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Which Journal Rankings Best Explain Academic Salaries? Evidence from the University of California

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Abstract

The ranking of an academic journal is important to authors, universities, journal publishers and research funders. Rankings are gaining prominence as countries adopt regular research assessment exercises that especially reward publication in high impact journals. Yet even within a rankings-oriented discipline like economics there is no agreement on how aggressively lower ranked journals are down-weighted and in how wide is the universe of journals considered. Moreover, since it is typically less costly for authors to cite superfluous references, whether of their own volition or prompted by editors, than it is to ignore relevant ones, rankings based on citations may be easily manipulated. In contrast, when the merits of publication in one journal or another are debated during hiring, promotion and salary decisions, the evaluators are choosing over actions with costly consequences. We therefore look to the academic labor market, using data on economists in the University of California system to relate their lifetime publications in 700 different academic journals to salary. We test amongst various sets of journal rankings, and publication discount rates, to see which are most congruent with the returns implied by the academic labor market.

Keywords

journal rankings

academic labor market

JEL Codes

A14; I23

I. Introduction

The scholarly influence of research outputs affects decisions made by authors, universities, funding agencies and potential students. Impetus for measuring scholarly influence comes from formal research assessment exercises initiated in many countries to guide tertiary education funding and inform public perceptions of university quality.[1] As publication in academic journals represents the principal research output for most academics, journal rankings have become increasingly important. While the growing coverage and ease of use of bibliometric databases is facilitating direct evaluation of individual research outputs, the use of journal rankings as a proxy for the value of published research remains the basis for many assessments of the research outputs of departments and individuals (e.g., Combes and Linnemer, 2003; Kalaitzidakis et al, 2003; Coupé, 2003; and Macri and Sinha, 2006).[2]

Impact factors based on citations have become the most widely used indicator of journal quality.[3] The most common is the Two Year Impact Factor; the total citations by all journals in a database in a particular year to papers published in the journal considered over the previous two years, divided by the two-year total of papers in that journal.[4] Following the path-breaking work by Liebowitz and Palmer (1984), journal rankings in economics generally weight citations by an assessment of the quality of the source journal to provide adjusted impact factors.[5] Widely used examples of this approach include Laband and Piette (1994), Kalaitzidias et al (1999, 2003 and 2011), Koydrzki and Yu (2006) and recursive impact factors from RePEc.[6] Combes and Linnemer (2010) provide assessment measures for all journals in *EconLit* based on a hybrid of direct and adjusted citation based rankings, regression analysis and imposed assumptions about the desired convexity or quality aggressiveness of the journal quality weights.

The growing reliance on impact factors may encourage strategic behavior. For example, editors may coerce authors to add citations to their journals. Wilhite and Fong (2012) find 175 coercing journals in their survey of researchers in economics, sociology,

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1 For an international review of performance-based research funding in tertiary education see OECD (2010).

2 Government research assessment exercises tend to rely more on peer review assessments. Critiques of the use of journal rankings in evaluating the research they publish are Oswald (2007) and Chang, McAleer and Oxley (2011).

3 Journal rankings based on expert opinion have also been important. Examples in economics include assessments provided by Mason, Steagall and Fabritius (1997) and the Economic Society of Australia (Abelson, 2009). We use the term 'impact factor' broadly, to cover a variety of methods of assessing and ranking academic journals.

4 See the Thompson Reuters (ISI) Journal Citation Reports, http://wokinfo.com/products_tools/analytical/jcr/ .

5 Direct citation measures such as the Two Year Impact Factor are also 'adjusted' by the scope of the database used or the definition of the subject area, i.e. citations by journals not in the database or not in the subject are not counted.

6 Available at http://ideas.repec.org/top/.

psychology and business.[7] Collusion is also possible, as exemplified by the journal *Technological and Economic Development of Economy* (TEDE). Economists may be surprised to find this journal ranked third in the economics category in the Thompson Reuters (ISI) Journal Citation Reports for 2010, with a Two Year Impact Factor of 5.6; behind the *Journal of Economic Literature* and the *Quarterly Journal of Economics*. Thus, articles published in TEDE during the two previous years were cited an average of 5.6 times; this impact appears outstanding compared to, say, the *Journal of Political Economy* (4.1 citations per article) or the *American Economic Review* (3.2 citations). Closer inspection shows why. TEDE is published by Taylor and Francis on behalf of Vilnius Gediminas Technical University (VGTU) in Lithuania and 60 percent of the citations in 2010 to articles published in TEDE came from five journals published for the same university (including 24 percent that self-cite the journal).[8] A further 23 percent of citations to TEDE are from two journals published by the nearby Vilnius University and one published by Kaunas University of Technology, also in Lithuania. In other words, these journals seem to have formed a cross-citation club to help raise each other's impact factors (another VGTU journal has an impact factor that was seventh in economics, just ahead of the *Journal of Financial Economics*).

While it is possible to exclude journal self-citations and to weight citations according to the impact of the citing journal, even these rules can be easily circumvented.[9] For example, since VGTU managed to lift two of their journals into the top ten in economics, cross-citations between these two would not be ruled out and would be from journals that are themselves highly ranked. Moreover, individual authors could form cross-citation clubs to raise their personal citation counts and h-index (the author has written h papers that are each cited at least h times), which also inflate the impact factors of the journals they publish in. These individual clubs would be harder to detect than the Lithuanian-based cross-citation club described above.

Common alternatives to impact factors, such as defining the 'best' journals as those where people in the best departments publish, run the risk of circularity, since the best departments are often defined as those publishing in the best journals. Moreover, reputational rankings are inherently backward looking and ossify a group of journals that once were best while failing to acknowledge the rise of dynamic new journals. Given the disruption to the world economy from the rise of China, India, Korea and other countries, it would be surprising if there were not a similar disruption to the global hierarchy of economics journals from this reordering of the leading nations. Hence, what is required is a robust measure of

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7 See also the supporting analysis available from www.sciencemag.org/cgi/content/full/335/6068/542/DC1.

8 The VGTU journals and their citations to TEDE are: *Technological and Economic Development of Economy* (that is, journal self-citations) (138), *Journal of Business Economics and Management* (70), *International Journal of Strategic Property Management* (50), *Transport* (45), and *Journal of Civil Engineering and Management* (44).

9 For a discussion of measures of 'citation inflation' from journal self-citation see Chang, McAleer and Oxley (2011). For the 40 economics journals they consider self-citation rates vary between 0 and 99% of non-self citations.

journal impacts which is not easily manipulated and which can be applied in a non-parochial manner.

In this paper we use academic labor market data to sift between different rankings of economics journals. The basis of our approach is that for research intensive universities, hiring, promotion and salary advancement is likely to be directly related to perceived research impacts. While citations can be manipulated, when faculty debate merits of publication in one journal or another during salary deliberations, they are choosing over actions with costly consequences and so the signals provided by these decisions should be less prone to strategic manipulation. In our specific example, we relate salaries of economists in the University of California system to their lifetime publications in 700 different academic journals. These data enable us to test amongst various sets of competing journal rankings, looking in particular at the revealed convexity or aggressiveness of the weightings as they are applied to perceived quality of the journal. We also examine whether the academic labor market discounts older articles.

While there is a substantial empirical literature on the academic labor market, especially for economists, this research has not focused on uncovering measures of journal quality.[10] Instead, academic earnings equations have been used to consider the negative impact of seniority (Ransom, 1993; Moore et al, 1998; Bratsberg et al, 2003 and 2010), the returns to co-authorship (Sauer, 1988; Moore et al, 2001; Hilmer and Hilmer, 2005; Hilmer et al, 2011), and the returns to the quantity versus the quality of research, with citations typically a proxy for quality and article counts a proxy for quantity (Hamermesh et al, 1982; Hilmer et al, 2011).[11] The question of quantity versus quality is revisited by Hamermesh and Pfann (2012), who find that both matter to salary whereas citations (quality) are an important determinant of reputation (using Nobel prizes, Clark medals, Econometric Society fellowships and departmental reputation as proxies) but the quantum of publications is not.

The closest study in the literature to the present paper is Ellison (2010), who examines a particular academic labor market outcome – which young economists (a PhD since 1988) had gained tenure at the top 25 U.S. economics departments by 2006/07. Since there is a hierarchy of departments, where each economist gains tenure is a proxy for the labor market's assessment of his or her quality. Tenure decisions are actions with costly consequences, so should be highly informative and Ellison uses this information to discriminate between variants of the Hirsch (2005) index that is widely used in bibliometric research, noting:[12]

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[10] Coupé (2003) provides a somewhat dated review of research on the market for academic economists.

[11] Academic earnings equations have also been used to compare returns to research productivity between countries (Moore et al, 2007) and to compare rankings of departments (Gibson, 2000).

[12] The original Hirsch index is defined as the largest number *h* such that the author has written *h* papers that are each cited at least *h* times. Ellison (2010) introduces a generalised form of the Hirsch index and finds that labor market outcomes support the case for a version that places more emphasis on a smaller number of more highly cited papers.

