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Publishing and Promotion in Economics: The Tyranny of the Top Five†

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This paper examines the relationship between placement of publications in top five (T5) journals and receipt of tenure in academic economics departments. Analyzing the job histories of tenure-track economists hired by the top 35 US economics departments, we find that T5 publications have a powerful influence on tenure decisions and rates of transition to tenure. A survey of the perceptions of young economists supports the formal statistical analysis. Pursuit of T5 publications has become the obsession of the next generation of economists. However, the T5 screen is far from reliable. A substantial share of influential publications appear in non-T5 outlets. Reliance on the T5 to screen talent incentivizes careerism over creativity. (*JEL* A14, I23, J44, J62)

1. *Introduction*

This paper examines how academic economics incentivizes young scholars and thereby shapes the values and goals of the next generation of professional economists. Talking with young economists entering academia and with their peers about their career prospects, one cannot fail to note their obsession with publication in the top five journals, henceforth T5. Faculty meetings about hiring, promotion, tenure, and prize committee discussions assess candidates by the number of T5 articles they

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have published or have in the pipeline and the rapidity with which they were generated. Research proposals are often appraised by their potential to generate T5 publications.

The T5 journals are: *The American Economic Review* (*AER*), *Econometrica* (*ECMA*), the *Journal of Political Economy* (*JPE*), the *Quarterly Journal of Economics* (*QJE*), and the *Review of Economic Studies* (*ReStud*). These "general interest" journals publish papers on a broad range of topics. They are classified in the T5 based on aggregate proxies of journal influence. Assessing researchers based on proxy measures is now common across fields. The use of impact factors[1] is one such example. Originally devised as an advisory system for library purchasing decisions, it has now morphed into an assessment system widely used in many fields.[2] Proxies of aggregate journal performance such as the impact factor do not assess the creativity or value of any individual paper, but only assess the scale of subscribership of the publication in which a paper appears and the company it keeps.

Publication in the T5 journals has become a professional standard. Its pursuit shapes research agendas. For many young economists, if a paper on any topic cannot be published in a T5 outlet, the topic is not worth pursuing. Papers published in non-T5 journals are commonly assumed to have descended into their "mediocre" resting places through a process of trial and failure at the T5s and are discounted accordingly. This mentality is not confined to the young. Habits formed early are hard to break. Pursuit of the T5 has become a way of life for experienced economists as well. Falling out of the T5 is viewed as a sign of professional decline. Decisions about promotions, recognitions, and even salaries[3] are tied to publication counts in the T5. Relying on the T5 to assess productivity rewards pursuit of publication counts in the "proper" places, and not the development of coherent bodies of research.

To a certain degree there is a strong case for relying on the T5 signal. The profession has grown in size and has become more specialized. There is a demand for certification of quality that publication in the T5 is used to meet. Publication in a highly rated general interest journal is now considered a proxy for the likelihood that a candidate publishes highly influential general interest papers. In this paper, we demonstrate that readership and citation of a paper and aggregate citations to a journal in which the paper appears are far from the same thing.

The T5 standard has become increasingly difficult to attain. Card and DellaVigna (2013) document that the amount of space available in the T5 has remained roughly constant during the period 1990–2012.[4] At the same time, the number of submissions to the T5 and the length of submitted papers have greatly increased (Card and DellaVigna 2013) with concomitant growth in rejection rates and delays in the refereeing process (Ellison 2002). Editors now tend to use more referees than in the past. The acceptance rates at T5 journals declined from 15 percent in 1980 to 6 percent in 2012 (Card and DellaVigna 2013).

Economists with established reputations and in highly ranked departments are increasingly not publishing in T5 or field journals (Ellison 2011) and are increasingly posting papers online in influential working paper series, which are highly cited but not

[1] Impact factors are assessed by Web of Knowledge, a scientific citation indexing service produced by the Institute for Scientific Information that advises library acquisitions.

[2] See Bertuzzi and Drubin (2013).

[3] See table 7 of Gibson, Anderson, and Tressler (2014). Economics faculty in the University of California system appear to face salary penalties for not publishing in the T5.

[4] See the online appendix figure O-A31 for a summary of Card and DellaVigna's (2013) data.

counted as T5s. This practice likely dilutes the quality of the T5 signal.

The declining acceptance rate and the reliance on the reports of multiple referees (and concomitant scrutiny and delay) might suggest a rise in the quality of the T5 filter. But it also raises some potentially worrisome issues, which we address in this paper.

We examine the influence of T5 publication on promotion and tenure decisions in academic economics. We analyze data on tenure-track faculty hired by the top 35 economics departments in the United States between the years of 1996–2010. The top 35 is assessed based on an average of the *US News and World Report* rankings assigned to economics departments during the years 2008, 2010, and 2015 (US News and World Report 2008, 2010, 2015). The chosen period gives sufficient time to assess the early impacts of papers and yet is recent enough to describe the current professional environment.

We assess the degree to which tenure decisions are influenced by publication in the T5. We estimate the probability of receiving tenure in the first spell of employment and by the seventh year of tenure-track employment. We supplement this analysis with estimates from duration analyses that show that publishing three T5 articles is associated with a 310 percent increase in the rate of receiving tenure, compared to candidates with similar levels of publications who do not place any in the T5. Candidates with one or two T5 articles are estimated to experience increases in the rate of receiving tenure of 80 percent and 230 percent respectively, compared to those with the same number of non-T5 publications. The estimated effects of publication in non-T5 journals pale in comparison. For the same number of citations measured ten or more years after tenure, publication in the T5 remains a strong determinant of tenure probabilities and transition rates to tenure.

We explore heterogeneity in the tenure-generating power of the T5 with respect to department quality. Requirements for T5 publication decline with department quality and the impact on tenure of T5 publication increases with declines in department quality as measured by faculty publications. Publishing in the T5 is the most effective means of improving one's chances of obtaining tenure in all of the top 35 US economics departments.

There are differences in rates of tenure by gender, although they are not precisely determined due to our small sample size for women. For men, two T5s is more than enough to get a 50 percent or higher probability of attaining tenure in the first spell. It takes three for a woman, but this is only a point estimate and its standard error is big.

After documenting the potency of publishing in the T5, we examine the validity of this filter using citation counts as a measure of validity. While T5 articles are highly cited, so are articles published in non-T5 journals. Many non-T5 articles are better cited than many articles in T5 journals.[5] Numerous influential papers are published outside of the T5. Indeed, many of the most important papers published in the past 50 years have been too innovative to survive the T5 gauntlet.[6] Many of the 20 most cited RePEc papers were not published in the T5.[7]

[5] See, e.g., Hamermesh (2018), who makes this point. We build on and extend his analysis.

[6] Akerlof (2020) suggests that the T5 journals often endorse "safe research" that extends the boundaries of a field slightly, but does not advance it by much. This is likely a consequence of the peer review process, which engenders an inherent conservatism. See also the discussion in the AEA symposium linked here: https://www.aeaweb.org/webcasts/2017/curse.

[7] RePEc (www.RePEc.org) stands for Research Papers in Economics and is a major source for rankings of citations in the profession. According to the RePEc website: "…over 2,000 archives from 99 countries have contributed about 2.6 million research pieces from 3,000 journals and 4,600 working paper series. Over 50,000 authors have registered and 75,000 email subscriptions are served every week."

In principle, insisting that scholars publish in general interest journals works against the growing trend in academic economics toward specialization and Balkanization. However, it flies in the face of current scholarly practice. Leading scholars in most fields largely publish in non-T5 field journals. In addition, non-T5 journals generally dominate T5 journals in terms of citations in the top journals within most subfields of economics. The T5 journals typically rely on field specialists to review papers submitted in their fields. Scholars who themselves primarily publish in, read, and cite papers from non-T5 field journals appraise the quality of prospective candidates for promotion and hiring using their T5 publications.

The tenure of editors is long, especially at house journals whose editors are mostly, if not exclusively, affiliated with a single department. Low turnover in editorial boards creates the possibility of clientele effects surrounding both journals and editors, whereby authors, in an effort to increase their chances of publication, choose to conduct research that caters to the policy and/or methodology preferences of editors. Given the large rewards associated with publishing in the T5, and the consequences of failing to do so, it is not implausible that such clientele effects are both prevalent and large in magnitude.

It is well-documented that journals in economics tend to publish work by authors who are connected with the journal's editors (see Brogaard, Engelberg, and Parsons 2014, Laband and Piette 1994, and Colussi 2018). We corroborate this literature by estimating *incest coefficients* that quantify the degree of inbreeding in publications in the T5. Editors are likely to select the papers of those they know. Network effects are empirically important.[8]

Whether this practice capitalizes on the benefits of using inside information that improves journal quality as measured by citations or whether it is unproductive cronyism is much discussed.[9] The evidence on this issue is not conclusive, but it appears to favor the story of net benefits to insider knowledge. Although evidence on the source of the observed network effects is inconclusive, the mere existence of such network effects gives cause for concern. The T5's tendency to publish work written by authors who are connected to the editorial board has the possibly unintended but real effect of penalizing authors who lack such connections. Unconnected authors are thus worse-off due to network effects that are biased against them, regardless of whether such network effects stem from favoritism or insider knowledge. However, this paper does not address in depth the larger question of the value of using citation counts to judge productivity and the self-referential nature of groups within economics who referee and cite each other's papers and tend to exclude outsiders.[10]

Given the many adverse consequences associated with the current reliance on the T5, we believe the discipline should reevaluate its current strong weighting of T5 publications as a measure of research achievement and as a filter for tenure and promotion decisions. The case for change is bolstered by the inadequacy of the T5 in predicting the quality of an article.

The rest of this paper proceeds as follows. Section 2 documents the power of the T5 in determining tenure and the time to tenure.

[8] Colussi (2018) is a recent study.

[9] Laband and Piette (1994) find that articles with author–editor connections are indeed more likely to be published, however, these articles also tend to attract higher citations on average. Brogaard, Engelberg, and Parsons (2014) estimate that authors publish 100 percent more papers in a journal when the journal is edited by a colleague, compared to periods when such department–editor networks do not exist. They also find that connected articles generate 5–25 percent more citations than unconnected articles on average.

[10] See Kapeller, Aistleitner, and Steinerberger (2017).

Section 3 reports responses to a survey of junior faculty about their perceptions of current tenure and promotion practices. They are consistent with the evidence from our empirical analysis. Section 4 examines the quality of the T5 filter as measured by citations to papers published there. Section 5 presents evidence on editorial tenure length in house journals and on incest.

The paper concludes with a summary. We discuss what—if anything—should be done about the practice of relying on T5 publications. We use an online appendix[11] to present background information and to report sensitivity analyses. We attach a within-text-appendix to explain certain points of methodology.

We note at the outset what this paper *does not* do. It does not offer an empirical assessment of whether current incentives in economics lead to meritocratic outcomes in academic economics. To do so would require accurate measures of academic productivity and research quality that do not yet exist. We rely on citation counts as a crude proxy for productivity and quality, noting that the measure is flawed but conventional. We also do not prove that the incentives we measure lead young economists to focus on pursuing those incentives. We document certain strong incentives built into the current tenure and promotion system and presume that junior academics respond to them just as agents would respond to incentives in the models we teach and in the data we study.

2. *Empirical Evidence on the Potency of the Top Five*

This section presents an extensive analysis of the basis for incentives facing young economists. Publication in T5 journals is the path to success. We note at the outset that finance has emerged as a major field that abuts economics and has many influential scholars. In our main analyses we pool papers in finance along with those in other fields of economics. Online appendix section 5 conducts a parallel analysis excluding papers in finance. Our point estimates are barely affected. Under either treatment of the data, we document that publication in the T5 is an important predictor of professional success.

2.1 *Data*

We investigate the relationship between tenure decisions and T5 publications using panel data on the job and publication histories of tenure-track faculty hired by the top 35 US economics departments between the years 1996 and 2010. Panel data are constructed in four steps.[12] Online appendix section 1 presents details on how we construct our data.

Tenure rates by the end of the first spell vary between 26 percent and 31 percent across the department groupings, and do not exhibit systematic differences with respect to department ranking.[13] Not surprisingly, a substantial percentage of junior faculty move downward.[14] The incidence of lateral movement is highest among the top five departments with a rate of 21 percent.

[11] See https://doi.org/10.1257/jel.20191574.

[12] The four steps are: (i) construction of a roster of tenure-track faculty hired by the top 35 departments between 1996 and 2010 using publicly available historical snapshots of departmental websites archived by Wayback Machine; (ii) construction of work histories for tenure-track faculty using CVs and other public sources of work-history data; (iii) construction of tenure decisions based on multiple sources of publicly available information including official announcements of tenure conferral; and (iv) construction of publication and citation profiles using data from Scopus.com.

[13] See online appendix table O-A4.

[14] The top five departments exhibit the largest difference between the percentage of downward movers and the percentage of tenure recipients. This discrepancy in relative differences arises partly because faculty at the top five departments are unable to move upward by definition, thereby restricting their outcome destinations to four options instead of five.

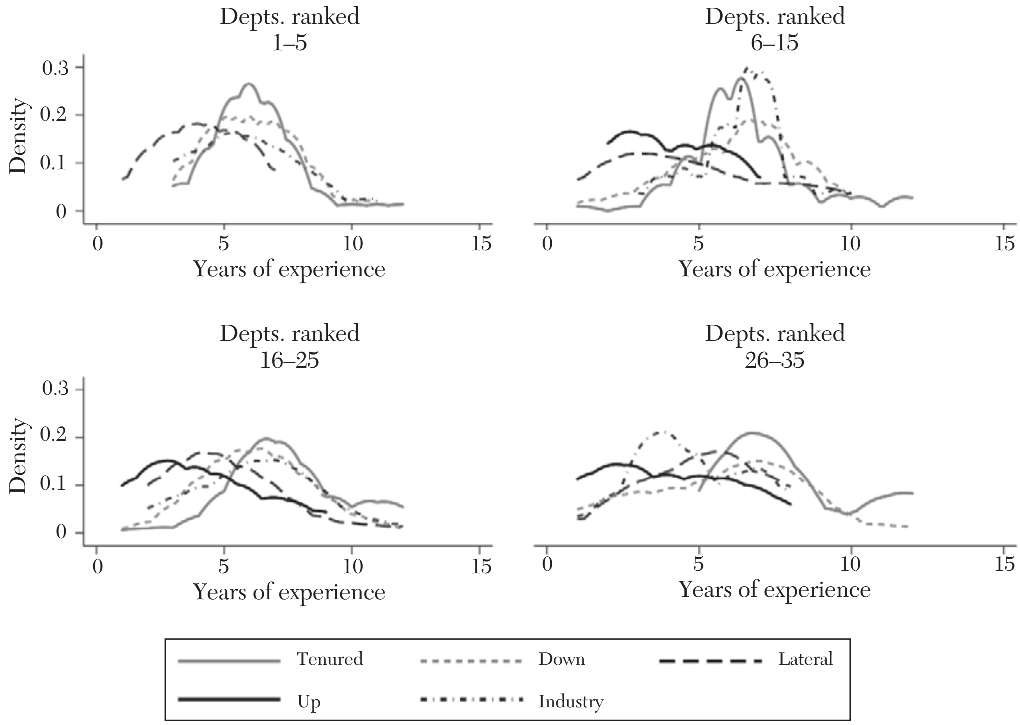

Figure 1. Length of First Tenure-Track Employment by Tenure Outcome

It is lowest for departments ranked 26 to 35 with a rate of 6 percent. Conversely, upward movement and exits to industry are more common among lower-ranked departments, and become less frequent for higher-ranked departments.[15] Tenure rates are considerably higher at the end of the second spell across all department rank groupings, with tenure rates ranging from 34 percent to 54 percent.[16,17]

Figure 1 plots department rank-specific distributions for the length of first tenure-track employment for individuals who received tenure or moved to other opportunities following the first spell of tenure-track employment. The distributions for tenure recipients have means between 5.4 and 7.0 years and standard deviations between 2.0 and 3.0 years.[18,19] The distributions for upward and lateral departmental movements are left-shifted relative to the tenured distributions. In comparison, the distributions for downward movement and exits to industry are more similar to the tenured distributions. These differences suggest that downward movements and movements

[15] Rates of upward and lateral movement combined are similar across all rank groups.

