



EJW

ECON JOURNAL WATCH
Scholarly Comments on
Academic Economics

ECON JOURNAL WATCH 16(2)
September 2019: 239–257

Publications, Citations, Position, and Compensation of Economics Professors

Yifei Lyu¹ and Alexis Akira Toda²

[LINK TO ABSTRACT](#)

As academic economists, we are constantly under pressure to publish, and in good journals. We are encouraged to obtain extramural grants and promote our work to get citations. In this paper, we explore whether publications, citations, and grants reward the researcher financially.

Using public data on faculty pay from 2010 to 2017 at University of California San Diego (UCSD), we explore how salary (or ‘regular pay’) is related to observable characteristics such as job ranks, productivity (the number of publications in top-5/non-top-5 journals), and experience (years since obtaining Ph.D.). With 291 person-year observations, we find that these variables alone explain 81 percent of variations in faculty salary. We find that a top-5 publication increases salary by 2.8 percent, and a non-top-5 publication increases salary by 0.6 percent, suggesting that the return on a top-5 publication is almost five times that of a non-top-5 publication. The number of citations has a nonlinear effect on salary. The salary is essentially flat with fewer than 400 citations, but it starts to increase beyond that threshold. ‘Stars’ that have more than 1,000 citations earn significantly more than other faculty, even when controlling for publications and other variables. Other observable characteristics such as the number of grants, field of specialization, gender, and mother tongue (English or not) are insignificant.

1. New Zealand Treasury, Wellington 6011, New Zealand. We thank Shweta Singh and Yixiao Sun for comments. The views in the paper are those of the authors and do not necessarily reflect those of the New Zealand Treasury.

2. University of California San Diego, La Jolla, CA 92093.

Large salary deviations (more than 10 percent) from the predicted values are observed only among senior faculty, suggesting that the junior market has smaller frictions and that the heterogeneity among senior faculty may be due to unobserved factors such as outside offers.

There is a fairly large literature on the determination of faculty pay. David Katz (1973) obtains salary data of 596 tenure-track faculty members in fiscal year 1969–1970 in eleven departments at a highly ranked public university, and finds a positive relation between salary and many variables, including research productivity. However, since he does not control for department fixed effects, it is not clear whether the effects are homogeneous across disciplines. John Siegfried and Kenneth White (1973a; b) carry out a similar exercise to ours using salary data of 45 faculty members in fiscal year 1971–1972 at University of Wisconsin–Madison. Using survey data, Howard Tuckman and Jack Leahey (1975) calculate the monetary value of an article and find that there are diminishing returns to scale. Lee Hansen, Burton Weisbrod, and Robert Strauss (1978) consider the interaction between earnings and productivity. Daniel Hamermesh, George Johnson, and Weisbrod (1982) and Arthur Diamond, Jr. (1986) consider the effect of citations on salary. Michael Ransom (1993) finds a negative relation between the number of years employed at the current institution (“seniority”) and salary. Using salary data on nine top-30–75 state universities, William Moore, Robert Newman, and Geoffrey Turnbull (1998) find that seniority becomes insignificant once controlled for research productivity. Ronald Ehrenberg (2003; 2004) provides some review on academic economists’ labor market.

The main contribution of our paper is that we analyze the determination of faculty salary using more recent and high-quality data. Existing studies only consider one fiscal year, while we have a more recent and longer sample (unbalanced panel from 2010 to 2017). Furthermore, our measure of salary is also more accurate. Existing studies use the gross pay during the fiscal year, which includes discretionary summer salary and compensation for administrative positions, and do not account for leaves without pay. Our data enable us to distinguish regular pay set by the contract from other pay, and we identify the number of months that salary was paid from information on individuals’ curricula vitae (CVs). In addition to a sharper measure of pay, we account for the quality of publication outlets and track the number of citations over time.

Unlike Tuckman and Leahey (1975), we find no diminishing returns to publishing articles: in our regressions, the coefficient on the quadratic term on the number of publications is insignificant. This is probably because we distinguish top-5 and non-top-5 publications, and senior faculty tend to publish fewer papers in top journals (Oster and Hamermesh 1998). Unlike Hamermesh, Johnson and Weisbrod (1982) and Diamond (1986), we do not find such a strong effect of

citations on salary, a difference due perhaps to the fact that they do not control for the number of publications or the quality of publication outlets. Since top-5 journals are much more often cited, not distinguishing top-5 and non-top-5 publications may bias the effect of citations upwards. However, we do find that faculty with more than 1,000 citations are rewarded more.

One limitation of our study is that focusing on UCSD makes it a case study of a single institution. Siegfried and White (1973a) mention that an advantage of focusing on a single academic department is to avoid complications arising from differences in the quality of the faculty, geographical considerations, etc. Furthermore, we think that focusing on UCSD in particular does not necessarily compromise external validity. According to the recent *U.S. News* ranking ([link](#)), the UCSD economics department is ranked 12th nationwide. Given that the academic labor market is relatively fluid and competitive, analyzing one top 20 department using high-quality data is likely to shed light on market conditions. That said, to test external validity, we repeat our analysis using the 2017 cross-section of all the University of California economics departments (241 faculty members). We obtain similar coefficients on job rank and R-squared, but the coefficients on publications become smaller though still statistically significant.