> '…I propose that a useful criterion for assessing competing indexes (and for assessing whether the indexes have any value at all) is to examine whether they are consistent with labor market outcomes.' (Ellison, 2010, p.1)

While Ellison (2010) does not examine journal rankings, the same logic of seeking congruence with labor market data can be applied to sifting between the various journal ranking schemes, using information from salary decisions that have costly consequences. Our focus on journal rankings rather than citations is because the time lag from publication to receiving citations is impractical for research assessment exercises that often examine just the last six years (Tressler and Anderson, 2012). For this reason, journal quality measures remain widely used as a proxy for the value of published research, not just in tea room conversations but also when universities make forward-looking decisions on hiring, tenure, promotion and salary increases.

II. Journal Assessment Measures

This section outlines key characteristics of some representative journal assessment measures that have been used in the economics literature. An illustration of their implications is provided by applying them to economists in the University of California system. Laband and Piette (1994) ('LP94' below) apply the pioneering methodology of Liebowitz and Palmer (1984), where adjusted impact factors are determined by using the sum of citations to each journal in an iterative process. The adjusted impact factors are used to weight the citation sources and to provide journal weights. This approach is sometimes referred to as an Eigenfactor approach. The ISI Journal Citation Reports provide the database of articles published in 1990 and their citations to papers published from 1985-1989. Only 130 economics journals are given weights in the Laband and Piette scheme, which is the least permissive of any scheme considered here.

Kodrzycki and Yu (2006) also apply the Liebowitz and Palmer methodology, but adjust for the citing intensity of sub-disciplines. While also using the ISI Journal Citation Reports, they develop a list of journals commonly used by economists, rather than relying primarily on the ISI list of economics journals. Unlike Liebowitz and Palmer and Laband and Piette, they consider citations from all social science journals, to provide one set of journal assessment measures ('K&Y_all' below), and citations from those journals they classified as economics journals for a second set of measures ('K&Y_econ' below).[13] Citations are from 2003 to articles published over the eight years from 1996 to 2003. The rankings are provided for 181 economics journals. A more recent application of the Liebowitz and Palmer methodology by Kalaitzidakis, Mamuneas and Stengos (2011) ('KMS' below) uses the average of the citations in each of the years 2003 to 2008 to articles published in the

[13] Kodczychi and Yu also provide assessment measures based on citations from a set of journals they refer to as 'policy' oriented, which we do not use in this paper.

preceding ten years.[14] The ISI Journal Citation Reports database is used and only journals classified as economics journals are considered, which gives non-zero rankings to 209 journals.

While iterative (or Eigenfactor) approaches are widely used, some popular journal rankings are based on the simpler direct count of citations. For example, Coupé (2003) uses an average of two year impact factors from 1994 to 2000 based on the ISI Journal Citation Reports for 273 economics and related journals.[15] The Research Papers in Economics (*RePEc*) website provides a number of different journal impact assessments using the *RePEc* citation database. The assessment measure used in this paper is the basic impact factor based on direct citations, which is corrected for self-cites to journals, but not self-cites to an author's own papers. This is one of the most permissive schemes, in that impact factors are provided for 984 journals.[16]

The other permissive ranking, in the sense of trying to not exclude any economics journal, is from Combes and Linnemer (2010). These authors use a number of approaches in order to cover all *EconLit* journals. They start with 304 journals drawn from *EconLit* and the ISI Journal Citation Reports, then combine several citation indices, adjusted for the field of specialization, and use a *Google Scholar h*-index to regress their index on *Google Scholar* citation data to extrapolate it to all *EconLit* journals. Assessment measures are proposed based on assumptions about the degree of convexity or quality aggressiveness desired. We use the Combes and Linnemer 'medium' convexity measure and the 'high' convexity measure ('CLm' and 'CLh' below). These assessment measures are available for 1168 journals.

The difference between the 'medium' and the 'high' convexity measures is illustrated in Figure 1, for the top 102 journals in the Combes-Linnemer scheme. These comprise their 'AAA', 'AA' and 'A' groups, with the bottom ranked journal in the 'A' group being *Applied Economics*. The 'medium' and 'high' convexity indexes are similar for the top four journals but then a large gap opens up, with the fifth ranked journal (*Review of Economic Studies*) being equivalent to either 0.81 of the top journal (*QJE*) under medium convexity or else just 0.66 under high convexity. The relative penalty for lower ranked journals then grows, with the 20th journal being either 0.54 or 0.29 of the *QJE* and the 50th ranked being just 0.30 or 0.09 of the *QJE*. To provide a sense of the type of journal at various ranks, Figure 1 highlights the position of four general interest journals of varying quality and their CLm and CLh indexes: the *Economic Journal* (64.5, 41.6), *Economics Letters* (30.4, 9.2), *Economic Inquiry* (24.2, 5.9) and the *Southern Economic Journal* (19.0, 3.6). These are large gaps in the

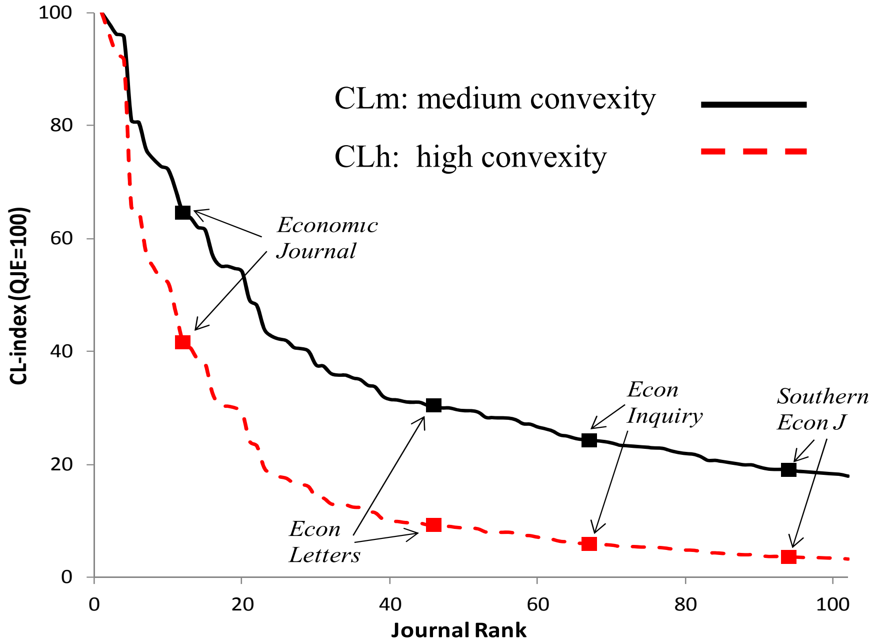
[14] This is an update of the widely used Kalaitzidakis, Mamuneas and Stengos (2003) measures. In our analysis the journal impact factors used are taken from their 2010 Working Paper.

[15] The list we use was obtained from http//homepages.ulb.ac.be/~tCoupe/update/journals.html (on 20 August 2007).

[16] The list we use was obtained on May 6, 2012 and as of July 2012 RePEc had grown to cover 1004 journals.

assessment of relative impact and so it should be possible to detect which degree of convexity is most congruent with labor market data.

Figure 1: Convexity of Journal Rankings in Combes-Linnemer Scheme (classes A-AAA)



The final approach to ranking journals we consider gives an alternative to using citations. Instead, Mason, Steagall and Fabritius (1997) ('MSF' below) derive reputational weights from a survey of chairs of economics department in the United States. All 965 departments listed in the December 1989 *AER* were surveyed in 1992 and 1993 with a response rate of 22.4% yielding 216 usable replies. Respondents ranked journals on a 0 to 4 scale (allowing non-integer scores). This ranking has a relatively low degree of convexity, in the sense of not heavily penalizing lower ranked journals.[17] But these reputational weights are only available for 142 journals so MSF is the second least permissive of the schemes that we consider.

It is clear from this discussion that journal assessment schemes differ in three main ways: the ranking of journals, the degree of coverage or non-zero weights, and the convexity of the weights applied. We illustrate these aspects by applying each of the nine schemes considered to the lifetime publications by the University of California economists in our sample (described below). Applying these schemes to the output of actual economists helps show the important impact of coverage assumptions. In fact, the two least permissive schemes (MSF and LP94) would exclude over one-third of the academic articles published by

[17] For example, the relative weight for the *Southern Economic Journal* compared with the *AER* is from 0.02 to 0.20, with an average of 0.12, for eight of the nine schemes that we use. But the MSF scheme gives it a weight of 0.73.

economists working in economics departments in the largest research-intensive public university system in the United States (Table 1). It is unclear that the academic labor market also places zero value on publication in these excluded journals. Even the most permissive schemes that attempt to cover the universe of economics journals (*RePEc* and Combes-Linnemer) would miss over one-tenth of the articles published by these economists.[18]

Table 1

To show the convexity of each scheme we estimate: log(relative weight)=α+βlog(rank), where the relative weight=1.0 for the highest ranked journal and the regressions are estimated on the non-zero weighted journals published in by the academics in our sample. The rank elasticities in Table 1 range from -0.22, for the least aggressive scheme (MSF), to -1.92, for the most convex (LP94). It is clear that CLh is hardly the most convex of the schemes, with four others having a more elastic response of journal weights to rank (K&Y_all, K&Y_econ, KMS and LP94). These same four schemes also exclude at least one-quarter of lifetime articles, so they can be considered to be especially aggressive in their focus on perceived journal quality.