[16] See online appendix table O-A6 for tenure rates during the second spell.

[17] Online appendix table O-A7 gives estimates for rates of tenure conferral for the top 35 departments.

[18] See online appendix table O-A5 for means and standard deviations corresponding to each group.

[19] The right tails for the tenured distributions extend beyond ten years. The presence of such outliers is consistent with what one would expect given the adoption of tenure clock extension policies that allow faculty to extend the length of tenure clocks in the event of pregnancies, adoptions, and other permissible circumstances.

to industry are more likely to result from denial of tenure, compared to upward and lateral movements, which tend to occur considerably earlier than receipt of tenure. We discuss differences by gender in subsection 2.4.

2.1.1 *Categorizing the Journals*

To compare the relationships between tenure decisions and publications in T5 and non-T5 journals, we categorize non-T5 journals into "quality" categories. Such categorization allows us to estimate the influence of publishing in non-T5 journals of similar standing on tenure. We use the field-specific rankings of Combes and Linnemer (2010) to categorize journals into the following groups: tier A field, tier B field, and non-T5 general interest.[20] Online appendix table O-A9 presents the journals in these categories.

A summary of the publications data follows. Figure 2 differentiates faculty in the top 15 departments by tenure decision and plots mean publication counts in the four journal categories over the first eight years of academic experience.[21] The plots reveal a striking pattern. In terms of research productivity in peer-reviewed journals, tenured faculty at the top five departments differentiate themselves from their tenure-denied colleagues primarily based on T5 publications. The evolution of T5 publications exhibits considerable separation between tenured and tenure-denied faculty, with the average publication count reaching a difference of almost three publications by the eighth year of academic experience. The stark difference in separation between the T5 and non-T5 journals strongly suggests that top departments place a disproportionately large emphasis on T5 publications.

The degree of T5 differentiation falls among departments ranked 6–15. This decrease in T5 separation is accompanied by an increase in separation for tier A field journals, with differences in average publication counts in tier A journals as of the eighth year increasing from 0.4 for the top 5 departments to 0.6 for departments ranked 6–15. Despite these changes, the T5 continues to serve as the main differentiator between tenured and tenure-denied faculty among departments ranked 6–15. The relative importance of tier A journals continues to increase as we consider lower-ranked departments, with the separation for tier A journals surpassing the separation for T5 journals among departments ranked 16–25.

The observed pattern of publication behavior suggests that the number of T5 publications required for tenure decreases with department ranking. Non-T5 publications are valued more at lower ranked schools. Faculty at lower ranked departments can publish more non-T5 articles to compensate for their fewer T5 publications. This evidence of heterogeneity suggests that it might be informative to conduct a deeper examination of department rank-based heterogeneity in the relationship between tenure decisions and publications. In our formal analysis, we use econometric models that allow for such heterogeneity.

2.2 *Probability of Receiving Tenure*

We discuss the relationship between tenure and publication in journals of different quality tiers. Figure 3 plots average predicted probabilities of tenure associated with different numbers of publications in the four journal categories estimated using a logit

[20] Tier A field consists of the two highest-ranked journals in the fields of development, econometrics, finance, microeconomics/game theory, health economics, industrial organization, labor economics, macroeconomics and public economics. Tier B field is composed of journals ranked three to five in the same fields. The non-T5 general interest category includes the five highest ranked non-T5 general interest journals.

[21] See online appendix figure O-A1 for plots corresponding to departments ranked 16–35.

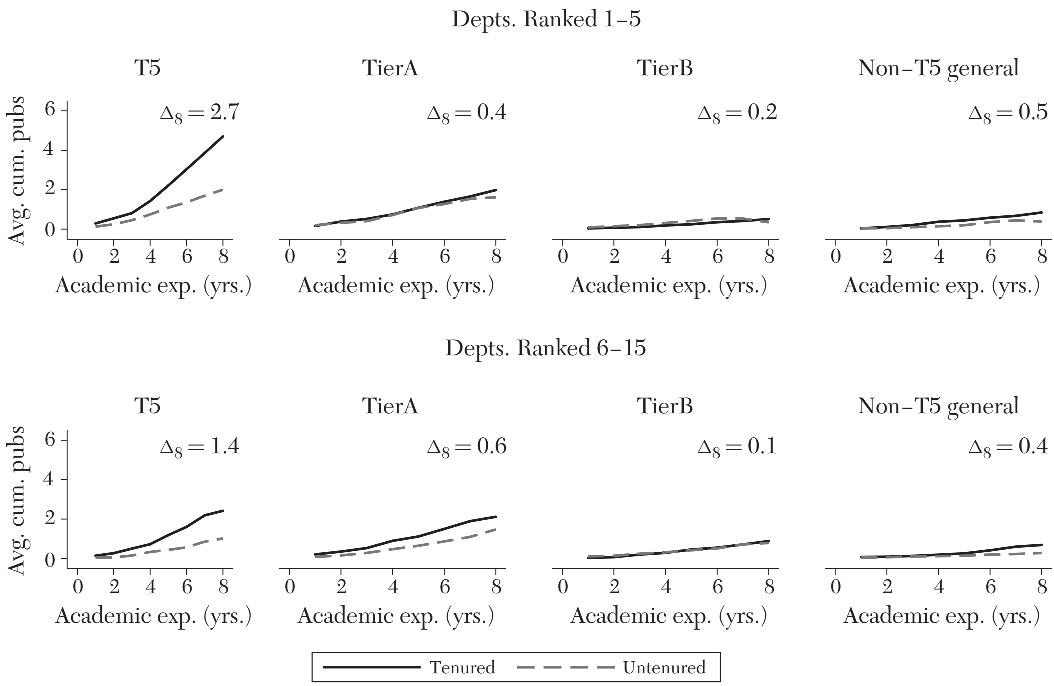

Figure 2. Evolution of Average Publication Portfolios by Tenure Outcome and by Departmental Ranks

Note: This figure plots the evolution of average publications in four different journal categories by tenure outcome. The plotted means are calculated over tenure-track faculty hired by departments belonging to the referenced department rank group. Δ_8 denotes differences in average cumulative publications as of year eight between the tenured and untenured groups.

model.[22,23] Controlling for the total number of publications in all specifications, we isolate a composition effect from a scale effect. We control for gender, number of coauthors, and the quality of the graduate school attended. Lastly, we control for the quality of authors' publication portfolios by including a vector of statistics that summarize the distribution of field-adjusted citations received by each author's portfolio of publications.[24,25]

[22] See text appendix subsection 1.1 for the exact specification used in our logit estimations.

[23] The corresponding marginal effects are presented under the "Pooled" columns of the online appendix table O-A13. Online appendix table O-A10 presents comparable estimates of partial effects obtained from our linear probability model (LPM) estimation. Results are qualitatively the same. The T5 remains the most influential category by far.

[24] Relevance of an article varies by analysis. Estimates of tenure by the first spell utilize citations for all articles published during the first spell. Estimates for tenure by the seventh year utilize citations to articles published by the seventh year of tenure-track experience.

[25] The vector of citation controls includes the following statistics that summarize the distribution of field-adjusted citations received by each author's portfolio of publications: twenty-fifth percentile, median, seventy-fifth percentile, minimum, maximum, and mean field-adjusted citations. Our adjustment follows a citation-rescaling procedure similar to the one introduced by Radicchi, Fortunato, and Castellano (2008) and discussed by Perry and Reny (2016). Specifically, it rescales citations received by each article i with the mean number of citations received by all articles

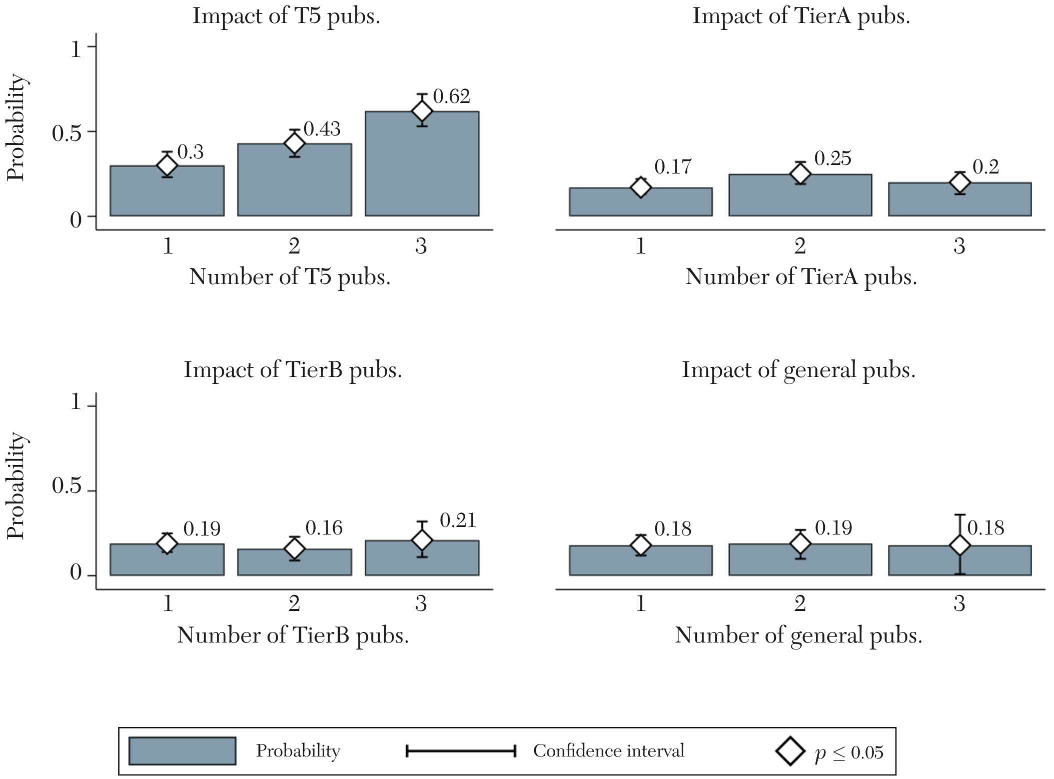

Figure 3. Predicted Probabilities for Tenure Receipt in the First Spell of Tenure-Track Employment (Logit)

Notes: This figure plots the predicted probabilities associated with different levels of publications in different journal categories. The predicted probability is defined in equation (5) in the text appendix (equation (5) uses parameter estimates from equation (4), also in the text appendix). White diamonds on the bars indicate that the prediction is significantly different from zero at the 5 percent level.

Figure 3 shows that publishing in T5 journals is associated with the largest increases in probabilities of receiving tenure. An individual with a single T5 publication is predicted to have a 0.3 probability of receiving tenure. The predicted probability increases to 0.43 and 0.62 for individuals with two and three T5 publications respectively. Although publishing in non-T5 outlets is associated with nonzero probabilities of receiving tenure that are statistically significant at the 5 percent level, the predicted probabilities associated with these publications are considerably lower than those associated with T5 publications. Among the non-T5 estimates, the largest probability of receiving tenure is 0.25 and it is associated with publishing two articles in tier A journals. This probability is lower than the probability of 0.3 associated with

in *i*'s field published during *i*'s year of publication. See online appendix section 2 for detailed documentation of the procedure undertaken to adjust citations by field and year.

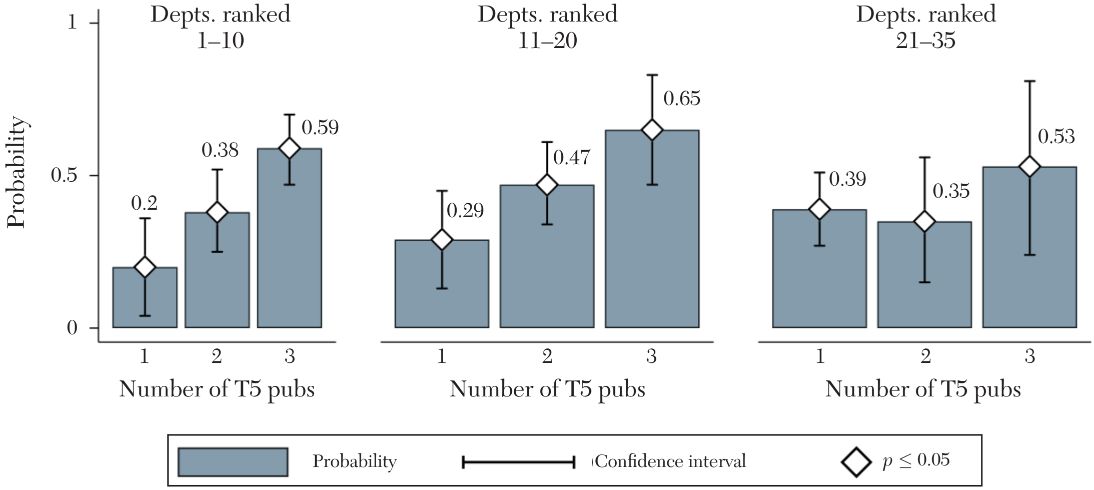

Figure 4. Predicted Probabilities for Tenure Receipt in the First Spell of Tenure-Track Employment, by Department Rank (Logit)

Notes: This figure plots the predicted probabilities associated with different levels of publications in different journal categories. The predicted probability is defined in equation (5) in the text appendix (equation (5) uses parameter estimates from equation (4), also in the text appendix). Department rank-specific estimates are obtained by restrictively estimating equation (4) over subsamples of faculty belonging to the department rank group in question. White diamonds on the bars indicate that the prediction is significantly different from zero at the 5 percent level.

publishing a single T5 article. The probability of 0.62 associated with three or more T5 publications is approximately 150 percent greater than this largest non-T5 estimate. The pattern of large differences between the probability of tenure associated with T5 and non-T5 publications persists when we investigate the relationship between publications and the probability of receiving tenure by the seventh year of tenure-track employment.[26]

2.2.1 *The Power of the T5 by Department Rank*

Figure 4 plots department rank-specific predicted probabilities for receipt of tenure during the first spell of tenure-track experience associated with different levels of T5 publications.[27] The length of the first spell varies by individual.[28] Predictions for each rank group is obtained by estimating logit models for subsamples of faculty who had their first spell of tenure-track experience at a department within the rank group in question. For empirical models of tenure probablities estimated in this paper we include departmental fixed effects and adjust standard errors for clustering at the department level.

[26] See online appendix subsection 3.3 for results and details on specification used.

[27] The corresponding marginal effects are presented under the department rank-specific columns of online appendix table O-A13.

[28] We also estimate models that fix duration to seven years of tenure-track experience. Pooled estimates are presented in online appendix figure O-A7. The results of that analysis are qualitatively similar to the analysis in the main text. Department rank-specific estimates for tenure by the seventh year are presented in online appendix figures O-A8–O-A10.

The figure reveals heterogeneity in the associated impact of each T5 publication in the probability of receiving tenure. Faculty at lower-ranked departments face higher probabilities of tenure receipt with the same number of T5 publications. An individual with one T5 publication is predicted to face a probability of tenure of 0.2 in a top ten department, but the same individual experiences probabilities of 0.29 and 0.39 at departments ranked 11–20 and 21–35 respectively. Faculty with two and three T5 publications at departments ranked 11–20 are similarly predicted to experience higher probabilities of tenure than individuals in top ten departments who have published the same number of T5 articles.[29]

2.2.2 *The Power of the T5 by Quality of T5 Publications*[30]

This subsection investigates the staying power of the T5. Results from the previous subsections show that T5 publications have a powerful impact on tenure decisions, after controlling for differences in the quality of publication portfolios as proxied by citation performance of published articles. These findings suggest that the T5 influence operates through channels that are independent of publication quality. Figure 5 presents evidence in support of this hypothesis. The figure bins faculty into four quartiles based on average citations accrued through 2018 by all journal articles published by authors during the first spell of tenure-track employment. Bins are designated in the natural order of citation quality from lowest (bin 1) to highest (bin 4). Probabilities of tenure associated with different levels of T5 publications are presented within each quartile.[31] To investigate the staying power of T5 publications conditional on article quality, we require all publications to accrue citations over a minimum of ten years.[32] The analysis in this subsection does not adjust for departmental fixed effects and differences in the tenure process by department rank due to sample size issues. We lose a large number of observations due to restriction of the sample to individuals who completed their first spells by 2008.

