we made progress? *American Economic Association Papers and Proceedings*.

Groysberg, B., Healy, P., & Lin, E. (Forthcoming). Determinants of gender differences in change in pay among job-switching executives. *Industrial and Labor Relations Review*.

Haas, L. (1986). Wives' orientation toward breadwinning: Sweden and the United States. *Journal of Family Issues*, 7(4), 358–381.

Hussey, A., Murray, S., and Stock, W. (2022). Gender, coauthorship, and academic outcomes in economics. *Economic Inquiry* 60(2), 465-484.

Laughter, J. (2018). Race in educational researcher: A technical comment on Li and Koedel (2017). *Educational Researcher*, 47(4), 259–261.

Leslie, L.M., Manchester, C.F., and Dahm, P.C. (2017). Why and when does the gender gap reverse? Diversity goals and the pay premium for high potential women. *Academy of Management Journal* 60(2).

Li, D., & Koedel, C. (2017). Representation and salary gaps by race-ethnicity and gender at selective public universities. *Educational Researcher*, 46(7), 343–354.

Li, D., & Koedel, C. (2018). A technical comment on Li and Koedel (2017): Author response. *Educational Researcher*, 47(4), 262–263.

Manchester, C.F., Leslie, L.M., and Kramer, A. (2013). Is the clock still ticking? An evaluation of the consequences of stopping the tenure clock. *Industrial and Labor Relations Review* 66(1), 3-31.

Obloj, T., & Zenger, T. (forthcoming). The influence of pay transparency on (gender) inequity, inequality, and the performance-basis of pay. *Nature Human Behavior*.

Perry, M., & Reny, P. J. (2016). How to count citations if you must. *American Economic Review*, 106 (9), 2722–2741

Porter, S. R., Toutkoushian, R. K., & Moore III, J. V. (2008). Pay inequities for recently hired faculty, 1988–2004. *The Review of Higher Education*, 31(4), 465–487.

Sarsons, H. (2017). Recognition for group work: Gender differences in academia. *American Economic Review*, 107(5), 141–45.

Sarsons, H., Gerxhani, K., Reuben, E., and Schram, A. (2020). Gender differences in recognition for group work. *Journal of Political Economy* 129(1), 101-147.

Snyder, S. (2021). Rutgers professors say they were shortchanged in salary equity adjustments, especially those who work in Camden. *The Philadelphia Inquirer* (09.29.2021).

Taylor, L. L., Lahey, J. N., Beck, M. I., & Froyd, J. E. (2020). How to do a salary equity study: With an illustrative example from higher education. *Public Personnel Management*, *49*(1), 57–82.

Toumanoff, P. (2005). The effects of gender on salary-at-hire in the academic labor market. *Economics of Education Review*, 24(2), 179–188.

Toutkoushian, R. K. (1998). Sex matters less for younger faculty: Evidence of disaggregate pay disparities from the 1988 and 1993 NCES surveys. *Economics of Education Review*, 17(1), 55–71.

Toutkoushian, R. K., & Conley, V. M. (2005). Progress for women in academe, yet inequities persist: Evidence from NSOPF: 99. *Research in Higher Education*, 46(1), 1–28.

Umbach, P. D. (2006). Gender equity in the academic labor market: An analysis of academic disciplines. *Research in Higher Education*, 48(2), 169–192.

Ward, M. (2001). The gender salary gap in British academia. *Applied Economics,* 33, 1669–1681.

Weisshaar, K. (2017). Publish and perish? An assessment of gender gaps in promotion to tenure in academia. *Social Forces*. 96(2), 529–560.

Table 1: Documentation of sample attrition from original Li and Koedel (2017) dataset.

Data collection year	2016 (Li and Koedel dataset)	2021	Share of original 2016 sample
Salary included, total	3,804	3,098	0.814
Reasons for data loss			
Retiree		288	0.076
Cannot find salary (unknown reason)		110	0.029
Academic mover with no post-move wages		98	0.026
Mover outside academia		50	0.013
Salary excluded due to measurement problem [-30%; +100%]		160	0.042
Salary missing or excluded, total		706	0.186

Notes: One faculty member with non-identified gender was removed from the original Li and Koedel (2017) sample (their original N was 3,805).