The final column of Table 1 reports the average lifetime weighted journal output of the economists in our sample, in terms of *AER*-sized pages (using $1/n$ for co-authored papers). This is the key variable which will be used to explain academic salaries, and it varies from 144 pages under the MSF journal rankings to just 36 pages with the LP94 weights. This four-fold difference should be large enough to allow the salary data to discriminate between the various schemes, which are ranked in Table 1 from least aggressive to most aggressive, in terms of the combined impact of the assumptions about non-coverage and convexity.

III. Data

Our approach of using labor market data to uncover the implied quality of academic journals can be applied to any group of academics, in any discipline in any country. We decided to focus on economists within economics departments in the nine campuses of the University of California system for three reasons. First, the public disclosure database of California state worker salaries (http://www.sacbee.com/statepay/) is unusually detailed, as we describe below. Second, this gives us a well-defined target sample frame that is likely to be of inherent interest – the largest research-intensive public university system in the United States. While the salary returns to various journals may differ in private universities or in other public systems, for the first study of journal rankings using salary data it makes sense to start with the largest system (that is, there is good external validity in studying the University of California). Third, while all University of California campuses are research-intensive, they span the perceived quality range from excellent (e.g. Berkeley), to very good (e.g. Davis) to those that are less highly ranked (e.g. Riverside) and emerging (e.g. Merced). This range of

[18] These are all academic articles, as captured in the union of the *EconLit*, *RePEc* and *Web of Science* databases, so the under-coverage of articles is not because they are not part of the peer-reviewed scientific literature.

quality allows us to test if some journal ranking schemes do a better job of matching labor market outcomes in the best departments.[19]

In order for labor market data to provide a valid signal of perceived journal quality, the sample has to be relatively homogeneous in terms of the weight placed on research performance in salary determination. So we excluded anyone with significant non-department administrative responsibilities (e.g. Deans) and those with primarily teaching roles (including affiliated faculty, adjuncts and those obviously on part-time contracts). While economists infiltrate many other departments we did not consider those for our sample since the returns to publishing in particular economics journals may differ in, say, an agricultural economics department or even in an economics department in the business school. These restrictions left us with a sample of 223 and while this is smaller than in many other studies using academic earnings equations, it has the advantage of being for a well-defined population of interest rather than simply a hodge-podge of universities with publicly available salary data.

The salary data are unusually detailed, with the base salary reported for 2007, 2009 and 2010 and the total salary reported for those three years and also for 2008. Total salary is more temporally volatile than base salary, with squared deviations of annual salary around the multi-year mean for an individual being 32 percent higher, on average, when using total salary rather than base salary.[20] When we calculate the ratio of total salary to base salary for each individual, this varies from 0.8 to 2.7, suggesting that the total salary received in any year may not be a good guide to the long-run 'permanent' salary. Moreover, while the total-to-base ratio averages 1.10 across all three years, it fell from 1.14 in 2007 to 1.07 in 2010, presumably because the worsening financial position of the State of California meant that cuts were being made in extra-ordinary salary payments. For these reasons we use the base salary rather than the total salary.

Another helpful feature of the salary data provided by the *Sacramento Bee* website is that details are provided on the nature of the employment contract, in terms of the pay period. Almost all academics in economics departments at the University of California are on academic year rather than financial year contracts (in contrast to, say, those in agricultural economics departments). In a few cases, especially at UC Berkeley, some economists are on law school scales, so we include a dummy variable in our regressions for individuals whose reported salary is not for a standard scale and 9-month academic year. In contrast, some previous studies of faculty salaries have had to drop individuals for whom it was unclear if their reported salaries were on a 9-month academic year basis (Hamermesh and Pfann, 2012).

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[19] Combes and Linnemer (2010) suggest that their high convexity index 'is useful to compare the best departments' (p.2), while their medium convexity index is better suited to study middle ranked departments.

[20] This calculation is limited to individuals with three years of data for each type of salary and with no decline in base salary over time (which may signal only a partial year's employment as could occur from someone moving to another position). For these individuals, the squared deviation of annual salary from the three-year average has a mean (median) of $1443 ($312) for total salary and $1093 ($213) for base salary (all in millions).

In addition to salaries we gathered data on gender, the year of first appointment and of hire at the current department, the year of obtaining a PhD (and the department and university) and whether the current appointment was named (such as an endowed or distinguished chair). These details were available from departmental web pages and on-line CVs for most academics and otherwise we obtained them from dissertation databases and from changes in affiliations on journal articles to date movements. The on-line CVs also provided the initial information on publications, which were supplemented with searches of *EconLit*, *RePEc* and the *Web of Science*. Measuring the research outputs of academics with common names can be difficult, but with so many of the sample having their CVs on-line it helped cross-validate the database search results. We restrict attention to articles that were actually published (with pagination) by the end of 2010. Since our focus is on journal articles, we did not include book reviews, book chapters, editorial introductions or conference proceedings.[21] The one exception is *AER Papers and Proceedings* (even though many CVs listed this in the 'non-refereed' section) because seven of the journal assessment schemes make no distinction between the May issue of the *AER* and other issues, while LP94 weight the May issue at one-quarter of ordinary issues. Only KMS give *Papers and Proceedings* a weight of zero. In total, our procedures recorded 5,721 articles in 700 different journals that the 223 economists in our sample had published in over their careers.

Appendix Table 1 presents definitions and summary statistics for the variables used in the academic earnings equations. The dependent variable is (log) base salary in 2010, with a mean for the underlying salary data of \$156,700 and a range from \$78,000 to \$310,000 (the maximum total salary is \$458,900).[22] The average economist in the sample had spent 12.2 years at the current university and 18 years at all appointments. One-sixth of the sample is female. Three indicator variables for atypical salary levels (and potentially influential data points) are included: whether the academic is on a non-standard contract, whether they have a named position (which may provide funds for additional salary) and whether they are a Nobel Prize winner (only one individual). Finally, three indicators of PhD quality are also included: the rank of the PhD-granting department in either the 1995 National Research Council rankings or the Amir and Knauff (2008) rankings, and an indicator for those economists whose PhD was not from an economics department.

IV. Results

The first step in our analysis is to obtain a well-specified academic earnings equation to then use as the testing ground for comparing each journal ranking scheme. In Table 2 we report the results of various specifications which suggest the following: indicators of quality for the

[21] We did gather the number of *authored* books (but not *edited* volumes) from *EconLit* but this proved to have no explanatory power in the earnings equations.

[22] In a few cases the 2010 base salary was lower than in 2009 or 2007, which may signal partial year employment as could occur from someone moving to another position, so for these individuals we used their maximum base salary from 2007 or 2009.

PhD-granting department are not relevant to salary for this sample (columns (1) to (3)); all three of the indicators that we use for atypical salary levels (and potentially influential data points) are statistically significant (columns (4) to (6)); the effects of seniority and experience on salary are best modeled as quadratics; there is weak evidence of a premium for males; and, location fixed effects are highly significant. Based on these observations, the equation in column (7) of Table 2 is used as the base specification, to which we will then add an output variable measuring lifetime publications in journals, as weighted under each of the nine assessment schemes. Even without the output variable, the base specification explains 72 percent of the variation in log salary, which is higher than the predictive power of academic earnings equations in other studies.

Table 2

To create the output variable, the number of pages of each of the 5,721 journal articles published by our sample members are multiplied by the assessment weight of the journal. We also adjust for the number of authors of each article (using the '1/n rule') and standardize pages to the size of a typical page in the *AER*.[23] Thus for each article published by each individual academic the measured output is:

$$ArticlePages \times SizeCorrection \times (1/number of\ authors) \times Journal\ Assessment\ Weight$$

and to calculate the lifetime output measure we sum over articles published from the year of the first article until the end of 2010. The full results for the nine different earnings equations, where each in turn uses a different set of journal assessment weights to summarize lifetime output, are reported in Appendix Table 2. For these models, the R^2 ranges from 0.76 to 0.78, so the incremental R^2 from including the lifetime output measure is 0.04 to 0.06. However, since lifetime output is correlated with experience and seniority, another way to measure the explanatory power of this variable would be to include it first. If we run a simple regression of log salary on each of the lifetime output variables, the R^2 values would range from 0.46 (using MSF or Coupé weights) to 0.52 (using CLm or CLh weights).