Data

Data on pay and rank

We consider the regular pay of all tenure track faculty members (assistant, associate, and full professors) affiliated to the UCSD economics department in any of the calendar years between 2010 and 2017. The regular pay data are obtained from the website of the University of California Office of the President ([link](#)). By selecting the calendar year (which is available from 2010 to 2017 as of the time of writing), location (San Diego), and entering the first and last names of the faculty, one can see the information on ‘gross pay’, ‘regular pay’, ‘overtime pay’, and ‘other pay.’ We only consider the regular pay because ‘other pay’ includes discretionary summer support, compensation for administrative positions, etc.³ We consider all faculty that worked at UCSD during that period, including those who left or

3. In the University of California system, the annual (nine-months) salary for the academic year (from July 1st to June 30th) is set by contract and is paid out monthly in equal amounts. The sum of these monthly payments over the calendar year defines the ‘regular pay.’ In addition, if a faculty member has other University-administered funding sources (research grants, etc.) she may choose to pay herself ‘summer support’ equivalent to two months of salary, which would be included in ‘other pay.’ Faculty members never receive ‘overtime pay.’

were newly hired. However, we exclude faculty affiliated to the Rady School of Management because business schools operate on a different salary scale. The distinctive feature of this data set is that it is public, comprehensive, and accurate. In total, we have 291 person-year observations.

The dummy variable ‘Associate’ takes the value 1 if the faculty member is either associate or full professor in that particular year. Similarly, the dummy variable ‘Full’ takes the value 1 if the faculty member is full professor. If the faculty member is promoted to the next rank during the year, we assign the value 5/12 to these dummy variables because promotion is effective as of July 1st and the new salary is paid from August to December, for five months. The number of months of salary paid is calculated from the information on hiring/leaving and visiting positions. For example, new hires are paid for five months (from August to December), permanent leaves are paid for seven months (from January to July), and for visiting positions we count the exact months if the information is provided in the CV.⁴

Data on publications

We collect other information from the CVs available on faculty members’ personal websites.⁵ This information includes (1) the year the Ph.D. degree was awarded, (2) the cumulative number of publications up to each year, (3) the cumulative number of publications in top-5 economics journals (*American Economic Review*, *Econometrica*, *Journal of Political Economy*, *Quarterly Journal of Economics*, *Review of Economic Studies*) up to each year, (4) the cumulative number of National Science Foundation (NSF) grants up to each year, (5) indicators for associate or full professor, and (6) the number of months salary was paid in each year.

In terms of publications, we exclude books, book chapters, book reviews, comments, replies to comments, conference proceedings (e.g., *American Economic Association Papers and Proceedings*), corrigenda, etc., but we include review articles in journals such as *Annual Review of Economics*, *Journal of Economic Literature*, and *Journal of Economic Perspectives*. That is, we only include peer-reviewed research (and review) articles. Some of the faculty members publish interdisciplinary works. It is hard to define an inclusion criterion for non-economics journals, so we decided to include research articles regardless of the field (e.g., mathematics, statistics, law, social science, policy analysis) whenever we felt reasonably confident that the

4. For a few observations, we see that the regular pay is unusually low for a particular year and the CV lists a visiting position for that year without specifying the months. We exclude these observations from the analysis (there are 4 such person-year observations).

5. In exceptional cases (such as Hal White, who passed away in 2012), we could not find CVs. In these circumstances we use the information listed on IDEAS ([link](#)).

journal is peer-reviewed. In cases of ambiguity, we tended to include an article if it is listed in the main publication list in the CV, and not include it if listed under a separate list such as ‘other publications.’ Most of the non-top-5 articles are indeed in economics journals, but, in fact, that category is determined largely by what professors list on their CVs as ‘refereed,’ ‘peer-reviewed,’ etc. The professors themselves have incentives not to stretch those designations too far on their publicly displayed CV.

Thus, *Review of Economics and Statistics* and *Economics Letters* are equally treated as merely ‘non-top-5,’ even though there is no doubt that the former is significantly more prestigious than the latter. In principle one could define some quality- or contribution-adjusted measure of publications using journal rankings or by discounting by the number of (senior) coauthors. For instance, Raymond Sauer (1988) finds that a coauthored paper with n coauthors is worth $1/n$ of a single-authored paper. Since such a measure requires significantly more effort in data collecting, and journal rankings differ and change over time, we settled on a simple bean counting.

Data on citations

In some specifications we use the number of citations taken from Google Scholar.⁶ To obtain the cumulative number of citations up to each year, we do as follows. First we check whether the faculty member has a Google Scholar profile, and if so we subtract the number of citations since 2014 from total citations to compute the cumulative number of citations up to 2013. We then add and subtract the number of citations in the surrounding years to compute the cumulative number of citations up to each year. One issue with this procedure is that not all faculty have a Google Scholar profile. Of 291 observation points, 56 (19 percent) cannot be collected that way. To deal with missing values, we first use Google Scholar to find each faculty member’s most cited published work (regardless of type; for example, Jim Hamilton’s is the textbook *Time Series Analysis*). Using only the data of faculty who have Google Scholar profiles (235 data points), we then regress $\log(1 + \text{cumulative citations})$ on the field dummies, $\log(1 + \text{years since Ph.D.})$, $\log(1 + \text{top-5})$, $\log(1 + \text{non-top-5})$, the logarithm of the citation count of the most-cited work, and a constant.⁷ The R-squared of this predictive regression is

6. An alternative to Google Scholar is Web of Science (WoS). An advantage of using Google Scholar is that, unlike WoS, we can track the number of citations over time, which is important for the panel analysis. Hamermesh (2018) shows that WoS and Google Scholar citations are highly correlated.