Table 2: Descriptive statistics.

	Original cross-sectional dataset	Panel sample with 2016 and 2021 wages: Non-movers	Movers	Assistant prof. in original 2016 data	Associate prof. in original 2016 data
	(1)	(2)	(3)	(4)	(5)
Salary in 2016	120,206.09 (52,664.63)	121,072.03 (52,218.14)	120,912.70 (51,205.87)	84,091.44 (24,008.68)	93,068.24 (25,302.94)
Salary in 2021 (nominal dollars)	144,451.2 (64,818.9)	145,744.51 (64,366.74)	181,222.01 (91,361.48)	105,927.52 (34,028.92)	115,281.53 (39,067.38)
Salary increase > 20% over panel period (real dollars)	-	0.22 (0.41)	0.54 (0.50)	0.28 (0.45)	0.24 (0.43)
Salary increase > 30% over panel period (real dollars)	-	0.12 (0.33)	0.46 (0.50)	0.20 (0.40)	0.15 (0.36)
Faculty Rank (2016)					
Assistant Professor	0.17 (0.38)	0.16 (0.37)	0.32 (0.47)	1.00 (0.00)	0.00 (0.00)
Associate Professor	0.29 (0.45)	0.32 (0.46)	0.30 (0.46)	0.00 (0.00)	1.00 (0.00)
Full Professor	0.53 (0.50)	0.52 (0.50)	0.38 (0.49)	0.00 (0.00)	0.00 (0.00)
Promoted	-	0.18 (0.39)	0.20 (0.40)	0.50 (0.50)	0.28 (0.45)
Gender					
Male	0.65 (0.48)	0.64 (0.48)	0.58 (0.50)	0.58 (0.49)	0.56 (0.50)
Female	0.35 (0.48)	0.36 (0.48)	0.42 (0.50)	0.42 (0.49)	0.44 (0.50)
Field					
Biology	0.32 (0.47)	0.34 (0.47)	0.32 (0.47)	0.34 (0.47)	0.29 (0.45)
Chemistry	0.14 (0.35)	0.15 (0.35)	0.13 (0.33)	0.15 (0.35)	0.09 (0.28)
Economics	0.13 (0.34)	0.13 (0.33)	0.24 (0.43)	0.19 (0.39)	0.11 (0.31)
Education (leadership/policy)	0.07 (0.25)	0.06 (0.25)	0.10 (0.30)	0.08 (0.27)	0.09 (0.29)
English	0.22 (0.42)	0.22 (0.42)	0.15 (0.36)	0.15 (0.36)	0.32 (0.47)
Sociology	0.11 (0.31)	0.11 (0.31)	0.06 (0.25)	0.10 (0.30)	0.11 (0.31)
PhD school rank					
PhD school U.S 1-10	0.23 (0.42)	0.24 (0.43)	0.25 (0.44)	0.23 (0.42)	0.22 (0.41)
PhD school U.S. 11-50	0.33 (0.47)	0.34 (0.47)	0.33 (0.47)	0.35 (0.48)	0.35 (0.48)
PhD school U.S. 50+	0.25 (0.43)	0.25 (0.43)	0.24 (0.43)	0.23 (0.42)	0.27 (0.44)
PhD school outside U.S.	0.11 (0.31)	0.11 (0.31)	0.11 (0.32)	0.14 (0.35)	0.09 (0.29)
PhD school missing	0.06 (0.23)	0.06 (0.23)	0.05 (0.22)	0.04 (0.20)	0.07 (0.25)
No PhD (English only)	0.01 (0.12)	0.01 (0.12)	0.01 (0.11)	0.01 (0.08)	0.01 (0.10)
Experience (years, 2016)	22.18 (11.97)	21.37 (11.10)	15.81 (9.61)	8.72 (5.70)	17.63 (8.18)
Source: Curriculum vitae/website	0.77 (0.42)	0.77 (0.42)	0.81 (0.39)	0.82 (0.39)	0.76 (0.43)
Source: Website, publication-based	0.02 (0.12)	0.01 (0.11)	0.03 (0.16)	0.00 (0.05)	0.01 (0.12)
Source: Scopus publications	0.19 (0.40)	0.20 (0.40)	0.15 (0.36)	0.15 (0.36)	0.20 (0.40)
Experience unavailable from any source	0.02 (0.13)	0.02 (0.13)	0.01 (0.11)	0.03 (0.18)	0.02 (0.15)
Research productivity (2016)					
Scopus publications	49.72 (81.43)	48.63 (76.52)	38.39 (60.92)	17.28 (19.75)	22.16 (23.44)
Scopus citations	2,062.01 (4377.17)	2,028.89 (4225.62)	1,306.40 (2518.53)	640.66 (1329.17)	785.42 (1355.04)
Scopus H-index	15.53 (15.98)	15.65 (15.49)	11.85 (12.22)	7.91 (7.44)	9.37 (8.85)
Scopus missing	0.06 (0.23)	0.05 (0.23)	0.05 (0.22)	0.11 (0.32)	0.07 (0.25)
Race/Ethnicity					
White	0.80 (0.40)	0.80 (0.40)	0.65 (0.48)	0.70 (0.46)	0.75 (0.44)
Black	0.05 (0.21)	0.05 (0.21)	0.13 (0.33)	0.05 (0.21)	0.08 (0.27)
Asian	0.11 (0.32)	0.12 (0.32)	0.16 (0.37)	0.19 (0.40)	0.12 (0.32)
Hispanic	0.04 (0.19)	0.04 (0.19)	0.05 (0.22)	0.06 (0.24)	0.05 (0.22)
Other/unknown	0.00 (0.06)	0.00 (0.04)	0.01 (0.11)	0.00 (0.00)	0.01 (0.08)
N	3,804	3,019	79	663	1,111