The coefficients on the output measures and a series of model comparison statistics are reported in Table 3. The nine different earnings equations are non-nested, in the sense that it is not possible to impose a set of linear restrictions to derive one model from the other. A standard procedure for model comparison in this case is to use information criteria, with the Akaike's Information Criteria (AIC) and Schwarz's Bayesian Information Criteria (BIC) typically used. We can also compare R^2 since all the equations have the same number of explanatory variables. The maximized R^2 and log-likelihood, and the minimized loss of information, is for the earnings equation that uses CLm – the medium convexity weights of Combes and Linnemer (2010). Even though the MSF weights are the second least permissive,

[23] Page correction factors were supplied by Joseph Macri, based on his work with the late Dependra Sinha. A value of 0.72 was used for journals with no factor available. This is the average page size for the lowest ranked journals in Gibson (2000), and these are typically the ones without their own size correction factors available.

in excluding one-third of the lifetime articles published by this sample, they provide the second best congruence with the labor market data. The greatest loss of information comes from using the KMS weights, which are the second most convex and the third least permissive.

Table 3

Our focus is on which journal ranking scheme is most congruent with the salary data, but it is also worth interpreting the magnitudes of some of the regression coefficients. Using the best-fitting model, the coefficient on the output measure suggests that a 10-page article would raise salary by 1.3 percent, which is an increase of $2090 at the mean. With a 40-year career and a five percent discount rate, for the average economist in the sample (who is 18 years into their career) such an article would have a net present value of just over $27,500. Amongst the other variables previously identified from the specification search in Table 2, all are statistically significant at conventional levels except for *Male* (which has *t*-statistics between 1.0 and 1.5). The location fixed effects are smaller than in Table 2, suggesting that some of the apparent salary premium at UC Berkeley was productivity-related, but all remain statistically significant.[24] The quadratics suggest that for the average economist, salary is maximized after 30 years of labor market experience and minimized after 27 years of seniority at the current university.

Formal Non-nested Tests

Non-nested tests can help formally discriminate between the competing models in Table 3. These test the validity of one linear model, H_0 as opposed to its non-nested alternative H_1:

$$H_0\text{: } \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \varepsilon_0$$
$$H_1\text{: } \mathbf{y} = \mathbf{Z}\boldsymbol{\gamma} + \varepsilon_1$$

where **X** and **Z** are matrices of explanatory variables, and neither is a linear combination of the other, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are corresponding parameter vectors, and ε_0 and ε_1 are random errors. Forming a 'compound' model with each competing measure of lifetime output included at the same time is not advisable because of possible multicollinearity. Moreover, this artificial nesting approach does not distinguish between H_0 and H_1; instead, it distinguishes between each competing model and a hybrid (Greene, 2012). This can be seen by writing the compound model as:

$$\mathbf{y} = \overline{\mathbf{X}\boldsymbol{\beta}} + \overline{\mathbf{Z}}\overline{\boldsymbol{\gamma}} + \mathbf{W}\boldsymbol{\delta} + \varepsilon$$

where $\overline{\mathbf{X}}$ holds the set of variables in **X** not in **Z**, $\overline{\mathbf{Z}}$ holds the set of variables in **Z** not in **X**, and **W** has the variables common to the two models. While the test of $\overline{\boldsymbol{\gamma}} = 0$ might seem to reject H_1 and $\overline{\boldsymbol{\beta}} = 0$ might reject H_0, since $\boldsymbol{\delta}$ remains a mixture of parts of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ it is not

[24] The UCLA fixed effects become larger (and more significant) positive values once output measures are included.

established by the *F*-test on the compound model that either of these parts is zero (Greene, 2012).

Instead, we use Vuong's (1989) likelihood ratio test that does not presume that either competing model is 'true', and instead determines which competitor has verisimilitude (that is, is closer to the truth). This approach relies on the Kullback-Leibler Information Criterion (KLIC), which intuitively, is the log-likelihood function under the hypothesis of the true model minus the log-likelihood function for the (potentially misspecified) model under the assumption of the true model. One model is 'better' than another if it is closer to the 'truth' under the KLIC (Greene, 2012, p.535). Vuong's test is directional, with large positive values favoring the null model while large negative values favor the alternative (and values between -1.96 and +1.96 are inconclusive, for 95 percent significance). We corroborate results for a subset of the bilateral comparisons using Pesaran's (1974) version of a Cox likelihood ratio test, where the null model is rejected against the alternative if there are large negative values of the test statistic. The test is then reversed to see if the alternative is rejected against the null.

The pairwise comparisons of each model, using Vuong's test to see which is closer to the truth, are reported in Table 4. For ease of interpretation, the models are ordered with those using the least aggressive weighting schemes listed first. The format of the table is that each cell contains a bilateral *z*-statistic test result, with significant positive values counting as evidence in favor of the model in the column against the model in the row and negative values counting as evidence for the row model against the column model. The model that uses CLm, the medium convexity weights of Combes and Linnemer, is favored against all of the competing models except for the one using MSF weights, for which the comparison is inconclusive (z=-1.40). The comparison of models that use the CLm and CLh weights to calculate lifetime output yields a significant rejection of the high convexity weights (z=2.27), which is notable since there is no difference in coverage between these rankings. The only other significant results in the table are that the model using KMS weights is rejected against the model using CLh weights, and also weakly rejected against the model using MSF weights (at p=0.052).[25]

Table 4

The results in Table 4 suggest the less aggressive journal weighting schemes are most congruent with salaries of University of California economists. To see how robust this finding is, Cox-Pesaran tests were carried out to compare the models using CLm and CLh weights, and those using MSF, KMS and LP94 weights, since these capture the extremes in terms of least and most aggressive down-weighting for lower ranked journals. The model using CLh weights is rejected against the one using CLm weights (p=0.00) while there is no reverse rejection (p=0.30). Similarly, the model using LP94 weights is rejected against the model using CLm weights (p=0.00) but not the reverse (p=0.26). When the least aggressive MSF weights are used, the model using KMS weights (the second most aggressive) is

[25] The model using Coupé weights is also weakly rejected against the model using MSF weights (at p=0.099).

rejected against it (p=0.00) while there is no reverse rejection (p=0.23), and the models with MSF weights and LP94 weights reject against each other. Thus the congruence of the less aggressive journal weighting schemes with the salary data appears to be a robust finding that does not depend on using just one type of non-nested test.

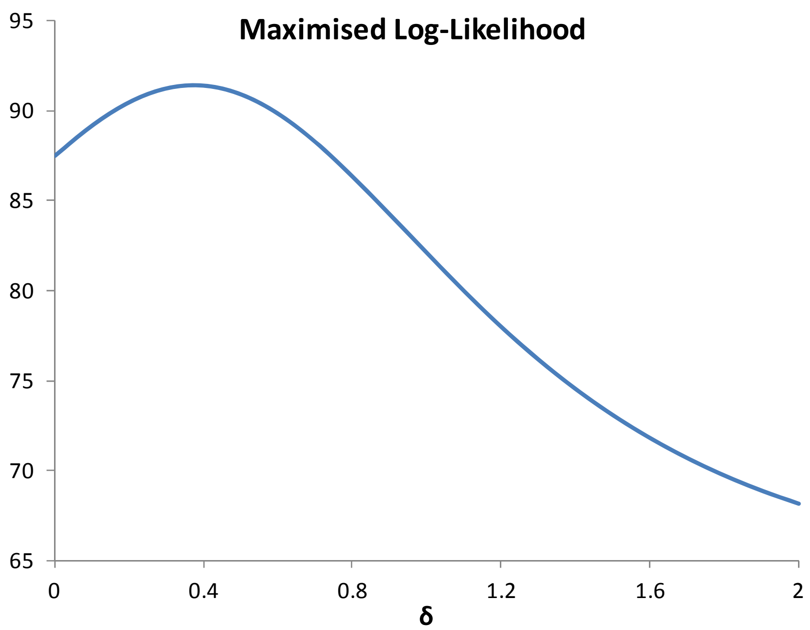
Should Older Articles be Discounted?

The results reported thus far treat an article published in, say, 1978 the same as one from 2008; adjustments are made for length, co-authors, page sizes and journal impact factor, but not for vintage. To test if this assumption of no age discounting is appropriate, we calculated for each article published by each academic in year t:

$$ArticlePages \times \left(1/(Age)^{\delta}\right) \times SizeCorrection \times \left(1/number of\ authors\right) \times Journal\ AssessmentWeight$$

where $Age = 2011 - t$, and the age discount factor, δ varied from 0 to 2, in increments of 0.1. In other words, we allowed for no age discounting (δ=0), for inverse age discounting (δ=1) where a 20-year old article has 1/20th the impact on current salary of a 1-year old article, and for a variety of more extreme and intermediate cases. The best-fitting model, using CLm weights, was estimated for each of these 21 values of δ and the maximized log-likelihoods are compared in Figure 2. There appears to be weak age discounting, with the log-likelihood maximized at δ=0.4, which is four-points above the value at δ=0. The maximized likelihood declines steeply at higher discount rates.[26]

Figure 2: Searching for Optimal Discount Factor for Age Discounting of Articles



Notes: Based on the regression specification in Appendix Table 2, using CLm weights.

[26] If the models with different values of δ were instead estimated after using the CLh weights to summarize lifetime output, the log-likelihood would maximise at δ=0.3 (although at just 0.35 points above the log-likelihood at δ=0.4). So this evidence of weak age discounting is not specific to the journal weighting scheme used.