7. The categories are the three core fields (theory, econometrics, macro) and everything else (applied). For most faculty the field of specialization is unambiguous. For a few interdisciplinary faculty, we set the numbers as follows: Jim Hamilton is 1/2 econometrics and 1/2 macro; Garey Ramey is 1/2 theory, 1/4

0.965, and we impute the missing cumulative citations for faculty members who do not have Google Scholar profiles.

Table 1 shows the summary statistics in 2017.

TABLE 1. Summary statistics for 2017

Variable	Mean	Std. Dev.	Minimum	Maximum
12-month pay	\$211,002	\$55,633	\$130,875	\$315,000
Years since Ph.D.	18.8	13.2	1	44
Non-top-5 publications	21.9	19.8	0	75
Top-5 publications	4.2	4.2	0	14
NSF grants	2	2.9	0	12
Citations	7,297	11,158	15	52,694

Results

Model

The baseline specification is

$$\begin{aligned} \log(\text{AnnualPay}_{it}) = & \alpha_t + f(E_{it}) + \beta_1 \text{Associate}_{it} + \beta_2 \text{Full}_{it} \\ & + \beta_3 \text{NonTop5}_{it} + \beta_4 \text{Top5}_{it} + \beta_5 \text{NSF}_{it} + \epsilon_{it} \end{aligned} \tag{3.1}$$

Here *AnnualPay* is the actual regular pay in the year multiplied by 12 and divided by the number of months worked, which is the regular pay the faculty would have obtained if he or she stayed for the entire year. Time fixed effects (e.g., inflation, aggregate market conditions) are captured by α_t . *E*, for ‘experience,’ is the number of years elapsed since obtaining the Ph.D. (Johnson and Stafford 1974), and

$$f(E) = f_1 E + f_2 \left((E - \bar{E})^2 - \bar{E}^2 \right) \tag{3.2}$$

is a quadratic function with zero intercept, where \bar{E} is some constant.⁸ The

macro, and 1/4 applied; Alexis Toda is 1/2 theory, 1/6 econometrics, 1/6 macro, and 1/6 applied.

8. We set $\bar{E} = 15$ in the analysis, although this is without loss of generality since any quadratic function is determined by the coefficients of the first and second order term and the constant term is absorbed by the year fixed effect.

parameter f_1 captures the overall slope, f_2 the curvature, and \bar{E} the point with maximum/minimum slope. *Associate* and *Full* are dummy variables for job ranks. *NonTop5*, *Top5*, and *NSF* are the cumulative sums of top-5/non-top-5 publications and NSF grants up to (and including) year t . The reason why we include the year t publications in the year t regression is because there are significant publication delays in economics journals. However, to account for the potential interaction between pay and publications (more publications lead to higher pay, and faculty publish more to get higher pay), we also use lagged publications as instruments. We do not include teaching evaluations because some faculty may or may not teach undergraduate classes in particular years, which makes it difficult to define a consistent measure, and we also find large variations in teaching evaluations over time within the same faculty member, suggesting that the measure is noisy. Previous studies (Katz 1973; Tuckman and Leahy 1975) have found that teaching evaluations have no predictive power for salary.

The interpretation of the coefficients is as follows. Since all terms in equation (3.1) except the year fixed effect are zero for a new Ph.D. graduate with no publications or grants, α_t is the log nominal salary of a new assistant professor hired in year t without any publications or grants. The function $f(E)$ specifies the ‘experience’ term in the usual Mincer equation. The coefficients β_1 , β_2 capture the percentage increase in pay when promoted to the next rank, and β_3 , β_4 , β_5 capture the percentage increase in pay for each additional publication or grant. However, since we do not have the post-departure pay data of faculty who have left the department for various reasons, the coefficients should be interpreted as those conditional on staying at the department.

In some of the specifications below, we also include other control variables such as field of specialization (since historically UCSD has a high reputation in theory and econometrics, perhaps the department offers more to these fields to attract high quality researchers, or perhaps faculty in these fields are willing to accept a lower salary in exchange for prestige), gender (perhaps men are less geographically constrained and hence more likely to seek outside offers; see Blackaby, Booth, and Frank 2005), native English/non-English speaker (perhaps native English speakers have higher communication/presentation skills in English and hence are more likely to get outside offers), and the last name initial (A = 1, B = 2, etc., inspired by findings that faculty with earlier surname initials are significantly more likely to receive tenure at top-ten economics departments; see Einav and Yariv 2006).

Estimation

We estimate the parameters using both ordinary least squares (OLS) and the method of moments using the one-year lag of job rank, publications, and grants as instruments. Since these instruments are predetermined and highly correlated with the regressors, they are valid instruments. Table 2 shows the estimation results.