Notes: One faculty member with non-identified gender was removed from the original Li and Koedel (2017) sample.

Table 3: Conditional gender wage gap in 2016 and 2021, and differential salary growth by gender from 2016-2021, non-mover sample.

VARIABLES	(1) 2016 salary ($) (Replication of Li and Koedel, 2017)	(2) 2021 salary ($)	(3) pct salary increase 2016-2021, relative to 2016 own salary	(4) pct salary increase 2016-2021, relative to 2016 avg. salary
Female	-4,279.70***	-1,691.50	2.57***	2.11***
	(1,097.19)	(1,297.81)	(0.59)	(0.60)
Observations	3,804	3,019	3,019	3,019
R-squared	0.53	0.57	0.26	0.25
Race	X	X	X	X
PhD school rank	X	X	X	X
Experience	X	X	X	X
Research productivity	X	X	X	X
University fixed effects	X	X	X	X
Field fixed effects	X	X	X	X
Sample	2016 cross-section	2021 panel	2021 panel	2021 panel

Note: All dollar values are in 2016 dollars. Standard errors clustered by university are reported in parentheses.
*** p<0.01, ** p<0.05

Table 4: Salary growth heterogeneity between fields with high and low female representation, non-mover sample.

VARIABLES	(1) pct salary increase 2016-2021 on 2016 own salary	(2) pct salary increase 2016-2021 on 2016 avg. salary
Female	2.00**	0.72
	(0.81)	(0.61)
Female*(low representation field)	1.06	2.59**
	(1.26)	(1.05)
Observations	3,019	3,019
R-squared	0.26	0.25
Race	X	X
PhD school rank	X	X
Experience	X	X
Research productivity	X	X
University fixed effects	X	X
Field fixed effects	X	X

Note: Low representation fields are biology, chemistry, and economics. Standard errors clustered by university are reported in parentheses.
*** p<0.01, ** p<0.05

Table 5: Conditional gender wage gap in 2016 using the original cross-sectional dataset (N=3,804) and the panel sample of non-movers (N=3,019).