To check if our finding of greater congruence between salary and the less aggressive journal weighting schemes is robust to different assumptions about the age discounting of articles, the academic earnings equations were re-estimated. Since there is no rule-of-thumb for $\left(1/(Age)^{0.4}\right)$ we discounted according to the inverse of the square root of age, $\left(1/(Age)^{0.5}\right)$ noting that there was only a half-point difference in the maximized log-likelihoods at δ=0.4 and δ=0.5. The full set of estimation results is reported in Appendix Table 3 and the results of the Vuong non-nested tests are in Table 5.

Table 5

The salary data continue to favor the less aggressive journal weighting schemes when age-discounting of articles is allowed for. The model using the least aggressive MSF weights previously weakly rejected against two models but it now rejects against four (KMS, Coupé and both Kodrzycki and Yu schemes). Similarly the model with CLm weights now rejects against six models (and against the model using Coupé weights at *p*=0.118). Moreover, the models using six of the assessment schemes now reject against the model using the KMS weights (which are the second most aggressive), whereas previously only three models rejected against this scheme. The final change caused by allowing age discounting is that the model using the simple RePEc impact factors now rejects against three others (both Kodrzycki and Yu schemes and KMS) whereas previously that model rejected against no others.

Are Results Different for the Best Departments?

Combes and Linnemer (2010) suggest that their high convexity weights are useful to compare the best departments while their medium convexity index is suitable for middle ranked departments. We therefore examine whether the finding that the salary data favor less convex journal weights for calculating lifetime output is also found if we restrict attention just to the top four economics departments in the University of California system: Berkeley, San Diego, Davis and Los Angeles. In keeping with the results on age discounting, the lifetime output is calculated using the inverse of the square root of the age of each article. The full set of estimation results is reported in Appendix Table 4 and the results of the Vuong non-nested tests for the sub-sample of academics in the best four departments are in Table 6.

Table 6

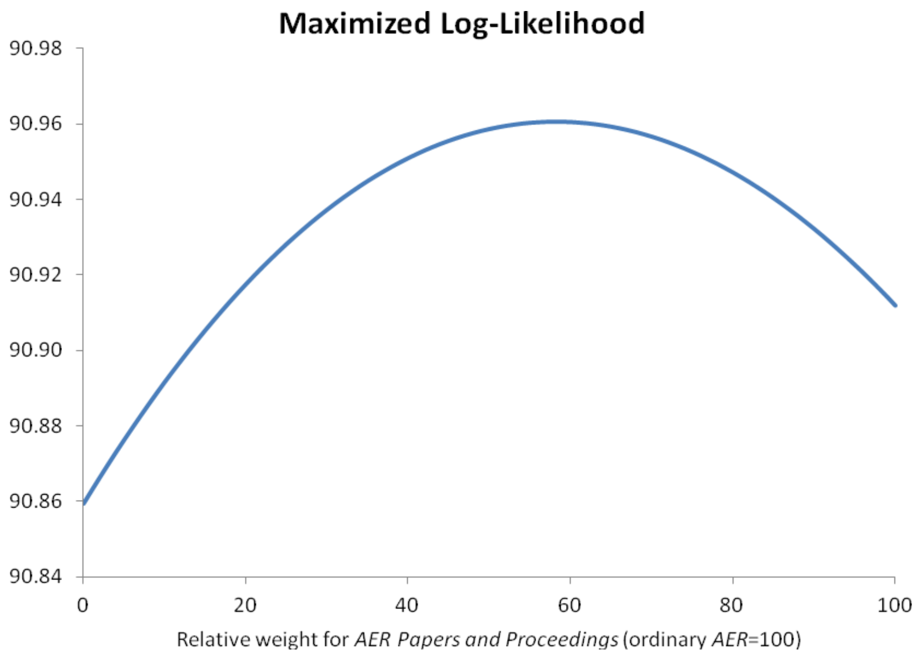
There is no evidence that salaries of academics in the best four departments are better explained by more convex journal weighting schemes. In fact, the Vuong tests suggest that the model using the least convex MSF weights now rejects against six of the other models (being inconclusive only against the models with CLm and LP94 weights). Moreover, the Cox-Pesaran test suggests that the model using LP94 weights is rejected against the model using MSF weights (*p*=0.00) but the reverse rejection is only weakly significant (*p*=0.07). The other change between Table 5 and Table 6 is that the model using the Coupé weights, which are the third least convex, now rejects against two of the models using more convex weights (K&Y_all and KMS) whereas previously it only rejected against the model using

KMS weights. Finally, in terms of the specific claim of Combes and Linnemer that their high convexity weights are most suitable for comparing the best departments, the salary evidence suggests the opposite. Under both the Vuong test (z=3.00) and the Cox-Pesaran test (p=0.00) the model using CLh weights is significantly rejected against the model using CLm weights.

What Weight should be placed on AER Papers and Proceedings?

The journal assessment schemes that we use differ in their treatment of the *Papers and Proceedings* May issue of the *AER*. While seven of the schemes do not discriminate, KMS places zero weight on articles in the May issue and LP94 gives them about one-quarter of the weight of ordinary issues. The *Papers and Proceedings* issue is a common outlet for the University of California economists in our sample, with 160 articles published there (and 242 in the other issues of the *AER*). We therefore use our academic earnings equations to see what the data indicate about the appropriate weight to place on *Papers and Proceedings* compared with ordinary issues of the *AER*. Our best-fitting model, using CLm weights with articles discounted according to the inverse of the square-root of their age, was re-estimated 101 times, incrementally decreasing the weight for articles in the *Papers and Proceedings* issue from 100 percent of an ordinary *AER* down to zero. The maximized log-likelihoods from this search procedure are illustrated in Figure 3.

Figure 3: Maximized Log-Likelihoods from Search for Best Fitting Relative Weight for *AER Papers and Proceedings*



The salary data suggest that treating one page in the *Papers and Proceedings* issue as equivalent to 58 percent of a page in the other issues of the *AER* is most appropriate. Thus journal assessment schemes that do not discriminate between the May issue and other issues (likely because they rely on ISI data that do not distinguish journal issue numbers when counting citations) would seem to overstate the impact of *Papers and Proceedings*. On the other hand, the two assessment schemes that do discriminate may have down-weighted *Papers and Proceedings* too heavily. Nevertheless we caution that the difference in the maximized log-likelihoods is very small, across any of the values of the relative weight term for *Papers and Proceedings*. These small differences suggest that even for journals in which our sample have published a large number of articles, deriving journal-specific impact factors from the salary data – what might be dubbed 'Market Impact Factors' – would be difficult. While we have statistical power to discriminate between different schemes for weighting the entire spectrum of journals, to derive valuations for individual journals would likely take a far larger sample.

V. Conclusions

In this paper we have compared nine different sets of economics journal assessment measures to find which is most consistent with labor market outcomes. These journal assessment measures differ according to the ranking of journals, the degree of coverage, and the convexity of the weights applied. The most aggressive schemes, in terms of either ignoring or down-weighting lower ranked journals, exclude more than one-quarter of the lifetime output of our sample of University of California economists. The aggressive schemes also imply a very substantial penalty for publishing in lower ranked journals; for example, an article in a journal like *Economic Inquiry* that is just outside the top 50 journals is equivalent to less than ten percent of a similarly-sized article in the *American Economic Review* or the *Quarterly Journal of Economics*.

The clear picture that emerges from the empirical results is that the labor market does not reward publication in ways consistent with the weights implied by the most aggressive journal assessment measures. Instead, it is when lifetime output is weighted according to the least convex schemes, such as those of Mason, Steagall and Fabritius (1997) and the CLm index of Combes and Linnemer (2010), that the greatest congruence with academic salaries is found. This finding is robust to different assumptions about the age discounting of articles and also holds if we restrict attention just to the best departments. Indeed, this last result, that a model using high convexity weights is rejected against a less convex alternative if tested on the top four University of California economics departments is contrary to the claim of Combes and Linnemer (2010) that a high convexity index is more suited for comparing the best departments.

We view this congruence with labor market information as an important criterion for the reasonableness of a journal ranking scheme. While highly convex journal ranking schemes can be derived from citation data, such data may be manipulated by editors who coerce authors to add superfluous citations and by authors and editors who collude in cross-citation clubs to raise the citation counts for particular journals or particular individuals. In contrast, labor market decisions have costly consequences, so the preference for convexity (or lack of) in journal ranking schemes that is revealed by labor market outcomes is a pattern that comes from information that should be less prone to strategic manipulation.