TABLE 2. Regressions of log pay on explanatory variables (equation 3.1)

	(1)	(2)	(3)	(4)
Slope	-0.010 (0.007)	-0.009 (0.007)	-0.012 [*] (0.006)	-0.012 (0.009)
Curvature	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Associate	0.209 ^{***} (0.066)	0.194 ^{***} (0.062)	0.217 ^{***} (0.067)	0.218 ^{***} (0.075)
Full	0.244 ^{***} (0.070)	0.237 ^{***} (0.068)	0.251 ^{***} (0.064)	0.305 ^{***} (0.088)
Non-top-5	0.006 ^{***} (0.002)	0.006 ^{***} (0.002)	0.006 ^{***} (0.002)	0.006 ^{***} (0.002)
Top-5	0.028 ^{***} (0.007)	0.029 ^{***} (0.007)	0.029 ^{***} (0.007)	0.028 ^{***} (0.007)
NSF	-0.003 (0.008)	-0.004 (0.008)	-0.002 (0.006)	-0.003 (0.007)
Theory		-0.002 (0.050)		
Econometrics		-0.012 (0.052)		
Macro		-0.037 (0.056)		
Male			-0.032 (0.078)	
English			0.018 (0.046)	
Initial			-0.002 (0.002)	
Field FE		√		
Demographics			√	
Instruments				√
Sample size	291	291	291	241
R squared	0.80	0.81	0.81	0.81

Notes. The table presents the coefficients of the model (3.1) (standard errors in parentheses). ‘Slope’ and ‘Curvature’ are the parameters f_1, f_2 in the quadratic function (3.2). ‘Non-top-5,’ ‘Top-5,’ and ‘NSF’ are the coefficients $\beta_3, \beta_4, \beta_5$ on publications and NSF grants. The other variables are job rank, field, and demographic dummies. Standard errors are clustered at individual level. ^{*}, ^{**}, ^{***}: significance at 10 percent, 5 percent, 1 percent.

As expected, both the top-5 and non-top-5 publications predict significantly

higher pay. Since a top-5 (non-top-5) publication increases the pay by 2.8 percent (0.6 percent), a top-5 publication is equivalent to $2.8 / 0.6 \approx 5$ non-top-5 publications. Interestingly, the number of NSF grants does not predict the pay. Hence there is no evidence here that the university favors researchers who obtain grants. That is to be expected if grants are an ‘input’ into producing publications and successful execution of a grant is effectively measured by the publications arising from it. Finally, promotion to associate or full professor increases the pay by 21 or 24 percent, respectively.

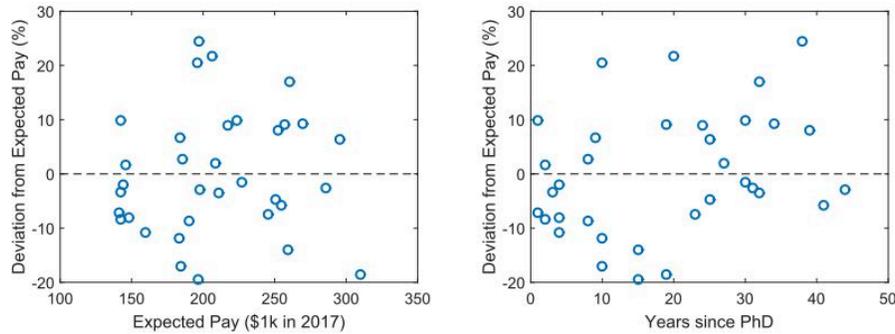
Figure 1a shows the relation between the fitted values from the regression (3.1) and the percentage deviations of actual pay relative to the expected pay (100 times the OLS residuals, which is essentially the amount overpaid in percentage points). There is no systematic pattern to the plot, suggesting that misspecification is not an issue.⁹ Figure 1b shows the relation between experience and the deviations from the predicted values. Large deviations (10 percent or more) are observed only among senior faculty ($E \geq 6$). The large heterogeneity among senior faculty may be due to outside offers, although we do not have actual data. Figure 1c plots the nominal salary of new Ph.D.s (computed as $\exp(\alpha_i)$ using equation (3.1)). The salary has increased from about \$110k to \$140k over the period 2010–2017, or 3.5 percent per year, exceeding inflation.

Controlling for the field of specialization and other demographic variables does not change the results. Macroeconomists are paid 3.7 percent less than applied economists, and men are paid 3.2 percent less than women, though both gaps are statistically insignificant.¹⁰ A faculty member whose last name starts with the letter A earns 5 percent more than one with initial Z, but again the difference is insignificant. We have also explored adding quadratic terms to the number of publications, but the R-squared was unchanged and the coefficients of the quadratic terms were insignificant, so there seems to be a constant return to publications. The results using OLS (with or without field and demographic dummies) and method of moments are roughly the same, suggesting that the endogeneity bias is not severe.

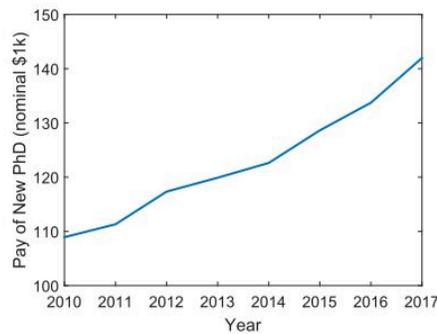
9. In case the reader is interested, one of the authors is apparently underpaid by 10 percent.

10. Koch and Chizmar (1976) report that women faculty members had significantly lower (higher) salary than men before (after) affirmative action. Monks and Robinson (2000) find that among faculty white women earn 4 percent less than white men. Blackaby, Booth, and Frank (2005) find both a gender promotions gap and a within-rank gender pay gap, and attribute to the fact that men receive more outside offers.

Figures 1a–1c. Results from regression (3.1)



(a) OLS residuals versus expected pay. (b) OLS residuals versus years since PhD.



(c) Nominal pay of new PhDs.