VARIABLES	(1) 2016 salary ($) (repeated from Table 3)	(2) 2016 salary ($)
Female	-4,279.70***	-4,222.46***
	(1,097.19)	(1,120.46)
Observations	3,804	3,019
R-squared	0.53	0.59
Race	X	X
PhD school rank	X	X
Experience	X	X
Research productivity	X	X
University fixed effects	X	X
Field fixed effects	X	X
Sample	2016 cross-section	2021 panel

Note: All dollar values are in 2016 dollars. Standard errors clustered by university are reported in parentheses. *** p<0.01, ** p<0.05

Table 6: Sample attrition from non-mover sample by gender, overall and by cause.

VARIABLES	Male	Female	p-value
	mean (std. err.)		
Salary in 2021 missing or excluded	0.228 (0.008)	0.184 (0.010)	***
cannot find salary	0.029 (0.003)	0.028 (0.004)	
salary data issues	0.051 (0.005)	0.048 (0.006)	
retired	0.089 (0.006)	0.049 (0.006)	***
mover within academia	0.046 (0.004)	0.052 (0.006)	
mover outside academic	0.012 (0.002)	0.016 (0.003)	

*** p<0.01, ** p<0.05

Table 7: Conditional gender wage gap in 2021, inclusive of academic movers.

VARIABLES	(1) 2021 salary ($) inclusive of public university movers with observed post-move wages	(2) 2021 salary ($) inclusive of all academic movers; post-move wages imputed for movers with missing post-move wages
Female	-$1,909.41	-2,860.48**
	(1,358.09)	(1,434.56)
Observations	3,098	3,196
R-squared	0.55	0.54
Race	X	X
PhD school rank	X	X
Experience	X	X
Research productivity	X	X
University fixed effects	X	X
Field fixed effects	X	X

Note: All dollar values are in 2016 dollars. Standard errors clustered by university are reported in parentheses. Imputed wages in column (2) are based on observed, gender-specific wage growth (in percent terms) for movers for whom post-move wages are observed. See text for details.

*** p<0.01, ** p<0.05

Table 8: Gender gaps in promotions.

VARIABLES	(1) promotion to associate prof.	(2) promotion to full prof.	(3) promotion to full prof., conditional on non- missing 2021 wage
Female	-0.034	0.016	0.009
	(0.043)	(0.023)	(0.024)
Observations	663	1,111	1,004
R-squared	0.238	0.209	0.216
Race	X	X	X
PhD school rank	X	X	X
Experience	X	X	X
Research productivity	X	X	X
University fixed effects	X	X	X
Field fixed effects	X	X	X

Note: Standard errors clustered by university are reported in parentheses.
*** p<0.01, ** p<0.05

Table 9: Gender differences in large-raise events.

	Non-movers only		Inclusive of public university movers with observed wages	
VARIABLES	(1) raise>=20%	(2) raise>=30%	(3) raise>=20%	(4) raise>=30%
Female	0.051***	0.033**	0.048***	0.032**
	(0.018)	(0.015)	(0.017)	(0.015)
Observations	3,019	3,019	3,098	3,098
R-squared	0.180	0.126	0.170	0.118
Race	X	X	X	X
PhD school rank	X	X	X	X
Experience	X	X	X	X
Research productivity	X	X	X	X
University fixed effects	X	X	X	X
Field fixed effects	X	X	X	X

Note: Wage increases are calculated in real dollars. Standard errors clustered by university are reported in parentheses. 23 and 14 percent of the panel sample (non-movers) received raises >=20% and >=30%, respectively (see Table 2).
*** p<0.01, ** p<0.05

APPENDIX TABLES

Appendix Table A1: Samples of universities and departments.