Tenure probabilities generally increase with number of T5 publications across all quartiles of author publication quality. Inter-quartile comparison of tenure probabilities reveals the extent of the T5 influence. It is more valuable to have a mediocre publication portfolio with T5 publications than an outstanding portfolio without any T5s. Individuals with top quartile T5-less publication portfolios composed of three or more non-T5 publications are estimated to face similar or lower probabilities of tenure receipt than individuals with bottom quartile publication portfolios consisting of one T5 article and two or more non-T5 articles. Faculty with bottom quartile portfolios composed of two or three T5 publications have substantially greater tenure probabilities than faculty with top quartile

[29] While differences are evident, one cannot reject the null of equalities of the probabilities across department rank groups. See online appendix table O-A14.

[30] The analysis of this section was motivated by the comments of Dan Black and Harold Uhlig.

[31] The probabilities are constructed in three steps: (i) the sample is restricted to only include faculty with three or more journal publications by the end of the first spell (three is the mean number of journal publications during the first spell); (ii) each individual is binned into one of four performance quartiles based on average citations accrued through 2018 by all journal articles published by the individual during the first spell; and (iii) conditional probabilities of tenure receipt (given T5 publications) are estimated within each performance quartile by taking the proportion of individuals who received tenure given publication of zero to three T5 articles during the first spell.

[32] This requirement is satisfied by restricting the estimation sample to only include individuals who completed their first spells of tenure track employment by 2008. Thus, all pre-tenure decision publications in the estimation sample must have been published in or before 2008.

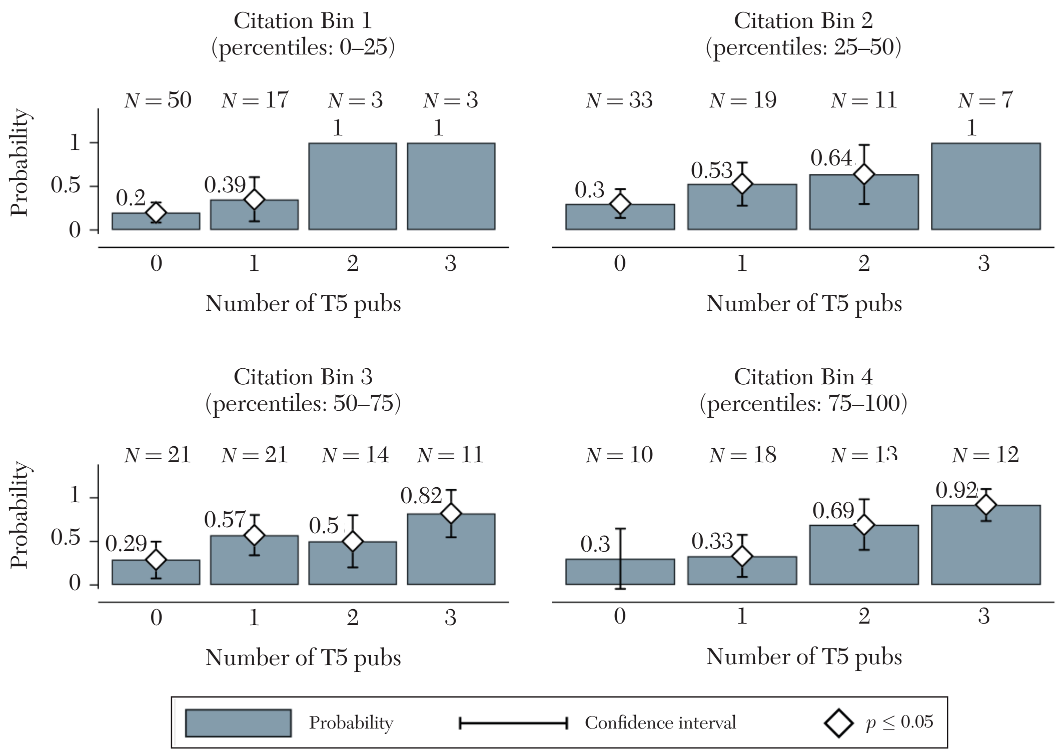

Figure 5. Raw Probabilities for Receipt of Tenure in the First Spell of Tenure-Track Employment, by Quality of Overall Publications for Faculty Whose First Spell Ended by 2008 (Quality Proxied by Average Citations Received through 2018 by First Spell Publications); Sample Restricted to Faculty with 3 or More Journal Publications by End of First Spell

Notes: This figure plots estimates of tenure probabilities (by the first spell) for individuals with different numbers of T5 publications by the quality of authors' publications as proxied by citations measures through 2018. Faculty are grouped into four quartiles based on average citations accrued through 2018 by all publications during the first spell. The figure plots quartile-specific probabilities of tenure associated with each level of T5 publication. For each quartile, probabilities are estimated as the proportion of individuals with a given level of T5 publication who received tenure during the first spell. The estimation sample is restricted to only include individuals who published three or more journal articles during the first spell. Confidence intervals are not plotted for probability estimates that equal one, since tenure was received by every individual within the group in question.

portfolios that lack T5 publications. This quality-invariant influence of T5 publications persists when we restrict the sample to include faculty who published at least four or five journal articles during their first job spell (see online appendix figures O-A16–O-A17).

The results presented in this subsection support the hypothesis that the T5 influence operates through channels that are independent of article quality. This finding is corroborated by responses to our survey of current tenure-track faculty at the top 50 US economics departments. Junior faculty believe that there is at least a 0.89 probability that tenure committees will choose to tenure a candidate who possesses T5 publications over an identical candidate who possesses an identical number of non-T5 publications of the same quality. The existence of such a strong quality-independent influence of T5 publications suggests that tenure and promotion committees rely overwhelmingly on journal-level indicators of quality (T5 versus non-T5) to predict the quality of individual articles. Such reliance on the T5 label is particularly problematic given the large intra-journal heterogeneity and inter-journal overlap in quality documented in section 4 for articles published in T5 and non-T5 journals. The discussion in this subsection highlights the folly in relying on journal-level indicators of quality to predict individual article quality—it simultaneously generates errors in actual decision making and leads junior faculty to (correctly) believe that the T5 has a quality-independent effect on tenure decisions. The formation of such beliefs is likely to influence the direction of research for faculty who seek tenure and career advancement.

2.3 *Duration Analysis of Time-to-Tenure*

This subsection expands on our analysis of the tenure–publication relationship by investigating the association between time to tenure and time-varying measures of publications in the four journal categories. We use a standard competing risks duration framework for the states given in table 1. This subsection presents the multi-spell hazard specification used in this paper to estimate the duration relationships between tenure and T5 publications. The reader is referred to text appendix section 2 for a more detailed discussion of the model.

Consider a multi-spell model where each individual enters the post-PhD academic job market as an untenured assistant professor at one of the top 35 departments. The probability that an individual is employed in an untenured tenure-track position during the first period of any lth spell of untenured tenure-track employment is 1. In subsequent periods, individuals can either remain untenured in the lth spell of tenure-track employment ($s=0$), begin a new spell $l+1$ of untenured tenure-track employment in another T35 department ($s=2$), or exit the sample by either receiving tenure within the department ($s=1$) or by ceasing to be employed as a tenure-track faculty member in a top 35 department ($s=3$).[33]

Assuming that Weibull hazards generate survival times,[34] the hazard rate that an untenured tenure-track faculty in the lth spell of employment transitions from state $s=0$ to a new state $k \in \{1,2,3\}$ in time period t is parametrized by:

$$(1)\quad h^{l}_{0,k}(t) = \exp\left\{ \sum_{j \in \mathcal{J}} \left(\sum_{n=1}^{3} \alpha^{j,n}_{0,k} \cdot \mathbf{1}\big(j(t) \geq n\big) \right) + \mathbf{X}\boldsymbol{\beta}_{0,k} + \overline{\mathbf{C}}\boldsymbol{\eta}_{0,k} + \delta_{0,k}(l-1) + V^{l}_{0,k} \right\} t^{\gamma_{1,0,k}},$$

where $h^{l}_{0,k}(t)$ is the hazard rate of transitioning from state 0 to k in period t of spell l; $\mathbf{1}\big(j(t) \geq n\big)$ is an indicator for having n or more publications in journals of type $j \in \mathcal{J}$ as of time period t; $\mathcal{J} = \{T5, General, TierA, TierB\}$; $\mathbf{X}$ is a vector that includes fixed effects for authors' academic department as well as measures of observable characteristics including

[33] Individuals cease to be employed as tenure-track faculty if they exit to a department below the top 35, move to an industry position, or transition to a non-tenure-track position in a top 35 department.

[34] See text appendix section 2 for a more detailed discussion of our duration model. The text appendix presents the Weibull model as a special case of a duration model that employs a Box–Cox transformation.

TABLE 1
Potential States of Employment for Untenured Tenure-Track Faculty in Period $t+1$ Relative to State in t

State = s	Description
0	Untenured tenure track in the same T35 department as period t
1	Tenured in the same T35 department as period t
2	Untenured tenure track in a different T35 department than period t
3	Not employed as a tenure track faculty in a T35 department

coauthor characteristics, gender, quality of authors' PhD granting institution, years since graduation, and a control for total volume of publications ln(#*Total Publications* + 1); $\overline{\mathbf{C}}$ is a vector of statistics that summarizes the distribution of field-adjusted citations received by each author;[35] $\gamma_{1,0,k}$ is the Weibull duration parameter; $\delta_{0,k}$ captures potential dependence between survival times and the number of spells that an individual has experienced prior to the current spell; and $V_{0,k}^{l} = \xi_{0,k} V$ is a one-factor spell-specific specification for individual-level unobserved heterogeneity.

The model imposes restrictions on the parameters associated with observed author characteristics and department fixed effects, forcing the parameters $\boldsymbol{\beta}$ to be equal across spells. We further restrict the parameters on the publication variables $\alpha_{0,k}^{j,n}$ to be constant across spells. This restriction is equivalent to assuming that tenure committees maintain the same publication standards for all untenured faculty regardless of the spell of employment.

2.3.1 *Pooled Estimates of Hazard Rates and Time to Tenure*

Figure 6 presents the increase in tenure hazards (rates of transition to tenure) associated with publishing different numbers of articles in the four journal categories. Estimates for individual parameters are presented in online appendix table O-A17. The estimates show that the transition rates to tenure associated with individuals who publish two and three T5 publications are 3.3 and 4.1 times the transition rates associated with those who have never published in the T5. In comparison, the transition rates associated with those who have published three tier A or tier B publications is no higher than 1.1 times the hazards associated with individuals who have never published in these outlets. None of the estimates for the non-T5 hazard ratios are statistically significant at the 5 percent level.

The differences in hazard rates translate into differences in the time required to attain tenure. Figure 7 plots predicted densities of time to tenure associated with publishing different numbers of articles in the four journal categories.[36] Publishing in the

[35] See footnote 25 for details.

[36] Each panel plots a baseline density associated with having no publications in any of the four journal categories. Journal category-specific densities are overlaid on this baseline density to highlight the deviation in time to tenure associated with publishing in the different categories. The first subfigure plots the densities associated with publishing one article in the journal category of interest, and none in the other three. The remaining two subfigures analogously plot densities associated with publishing two and three articles in the journal category of interest while holding the number of publications in the other three categories at zero.

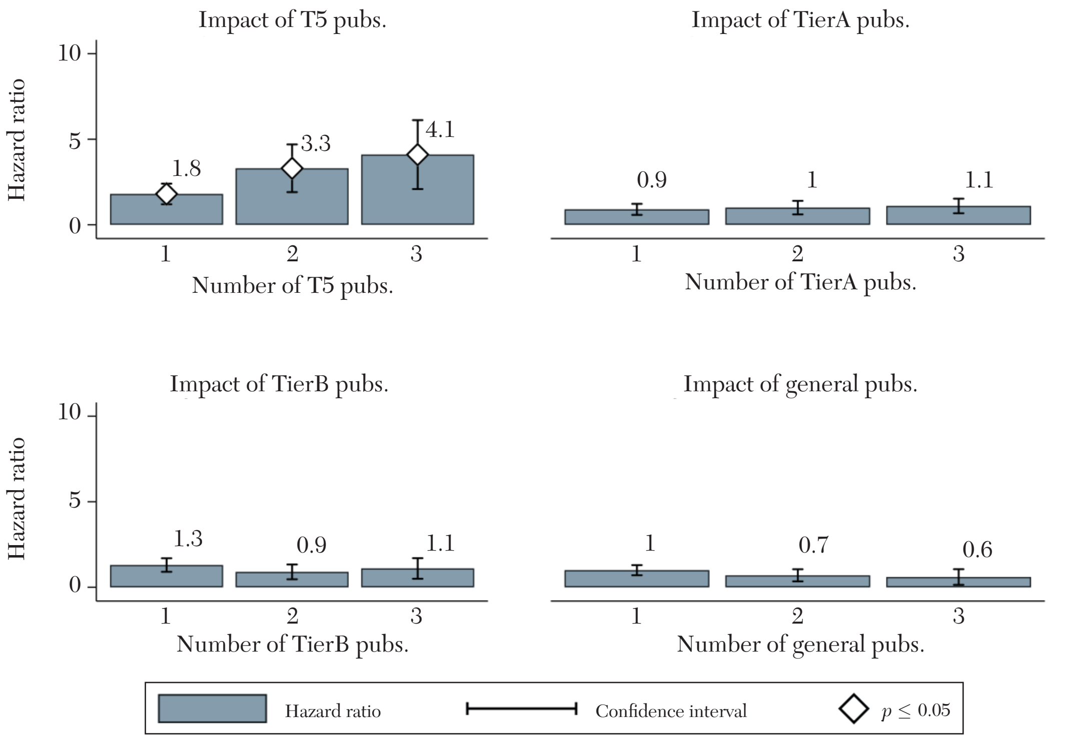

Figure 6. Relative Hazard Rates of Tenure Receipt Associated with Publications in Different Outlets

Notes: This figure plots hazard ratios associated with different levels of publications in different outlets. Hazard ratios are obtained by estimating text appendix equation (16). White diamonds on the bars indicate that the prediction is statistically significantly different from 1 at the 5 percent level.

T5 is associated with large decreases in the expected time to tenure as indicated by the large leftward shift in the T5-specific density of predicted time to tenure. In comparison, publications in non-T5 journals are associated with negligible deviations from the baseline distribution.

2.3.2 *Estimates of Hazard Rates by Department Rank*

This subsection presents hazard estimates corresponding to three rank-based groupings of departments: top ten, top 11–20, and top 21–35. To estimate rank-specific hazard ratios, we interact the publication variables in equation (1) with indicators for being employed by a department in each of the three rank-based groups during period t.[37] The estimates are heterogeneous across the different department rank groupings. The first T5 publication is estimated to have a significant impact on the hazard of tenure for only those individuals employed by departments ranked 21–35. Further, the magnitude of impact associated with the first T5 publication is higher for these departments compared to higher ranked

[37] See text-appendix subsection 2.3 for details.