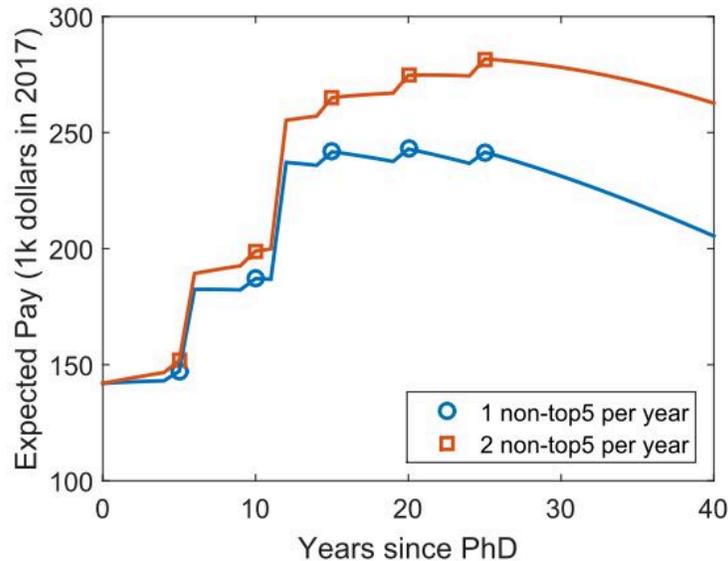
How do these parameters translate to a pay profile over a career? To address this issue, we consider the following scenario. Assuming our findings can be extrapolated to the future, consider a new assistant professor who is hired at UCSD in 2017 with no publications or grants. Suppose that this faculty member publishes one or two non-top-5 papers every year for 40 years, and one top-5 paper every five years for 25 years.¹¹ This faculty member is promoted to associate and full professor in years 6 and 12. Finally, the number of NSF grants is permanently zero. Figure 2 shows the results.

Figure 2 shows that under realistic publication records, the lifetime pay profile is roughly flat (relative to the market) except when promoted. This finding makes sense since the administration has no incentive to increase the pay (except for inflation adjustments) unless the faculty gets an outside offer, which is often the reason for promotion (unfortunately, outside offers are unobservable so we cannot

11. This assumption is roughly in line with the summary statistics in Table 1. Oster and Hamermesh (1998) document that senior faculty tend to publish less.

control for them). Thus, the academic labor market is consistent with monopsony (Ransom 1993). Perhaps the importance of top-5 publications depends largely on their making it more viable for the professor to generate outside offers.

Figure 2. Lifetime pay profile under hypothetical scenario



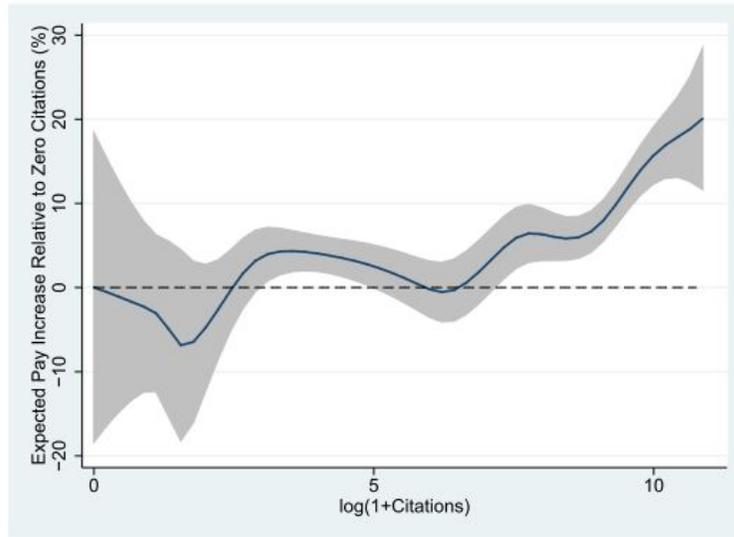
Note: The figure shows the lifetime pay profile of a new assistant professor hired in 2017, assuming (i) one or two non-top-5 publications per year for 40 years, (ii) one top-5 publication every five years for 25 years, (iii) no grants, and (iv) promotion to associate and full professor in years 6 and 12. Circles and squares indicate top-5 publications.

How are the results affected if we include the Google Scholar citations in the regression? Table 3 shows the results. In Column (1), we simply add $\log(1 + \text{Citations})$ to the regression model (3.1) as a regressor. The coefficient on that citations regressor is positive but insignificant, and other coefficients are hardly affected. To explore the potentially nonlinear effect of citations on salary, in Columns (2), (3), and (4), we introduce a dummy variable for citations above some threshold. Column (4) shows that the salary significantly increases, by 8 percent, when a faculty member has 10,000 or more citations. Finally, in Column (5) we consider the semiparametric case using Peter Robinson (1988)'s double residual estimator. In this case the pay increase for associate (full) professors is larger (smaller). Figure 3 shows the semiparametric estimation results.

TABLE 3. Regression results including citations (equation 3.1)