Universities	Biology	Chemistry	Economics	Education (Leadership/ Policy)	English	Sociology
University of California-Berkeley				X	X	X
University of California-Los Angeles		X	X	X		
University of Virginia			X	X	X	
University of Michigan-Ann Arbor			X	X		X
University of North Carolina-Chapel Hill		X	X			X
College of William & Mary		X	X		X	
Georgia Institute of Technology	X		X			X
University of California-Santa Barbara	X				X	X
University of California-Irvine	X	X	X			
University of California-San Diego	X				X	X
University of Illinois-Urbana-Champaign	X				X	X
University of Wisconsin-Madison		X		X		X
University of Florida	X		X		X	
Ohio State University-Columbus			X	X	X	
University of Texas-Austin		X		X		X
University of Washington	X		X	X		
University of Connecticut	X	X	X			
University of Maryland-College Park	X	X				X
Clemson University	X			X		X
Purdue University-West Lafayette	X		X	X		
University of Georgia		X		X	X	
University of Minnesota-Twin Cities	X		X	X		
Texas A&M University-College Station		X		X	X	
Virginia Tech	X			X	X	
Rutgers University-New Brunswick	X			X		X
Indiana University-Bloomington			X	X	X	
Michigan State University	X	X	X			
University of Massachusetts-Amherst	X		X		X	
Miami University-Oxford	X		X			X
University of Iowa		X	X		X	
Binghamton University-SUNY	X	X	X			
North Carolina State University-Raleigh	X		X		X	
Stony Brook University-SUNY	X				X	X
University of Vermont	X		X			X
Florida State University				X	X	X
University at Buffalo-SUNY		X		X	X	
University of Missouri		X		X	X	
University of Nebraska-Lincoln	X	X				X
University of Oregon			X	X	X	
Iowa State University	X	X				X
Total Departments	23	17	22	20	20	18

Notes: The sampling design is such that we would expect to collect data from 20 departments in each field. The small deviations from the expected number by field are the result of sampling variability.

Appendix Table A2: Estimation of gender wage gap with log-transformed salary, non-mover sample.

VARIABLES	log 2016 salary	log 2021 salary
Female	-0.033***	-0.012
	(0.009)	(0.009)
Observations	3,019	3,019
R-squared	0.61	0.59
Race	X	X
University fixed effects	X	X
Field fixed effects	X	X
PhD school rank	X	X
Experience	X	X
Research productivity	X	X

Note: Standard errors clustered by university are reported in parentheses.
*** p<0.01, ** p<0.05

Appendix Table A3: Estimation of gender wage gap with additional productivity controls, non-mover sample.

VARIABLES	2016 salary ($)	2021 salary ($)
Female	-4,085.94***	-1,619.32
	(1,095.63)	(1,246.04)
Observations	3,019	3,019
R-squared	0.60	0.58
Race	X	X
PhD school rank	X	X
Experience	X	X
University fixed effects	X	X
Field fixed effects	X	X
H index	X	X
Publications	X	X
Citations	X	X

Notes: All dollar values are in 2016 dollars. All productivity controls are standardized by field and interacted with the field indicators. Standard errors clustered by university are reported in parentheses.
*** p<0.01, ** p<0.05

Appendix Table A4: Estimation of gender wage gap with experience fixed effects, non-mover sample.

VARIABLES	2016 salary (real $)	2021 salary ($)
Female	-4,390.02***	-2,379.30
	(1,108.90)	(1,479.61)
Observations	3,019	3,019
R-squared	0.60	0.58
Race	X	X
PhD school rank	X	X
Experience fixed effects	X	X
Research productivity	X	X
University fixed effects	X	X
Field fixed effects	X	X

Note: All dollar values are in 2016 dollars. Standard errors clustered by university are reported in parentheses.
*** p<0.01, ** p<0.05

Appendix Table A5: Conditional gender wage gap in 2021 and differential salary growth by gender using the panel sample, restricted to faculty with 30 years of experience or below as of 2016, non-mover sample.