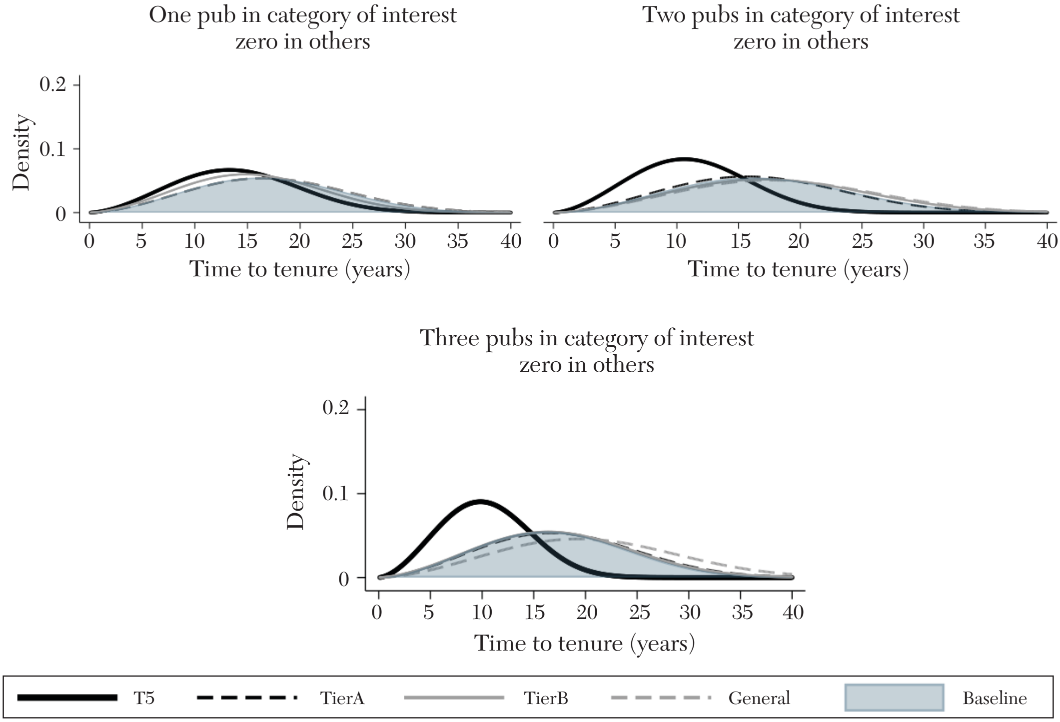

Figure 7. Densities of Time to Tenure (Weibull Distribution)

Notes: This figure plots distributions of time to tenure associated with different levels of publications in four different types of journals. Densities of time to tenure are derived from estimation of equation (16) in the text appendix. The blue shaded region in each plot represents the distribution of time to tenure associated with not having any publications in any journal.

departments. Conversely, the estimates associated with two or three T5 publications is only significant for the top 20 departments, and the magnitude of impact associated with these publications is higher for individuals hired by the top ten departments compared to individuals in departments ranked 11–20. Online appendix subsection 4.2 presents analogous rank-specific estimates for the non-T5 journal categories. T5 publications are estimated to have a larger impact on the hazard of tenure relative to non-T5 publications, across all department rank groupings.

2.4 *Heterogeneity in the Probability and Rate of Receiving Tenure by Gender*

We next investigate gender differences in time to tenure and in the probability of receiving tenure. Duration analyses in subsection 2.4.1 reveal that male faculty enjoy shorter times to tenure than their female colleagues. We investigate the source of this discrepancy by checking whether differences in time to tenure stem from differential returns to publication by gender. Our analysis shows that T5 publications are indeed associated with greater reductions in time to tenure for

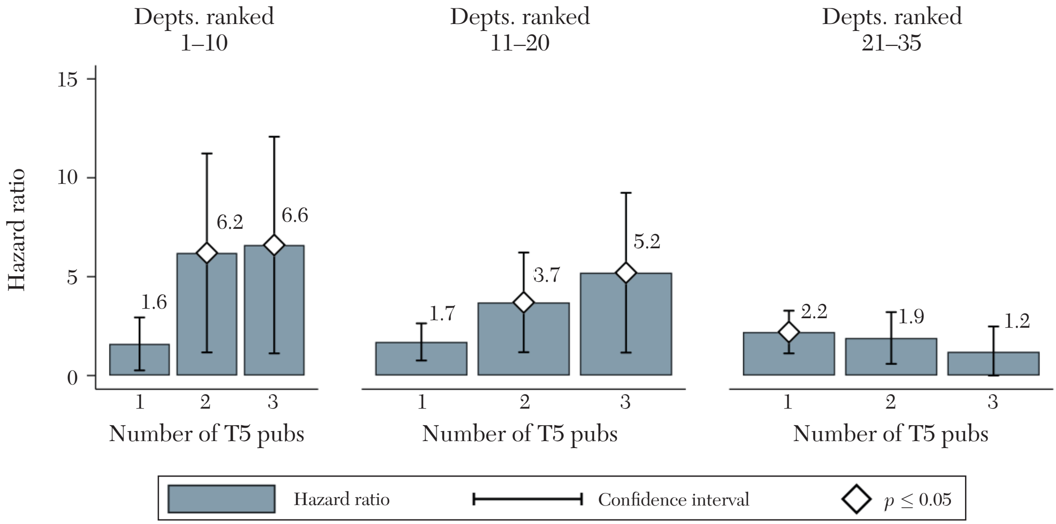

Figure 8. Relative Hazards of Tenure Associated with Different Levels of T5 Publications (by Department Rank)

Notes: This figure plots department quality-specific hazard ratios of tenure associated with different levels of publications in the T5. The department quality-specific hazard ratios are estimated by interacting the publication parameters in equation (16) in the text appendix with time-specific indicators for whether an author is hired by a department that belongs to each of the three department quality groupings.

male faculty. We are careful not to interpret these estimates as evidence of discrimination since we lack the data required to control for the confounding effect of fertility on female time to tenure. While gender differences exist for time to tenure, differences by gender are not present in our analyses of the probability of receiving tenure (both during the first spell and by the seventh year of tenure-track employment) in subsection 2.4.2. Our results thus suggest that female faculty take longer to receive tenure but are not less likely to eventually receive tenure.

2.4.1 *Heterogeneity in Time to Tenure*

This subsection investigates heterogeneity in time to tenure and tenure rates by gender. Estimation of the baseline hazard yields an estimated hazard ratio for the gender indicator (denoting that the subject is male) that ranges between 1.43 and 1.44 depending on the assumption made about unobserved heterogeneity (see online appendix table O-A17). The ratio of 1.44 for men indicates that male faculty have a rate of time to tenure that is 44 percent greater than those faced by their female colleagues, once differences in the number of publications and the vector of time-variant and -invariant controls $\mathbf{X}$ and $\overline{\mathbf{C}}$ are accounted for. Analyzing data for an older sample of individuals who were employed as economists in 1989, Kahn (1993) finds that men enjoy hazards of tenure that are 56 percent higher than that for women.[38] The difference in hazard rates translates into differences in time-to-tenure.

[38] Our estimate is not directly comparable with that of Kahn (1993) because we adopt different model

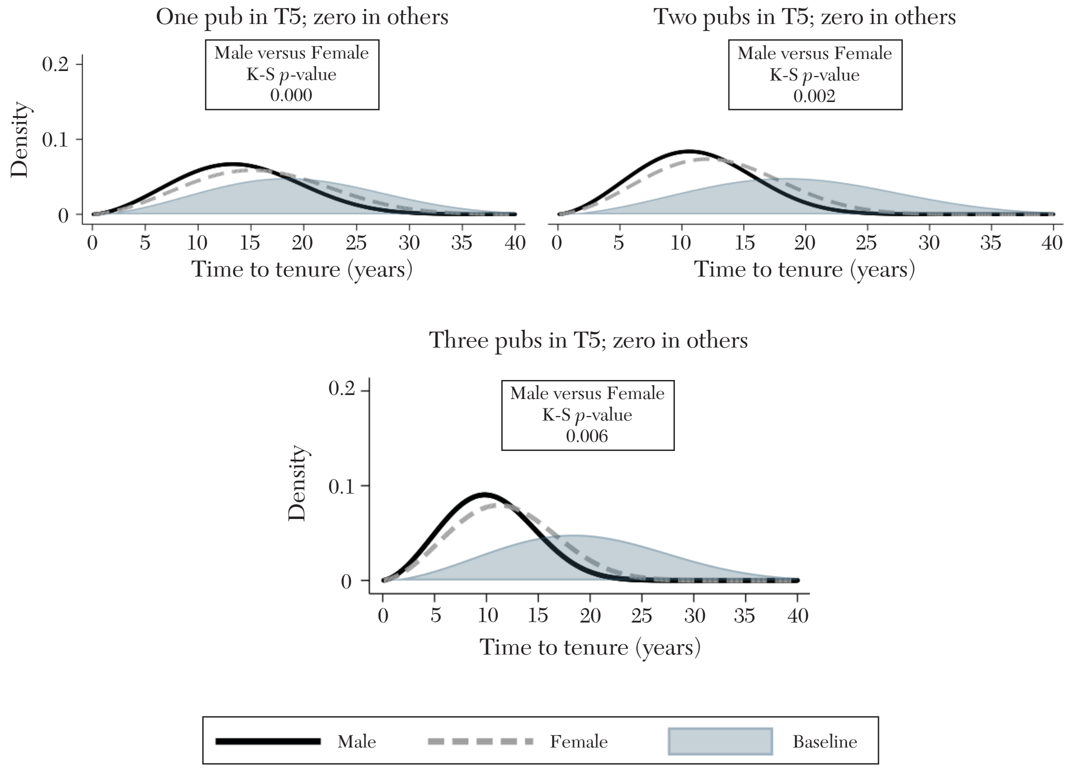

Figure 9. Densities of Time to Tenure (Weibull Distribution), by Gender (Publication Rewards Held Constant across Genders)

Notes: This figure plots conditional densities of time to tenure, given different levels of publications in the T5 journals, and gender. Densities of time to tenure are predicted using parameter estimates obtained by estimating text appendix equation (16) without interacting the publication parameters with gender. Conditional densities of time to tenure given gender g, x number of T5s, and 0 non-T5s is given by: $f(t\,|\,\#\mathrm{T5}=x,\#\mathrm{nonT5}=0,\mathrm{Gender}=g,\mathbf{X}) = h(t\,|\,\#\mathrm{T5}=x,\#\mathrm{nonT5}=0,\ \mathrm{Gender}=g,\mathbf{X}) \times S(t\,|\,\#\mathrm{T5}=x,$ $\#\mathrm{nonT5}=0,\mathrm{Gender}=g,\mathbf{X})$ where $h(t\,|\,\cdot)$ and $S(t\,|\,\cdot)$ give the conditional hazard and survivor rates at t respectively. The titles for the three subplots in figure 9 list the conditioning used for the publication variables. "Two pubs in T5; zero in others" gives the condition: $\#\mathrm{T5}=2, \#\mathrm{nonT5}=0$. The conditioning on gender is given by the legend that denotes whether the plot is associated with males or females. The conditioning on $\mathbf{X}$ is left implicit. Taken together, the black density for the plot labeled "Two pubs in T5; zero in others" plots the following density function: $f(t\,|\,\#\mathrm{T5}=2,\#\mathrm{nonT5}=0,\mathrm{Gender}=\mathit{Male},\mathbf{X})$. Plots for females and other quantity of T5s are analogously defined. The blue shaded region in each plot represents the conditional density of time to tenure for females given zero publications in all outlets. K–S means Kolmogorov–Smirnov test for equality of distributions. Each plot also presents p-values obtained from Kolmogorov–Smirnov tests between the male and female distributions.

Figure 9 plots gender-specific densities of time to tenure associated with publishing one to three T5 publications (see online appendix figure O-A24 for nonparametric Kaplan–Meier plots of survival probabilities

specifications and use a richer control set (our data collection procedure yields richer bibliographic data).

by gender and number of T5 publications). The densities for females exhibit a rightward shift relative to their male counterparts. Kolmogorov–Smirnov tests reported in the figure reject the null hypothesis of distributional equality across genders at the 5 percent level for each level of T5 publication.

Given the statistical significance of the gender indicator, we next investigate differences in rewards associated with T5 publications by gender. We explore heterogeneity in rewards to publication by interacting the publication variables in equation (1) with an indicator for gender. Online appendix figures O-A21–O-A23 present gender-specific tenure hazards associated with different levels of publishing in different journal categories. Figure O-A21 plots hazards associated with the first three T5 publications, by gender. Females are estimated to have higher hazard rates to tenure for the first T5 publication. However, the estimate associated with the first T5 is only statistically significant for male faculty at the 5 percent level. Males are estimated to have markedly higher hazard rates than females for the second and third T5 publication. The hazard rate associated with two T5 publications is 56 percent higher for males than for females. The hazard rate associated with three T5 publications is 86 percent higher for males. The hazard rate estimates for the second and third T5 publications are only statistically significant for male faculty. These gender differences in hazard rates suggest that male faculty reap greater rewards for T5 publication—the same quantity of T5 publications is associated with greater reductions in time to tenure for male faculty compared to their female counterparts. Gender differences in T5 rewards are not attributable to gender differences in the quality of T5 articles. An inter-gender comparison of citation distributions for solo-authored T5 articles reveals that citations to T5 articles are not statistically significantly different across genders (see online appendix subsection 7.6 for details). However, point estimates for female faculty are more imprecisely determined than those for males due to the relatively small sample of female faculty.[39]

The difference in tenure hazards and time to tenure across genders suggests that female faculty receive lower and possibly more uncertain rewards than their male counterparts for the same level of publications. It is unclear how much of the slower female rate to tenure is accounted for by fertility and differences in the take-up rate of parental leave (pregnancy-related leave) between male and female faculty. Antecol, Bedard, and Stearns (2018) present evidence that gender-neutral tenure clock-stopping policies have differential impacts on rates of tenure receipt by gender. The adoption of gender-neutral tenure clock-stopping policies is found to be associated with significant reductions in the rate of tenure receipt for female faculty in economics, but not for their male counterparts. Ginther and Kahn (2004) find that ten years post-PhD, female faculty in economics with children are statistically significantly less likely to receive tenure than female faculty without children. Such differences do not exist between male faculty with and without children. The existence of such discrepancies across male and female faculty suggest that childbearing and rearing have important differential impacts on time to tenure by gender, and that such differences would be exacerbated by tenure clock-stopping policies. Unfortunately, we lack the requisite data to make the appropriate adjustment to female exposure sets.

[39] The sample size is small for two reasons: (i) there are fewer females than males in academic economics (Scott and Siegfried 2018 report that women accounted for 21.7–26.6 percent of assistant and associate professor positions in the 2017–18 academic year across 103 PhD-granting institutions in the United States); and (ii) women who publish three or more T5 articles are much fewer in number.

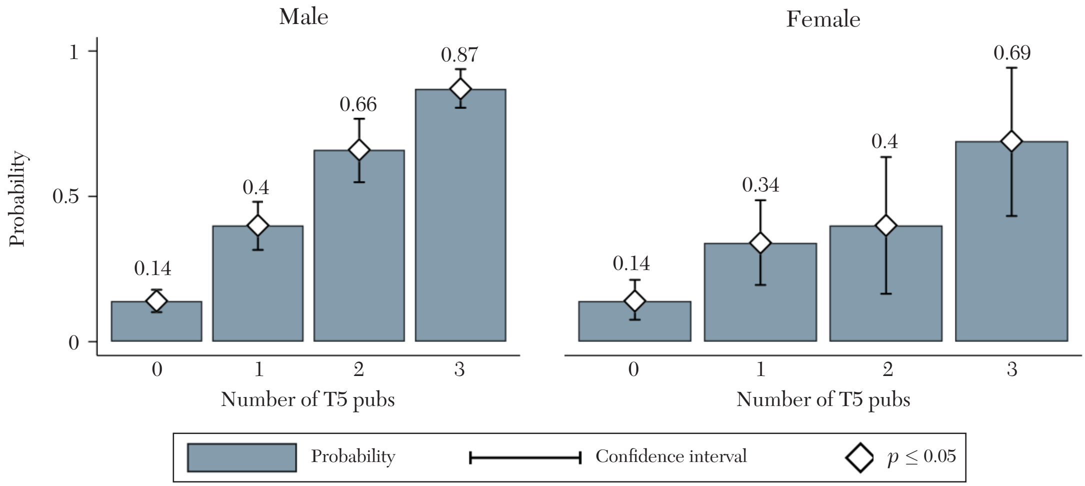

Figure 10. Conditional Probabilities of Receiving Tenure during the First Spell of Tenure-Track Employment Given T5 Publications and Gender

Notes: This figure plots conditional probabilities of receiving tenure during the first spell of tenure-track employment, given the quantity of T5 publications and gender. The probabilities are estimated as proportions of individuals within each gender–T5 quantity cell who received tenure during the first spell of tenure-track employment.