	(1)	(2)	(3)	(4)	(5)
Slope	-0.012 (0.008)	-0.013** (0.007)	-0.010 (0.008)	-0.011 (0.007)	-0.012 (0.008)
Curvature	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Associate	0.212*** (0.067)	0.217*** (0.068)	0.213*** (0.071)	0.233*** (0.066)	0.271*** (0.074)
Full	0.245*** (0.068)	0.212** (0.083)	0.243*** (0.068)	0.255*** (0.065)	0.231*** (0.079)
Non-top 5	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)	0.005*** (0.002)	0.005*** (0.002)
Top 5	0.027*** (0.007)	0.029*** (0.007)	0.028*** (0.007)	0.025*** (0.007)	0.024*** (0.007)
NSF	-0.004 (0.008)	-0.003 (0.008)	-0.004 (0.008)	-0.006 (0.009)	-0.006 (0.009)
Log(1+Citations)	0.014 (0.018)				
Citations ≥ 1,000		0.091 (0.086)			
Citations ≥ 5,000			0.012 (0.061)		
Citations ≥ 10,000				0.079* (0.043)	
Semiparametric					√
Sample size	291	291	291	291	291
R squared	0.81	0.81	0.8	0.81	0.82
<i>Notes:</i> The table presents the coefficients of the model (3.1) (standard errors in parentheses). ‘Slope’ and ‘Curvature’ are the parameters f_1, f_2 in the quadratic function (3.2). ‘Non-top-5,’ ‘Top-5,’ and ‘NSF’ are the coefficients $\beta_3, \beta_4, \beta_5$ on publications and NSF grants. The other variables are constructed from the number citations. ‘Citations ≥ x ’ is a dummy for Google citations exceeding x . Column (5) considers nonparametric form of Google citations. Standard errors are clustered at individual level. *, **, ***: significance at 10 percent, 5 percent, 1 percent.					

According to Figure 3, the salary is hardly affected up to about $\exp(6) \approx 400$ citations. However, the salary monotonically increases beyond that point, and faculty having at least $\exp(7) \approx 1,100$ citations significantly earn more than the rest. Thus the effect of citations seems to be nonlinear, rewarding ‘stars.’

Figure 3. Relationship between citations and pay

Note: The figure shows the nonparametric term in Robinson (1998)'s double residual estimator along with the 95-percent confidence band.

External validity: other UC campuses

Our analysis so far has focused on the salary of UCSD faculty members. A legitimate concern is external validity—whether UCSD is a representative department. To address this concern, in this section we collect salary data on faculty members at economics departments across the entire University of California system, namely Berkeley, Davis, Irvine, Los Angeles, Merced, Riverside, Santa Barbara, and Santa Cruz.¹²

Unlike UCSD, for which we have internal knowledge of who has ever been affiliated, for other campuses it is difficult to know exactly who were affiliated at which point in time. Therefore we focus on the most recent year, 2017. To collect data, we first accessed the website of each department and obtained the list of currently affiliated faculty members. We have then gathered the ‘regular pay’ data from the Office of the President’s website and information on job rank and publications from each faculty member’s CV.¹³ Table 4 shows the summary statistics on economics professors’ salaries and Table 5 shows summary statistics

12. UC San Francisco does not have an economics department.

13. We exclude faculty members with unreasonably low salaries for reasons we cannot clearly identify (such as long-term visits) or whose CVs are not available.

on the sources of revenue for each UC campus.

TABLE 4. Summary statistics on faculty salaries for UC economics departments, 2017

Campus	Faculty size	Mean	SD	Min	Max
Berkeley	42	\$257,074	\$71,770	\$138,999	\$415,283
Davis	35	171,961	41,585	132,106	298,712
Irvine	24	194,785	51,546	133,858	297,883
Los Angeles	33	270,957	93,384	140,917	415,967
Merced	9	147,888	44,426	120,725	241,042
Riverside	19	150,309	54,560	109,958	278,008
San Diego	34	211,002	55,633	130,875	315,000
Santa Barbara	23	203,014	60,330	120,067	342,733
Santa Cruz	22	164,459	45,062	105,925	254,017
All 9 UC campuses	241	\$207,803	\$74,283	\$105,925	\$415,967
<i>Note:</i> Salary is the 12-month pay, based on the regular pay from raw data and adjusted for the number of months salary was paid.					

Given the findings in Tables 2 and 3, we simply regress log annual pay on a constant, job rank, publications, gender, and department dummies for departments other than UCSD. Table 6 shows the results. Column (1) includes only job rank, publications, and gender as regressors. The coefficients on job rank and top-5 publications are similar to our baseline specification (Table 2). The coefficient on the non-top-5 coefficient is negative but insignificant. Column (2) controls for department fixed effect. The coefficients on job rank are similar. The top-5 coefficient becomes smaller (though still significant), and non-top-5 publications now has a positive sign and is significant. The R-squared increases from 0.62 to 0.75, which is similar to our baseline specification. The coefficients on campus dummies have signs that we would expect: the two UC campuses that are higher-ranked than UCSD (Berkeley and Los Angeles) have positive coefficients, while the lower-ranked campuses have coefficients that are negative and except Santa Barbara significant. Because we are already controlling for publications, this finding suggests that either our publication measure is too crude (we classify all peer-reviewed publications outside top-5 economics journals as ‘Non-top-5’) or there are other omitted factors that are correlated with a researcher’s quality.

One concern with using campus fixed effects is that perhaps the salary heterogeneity occurs mainly across senior faculty and the salary of junior faculty is more homogeneous. To address this concern, in Column (3) we also include the interaction of campus dummies and ‘Associate,’ which by definition is the indicator for senior faculty. The coefficients on job rank and publications remain unchanged. The coefficients on campus dummies are also similar, although for Davis and Los Angeles the coefficients become closer to 0 and the sign flips for Santa Barbara

COMPENSATION OF ECONOMICS PROFESSORS

(though insignificant). In fact, the coefficients on the interaction term for Davis, Los Angeles, and Santa Barbara are strongly significant. Therefore for these three campuses there seems to be heterogeneity across senior faculty members.