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Table 1: Indicators of the Aggressiveness of Various Journal Impact Factors as Applied to Publications of UC Economists

Source of Impact Factor	% of lifetime articles with zero weight	Rank-Elasticity Regression[a] Elasticity	Std Error	R-squared	Average lifetime output for UC economists[b]
MSF: Mason, Steagall & Fabritius	33.3	-0.22	0.01	0.74	143.6
CLm: Coomes-Linnemer (medium)	10.9	-0.67	0.01	0.97	106.3
CLh: Coomes-Linnemer (high)	10.9	-1.35	0.01	0.97	69.7
RePEc Simple Impact Factor	12.6	-1.17	0.04	0.76	65.2
Coupé (2003)	22.0	-0.78	0.03	0.81	45.5
K&Y_all: Kodrzycki & Yu (2006)	26.4	-1.48	0.05	0.85	40.0
K&Y_econ: Kodrzycki & Yu (2006)	26.0	-1.53	0.05	0.84	37.0
KMS: Kalaitzidakis et al (2011)	29.6	-1.74	0.07	0.80	38.2
LP94: Laband & Piette (1994)	36.4	-1.92	0.09	0.82	35.9

Note:
Author's calculations based on 5721 journal articles produced by 213 University of California economists and journal weights from the sources noted.
[a] Estimated over the journals with non-zero weights for each scheme using log(relative weight)=$\alpha+\beta$log(rank).
[b] Total number of *AER*-sized pages (with co-authors given 1/*n*) published in career through 2010, where journals are weighted such that the highest ranked journal for each scheme has weight 1.0 and there is no age-discounting for older articles.

Table 2: Salary Regressions for UC Economists:
Individual Characteristics, Salary Attributes and Location Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Seniority (years)	-0.020	-0.020	-0.020	-0.020	-0.022	-0.020	-0.021
	(3.05)**	(3.02)**	(3.04)**	(2.95)**	(3.38)**	(3.06)**	(3.28)**
Seniority squared (/100)	0.023	0.023	0.024	0.024	0.029	0.024	0.030
	(1.21)	(1.22)	(1.24)	(1.25)	(1.61)	(1.26)	(1.60)
Experience (years)	0.052	0.052	0.052	0.052	0.051	0.052	0.050
	(10.94)**	(10.99)**	(10.97)**	(10.72)**	(10.21)**	(10.79)**	(9.89)**
Experience squared (/100)	-0.072	-0.072	-0.072	-0.073	-0.074	-0.072	-0.075
	(6.06)**	(6.14)**	(6.17)**	(6.06)**	(6.16)**	(6.08)**	(6.02)**
Male	0.060	0.058	0.058	0.058	0.066	0.065	0.071
	(1.47)	(1.41)	(1.43)	(1.44)	(1.65)+	(1.61)	(1.81)+
PhD field not economics	-0.037						
	(0.90)						
PhD rank (A&K, 2008)		0.000					
		(0.33)					
PhD rank (NRC, 1995)			0.001				
			(0.08)				
Nobel prize winner				0.431			0.346
				(7.37)**			(6.36)**
Holder of a named chair					0.146		0.137
					(3.84)**		(3.70)**
Not standard pay scale						0.113	0.115
						(2.17)*	(2.07)*
Davis	-0.449	-0.445	-0.448	-0.449	-0.410	-0.432	-0.397
	(8.71)**	(8.38)**	(8.65)**	(8.67)**	(8.16)**	(7.97)**	(7.62)**
Irvine	-0.392	-0.386	-0.391	-0.389	-0.362	-0.376	-0.347
	(8.74)**	(8.27)**	(8.81)**	(8.71)**	(7.89)**	(7.99)**	(7.18)**
Merced	-0.454	-0.458	-0.465	-0.462	-0.445	-0.451	-0.428
	(9.08)**	(8.10)**	(8.62)**	(9.07)**	(6.61)**	(8.35)**	(6.38)**

Table 2 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Riverside	-0.472	-0.466	-0.472	-0.470	-0.412	-0.463	-0.404
	(8.83)**	(8.17)**	(8.63)**	(8.61)**	(7.42)**	(8.39)**	(7.19)**
San Diego	-0.200	-0.199	-0.200	-0.200	-0.142	-0.185	-0.131
	(3.85)**	(3.78)**	(3.84)**	(3.85)**	(2.72)**	(3.43)**	(2.45)*
Santa Barbara	-0.406	-0.400	-0.405	-0.422	-0.358	-0.389	-0.359
	(7.86)**	(7.50)**	(7.84)**	(8.46)**	(7.07)**	(7.18)**	(7.00)**
Santa Cruz	-0.439	-0.435	-0.440	-0.440	-0.384	-0.425	-0.373
	(7.87)**	(7.69)**	(7.93)**	(7.99)**	(7.30)**	(7.44)**	(6.92)**
Los Angeles	0.033	0.036	0.033	0.034	0.069	0.048	0.084
	(0.60)	(0.65)	(0.60)	(0.62)	(1.27)	(0.84)	(1.49)
Constant	11.696	11.689	11.692	11.695	11.662	11.678	11.647
	(210.07)**	(202.75)**	(189.47)**	(209.67)**	(207.02)**	(202.31)**	(202.41)**
R-squared	0.70	0.69	0.69	0.70	0.71	0.70	0.72

Note:
Dependent variable is log of base salary for the 2010 academic year, as reported at: http://www.sacbee.com/statepay/ with economists at UC Berkeley as the excluded group for the fixed effects. *N*=223, robust t statistics in parentheses, + significant at 10%; * at 5%; ** at 1%.

Table 3: Comparisons of Academic Earnings Equations
Using Different Journal Assessment Weights to Compute Lifetime Output

	Academic Earnings Equation Regression			Maximized log-likelihood	Akaike's Info Criteria	Bayesian Info Criteria
	Semi-elasticity[a]	Robust Std Error	R-squared			
MSF: Mason, Steagall & Fabritius	0.009	0.001	0.77	83.66	-133.33	-75.40
CLm: Coomes-Linnemer (medium)	0.013	0.002	0.78	87.49	-140.99	-83.07
CLh: Coomes-Linnemer (high)	0.017	0.003	0.77	83.06	-132.12	-74.20
RePEc Simple Impact Factor	0.016	0.002	0.77	80.00	-126.00	-68.07
Coupé (2003)	0.023	0.004	0.76	79.28	-124.57	-66.65
K&Y_all: Kodrzycki & Yu (2006)	0.023	0.004	0.76	79.07	-124.13	-66.21
K&Y_econ: Kodrzycki & Yu (2006)	0.025	0.004	0.76	78.92	-123.84	-65.92
KMS: Kalaitzidakis et al (2011)	0.024	0.005	0.76	75.63	-117.27	-59.34
LP: Laband & Piette (1994)	0.027	0.004	0.77	80.27	-126.53	-68.61

Notes:
The results are from nine separate regressions, where each includes all of the variables in column (7) of Table 2 plus the total number of *AER*-sized pages (with co-authors given 1/*n*) published in each economist's career through 2010, where journals are weighted such that the highest ranked journal for each scheme has weight 1.0 and there is no age-discounting for older articles. Full results of the regressions are reported in Appendix Table 2. *N*=223.

[a] The semi-elasticity shows the percentage increase in annual (academic year) salary for a 10-page increase in total career output of weighted journal articles.

Table 4: Vuong Test Results Comparing Academic Earnings Functions With Different Journal Assessment Weights Used to Calculate Lifetime Output

MSF	(a)	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
CLm	(b)	-1.40							
CLh	(c)	0.17	**2.27**						
RePEc	(d)	1.28	**3.00**	1.19					
Coupé	(e)	1.65	**2.41**	0.95	0.29				
K&Y_all	(f)	1.31	**2.80**	1.41	0.56	0.08			
K&Y_econ	(g)	1.34	**2.81**	1.46	0.68	0.13	0.49		
KMS	(h)	1.94	**3.49**	**3.11**	1.45	0.89	1.13	1.11	
LP94	(g)	0.80	**2.24**	1.11	-0.08	-0.23	-0.37	-0.42	-1.37

Note: Cell values are *z*-statistics, calculated from the models reported in Appendix Table 2.
Significant positive values favor the model in the column against the model in the row and negative values favor the row model over the column model.
Test values in **bold** are statistically significant at 5% level, those underlined are significant at 10% level.

Table 5: Vuong Test Results When Lifetime Output is Calculated With Journal Articles Square-Root-Age Discounted

MSF	(a)	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
CLm	(b)	-0.18							
CLh	(c)	1.45	**3.29**						
RePEc	(d)	1.20	1.76	-0.70					
Coupé	(e)	1.71	1.56	-0.14	0.47				
K&Y_all	(f)	**2.22**	**2.69**	1.01	**2.33**	1.42			
K&Y_econ	(g)	**2.14**	**2.60**	0.92	**2.21**	1.30	-0.72		
KMS	(h)	**2.80**	**3.94**	**3.26**	**2.62**	1.88	1.36	1.44	
LP94	(g)	1.47	1.93	0.18	0.68	0.26	-0.81	-0.72	-1.89

Note: Cell values are *z*-statistics, calculated from the models reported in Appendix Table 3.
Significant positive values favor the model in the column against the model in the row and negative values favor the row model over the column model.
Test values in **bold** are statistically significant at 5% level, those underlined are significant at 10% level.