2.4.2 *Heterogeneity in the Probability of Receiving Tenure*

Figure 10 plots raw probabilities of tenure given gender and number of T5 publications.[40] The probabilities are lower for females at all levels of T5 publication. This result suggests that females might reap lower rewards (in terms of the probability of receiving tenure) than males for the same number of T5 publications. Although figure 10 indicates that tenure probabilities vary by gender given the same number of T5 publications, these gender differences disappear when we estimate logit models that include an indicator for gender and control for publication in non-T5 journals and a vector of characteristics $\mathbf{X}$ and $\bar{\mathbf{C}}$.[41] The marginal effect for gender (indicator for male) is 0.019 (SE $=$ 0.038; $p = 0.607$) for tenure by the seventh year of tenure-track experience, and -0.045 (SE $=$ 0.033; $p = 0.175$) for tenure during first spell of tenure-track employment. Both estimates are statistically insignificant at the 5 percent level. Probabilities predicted from this model are comparable between genders (see online appendix figures O-A12–O-A15), with the first spell estimates showing greater gender similarity than the estimates at the seventh year.[42]

[40] These probabilities are computed as proportions of individuals of a certain gender with a certain number of T5 publications who receive tenure.

[41] See equation (4) in the text appendix for exact specification.

[42] These probabilities are obtained by adding a gender indicator variable to prediction equation (5) in the text appendix to obtain $\Pr\left(Tenure = 1 \mid \#\hat{J} = \hat{N}, \#\tilde{J} = 0, \text{Gender} = g, \mathbf{X}\right)$. The parameters used in these predictions are obtained by estimating equation (4) in the text appendix.

We note that the parameters associated with publication in non-T5 journals and the **X** that are used in constructing these predictions are not allowed to vary by gender. Therefore, any differences in predicted probabilities stem from gender differences in tenure rates that are unrelated to differences in rewards associated with publication. Unlike the gender-specific publication rewards estimated in the duration analysis of subsection 2.4, these logit estimates do not show any differences in rewards to publication by gender. It is not possible to estimate more sophisticated gender-specific publication specifications due to limited sample sizes for women.[43]

A recent study by Sarsons (2017) suggests the possible existence of bias in favor of male faculty in the tenure evaluation process. Specifically, her study finds that female faculty reap lower rewards (i.e., increases in the probability of receiving tenure) for papers written with male coauthors compared to papers written with female coauthors or solo-authored papers. The author observes that such patterns could arise if tenure committees are biased in favor of males in their attribution of credit for coauthored work. A competing hypothesis is that the nature of coauthor pairings between males and females could differ from other types of pairings in a way that generates the pattern observed in the data. Ductor, Goyal, and Prummer (2018) document differences in coauthor characteristics by authors' gender. The authors find that coauthor networks exhibit gender homophily. Further, they find that female authors tend to collaborate with smaller groups of coauthors who are more likely to be interlinked with one another. Lastly, they find that females tend to collaborate with more senior faculty.

[43] Many of the publication parameters are non-estimable for females due to sample size issues. Females account for only approximately 20 percent of the sample.

Our paper does not address the larger question of female representation in academic economics. A growing body of literature discusses female representation within the discipline and across academia in general (especially in the sciences). Analyzing data from the Survey of Earned Doctorates for the period 1974–2000, Ginther and Kahn (2004) find that women account for a substantially smaller share of doctoral degrees in economics and the physical sciences compared to the life sciences, political science, and statistics. Using more recent data from the Integrated Postsecondary Education Data System (IPEDS), Bayer and Rouse (2016) find that the share of doctorate degrees in economics awarded to women has stagnated since 1995, with women accounting for approximately 30 percent of doctorate degrees awarded in 2014. Female representation continues to fall as one progresses up the academic career ladder (Ginther and Kahn 2004).

2.5 *Sensitivity of Estimates to Inclusion and Exclusion of Finance and Econometrics Journals*

Finance has emerged as a separate field that coexists, and sometimes overlaps, with mainstream economics. Given the distinct nature of the field and the existence of separate finance departments in business schools, it is possible that top finance journals are valued differently than other field journals in making tenure decisions. We recognize this possibility by conducting separate analyses in online appendix section 5 that test the robustness of our estimates to: (i) pooling economics and finance journals together into combined field journal categories and (ii) separating them out. Our results are robust to inclusion or exclusion of finance journals. We similarly test for the sensitivity of estimates to alternative treatments of econometrics journals in online appendix section 6. Our results are robust to the inclusion and exclusion of econometrics journals.

3. *Junior Faculty Perceptions of Current Tenure and Promotion Practices*

We supplement our empirical analysis of job-history and publication data with findings from a survey of individuals currently employed as assistant and associate professors by the top 50 economics departments in the United States.[44] Respondents were surveyed about their perceptions of how tenure and promotion decisions are determined within their departments, with an emphasis on the role played by T5 publications in these decisions.[45] The survey responses corroborate and contextualize the evidence in section 2. Junior faculty have rational expectations about the power of the T5. Online appendix subsection 8.3 presents our survey instrument.

The survey has an overall response rate of 40 percent ($N = 308$) across all 50 departments, with response rates of 44 percent ($N = 210$) for assistant professors and 34 percent ($N = 97$) for associate professors. The overall response rate was highest for departments ranked 41–50 (43 percent), and lowest for the top ten departments (37 percent). Assistant professors had higher response rates than associate professors across all department rank groups except the top ten departments, for which the response rate was 37 percent in both groups. Position- and department rank-specific response rates are reported in online appendix figure O-A29.

The response rate gives rise to concerns about nonresponse bias. Of particular concern is the potential bias that could stem from respondents selecting into the survey based on their ability to publish in the T5. Comparisons of distributions of T5 publications between the respondents and the overall population of assistant and associate professors hired by the top 50 departments provides evidence against this form of selection. Department rank group-specific Mann–Whitney tests comparing T5 distributions between survey respondents and the overall population fail to reject the null of equality for all rank groups. See online appendix table O-A53 for these comparisons. Online appendix subsection 8.2 presents additional data description for the survey sample.[46]

3.1 *Survey Results*

One survey question asks respondents to rank eight different areas of research and teaching performance based on their perceptions of the degree to which tenure and/or promotion decisions are influenced by performance in these areas. Figure 11 summarizes responses to this question by presenting the mean ranking assigned by respondents to each performance area. The figure presents three sets of summaries, corresponding to rankings of performance areas for three different types of career advancement: receipt of tenure, promotion to assistant professor,

[44] See Liner and Sewell (2009) for a survey of department chairs on research requirements for promotion and tenure.

[45] The survey was designed with three goals in mind: (i) to confirm our empirical findings about the influence of T5 publications on tenure decisions; (ii) to collect new data on the perceived importance of factors such as teaching performance or external letters that are unobserved in the work-history data; and (iii) to provide junior faculty the opportunity to express their opinions about the consequences (either positive or negative) of current tenure and promotion practices for themselves and for the discipline as a whole.

[46] We note that the survey was terminated prematurely because of a complaint to our IRB board by some individuals we attempted to sample. The complainants were concerned that their identity might be determined by our survey protocol despite our efforts to assure anonymity. This source of nonresponse mechanically leads to a low response rate that does not necessarily produce a bias unless early responders are biased in the same general direction and have axes to grind.

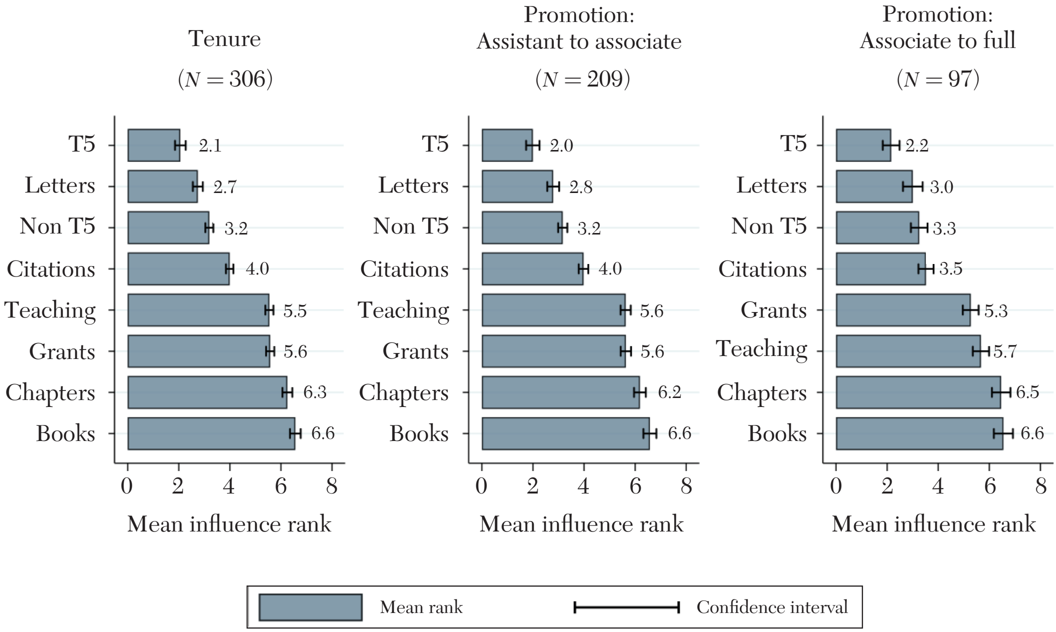

Figure 11. Ranking of Performance Areas based on Their Perceived Influence on Tenure and Promotion Decisions

Notes: This figure summarizes respondents' rankings of eight performance areas. Responses are summarized by type of career advancement: tenure receipt, promotion to assistant professor, and promotion to associate professor. The bars present mean responses for each performance area. Respondents were given the option to not rank any or all of the eight performance areas. As a result, the number of respondents vary across the performance areas.

and promotion to associate professor.[47] The quantity of T5 publications receives the highest mean rank across all forms of career advancement. Wilcoxon signed-rank tests performed between pairs of ranking distributions for the eight performance areas indicates that the distribution of rankings of the importance of the quantity of T5 publications is significantly different from the ranking distributions for all of the remaining seven performance areas at the 10 percent level.[48] In addition to confirming our previous findings of the substantial influence of T5 publications relative to publications in non-T5 journals, these survey results reveal that the T5 is also more influential than

[47] The tenure-specific ranking has a sample size of 306 respondents. The promotion-specific rankings have lower sample sizes because these rankings were presented to different subsets of respondents: rankings for promotion to associate professor was only requested from current assistant professors, and rankings for promotion to full professor was only requested from current associate professors. The reason for employing this form of sample restriction is twofold. First, it ensures that responses are current and well-informed since faculty are only surveyed about promotions to positions that they are currently working toward obtaining. Second, it improves the probability of survey completion by reducing the burden of response for each respondent from three to two rankings.

[48] See online appendix tables O-A56–O-A58 for pair-wise tests on rankings for each type of career advancement.

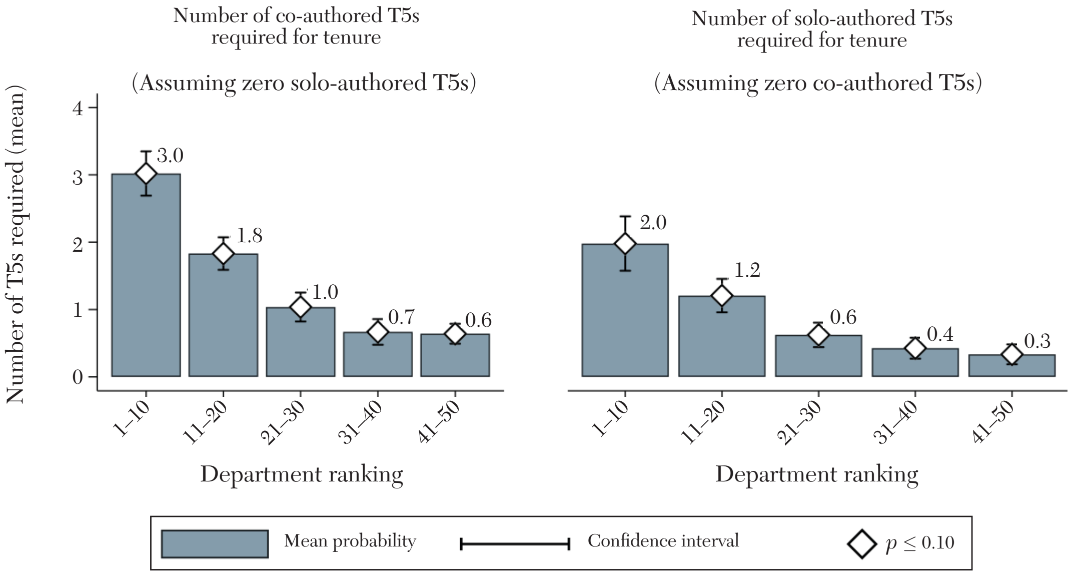

Figure 12. Minimum Number of T5 Publications Required for Tenure

Notes: This figure summarizes respondents' perceptions about the number of T5 publications that are required to obtain tenure in their department. The bars present mean responses for each performance area. White diamonds indicate that the responses were significantly different from zero at the 10 percent level.

measures of performance such as external letters of recommendation and teaching performance which are not available to us. These findings support the conclusion that junior faculty at the top departments perceive the quantity of T5 publications to be the most important source of influence on tenure and promotion decisions.

The quality of external letters of recommendation receives the second-highest mean ranking across all types of career advancement. External letters are meant to provide tenure and promotion committees an outside view of the quality and impact of candidates' research, especially in comparison to similarly experienced researchers working in comparable fields. The data do not allow us to test whether one's quantity of T5 publications influences the quality of external letters. However, given that external and internal reviews are both focused on judging candidates' research output, and given that external reviewers likely work in departments that are in the same class as the candidate's department (with similar levels of T5 emphasis in research evaluation), it is possible that external reviewers put as large an emphasis on a candidate's quantity of T5 publications as reviewers who are internal to the candidate's department. Indeed, it is not unusual for letter writers to focus on the number of T5 articles published or in the pipeline for a prospective candidate. Such dependence of external letters on the quantity of T5 publications would compound the pressure faced by junior faculty to publish in the T5.

Non-T5 publications receive the third-highest mean rank across all levels of career advancement. However, the rankings for both external letters and non-T5 publications are only significantly different from the rankings for citations when we consider tenure and promotion to associate professor. The Wilcoxon tests presented in online appendix table O-A58 fail to reject the null that the ranking distributions for external letters and non-T5 publications are equal to the distribution for citations for promotions to full professor. The remaining performance areas receive the four lowest mean ranks across all career advancement types. Teaching performance and success in securing grants receive rankings that are not significantly different from each other for any type of career advancement. Books and chapters in books are ranked last for all levels of career advancement. Long-term integrated bodies of research are valued much less than focused T5 articles.

These survey results offer important evidence on the large influence of T5 publications on tenure and promotion practices. However, they do not shed light on whether the difference in influence between T5 and non-T5 publications is merely a reflection of differences in article impact and quality between these outlets, or whether the T5's influence also operates through channels that are independent of article impact and quality. Figure 13 presents some evidence that answers this question. The figure summarizes responses to a survey question that asks respondents to compare the probabilities of receiving tenure and promotion associated with publishing in T5 and non-T5 journals, fixing the quality of the publications in question to be equal. Specifically, the question presents respondents with a thought experiment wherein respondents are asked to imagine a scenario where their departments must decide to tenure and/or promote one out of two candidates. The respondents are asked to assume that the two candidates are identical in every respect, with the exception that one candidate has published all of their articles in T5 journals whereas the other candidate has published the same number of articles of equal quality in non-T5 journals. The respondents are then asked to report the probability that the candidate with T5 publications receives tenure and/or promotion instead of the candidate with non-T5 publications. In a scenario where the T5 influence operates solely through differences in article impact and quality, both the T5 and non-T5 candidate would be expected to receive tenure and/or promotion with a probability of 0.5. Any deviation from 0.5 in favor of the T5 candidate indicates that the T5 influences tenure and/or promotion decisions through channels that are independent of article quality.