TABLE 5. Revenue sources for UC campuses, fiscal year 2017–18 (in thousands)

	Berkeley	Davis	Irvine	Los Angeles	Merced
Auxiliary enterprises	\$186,434 (6.5%)	\$114,957 (2.37%)	\$267,306 (8.4%)	\$477,307 (8.4%)	\$29,272 (8.77%)
Educational activities	88,108 (3.07%)	457,291 (9.44%)	335,290 (10.54%)	1,705,043 (22.28%)	85 (0.03%)
Grants and contracts	739,922 (25.8%)	765,730 (15.81%)	393,040 (12.36%)	1,083,434 (14.15%)	51,851 (15.53%)
Medical centers	0 (0%)	2,225,737 (45.97%)	1,183,808 (37.21%)	2,416,143 (31.57%)	0 (0%)
Other revenues	213,137 (7.43%)	132,202 (2.73%)	61,505 (1.93%)	300,727 (3.93%)	12,743 (3.82%)
Private gifts	315,857 (11.01%)	73,670 (1.52%)	50,427 (1.59%)	378,856 (4.95%)	2,585 (0.77%)
State educational appropriations	390,931 (13.63%)	397,508 (8.21%)	299,228 (9.41%)	448,284 (5.86%)	161,687 (48.43%)
Student tuition and fees	933,909 (32.56%)	674,801 (13.94%)	590,428 (18.56%)	844,592 (11.03%)	75,615 (22.65%)
Grand total	\$2,868,298	\$4,841,896	\$3,181,032	\$7,654,386	\$333,838
	Riverside	San Diego	Santa Barbara	Santa Cruz	All campuses
Auxiliary enterprises	\$72,671 (7.94%)	\$199,185 (3.91%)	\$141,307 (12.53%)	\$122,985 (14.06%)	\$1,611,424 (5.99%)
Educational activities	35,379 (3.87%)	693,517 (13.62%)	8,239 (0.73%)	30,637 (3.5%)	\$3,353,589 (12.47%)
Grants and contracts	183,893 (20.1%)	1,046,889 (20.55%)	229,562 (20.36%)	138,454 (15.82%)	\$4,632,775 (17.23%)
Medical centers	0 (0%)	1,927,998 (37.85%)	0 (0%)	0 (0%)	\$7,753,686 (28.83%)
Other revenues	52,725 (5.76%)	136,258 (2.68%)	72,586 (6.44%)	73,151 (8.36%)	\$1,055,034 (3.92%)
Private gifts	12,999 (1.42%)	110,161 (2.16%)	59,519 (5.28%)	20,038 (2.29%)	\$1,024,112 (3.81%)
State educational appropriations	265,643 (29.04%)	326,994 (6.42%)	222,258 (19.71%)	202,120 (23.1%)	\$2,714,653 (10.1%)
Student tuition and fees	291,566 (31.87%)	652,587 (12.81%)	394,182 (34.96%)	287,616 (32.87%)	\$4,745,296 (17.65%)
Grand total	\$914,876	\$5,093,589	\$1,127,653	\$875,001	\$26,890,569
<i>Notes:</i> Data are from the University of California website (link). Numbers are dollars in thousands and are not adjusted for inflation. Numbers in brackets are percentages of total revenue. Auxiliary enterprises are campus services that charge fees for goods and services such as housing, meals and bookstores. Grants and contracts include federal, state, local and private grants, including federal Pell grants and federal financing appropriations. Other revenues include investment income, patent income, UC's share of LANS and LLNS income, legal settlements, and non-operating revenues.					

TABLE 6. Regressions of log pay on explanatory variables, using 2017 UC data

	(1)	(2)	(3)
Associate	0.256*** (0.043)	0.231*** (0.039)	0.258*** (0.047)
Full	0.215*** (0.053)	0.198*** (0.043)	0.192*** (0.044)
Non-top 5	-0.001 (0.001)	0.001* (0.001)	0.002** (0.001)
Top 5	0.024*** (0.004)	0.011*** (0.003)	0.010*** (0.003)
Male	-0.000 (0.036)	-0.009 (0.027)	-0.005 (0.024)
Berkeley		0.151*** (0.044)	0.181*** (0.049)
Davis		-0.102*** (0.031)	-0.003 (0.029)
Irvine		-0.094** (0.044)	-0.043 (0.029)
Los Angeles		0.236*** (0.039)	0.074** (0.032)
Merced		-0.107*** (0.030)	-0.105*** (0.025)
Riverside		-0.225*** (0.043)	-0.219*** (0.022)
Santa Barbara		-0.086 (0.061)	0.148 (0.099)
Santa Cruz		-0.114*** (0.032)	-0.089*** (0.033)
Berkeley × Associate			-0.032 (0.074)
Davis × Associate			-0.157*** (0.050)
Irvine × Associate			-0.067 (0.055)
Los Angeles × Associate			0.237*** (0.056)
Merced × Associate			0.044 (0.054)
Riverside × Associate			-0.006 (0.082)
Santa Barbara × Associate			-0.296*** (0.113)
Santa Cruz × Associate			-0.045 (0.057)
Sample size	241	241	241
R squared	0.62	0.75	0.78
<i>Notes:</i> See the caption of Table 2 for the definition of variables. Robust standard errors are in parentheses. *, **, ***: significance at 10 percent, 5 percent, 1 percent.			