Table 6: Vuong Test Results for the Sub-sample at the Top Four University of California Departments
(Lifetime Output Calculated With Journal Articles Square-Root-Age Discounted)

MSF	(a)	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
CLm	(b)	0.95							
CLh	(c)	**2.20**	**3.00**						
RePEc	(d)	<u>1.67</u>	1.00	-1.21					
Coupé	(e)	**2.04**	0.98	-0.51	0.41				
K&Y_all	(f)	**2.64**	**2.09**	0.71	**2.20**	<u>1.75</u>			
K&Y_econ	(g)	**2.57**	**2.02**	0.63	**2.09**	1.62	-0.63		
KMS	(h)	**3.03**	**3.35**	**2.86**	**2.69**	**2.13**	1.49	1.55	
LP94	(g)	1.35	0.85	-0.94	0.13	-0.15	-1.38	-1.30	**-2.42**

Notes:
Cell values are z-statistics, calculated from the models reported in Appendix Table 3.
Significant positive values favor the model in the column against the model in the row and negative values favor the row model over the column model.
Test values in **bold** are statistically significant at 5% level, those <u>underlined</u> are significant at 10% level.

Appendix Table 1: Variable Definitions, Means and Standard Deviations

Variable	Mean	Std Dev	Description
Salary	156.66	57.07	Base salary in 2010 ($,000)
log (annual salary)	11.90	0.35	Logarithm of 2010 base salary
Experience (years)	18.00	12.43	Years since first appointment (or receipt of PhD if earlier)
Seniority (years)	12.15	9.97	Years of employment at current university
Male	0.83	0.37	Person is male (=1) or female (=0)
Holder of a named chair	0.19	0.40	Person holds an endowed or named position or a distinguished chair
Not standard pay scale	0.03	0.16	Person is not on a standard, 9-month, academic year pay scale
Nobel prize winner	0.00	0.07	Winner of the Nobel Prize
PhD field not economics	0.08	0.27	Person holds a PhD granted from a department that is not economics
PhD rank (A&K, 2008)	31.61	34.55	Score for PhD-granting department (100=best) using the placement-based ranking of Amir and Knauff (2008)
PhD rank (NRC, 1995)	3.78	1.63	Score for PhD-granting department (5=best) in the 1995 National Research Council rankings

Note: N=223.

Appendix Table 2: Salary Regressions for UC Economists with Lifetime Output of Journal Articles Not Age Discounted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MSF	0.009								
	(6.94)**								
CLm		0.013							
		(7.72)**							
CLh			0.017						
			(6.06)**						
RePEc				0.016					
				(6.39)**					
Coupé					0.023				
					(6.02)**				
K&Y (all)						0.023			
						(6.30)**			
K&Y (economics)							0.025		
							(6.14)**		
KMS (2011)								0.024	
								(5.34)**	
LP (1994)									0.027
									(6.35)**
Seniority (years)	-0.017	-0.019	-0.020	-0.021	-0.018	-0.020	-0.021	-0.021	-0.022
	(3.01)**	(3.32)**	(3.44)**	(3.49)**	(3.11)**	(3.41)**	(3.44)**	(3.47)**	(3.66)**
Seniority squared (/100)	0.029	0.034	0.034	0.036	0.029	0.034	0.035	0.036	0.036
	(1.80)+	(2.15)*	(2.09)*	(2.10)*	(1.74)+	(1.98)*	(2.01)*	(2.08)*	(2.10)*
Experience (years)	0.035	0.034	0.038	0.039	0.039	0.040	0.040	0.041	0.042
	(7.00)**	(6.79)**	(7.75)**	(7.73)**	(7.46)**	(8.05)**	(8.05)**	(8.37)**	(8.44)**
Experience sq (/100)	-0.058	-0.056	-0.060	-0.062	-0.064	-0.063	-0.063	-0.064	-0.067
	(4.90)**	(4.80)**	(5.15)**	(5.05)**	(4.96)**	(5.22)**	(5.22)**	(5.38)**	(5.42)**
Male	0.045	0.035	0.041	0.046	0.056	0.051	0.052	0.046	0.047
	(1.24)	(0.99)	(1.15)	(1.29)	(1.51)	(1.42)	(1.44)	(1.23)	(1.31)
Holds a named chair	0.085	0.072	0.071	0.083	0.086	0.082	0.083	0.078	0.066
	(2.54)*	(2.30)*	(2.17)*	(2.54)*	(2.55)*	(2.48)*	(2.52)*	(2.19)*	(1.97)*
Nobel prize winner	0.497	0.505	0.457	0.460	0.485	0.445	0.443	0.428	0.417
	(7.88)**	(9.29)**	(8.60)**	(8.17)**	(8.20)**	(8.22)**	(8.20)**	(7.86)**	(8.28)**
Not standard pay scale	0.173	0.169	0.165	0.180	0.177	0.191	0.190	0.160	0.149
	(3.30)**	(3.17)**	(2.77)**	(3.10)**	(3.15)**	(3.06)**	(3.05)**	(2.36)*	(2.37)*

Appendix Table 2 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Davis	-0.322	-0.299	-0.294	-0.297	-0.293	-0.291	-0.293	-0.304	-0.305
	(6.55)**	(6.19)**	(5.93)**	(5.81)**	(5.64)**	(5.60)**	(5.65)**	(6.01)**	(6.11)**
Irvine	-0.291	-0.271	-0.250	-0.252	-0.256	-0.240	-0.242	-0.257	-0.257
	(6.29)**	(6.16)**	(5.51)**	(5.38)**	(5.24)**	(5.00)**	(5.04)**	(5.49)**	(5.60)**
Merced	-0.366	-0.335	-0.322	-0.327	-0.332	-0.318	-0.320	-0.328	-0.338
	(7.38)**	(7.35)**	(6.69)**	(6.50)**	(6.33)**	(5.82)**	(5.87)**	(6.29)**	(6.59)**
Riverside	-0.283	-0.252	-0.256	-0.263	-0.257	-0.260	-0.261	-0.274	-0.275
	(4.77)**	(4.15)**	(4.19)**	(4.22)**	(4.00)**	(4.13)**	(4.16)**	(4.52)**	(4.51)**
San Diego	-0.104	-0.105	-0.106	-0.099	-0.089	-0.099	-0.099	-0.101	-0.126
	(2.19)*	(2.24)*	(2.17)*	(2.06)*	(1.82)+	(2.02)*	(2.02)*	(1.98)*	(2.63)**
Santa Barbara	-0.260	-0.245	-0.253	-0.252	-0.241	-0.246	-0.248	-0.274	-0.269
	(5.09)**	(4.89)**	(5.02)**	(4.80)**	(4.53)**	(4.69)**	(4.74)**	(5.51)**	(5.32)**
Santa Cruz	-0.306	-0.286	-0.274	-0.282	-0.275	-0.270	-0.271	-0.285	-0.277
	(6.31)**	(5.89)**	(5.50)**	(5.55)**	(5.26)**	(5.15)**	(5.17)**	(5.64)**	(5.42)**
Los Angeles	0.138	0.138	0.125	0.139	0.155	0.141	0.140	0.129	0.097
	(2.58)*	(2.62)**	(2.38)*	(2.56)*	(2.79)**	(2.60)*	(2.57)*	(2.40)*	(1.86)+
Constant	11.642	11.643	11.627	11.626	11.606	11.609	11.611	11.624	11.631
	(216.53)**	(217.89)**	(214.19)**	(212.88)**	(208.00)**	(210.03)**	(210.23)**	(207.99)**	(213.66)**
R^2	0.77	0.78	0.77	0.77	0.76	0.76	0.76	0.76	0.77
Log-likelihood	83.66	87.49	83.06	80.00	79.28	79.07	78.92	75.63	80.27
Akaike's info criteria	-133.33	-141.99	-132.12	-126.00	-124.57	-124.13	-123.84	-117.27	-126.53
Bayesian info criteria	-75.40	-83.07	-74.20	-68.07	-66.65	-66.21	-65.92	-59.34	-68.61

Note:
Dependent variable is log of base salary for the 2010 academic year, as reported at: http://www.sacbee.com/statepay/ with economists at UC Berkeley as the excluded group for the fixed effects. N=223, robust t statistics in parentheses, + significant at 10%; * at 5%; ** at 1%.