The results plotted in figure 13 reveal large and statistically significant deviations from 0.5 in favor of the candidate with more T5s. The deviations exist across department rank groupings, and for all three levels of career advancement: tenure receipt, promotion to assistant professor, and promotion to associate professor. The figure plots the mean response by department rank group and level of career advancement. For tenure decisions, the mean response is 0.89 or higher across all department rank groups. Thus, on average, junior faculty at the top 50 departments believe that their department would award tenure to the T5 candidate instead of the non-T5 candidate at least 89 times out of 100. The mean reported probability rises as one considers lower-ranked departments, with its value peaking at 0.93 for departments ranked 31–40. The reported probabilities are similarly high for promotions to associate professor. Mean reported probabilities are lower for promotions to full professor, and exhibit higher variation. However, the means continue to remain significantly different from 0.5 at the 10 percent level.

These results reveal that there exists a widely-held belief among junior faculty at the top 50 departments that the same quantity and quality of articles will yield rewards at vastly different rates based on whether

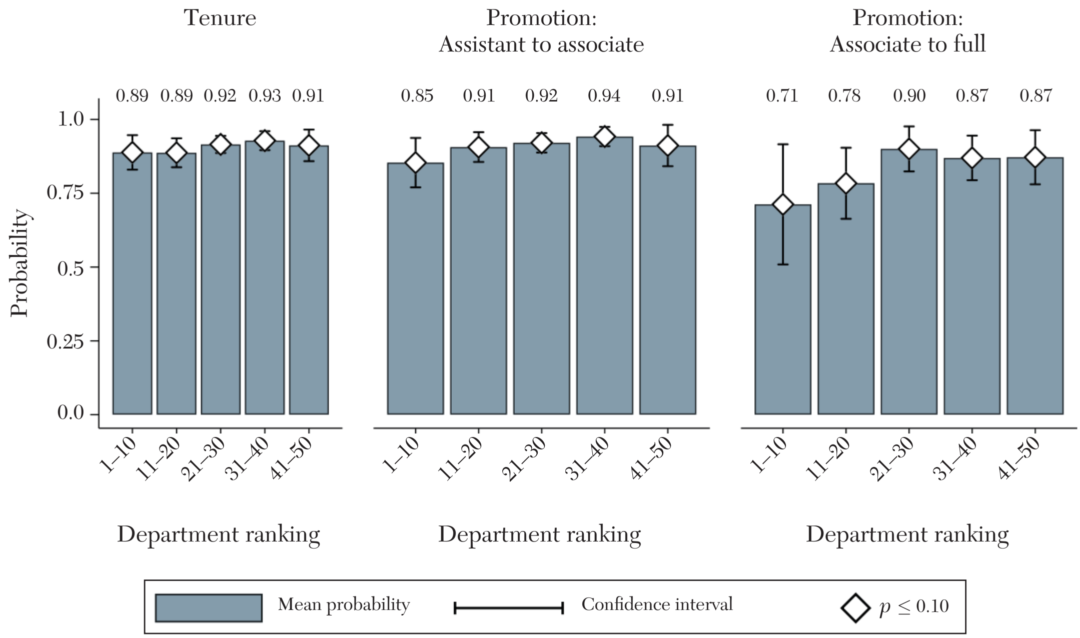

Figure 13. Probability That Candidate with T5 Publications Receives Tenure or Promotion Instead of Candidate with Non-T5 Publications, Ceteris Paribus

Notes: This figure summarizes respondents' perceptions about the probability that a candidate with T5s is granted tenure or promotion by the respondent's department instead of a candidate with non-T5s, ceteris paribus. Responses are summarized by type of career advancement: tenure receipt, promotion to assistant professor, and promotion to associate professor. The bars present mean responses for each performance area. White diamonds indicate that the mean response is significantly different from 50 percent at the 10 percent level.

their articles are published in T5 or non-T5 journals. Junior faculty form expectations based on past decisions, and past decisions are clearly biased in favor of T5 publishing (see figure 5). For rational career-oriented economists who prioritize tenure and career advancement, given the current incentives, academic careers should be little more than quests for publication in the T5.

4. *The T5 as a Filter of Quality*

The analysis of section 2 establishes the strong relationship between tenure decisions in the top 35 departments and T5 publications. The analysis of section 3 shows that junior faculty are acutely aware of the power of the T5. The analysis in this section evaluates quality of the T5 as a filter of research influence and quality. Using citations as a proxy for influence, subsection 4.1 compares citation distributions of individual journals against the citation distribution of T5 journals as a group. Subsection 4.2 compares journals with respect to the share of the most influential papers that have been published by T5 and non-T5 journals. Subsection 4.3 compares T5 and non-T5 journals based on impact factors. Subsection 4.4 examines the publishing behavior of influential economists from 14 major fields of economics.

4.1 *Comparison of Citations between T5 and Non-T5 Journals*

This subsection compares cumulative citation counts (measured as of 2018) of articles published in the T5 and those published in 25 non-T5 journals over the ten year period 2000–2010. We reluctantly follow the literature in using citation counts as a valid measure of productivity. However, it is obvious that citation counts are flawed measures of productivity. It is very likely that, following convention, authors are more likely to cite T5 papers even when comparable or superior non-T5 papers are available. Given current practices, the appeal to a T5-certified paper strengthens a reference in the eyes of many readers. Academic productivity is an elusive concept. In the absence of a better measure, we rely on a flawed measure. Our analysis shows large intra-journal heterogeneity and inter-journal overlap in the quality of published articles across T5 and non-T5 journals. Combined with our analysis in subsection 4.2, which identifies non-T5 journals that produce as many, if not more, influential articles than the T5, the findings of this subsection show that whether an article is published in the T5 or not is a poor predictor of the article's actual quality.

The comparisons in this subsection build on the analysis of Hamermesh (2018), who compares citations in the T5 journals, with citations in the *Review of Economics and Statistics* (*ReStat*) and the *Economic Journal* (*EJ*). We extend his analysis by expanding the set of non-T5 journals considered to 25, and by analyzing articles published in a wider and more recent time frame (2000–2010 in our analysis versus 1974–75 and 2007–08 in Hamermesh 2018).[49] Our results confirm his findings. There are large intra-T5 variation in citations and large overlaps in citations between papers published in the T5, and those published in *ReStat* and *EJ*. Our use of the expanded journal comparison set helps identify six additional non-T5 economics journals that share at least as large a citation overlap with the T5 as *EJ*. We conclude the analysis by comparing the overlap between non-T5 journals and different subsets of T5 journals. We find that the comparability between T5 and non-T5 publications greatly increases when one focuses on the lesser-cited T5 journals. As a case in point, the median-cited *ReStat* article ranks in the thirty-eighth percentile of year-adjusted citations among *all* T5 publications, but attains a rank of the fifty-eighth percentile when compared to *ReStud* alone. These comparisons illustrate the large heterogeneity in influence among the journals that comprise the T5.

We note at the outset that for want of a better measure, our comparisons of journal and article quality rely on citations. One concern with using citations is that it could undervalue the quality of non-T5 articles relative to those published in the T5.[50] If

[49] Our chosen time frame for the analysis in the current section necessarily excludes any analysis of the impact of the new AEA applied journals, which started publication in 2009.

[50] Long-standing and deeply entrenched perceptions about the superiority of T5 publications serve to increase the visibility of T5 articles. In the presence of such differences, it is possible that T5 articles will attract more citations than non-T5 articles, conditional on article quality. The T5 journals are among the most popular and well-perceived journals in the profession. Analyzing the results of a survey of 92 economists, Hawkins, Ritter, and Walter (1973) show that the *AER*, *ECMA*, *JPE*, and *QJE* were the four most highly regarded journals in the late 1960s and early 1970s (*ReStat* was ranked fifth, and *ReStud* was ranked sixth). The perceived superiority of these four journals has persisted over time. Analyzing the results of 2,103 responses to an online survey sent to AEA members in 2002, Axarloglou and Theoharakis (2003) replicate the findings of Hawkins, Ritter, and Walter (1973) and show that the *AER*, *ECMA*, *JPE*, and *QJE* have continued to be perceived as most influential in the early 2000s. To the extent that scholars prefer citing articles from journals that they perceive to be of the highest quality and influence, we should expect a negative bias against non-T5 citations. In other words, it is possible that holding constant both an article's quality and its relevance to the citing author's work,

such undervaluation exists, our analysis will understate the degree of comparability between T5 and non-T5 journals. Further, independent of quality, the T5 could attract more citations than field journals simply due to the fact that general interest journals are designed to target a wider audience than field journals. The reader should consider such potential biases when interpreting the results reported in this subsection.

4.1.1 *Comparisons against the Aggregate T5 Distribution*

Figure 14 plots distributions of residual $\ln(Citations + 1)$ for articles published between 2000–2010 in each of the thirty journals considered in our analyses.[51] The journal-specific distributions are overlaid on a shaded distribution that represents the distribution of residual citations for all articles published between 2000–2010 in the T5. The residualization adjusts log citations for exposure effects, and yields an exposure-adjusted measure that can be used to compare the performance of articles across publication cohorts.[52] The residuals are obtained by estimating an OLS regression of $\ln(Citations + 1)$ on a third-degree polynomial for the number of years elapsed between the year of publication and 2018 (the year when citations were recorded).[53]

The panel labeled T5 reveals that the distribution of citations to *QJE* articles has a considerable rightward shift relative to the other T5 journals. A comparison of the median *QJE* residual against the distribution of residuals for all T5 publications reveals that the median-cited *QJE* article ranks at the seventy-first percentile of all T5 publications in terms of residualized citations.[54] In terms of median citations, the *QJE* is followed by *AER*, *JPE*, *ECMA*, and *ReStud*, with the median-cited *ReStud* article reaching the thirty-first percentile of T5 citations.

The panel labeled Journals 6–10 in figure 14 plots distributions of residualized citations for the five non-T5 economics journals with the highest median citations. Among non-T5 economics journals, the greatest number of citations accrue to survey journals. Citations to the *Journal of Economic Literature* (*JEL*) exhibit a considerable rightward shift relative to the T5 distribution. Online appendix table O-A31 shows that the median-cited *JEL* article ranks at the seventieth percentile of all T5 publications in terms of residual citations, which is one percentile below the ranking for the median-cited *QJE* article. The *JEL* is followed by the *JEP*, whose median-cited article is ranked at the median of the T5 distribution. *ReStat* ranks first among the non-T5, non-survey economics journals, with its median citation reaching the thirty-eighth percentile of all T5 citations. It outranks *ReStud* by 7 percentile points and underperforms *ECMA* by only 3 points. The list of the five highest-cited non-T5 economics journals is rounded out by the *Journal of Economic Growth* (*JEG*) whose median-cited article

T5 articles receive more citations than non-T5 articles due to long-standing and deeply entrenched perceptions of the superiority of articles published in the T5.

[51] Similar to Hamermesh (2018), we exclude notes, comments, reports of editors, and papers published in the *AER*'s annual issue of *Papers & Proceedings*. We also exclude papers that are less than ten pages in length.

[52] The present analysis focuses on comparisons of this year-adjusted measure. The interested reader is referred to online appendix figures O-A25–O-A27 for analogous plots that are specific to articles published in 2000, 2005, and 2010 respectively.

[53] Online appendix table O-A32 presents a comparison of median residualized citations (aggregate T5 versus individual journals) using residuals obtained from four different specifications. The first three columns present comparisons that use residuals obtained from an OLS of $\ln(Citations + 1)$ on first-, second-, and third-degree polynomials of years of exposure, respectively. The last column uses residuals obtained from estimating $\ln(Citations + 1)$ as a function of indicators for exposure. The results are robust to the alternative specifications.

[54] See online appendix table O-A31 for comparisons of journal-specific median citations against the T5 distribution of citations.

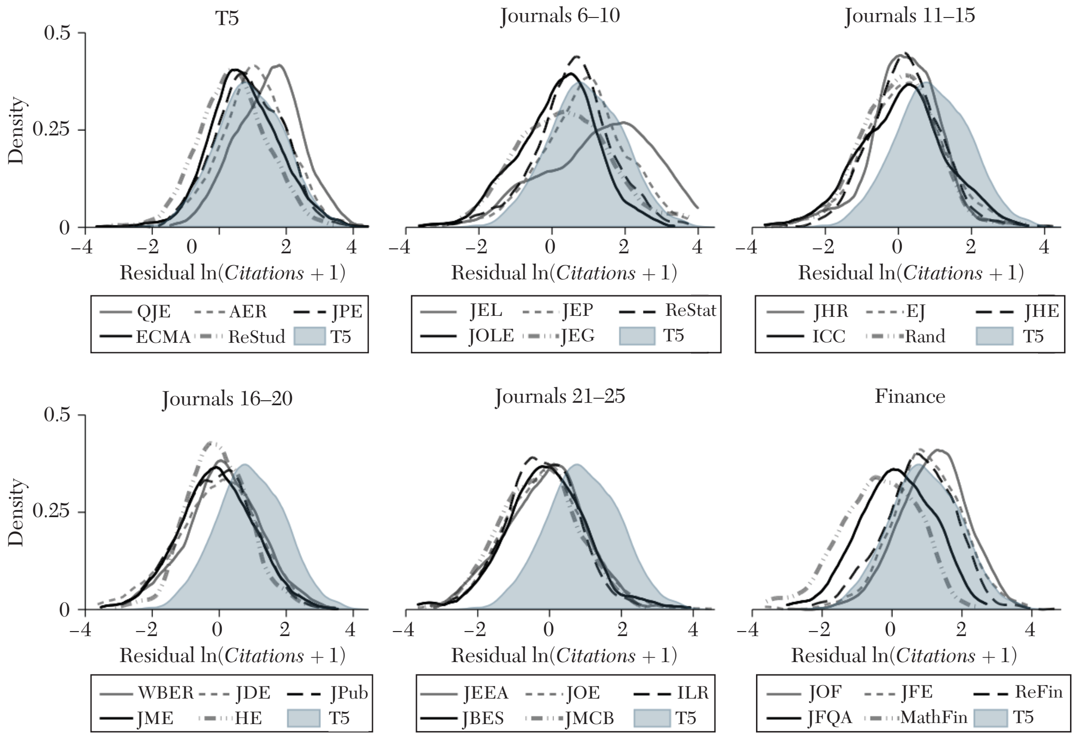

Figure 14. Distribution of Residual log Citations for Articles Published between 2000–2010 (Measured through July, 2018)

Source: Scopus.com; accessed in July, 2018.
Notes: Definition of journal abbreviations in order of appearance: *QJE–Quarterly Journal of Economics*, *AER–American Economic Review*, *JPE–Journal of Political Economy*, *ECMA–Econometrica*, *ReStud–Review of Economic Studies*, *JEL–Journal of Economic Literature*, *JEP–Journal of Economic Perspectives*, *ReStat–Review of Economics and Statistics*, *JOLE–Journal of Labor Economics*, *JEG–Journal of Economic Growth*, *JHR–Journal of Human Resources*, *EJ–Economic Journal*, *JHE–Journal of Health Economics*, *ICC–Industrial and Corporate Change*, *Rand–Rand Journal of Economics*, *WBER–World Bank Economic Review*, *JDE–Journal of Development Economics*, *JPub–Journal of Public Economics*, *JME–Journal of Monetary Economics*, *HE–Health Economics*, *JEEA–Journal of the European Economic Association*, *JOE—Journal of Econometrics*, *ILR–Industrial and Labor Relations Review*, *JBES–Journal of Business and Economic Statistics*, *JMCB–Journal of Money, Credit and Banking*, *JOF–Journal of Finance*, *JFE–Journal of Financial Economics*, *ReFin–Review of Financial Studies*, *JFQA–Journal of Financial and Quantitative Analysis*, and *MathFin–Mathematical Finance*.

is ranked at the thirtieth percentile of T5 citations, the *Journal of Labor Economics* (*JOLE*) which has an analagous ranking at the twenty-fifth percentile, and the *Journal of Human Resources* (*JHR*), the *Journal of Health Economics* (*JHE*), and *Industrial and Corporate Change* (*ICC*), which are all tied at the twenty-fourth percentile.[55]

[55]The next three panels in figure 14 present distributions for fifteen additional economics journals, listed in decreasing order of median citations. The first six of these

As previously noted, finance has emerged as an important subfield in economics. Not surprisingly, finance journals have lives of their own. They attract greater citations than non-T5, non-survey economics journals. The *Journal of Finance* (*JOF*) is most highly cited, with its median-cited article reaching the sixty-first percentile of all T5 publications. It is followed by the *Journal of Financial Economics* (*JFE*) and the *Review of Financial Studies* (*ReFin*), both of which have median citations above that of *ECMA* and *ReStud*.