	(1)	(2)	(3)
VARIABLES	2021 salary ($)	pct salary increase 2016-2021 on 2016 own salary	pct salary increase 2016-2021 on 2016 avg salary
Female	-1,561.49	1.92***	1.34**
	(1,337.68)	(0.67)	(0.59)
Observations	2,345	2,345	2,345
R-squared	0.58	0.26	0.26
Race	X	X	X
PhD school rank	X	X	X
Experience	X	X	X
Research productivity	X	X	X
University fixed effects	X	X	X
Field fixed effects	X	X	X

Note: All dollar values are in 2016 dollars. Standard errors clustered by university are reported in parentheses.
*** p<0.01, ** p<0.05

Appendix Table A6: Summary statistics for academic movers, by gender.

	Female	Male
	mean (standard deviation)	
All academic movers		
2016 salary	102,898.33 (40675.55)	131,104.69 (60107.20)
Moved to private university	0.333 (0.475)	0.333 (0.474)
Moved to foreign university	0.091 (0.29)	0.180 (0.386)
Moved to public university	0.576 (0.504)	0.486 (0.495)
PhD school U.S 1-10	0.303 (0.463)	0.252 (0.436)
PhD school U.S. 11-50	0.242 (0.432)	0.36 (0.482)
PhD school U.S. 50+	0.242 (0.432)	0.189 (0.393)
PhD school outside U.S.	0.136 (0.346)	0.171 (0.378)
PhD school missing	0.061 (0.24)	0.018 (0.134)
No PhD (English only)	0.015 (0.123)	0.009 (0.095)
Experience	13.818 (8.462)	15.207 (10.36)
H index	8.905 (12.67)	12.4 (13.671)
Biology	0.227 (0.422)	0.198 (0.4)
Chemistry	0.106 (0.31)	0.135 (0.343)
Economics	0.152 (0.361)	0.405 (0.493)
Education (leadership/policy)	0.106 (0.31)	0.063 (0.244)
English	0.273 (0.449)	0.090 (0.288)
Sociology	0.136 (0.346)	0.108 (0.312)
Assistant professor in 2016	0.455 (0.502)	0.432 (0.498)
Associate professor in 2016	0.273 (0.449)	0.234 (0.425)
Full professor in 2016	0.273 (0.449)	0.333 (0.474)
N	66	111
Movers to public sector with observed post-move wages		
2016 salary	105,898.03 (44,147.63)	131,684.09 (53,618.86)
2021 salary	151,721.44 (73,924.36)	202,385.46 (97,395.34)
N	33	46

The 2021 salaries for observed female and male movers are 43 and 53 percent higher on average, respectively, than their 2016 salaries. Post-move wages were not reported in public data for 13.2 and 14.8 percent of female and male movers to public universities, respectively (or 7.6 and 7.2 percent of the total samples of male and female movers).

Appendix Table A7: Gender gaps in promotions with experience fixed effects.

VARIABLES	(1) promotion to associate prof.	(2) promotion to full prof.	(3) promotion to full prof., conditional on non-missing 2021 wage
Female	-0.040	0.019	0.016
	(0.029)	(0.033)	(0.036)
Observations	663	1,111	1,004
R-squared	0.22	0.19	0.20
Race	X	X	X
PhD school rank	X	X	X
Experience fixed effects	X	X	X
Research productivity	X	X	X
University fixed effects	X	X	X
Field fixed effects	X	X	X

Note: Standard errors clustered by university are reported in parentheses.
*** p<0.01, ** p<0.05

Appendix Table A8: Gender gaps in promotions with field heterogeneity.

VARIABLES	(1) promotion to associate prof.	(2) promotion to full prof.	(3) promotion to full prof., conditional on non-missing 2021 wage
Female	-0.013	-0.009	-0.021
	(0.065)	(0.027)	(0.025)
Female*(low representation field)	-0.034	0.057	0.067
	(0.086)	(0.042)	(0.043)
Observations	663	1,111	1,004
R-squared	0.24	0.21	0.22
Race	X	X	X
PhD school rank	X	X	X
Experience	X	X	X
Research productivity	X	X	X
University fixed effects	X	X	X
Field fixed effects	X	X	X

Note: Low representation fields are biology, chemistry, and economics. Standard errors clustered by university are reported in parentheses.
*** p<0.01, ** p<0.05