Appendix Table 3: Salary Regressions for UC Economists
with Lifetime Output of Journal Articles Square-Root-Age Discounted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MSF	0.028 (7.85)**								
CLm		0.039 (7.93)**							
CLh			0.047 (6.19)**						
RePEc				0.052 (7.28)**					
Coupé					0.072 (7.04)**				
K&Y (all)						0.063 (6.34)**			
K&Y (economics)							0.069 (6.09)**		
KMS (2011)								0.065 (4.70)**	
LP (1994)									0.083 (7.15)**
Seniority (years)	-0.017 (3.17)**	-0.018 (3.37)**	-0.019 (3.36)**	-0.020 (3.53)**	-0.018 (3.20)**	-0.020 (3.37)**	-0.020 (3.42)**	-0.020 (3.39)**	-0.021 (3.68)**
Seniority squared (/100)	0.030 (1.94)+	0.033 (2.17)*	0.032 (2.01)*	0.036 (2.17)*	0.029 (1.85)+	0.032 (1.91)+	0.033 (1.95)+	0.034 (1.98)*	0.036 (2.16)*
Experience (years)	0.034 (7.64)**	0.034 (7.62)**	0.038 (8.62)**	0.037 (8.12)**	0.037 (7.87)**	0.040 (8.73)**	0.040 (8.69)**	0.042 (9.02)**	0.041 (9.00)**
Experience sq (/100)	-0.052 (5.11)**	-0.051 (5.10)**	-0.057 (5.42)**	-0.055 (5.10)**	-0.057 (5.08)**	-0.059 (5.40)**	-0.059 (5.39)**	-0.062 (5.65)**	-0.062 (5.59)**
Male	0.038 (1.10)	0.029 (0.85)	0.038 (1.07)	0.041 (1.16)	0.052 (1.43)	0.057 (1.56)	0.059 (1.58)	0.045 (1.21)	0.042 (1.17)
Holds a named chair	0.099 (3.07)**	0.088 (2.82)**	0.088 (2.66)**	0.094 (2.94)**	0.103 (3.16)**	0.103 (3.12)**	0.104 (3.15)**	0.098 (2.71)**	0.083 (2.50)*
Nobel prize winner	0.492 (8.33)**	0.483 (9.60)**	0.434 (8.63)**	0.450 (8.68)**	0.467 (8.83)**	0.408 (8.23)**	0.407 (8.19)**	0.398 (7.75)**	0.407 (8.34)**
Not standard pay scale	0.204 (4.06)**	0.198 (4.05)**	0.188 (3.52)**	0.216 (3.90)**	0.210 (3.83)**	0.212 (3.56)**	0.212 (3.56)**	0.177 (2.81)**	0.175 (3.07)**

Appendix Table 3 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Davis	-0.301	-0.278	-0.275	-0.263	-0.262	-0.275	-0.275	-0.290	-0.278
	(6.18)**	(5.65)**	(5.44)**	(5.09)**	(4.91)**	(5.17)**	(5.19)**	(5.74)**	(5.40)**
Irvine	-0.281	-0.255	-0.231	-0.222	-0.232	-0.229	-0.230	-0.242	-0.234
	(6.02)**	(5.73)**	(5.02)**	(4.73)**	(4.70)**	(4.72)**	(4.72)**	(5.18)**	(4.99)**
Merced	-0.346	-0.304	-0.289	-0.285	-0.297	-0.293	-0.295	-0.304	-0.303
	(6.61)**	(6.30)**	(5.62)**	(5.50)**	(5.38)**	(4.94)**	(4.95)**	(5.49)**	(5.58)**
Riverside	-0.265	-0.241	-0.247	-0.232	-0.233	-0.255	-0.255	-0.269	-0.256
	(4.60)**	(4.08)**	(4.18)**	(3.82)**	(3.75)**	(4.21)**	(4.18)**	(4.58)**	(4.29)**
San Diego	-0.090	-0.081	-0.076	-0.072	-0.065	-0.081	-0.082	-0.077	-0.100
	(1.92)+	(1.71)+	(1.55)	(1.51)	(1.33)	(1.63)	(1.64)	(1.48)	(2.08)*
Santa Barbara	-0.239	-0.226	-0.236	-0.220	-0.213	-0.232	-0.233	-0.261	-0.246
	(4.82)**	(4.57)**	(4.72)**	(4.26)**	(4.05)**	(4.44)**	(4.44)**	(5.33)**	(4.84)**
Santa Cruz	-0.290	-0.270	-0.260	-0.256	-0.247	-0.256	-0.256	-0.276	-0.257
	(5.81)**	(5.33)**	(5.00)**	(4.94)**	(4.59)**	(4.73)**	(4.72)**	(5.31)**	(4.83)**
Los Angeles	0.147	0.148	0.136	0.157	0.170	0.150	0.148	0.139	0.108
	(2.88)**	(2.89)**	(2.63)**	(2.97)**	(3.17)**	(2.79)**	(2.77)**	(2.64)**	(2.10)*
Constant	11.606	11.597	11.581	11.581	11.565	11.569	11.571	11.586	11.592
	(216.61)**	(213.42)**	(208.22)**	(206.95)**	(203.73)**	(200.92)**	(201.23)**	(205.99)**	(207.43)**
R^2	0.79	0.79	0.77	0.78	0.78	0.77	0.77	0.76	0.77
Log-likelihood	90.31	90.91	84.09	86.05	84.69	80.59	80.89	75.27	83.52
Akaike's info criteria	-146.62	-147.82	-134.18	-138.09	-135.38	-127.18	-127.78	-116.54	-133.05
Bayesian info criteria	-88.70	-89.90	-76.26	-80.17	-77.46	-69.26	-69.86	-58.62	-75.13

Note:
Dependent variable is log of base salary for the 2010 academic year, as reported at: http://www.sacbee.com/statepay/ with economists at UC Berkeley as the excluded group for the fixed effects. N=223, robust t statistics in parentheses, + significant at 10%; * at 5%; ** at 1%.

Appendix Table 4: Salary Regressions for UC Economists at the Top Four Departments
(Articles Square Root-Age Discounted)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MSF	0.031 (6.89)**								
CLm		0.038 (6.28)**							
CLh			0.043 (5.05)**						
RePEc				0.050 (5.89)**					
Coupé					0.071 (5.85)**				
K&Y (all)						0.057 (5.04)**			
K&Y (economics)							0.062 (4.87)**		
KMS (2011)								0.057 (3.51)**	
LP (1994)									0.081 (6.41)**
Seniority (years)	-0.011 (1.24)	-0.011 (1.20)	-0.010 (1.04)	-0.012 (1.29)	-0.011 (1.14)	-0.012 (1.17)	-0.012 (1.22)	-0.011 (1.07)	-0.012 (1.28)
Seniority squared (/100)	0.018 (0.78)	0.017 (0.73)	0.013 (0.53)	0.019 (0.78)	0.014 (0.57)	0.013 (0.51)	0.014 (0.55)	0.013 (0.49)	0.016 (0.66)
Experience (years)	0.038 (5.28)**	0.038 (5.40)**	0.041 (5.68)**	0.041 (5.60)**	0.042 (5.61)**	0.043 (5.68)**	0.043 (5.70)**	0.045 (5.87)**	0.043 (5.99)**
Experience sq (/100)	-0.071 (4.73)**	-0.068 (4.80)**	-0.072 (4.82)**	-0.073 (4.83)**	-0.076 (4.87)**	-0.074 (4.65)**	-0.074 (4.68)**	-0.078 (5.02)**	-0.076 (4.87)**
Male	0.053 (1.11)	0.041 (0.84)	0.047 (0.92)	0.049 (0.99)	0.062 (1.24)	0.068 (1.30)	0.069 (1.32)	0.054 (1.01)	0.044 (0.87)
Holds a named chair	0.094 (2.29)*	0.089 (2.20)*	0.098 (2.22)*	0.094 (2.29)*	0.104 (2.48)*	0.113 (2.62)**	0.114 (2.63)**	0.119 (2.47)*	0.092 (2.14)*
Not standard pay scale	0.224 (3.41)**	0.205 (3.17)**	0.193 (2.78)**	0.233 (3.29)**	0.230 (3.33)**	0.224 (3.02)**	0.225 (3.02)**	0.180 (2.28)*	0.186 (2.43)*

Appendix Table 4 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Davis	-0.305	-0.292	-0.296	-0.280	-0.276	-0.295	-0.295	-0.312	-0.294
	(5.89)**	(5.64)**	(5.59)**	(5.12)**	(4.87)**	(5.25)**	(5.26)**	(5.91)**	(5.49)**
San Diego	-0.088	-0.083	-0.079	-0.075	-0.066	-0.082	-0.083	-0.077	-0.100
	(1.84)+	(1.68)+	(1.55)	(1.49)	(1.31)	(1.57)	(1.59)	(1.46)	(1.99)*
Los Angeles	0.157	0.153	0.143	0.162	0.177	0.155	0.153	0.146	0.117
	(3.10)**	(3.01)**	(2.76)**	(3.07)**	(3.31)**	(2.85)**	(2.84)**	(2.80)**	(2.27)*
Constant	11.549	11.552	11.543	11.541	11.518	11.530	11.532	11.543	11.560
	(175.11)**	(173.55)**	(168.45)**	(167.95)**	(168.46)**	(163.76)**	(163.93)**	(165.68)**	(169.92)**
R^2	0.75	0.75	0.73	0.74	0.74	0.72	0.72	0.70	0.74
Log-likelihood	45.86	43.85	39.36	41.85	40.97	37.48	37.67	33.28	41.48
Akaike's info criteria	-67.72	-63.71	-54.72	-59.69	-57.94	-50.96	-51.34	-42.57	-58.96
Bayesian info criteria	-32.77	-28.76	-19.77	-24.74	-22.99	-16.01	-16.39	-7.61	-24.01

Note:
Dependent variable is log of base salary for the 2010 academic year, as reported at: http://www.sacbee.com/statepay/ with economists at UC Berkeley as the excluded group for the fixed effects. N=136, robust t statistics in parentheses, + significant at 10%; * at 5%; ** at 1%.