Finally, we note that the relative performance of non-T5 journals improves considerably when the comparison excludes the two highest-cited T5 journals (*AER* and *QJE*). Thus, while the median-cited *ReStat* article ranks in the thirty-eighth percentile of the overall T5 distribution, its rank improves to the forty-eighth percentile when the comparison set is restricted to articles in *JPE*, *ECMA*, and *ReStud*. Similar improvements are recorded for other non-T5 journals. The reader is referred to online appendix subsection 7.1 for further details on comparisons of non-T5 journals against subsets of the T5.

4.2 *Which Journals Publish Influential Research Papers?*

This subsection compares T5 and non-T5 journals with respect to the volume of influential articles published by each journal between the period 2000–2010. To proceed, we use the residualized citations used in the previous sections to group articles from the 30 economics journals into four performance-based bins: articles with the top 25 percent, top 10 percent, top 5 percent, and top 1 percent of residual citations. We then calculate the proportion of articles in each quality bin that was published by each of the 30 economics journals. Table 2 presents a ranking of the 30 journals based on unadjusted proportions.

The *AER* features prominently in these rankings, contributing the largest proportion of articles to each of the quality bins except the top 1 percent. The *QJE* ranks second in the 25 percent, 10 percent, and 5 percent bins, and ranks first in the top 1 percent bin. With the exception of the top 25 percent bin, *AER* and *QJE* account for a combined 30 percent or more of the articles in each citation bin (they account for 23.5 percent of the articles in the 25 percent bin). The other T5 journals contribute fewer influential articles.[56]

The non-T5, non-survey journals publish many influential articles. *JOE*, *ReStat*, and *JEG* account for a combined 13.6 percent of all articles in the top 1 percent of residual citations. The contributions from these three journals are not only significant in absolute terms, but also in relation to the T5. All three journals produce more top 1 percent articles than *ReStud*, two of the three journals produce more top 1 percent articles than *JPE*, and the remaining one produces as many top 1 percent articles as the *JPE*. *ReStud* is outranked by six additional non-survey, non-T5 journals. These journals contribute a further 16 percent to the top 1 percent bin. The contributions of non-T5, non-survey journals remains significant across the remaining three citation bins. The five most influential non-T5, non-survey journals in the top 5 percent bin produce a combined 20 percent of the articles in that bin. The top 10 percent and top 25 percent bins receive 19 percent

journals have median-cited articles that are ranked at or above the twentieth percentile of all T5 articles.

[56] With the exception of the 1 percent bin, *JPE* and *ECMA* are ranked within one point of each other. *ReStud*, on the other hand, ranks considerably lower than the other four T5 journals, and is outranked by many non-T5 journals in all four categories. The appearance of *ReStud* as an outlier among the T5 is consistent with the findings from the previous sections that show that the median *ReStud* article was ranked in the thirty-first percentile of all T5 publications in terms of residual citations.

TABLE 2
PUBLICATION VOLUME-UNADJUSTED PROPORTION OF INFLUENTIAL ARTICLES PUBLISHED BY INDIVIDUAL JOURNALS, 2000–2010

Rank	Top 25% citations $N = 3{,}321$		Top 10% citations $N = 1{,}329$		Top 5% citations $N = 665$		Top 1% citations $N = 133$	
1.	**AER**	(14.0%)	**AER**	(16.6%)	**AER**	(17.7%)	**QJE**	(17.3%)
2.	**QJE**	(9.5%)	**QJE**	(14.0%)	**QJE**	(15.6%)	JEL	(13.5%)
3.	**ECMA**	(6.7%)	JEP	(7.6%)	JEP	(9.6%)	**AER**	(12.8%)
4.	JEP	(6.6%)	**ECMA**	(7.4%)	JEL	(8.0%)	JEP	(9.8%)
5.	**JPE**	(5.7%)	**JPE**	(6.8%)	**ECMA**	(7.1%)	**ECMA**	(8.3%)
6.	EJ	(5.2%)	JEL	(5.5%)	**JPE**	(5.1%)	JOE	(5.3%)
7.	JOE	(5.2%)	ReStat	(4.5%)	JOE ReStat	(4.7%)	ReStat	(4.5%)
8.	ReStat	(4.8%)	EJ	(4.4%)		( )	JEG **JPE**	(3.8%)
9.	JPub	(4.5%)	JOE	(4.2%)	EJ	(4.5%)		( )
10.	JME	(3.8%)	**ReStud**	(3.5%)	JME **ReStud**	(2.6%)	EJ JHE RAND	(3.0%)
11.	JDE	(3.8%)	JPub	(3.1%)		( )		( )
12.	**ReStud**	(3.7%)	ICC	(3.0%)	ICC JPub	(2.4%)		( )
13.	JHE	(3.3%)	JDE	(2.7%)		( )	JBES JEEA JPub	(2.3%)
14.	JEL	(3.3%)	JME	(2.5%)	JHE	(2.0%)		( )
15.	ICC	(2.7%)	JHE	(2.2%)	JBES JEG	(1.4%)		( )
16.	HE	(2.5%)	HE	(2.0%)		( )	ICC **ReStud**	(1.5%)
17.	JMCB	(2.4%)	JMCB	(1.5%)	HE JDE JOLE RAND	(1.2%)		( )
18.	JHR	(2.1%)	JEG JOLE	(1.4%)		( )	JME JOLE WBER	(0.8%)
19.	RAND	(2.0%)		( )		( )		( )
20.	JOLE	(1.9%)	JEEA	(1.3%)		( )	( )	

Source: Scopus.com; accessed in July, 2018.
Notes: This table presents publication volume-unadjusted proportions of highly cited articles published by different journals.
Definition of journal abbreviations in order of appearance: *AER–American Economic Review, QJE–Quarterly Journal of Economics, JEL–Journal of Economic Literature, ECMA–Econometrica, JEP–Journal of Economic Perspectives, JPE–Journal of Political Economy, EJ–Economic Journal, JOE–Journal of Econometrics, ReStat–Review of Economics and Statistics, ReStud–Review of Economic Studies, JEG–Journal of Economic Growth, JPub–Journal of Public Economics, JME–Journal of Monetary Economics, JHE–Journal of Health Economics, RAND–Rand Journal of Economics, JDE–Journal of Development Economics, ICC–Industrial and Corporate Change, JHE–Journal of Health Economics, JBES–Journal of Business and Economic Statistics, JEEA–Journal of the European Economic Association, HE–Health Economics, JMCB–Journal of Money, Credit and Banking, JOLE–Journal of Labor Economics, JHR–Journal of Human Resources*, and *WBER–World Bank Economic Review*.

and 24 percent of their publications, respectively, from the five most influential non-T5 sources within their respective bins.

The discussion thus far focuses on each journal's absolute production of influential articles. The *AER* publishes at least twice as many papers as the next highest T5 journal. It is informative to compare contributions in light of each journal's total volume of publications. Table 3 produces a publication volume-adjusted version of the rankings presented in table 2.[57] The adjustment discounts the contribution of high-volume journals such as the *AER* in order to account for the increased probability of contribution (to the citation bins) associated with publishing a larger volume of articles.

The volume adjustment leads to a substantial reordering of journals within all of the citation bins. The *AER* falls in the rankings from first or third place in the unadjusted ranking (depending on the citation bin) to the third place or lower in the adjusted ranking. The adjustment increases the relative contributions from the *QJE* and *JPE*, reflecting the fact that these journals have a lower volume of publication than the *AER*. While the increase in their proportions improves the overall standing of these two journals, it does not result in improvements in rankings across all bins, since other journals such as the *JEL* get even larger increases in their proportion of contributions. *ECMA* experiences a negative adjustment and falls to sixth place in the top 25 percent, top 10 percent, and top 5 percent bins. *ReStud* shows ranking improvements in the top 25 percent and top 10 percent bins. However, its rankings are not affected in the top 5 percent and top 1 percent bins despite the volume adjustment.

Among non-T5 non-survey journals, the *JEG* has the largest upward shift, consistently ranking within the top seven across all citation bins. *ReStat* falls in rank. However, it continues to remain influential across the various citation bins. The *EJ* and *JOE* both move down the scale.

The major takeaway from the rankings in tables 2 and 3 is that non-T5 non-survey journals publish a significant volume of influential research in economics, frequently outperforming some of the less influential T5 journals. Their influence on the discipline is highly visible regardless of whether one considers their absolute volume of contributions or contributions per unit of publication.

4.3 *The T5 Are Not the Journals with the Top Five Impact Factors in Economics*

Table 4 presents impact factors by lag (two year; five year;. . .; 20 year) with the longest lag showing the lasting contributions (citations at 20 years). Among the T5, only the *QJE* is in the T5 impact in any listed year, and is ranked first at all lags except the 10 year lag. Finance journals have much higher impact factors, reflecting the scale of practitioners in that field. Journals with high short-term (two year) impacts often do not keep their rankings over the long term. The very basis for the ranking of the T5—that it signals journals with the most cited papers—is flawed. Only the *QJE* deserves that status.

The scale of the impact of economics journals pales into insignificance compared to that of science journals (see online appendix

[57] The rankings are based on volume-adjusted proportions of contributions to each citation bin, where the adjusted proportion for journal j in citation bin b is computed as follows:

$$P_{j,b} = \frac{1}{N_b} \sum_{y=2000}^{2010} C_{j,y,b} / \left(\frac{v_{j,y}}{V_y}\right), \tag{2}$$

where N_b is the total number of articles in citation bin b, $C_{j,y,b}$ is the count of all articles published by journal j during year y that received enough citations to be included in citation bin b, $v_{j,y}$ is the number of articles published by journal j during year y, and V_y is the total number of articles published in year y by all of the 30 economics journals included in this exercise. The term $\left(v_{j,y}/V_y\right)$ is a year-specific volume adjustment that weights the contribution of each journal by the inverse of its publication volume during a given year.

TABLE 3
Publication Volume-Adjusted Proportion of Influential Articles Published by Individual Journals between 2000–2010

Rank	Top 25% citations $N = 3{,}321$		Top 10% citations $N = 1{,}329$		Top 5% citations $N = 665$		Top 1% citations $N = 133$	
1.	**QJE**	(12.0%)	**QJE**	(16.6%)	JEL	(19.8%)	JEL	(26.6%)
2.	JEL	(8.9%)	JEL	(14.2%)	**QJE**	(17.8%)	**QJE**	(18.0%)
3.	**AER**	(7.8%)	**AER**	(8.6%)	JEP	(8.8%)	JEG	(11.8%)
4.	**JPE**	(7.3%)	**JPE**	(8.3%)	**AER**	(8.7%)	JEP	(7.8%)
5.	JEP	(6.9%)	JEP	(7.5%)	**JPE**	(6.0%)	**ECMA**	(5.5%)
6.	**ECMA**	(5.7%)	**ECMA**	(5.9%)	**ECMA**	(5.2%)	**AER**	(5.5%)
7.	JEG	(4.6%)	JEG	(5.3%)	JEG	(5.0%)	**JPE**	(3.5%)
8.	**ReStud**	(4.6%)	**ReStud**	(4.1%)	ReStat	(3.5%)	ReStat	(2.8%)
9.	ReStat	(3.9%)	ICC	(3.8%)	ICC	(3.0%)	RAND	(2.7%)
10.	JOLE	(3.6%)	ReStat	(3.4%)	**ReStud**	(3.0%)	JBES	(2.6%)
11.	ICC	(3.4%)	EJ	(2.7%)	EJ	(2.6%)	JHE	(2.0%)
12.	WBER	(3.4%)	WBER	(2.5%)	WBER	(2.3%)	JOE	(2.0%)
13.	EJ	(3.4%)	JOLE	(2.3%)	JOE	(2.1%)	ICC	(1.9%)
14.	JHR	(3.2%)	JOE	(1.9%)	JOLE	(1.8%)	EJ	(1.7%)
15.	JDE	(2.8%)	JDE	(1.9%)	JME	(1.6%)	WBER	(1.4%)
16.	JHE	(2.5%)	JHE	(1.6%)	JHE	(1.4%)	**ReStud**	(1.3%)
17.	RAND	(2.5%)	JME	(1.5%)	JBES	(1.3%)	JPub	(1.2%)
18.	JOE	(2.4%)	JPub	(1.5%)	RAND	(1.3%)	JOLE	(1.2%)
19.	JME	(2.4%)	JBES	(1.2%)	JPub	(1.1%)	JME	(0.6%)
20.	JPub	(2.3%)	RAND	(1.2%)	JHR	(1.0%)	JEEA	(0.0%)

Source: Scopus.com; accessed in July, 2018.
Notes: This table presents publication volume-adjusted proportions of highly cited articles published by different journals. Adjusted proportions are calculated according to equation (2).
Definition of journal abbreviations in order of appearance: *QJE–Quarterly Journal of Economics*, *JEL–Journal of Economic Literature*, *JEP–Journal of Economic Perspectives*, *JEG–Journal of Economic Growth*, *JPE–Journal of Political Economy*, *ECMA–Econometrica*, *AER–American Economic Review*, *ReStud–Review of Economic Studies*, *ReStat–Review of Economics and Statistics*, *ICC–Industrial and Corporate Change*, *RAND–Rand Journal of Economics*, *JOLE–Journal of Labor Economics*, *JBES–Journal of Business and Economic Statistics*, *EJ–Economic Journal*, *JHE–Journal of Health Economics*, *WBER–World Bank Economic Review*, *JOE–Journal of Econometrics*, *JDE–Journal of Development Economics*, *JME–Journal of Monetary Economics*, *JPub–Journal of Public Economics*, and *JEEA–Journal of the European Economic Association*.

table O-A34). The two-year impact factors for any of the six leading journals listed in that table exceed those of any economics journal. *Science* is ranked fourth, with two- and five-year impact factors around 41. Also notable is the *Proceedings of the National Academy of Sciences*—an outlet in which many important papers by economists have appeared, but which is off the table in T5 assessments. Its impact factor rivals the highest ranked journal economics impact factor.