It is also worth noting that gender has a negligible and statistically insignificant effect on pay after controlling for job rank and publications, which is consistent with the result in Table 2 based only on UCSD data. Our finding stands in contrast to David Blackaby, Alison Booth, and Jeff Frank (2005), who argue that there exists a within-rank gender pay gap among academic economists. There could be various explanations for our reaching a different conclusion. First, we focus on the University of California system, while they use UK data. Second, our productivity measure counts the number of top-5 and non-top-5 publications, whereas their measure is based only on the self-reported three best publications, which captures quality but misses quantity. Finally, the discrimination against women might have diminished over time.

Conclusion

This paper explored the determination of salary among economics professors. We found that only three variables—top-5 publications, non-top-5 publications, and job rank—explain 81 percent of variations in faculty pay. The effect of the number of citations is nonlinear, and faculty with more than 1,000 citations are rewarded. Our study sheds light on the determination of economics professors' salary and may be useful for hiring/retention and for current and prospective employees to have rational expectations.

Data and code

Data and code for this research may be downloaded [here](#).

References

- Blackaby, David, Alison L. Booth and Jeff Frank.** 2005. Outside Offers and the Gender Pay Gap: Empirical Evidence from the UK Academic Labour Market. *Economic Journal* 115(501): F81–F107.
- Diamond, Arthur M. Jr.** 1986. What is a Citation Worth? *Journal of Human Resources* 21(2): 200–215.
- Ehrenberg, Ronald G.** 2003. Studying Ourselves: The Academic Labor Market. *Journal of Labor Economics* 21(2): 267–287.
- Ehrenberg, Ronald G.** 2004. Prospects in the Academic Labor Market for Economists. *Journal of Economic Perspectives* 18(2): 227–238.
- Einav, Liran, and Leeat Yariv.** 2006. What's in a Surname? The Effects of Surname Initials

- on Academic Success. *Journal of Economic Perspectives* 20(1): 175–188.
- Hamermesh, Daniel S.** 2018. Scholarship, Citations in Economics: Measurements, Uses, and Impacts. *Journal of Economic Literature* 56(1): 115–156.
- Hamermesh, Daniel S., George E. Johnson, and Burton A. Weisbrod.** 1982. Scholarship, Citations and Salaries: Economic Rewards in Economics. *Southern Economic Journal* 49(2): 472–481.
- Hansen, W. Lee, Burton A. Weisbrod, and Robert P. Strauss.** 1978. Modeling the Earnings and Research Productivity of Academic Economists. *Journal of Political Economy* 86(4): 729–741.
- Johnson, George E., and Frank P. Stafford.** 1974. Lifetime Earnings in a Professional Labor Market: Academic Economists. *Journal of Political Economy* 82(3): 549–569.
- Katz, David A.** 1973. Faculty Salaries, Promotions, and Productivity at a Large University. *American Economic Review* 63(3): 469–477.
- Koch, James V., and John F. Chizmar.** 1976. Sex Discrimination and Affirmative Action in Faculty Salaries. *Economic Inquiry* 14(1): 16–24.
- Monks, James, and Michael Robinson.** 2000. Gender and Racial Earnings Differentials in Academic Labor Markets. *Economic Inquiry* 38(4): 662–671.
- Moore, William J., Robert J. Newman, and Geoffrey K. Turnbull.** 1998. Do Academic Salaries Decline with Seniority? *Journal of Labor Economics* 16(2): 352–366.
- Oster, Sharon M., and Daniel S. Hamermesh.** 1998. Aging and Productivity Among Economists. *Review of Economics and Statistics* 80(1): 154–156.
- Ransom, Michael R.** 1993. Seniority and Monopsony in the Academic Labor Market. *American Economic Review* 83(1): 221–233.
- Robinson, Peter M.** 1988. Root-N-Consistent Semiparametric Regression. *Econometrica* 56(4): 931–954.
- Sauer, Raymond D.** 1988. Estimates of the Returns to Quality and Coauthorship in Economic Academia. *Journal of Political Economy* 96(4): 855–866.
- Siegfried, John J., and Kenneth J. White.** 1973a. Financial Rewards to Research and Teaching: A Case Study of Academic Economists. *American Economic Review Papers and Proceedings* 63(2): 309–315.
- Siegfried, John J., and Kenneth J. White.** 1973b. Teaching and Publishing as Determinants of Academic Salaries. *Journal of Economic Education* 4(2): 90–99.
- Tuckman, Howard P., and Jack Leahey.** 1975. What Is an Article Worth? *Journal of Political Economy* 83(5): 951–967.

About the Authors



Yifei Lyu is an analyst at the New Zealand Treasury. His research fields include macroeconomics and applied econometrics. He has been working on cyclical variation in government spending multipliers, disentangling the effects of oil market shocks, and the time-varying effects of oil price shocks. He received his Ph.D. degree in economics from University of California San Diego in 2019 and received his Bachelor's degree in economics and mathematics from Wuhan University in 2013. His email address is yifeilyu@gmail.com.



Alexis Akira Toda is Associate Professor of Economics at University of California San Diego. He does research in applied econometrics, computational economics, economic theory, finance, macroeconomics, and power law in economics. His papers have appeared in outlets including *Economic Theory*, *Journal of Applied Econometrics*, *Journal of Economic Theory*, *Journal of Financial Economics*, *Journal of Mathematical Economics*, *Journal of Monetary Economics*, *Journal of Political Economy*, *Quantitative Economics*, and *SIAM Journal on Numerical Analysis*. His email address is atoda@ucsd.edu.

[Go to archive of Investigating the Apparatus section](#)
[Go to September 2019 issue](#)



Discuss this article at Journaltalk:
<https://journaltalk.net/articles/5995/>