4.4 *Where Influential Economists Publish*

This subsection explores where influential economists publish classified by their field of specialization. We use RePEc's field-specific author rankings to compile a list of the

TABLE 4
2, 5, 10, 15, and 20 Year Impact Factors for 25 Economics Journals Constructed Using Citations Data from 2017, Ordered by 5 Year Impact Factor

	2 Year IF		5 Year IF		10 Year IF		15 Year IF		20 Year IF	
	Rank	IF	Rank	IF	Rank	IF	Rank	IF	Rank	IF
1. *Quarterly Journal of Economics*	1	(8.57)	1	(12.80)	2	(15.53)	1	(18.62)	1	(20.11)
2. *Journal of Economic Perspectives*	2	(7.21)	2	(10.82)	4	(11.52)	4	(11.91)	5	(11.03)
3. *Journal of Economic Literature*	11	(4.29)	3	(9.91)	1	(17.24)	2	(17.13)	2	(18.60)
4. *Journal of Finance*	5	(5.54)	4	(9.38)	3	(11.98)	3	(13.99)	3	(15.04)
5. *Journal of Financial Economics*	6	(5.53)	5	(8.11)	5	(10.54)	5	(11.53)	4	(11.97)
6. *American Economic Review*	9	(4.63)	6	(6.53)	9	(7.41)	10	(8.04)	9	(8.25)
7. *Review of Financial Studies*	10	(4.45)	7	(6.27)	6	(9.39)	7	(9.49)	8	(9.32)
8. *Journal of Economic Growth*	4	(6.17)	8	(6.15)	12	(6.07)	9	(8.93)	10	(8.23)
9. *Journal of Political Economy*	8	(5.08)	9	(6.09)	7	(8.48)	6	(10.09)	6	(10.75)
10. *American Economic Journal: Applied Economics*	7	(5.42)	10	(6.08)	—	(.)	—	(.)	—	(.)
11. *Review of Economic Studies*	20	(3.12)	11	(6.03)	11	(6.42)	12	(7.00)	12	(7.14)
12. *Econometrica*	14	(3.87)	12	(5.94)	8	(7.86)	8	(9.25)	7	(9.69)
13. *Review of Economics and Statistics*	15	(3.64)	13	(5.55)	10	(6.81)	11	(7.62)	11	(7.31)
14. *American Economic Journal: Economic Policy*	12	(3.99)	14	(5.51)	—	(.)	—	(.)	—	(.)
15. *Journal of Human Resources*	3	(6.86)	15	(5.11)	13	(5.89)	15	(5.33)	15	(4.90)
16. *American Economic Journal: Macroeconomics*	17	(3.45)	16	(4.83)	—	(.)	—	(.)	—	(.)
17. *Journal of the European Economic Association*	21	(3.04)	17	(4.70)	17	(4.82)	—	(.)	—	(.)
18. *Journal of Labor Economics*	13	(3.88)	18	(4.62)	14	(5.14)	14	(5.33)	13	(5.21)
19. *Economic Journal*	19	(3.27)	19	(4.27)	15	(5.01)	13	(5.41)	14	(5.11)
20. *Journal of Health Economics*	16	(3.49)	20	(4.00)	18	(4.32)	19	(4.50)	22	(4.45)
21. *Journal of Development Economics*	23	(2.48)	21	(3.89)	16	(4.90)	16	(4.90)	20	(4.53)
22. *Journal of Monetary Economics*	26	(2.24)	22	(3.27)	25	(3.51)	25	(3.86)	26	(3.83)
23. *Journal of Financial and Quantitative Analysis*	27	(2.22)	23	(3.23)	19	(4.25)	18	(4.60)	16	(4.63)
24. *Journal of Applied Econometrics*	24	(2.46)	24	(3.16)	23	(3.83)	23	(4.15)	17	(4.59)
25. *Industrial and Corporate Change*	25	(2.35)	25	(3.08)	22	(3.91)	20	(4.47)	19	(4.58)

Source: Scopus; Accessed in July, 2018.
Notes: This table presents two-, five-, ten-, 15-, and 20-year impact factors for 25 different journals. Impact factors are calculated using citations accrued during the year 2017. The table also presents five different journal rankings corresponding to each of the five impact factors. Due to data unavailability, we exclude the *AEJ*s from the ten-, 15-, and 20-year impact factor calculations and rankings. We also exclude *JEEA* from the 15- and 20-year impact factor calculations and rankings.
Definition of impact factor*:* For any given journal, an x-year impact factor as of 2017 is defined as the sum of citations received in 2017 by all articles published in the journal during the time period $2016 - x$ to 2016 divided by the journal's total volume of publications during the same time period:

$$IF_{x,j}^{2017} = \sum_{y=2016-x}^{2016} \frac{citations_{y,j}^{2017}}{volume_j},$$

where $citations_{y,j}^{2017}$ represents the sum of citations received in 2017 by all articles published by journal j during year y, and $volume_j$ represents journal j's total volume of publication during the period $2016 - x$ to 2016.

50 most influential authors[58] within 14 fields of specialization.[59] We analyze their publication histories to identify the journals that account for the largest share of publications by the T50 authors of each field.

We use EconLit to obtain lists of articles published by each author between 1996–2017. We use the classification scheme of Card and DellaVigna (2013) to assign articles to different fields based on *JEL* codes included in the EconLit data.[60] The assignment yields 14 different publication lists corresponding to the 14 field-specific author groupings, where each publication list is restricted to only include journal articles that were identified as being related to the author's field of specialization.

Online appendix table O-A40 presents publication-volume-unadjusted field-specific journal rankings based on the share of field *f*-specific articles written by field *f*'s T50 authors that was published in each journal *j*. The table presents rankings for the ten journals that accounted for the largest share of publications. The rankings show that the top authors in each field publish the largest volume of their field-specific publications in either the *AER* or in non-T5 specialist field journals. The remaining four T5 journals do not feature in the top three for any field, except *ECMA* which ranks third in econometrics and microeconomics. These patterns reveal that the foremost economists working in the major fields of specialization within economics publish most of their articles in non-T5 field journals.

The importance of non-T5 field journals becomes even more pronounced when we rank journals by publication shares that have been adjusted for inter-journal differences in volume of publication.[61] The publication volume-adjusted rankings in table 5 show that once one adjusts for differences in publication volumes, the T5 journals account for a considerably smaller share of field-specific articles published by the T50 authors of each field. The difference between the adjusted and unadjusted rankings stems largely from differences in rankings assigned to *AER*. The rank of the *AER* declines considerably. Rankings for the non-*AER* T5 journals are fairly stable across the ranking methods. Table 6 ranks journals based on how well they are cited by the top two leading journals within the different fields. The T5 fare a little better, but the non-T5 still dominate.

4.5 *The Forgotten (by the Top 5) Classics*

The T5 excludes many influential papers. Figures 15(a) and 15(b) show that papers pub-

[58] Online appendix tables O-A43–O-A46 present the list of top 50 authors within each field. The fields of finance and industrial organization include fewer than 50 authors because RePEc's ranking for these fields included fewer than 50 authors.

[59] The fields include demographic economics, development economics, econometrics, environmental economics, experimental economics, finance, health economics, international finance, international trade, industrial organization, labor economics, macroeconomics, microeconomics, and public economics.

[60] We make the following changes to Card and DellaVigna's (2013) classification scheme: (i) We break out the labor economics category into labor (*JEL* codes I2 and J except J1), and demographic economics (*JEL* code J1); (ii) environmental economics is added as a field (*JEL* code Q5); (iii) international economics is broken out into international finance (*JEL* codes F3, F4, and F65) and international trade (*JEL* codes F1 and F4); and (iv) urban economics is removed from the health and urban economics category to yield a health-only category (*JEL* code I0 and I1). The rest of the fields are classified identically to Card and DellaVigna (2013).

[61] Table 5 presents weighted rankings based on a field *f*-specific volume-adjusted proportion, $\tilde{S}_j^f$:

$$\tilde{S}_j^f = \frac{1}{N^f} \sum_{y=1996}^{2017} C_{j,y}^f / \left(\frac{v_{j,y}}{V_y}\right), \tag{3}$$

where N^f is the total number of field *f*-specific articles published by field *f*'s T50 authors over the period 1996–2010, $C_{j,y}^f$ is the total number of field *f*-specific articles published by field *f*'s T50 authors in journal *j* during year y, $v_{j,y}$ is the total number of articles published by journal *j* during year y, and $V_y = \sum_{j \in \mathcal{J}} v_{j,y}$ is the total number of articles published during year y by all journals *j* that published articles by field *f*'s T50 authors over the period 1996–2017.

TABLE 5
Journals That Account for Largest Share of **Field-Specific Publications**, 1996–2017 by RePEc's Top 50 Authors within Different Fields (Adjusted for Publication Volume)

Rank.	dem	dev	ecmt	env	exp	fin	health
1.	AEJae	JEG	JOE	IntRevEnvResEc	ExpEc	JOF	JHE
2.	JOLE	WBRschObs	EctT	REnvEcPol	JEcMeth	JFE	AmJHealEc
3.	JPop	WBER	JBES	EnvEcPol	JRU	ReFin	HE
4.	JHR	EDCC	**ECMA**	JEnvEcMgmt	AEJmi	WBRschObs	**AER**
5.	CES	JDE	EctJ	EnvDevEc	JEBO	JFinInterm	EcHumBio
6.	**AER**	JAfrEc	EctRev	ResEnerEc	RevEcDsgn	JFinMkt	JHumCap
7.	JEG	**QJE**	JAE	JEL	**AER**	RevFin	JHR
8.	JHumCap	FrntEcChn	JFinEcmt	ClmChgEc	GAMES	WBER	FormHeaEcPol
9.	LabEc	**AER**	OxES	EnvResEc	SthEcJ	JFinEcmt	WBRschObs
10.	JDemEc	JEL	ReStat	OxRevEcPol	NZEcPap	JPortMgmt	**QJE**

Rank.	intFin	intTr	IO	labor	macro	micro	pubEcon
1.	EcPol	JIE	RAND	JOLE	BPEA	**ECMA**	NTJ
2.	JIntComEcPol	EcPol	JInE	BPEA	JME	**ReStud**	ITPF
3.	JIMF	WrldTrdRev	IJIO	**AER**	**AER**	RAND	FiscSt
4.	IntJFinEc	WrldEc	InfEcPol	ILR	JMCB	JET	JPub
5.	JIE	RevWrldEc	JEMS	LabEc	AEJma	**JPE**	EcPol
6.	BPEA	**AER**	RevIO	**QJE**	FedSTLRev	**QJE**	AEJep
7.	IntFin	IEJ	JEEA	IndRel	IntJCentrBank	JEEA	FinanzArchiv
8.	OpEcRev	**QJE**	EcPol	EducEc	FrntEcChn	**AER**	CES
9.	JJapIntEc	RevIntEc	JIndCmpTr	JEL	**JPE**	GAMES	**AER**
10.	IMFEcRev	Empirica	**AER**	JHR	EcPol	RschInEc	PubFinRev

Sources: RePEc, EconLit.
Notes: Adjusted proportions are calculated according to equation (3).
Definition of journal abbreviations, alphabetical: *AEJae–American Economic Journal: Applied Economics*; *AEJep–American Economic Journal: Economic Policy*; *AEJma–American Economic Journal: Macroeconomics*; *AEJmi–American Economic Journal: Microeconomics*; *AER–American Economic Review*; *AmJHealEc–American Journal of Health Economics*; *BPEA–Brookings Papers on Economic Activity*; *CES–CESifo Economic Studies*; *ClmChgEc–Climate Change Economics*; *EcHumBio–Economics and Human Biology*; *ECMA–Econometrica*; *EcPol–Economic Policy*; *EctJ–Econometrics Journal*; *EctRev–Econometric Reviews*; *EctT–Econometric Theory*; *EDCC–Economic Development and Cultural Change*; *EducEc–Education Economics*; *EJ–Economic Journal, Empirica–Empirica*; *EnvDevEc–Environment and Development Economics*; *EnvEcPol–Environmental Economics and Policy Studies*; *EnvResEc–Environmental and Resource Economics*; *ExpEc–Experimental Economics*; *FedSTLRev–Federal Reserve Bank of St. Louis Review*; *FinanzArchiv–FinanzArchiv*; *FiscSt–Fiscal Studies*; *FormHeaEcPol–Forum for Health Economics and Policy*; *FrntEcChn–Frontiers of Economics in China*; *GAMES–Games and Economic Behavior*; *HE–Health Economics*; *IEJ–International Economic Journal*; *IJIO–International Journal of Industrial Organization*; *ILR–Industrial and Labor Relations Review*; *IMFEcRev–IMF Economic Review*; *IndRel–Industrial Relations*; *InfEcPol–Information Economics and Policy*; *IntFin–International Finance*; *IntJCentrBank–International Journal of Central Banking*; *IntJFinEc–International Journal of Finance and Economics*; *IntRevEnvResEc–International Review of Environmental and Resource Economics*; *ITPF–International Tax and Public Finance*; *JAE–Journal of Applied Econometrics*; *JAfrEc–Journal of African Economies*; *JBES–Journal of Business and Economic Statistics*; *JDE–Journal of Development Economics*; *JDemEc–Journal of Demographic Economics*; *JEBO–Journal of Economic Behavior and Organization*; *JEcMeth–Journal of Economic Methodology*; *JEEA–Journal of the European Economic Association*; *JEG–Journal of Economic Growth*; *JEL–Journal of Economic Literature*; *JEMS–Journal of Economics and Management Strategy*; *JEnvEcMgmt–Journal of Environmental Economics and Management*; *JET–Journal of Economic Theory*; *JFinEcmt–Journal of Financial Econometrics*; *JFinServRes–Journal of Financial Services Research*; *JHE–Journal of Health Economics*; *JHR–Journal of Human Resources*; *JHumCap–Journal of Human Capital*; *JIE–Journal of International Economics*; *JIMF–Journal of International Money and Finance*; *JIndCmpTr–Journal of Industry, Competition and Trade*; *JInE–Journal of Industrial Economics*; *JIntComEcPol–Journal of International Commerce, Economics and Policy*; *JJapIntEc–Journal of the Japanese and International Economies*; *JLawEcOrg–Journal of Law, Economics, and Organization*; *JMCB–Journal of Money, Credit and Banking*; *JME–Journal of Monetary Economics*; *JOE–Journal of Econometrics*; *JOLE–Journal of Labor Economics*; *JPE–Journal of Political Economy*; *JPop–Journal of Population Economics*; *JPub–Journal of Public Economics*; *JRU–Journal of Risk and Uncertainty*; *LabEc–Labour Economics; NTJ–National Tax Journal*; *NZEcPap–New Zealand Economic Papers*; *OpEcRev–Open Economies Review*; *OxES–Oxford Bulletin of Economics and Statistics*; *OxRevEcPol–Oxford Review of Economic Policy*; *PubFinRev–Public Finance Review*; *QJE–The Quarterly Journal of Economics*; *RAND–RAND Journal of Economics*; *REnvEcPol–Review of Environmental Economics and Policy*; *ResEnerEc–Resource and Energy Economics*; *ReStat–The Review of Economics and Statistics*; *ReStud–Review of Economic Studies*; *RevEcDsgn–Review of Economic Design*; *RevIntEc–Review of International Economics*; *RevIO–Review of Industrial Organization*; *RevWrldEc–Review of World Economics*; *RschInEc–Research in Economics*; *SthEcJ–Southern Economic Journal*; *WBER–World Bank Economic Review*; *WBRschObs–World Bank Research Observer*; *WrldEc–World Economy*; *WrldTrdRev–World Trade Review*.

TABLE 6
Journals That Received the Highest Number of Citations from Articles Published 2010–17 in the Top 2 Journals within Different Fields of Specialization (Rankings Use Citations to Articles Published 1996–2017; Rankings Are Adjusted for Publication Volume of Cited Journal)

Ranking	T5	dev	ecmt	fin	health
1	**QJE**	**QJE**	**ECMA**	JOF	JHE
2	**ECMA**	JEG	JOE	JFE	HE
3	**JPE**	JDE	EctT	ReFin	**QJE**
4	**AER**	JEL	JBES	**QJE**	JHR
5	**ReStud**	WBER	JAE	**JPE**	JEL
6	JEL	**JPE**	AnnStat	JFQA	**JPE**
7	JEP	**ReStud**	EctRev	JAccEc	JEP
8	JET	**AER**	EctJ	JFinMkt	ReStat
9	ReStat	ReStat	**ReStud**	JFinInterm	**AER**
10	BPEA	AEJae	JASA	FoundTrFin	HtlhServRes

Ranking	IO	labor	macro	micro	pubEcon
1	RAND	JOLE	JME	**ECMA**	**QJE**
2	JInE	**QJE**	**JPE**	JET	JPub
3	**JPE**	JHR	JMCB	GAMES	**JPE**
4	**ReStud**	**JPE**	**QJE**	**ReStud**	JEL
5	JEMS	JEL	**AER**	IJGT	**AER**
6	IJIO	AEJae	RED	**QJE**	**ReStud**
7	**QJE**	ReStat	AEJma	**JPE**	AEJep
8	**ECMA**	**ECMA**	BPEA	EcT	**ECMA**
9	**AER**	**AER**	JOF	**AER**	ExpEc
10	JLawEcon	**ReStud**	**ReStud**	SocChWelf	JEP

Source: Scopus; Accessed in August, 2018.

Notes: This table presents a publication volume-adjusted (volume of cited journal) ranking of journals that received the highest citations from the top two field journals in nine different fields of specialization. The nine fields used in this table are the same ones used in our analysis of work-history data and categorized in table O-A9. Construction of the ranking proceeds in three steps. First, the top two journals in a field is defined as being composed of the two journals that received the highest rank within the field in Combes and Linnemer's (2010) field-specific rankings (the column titled "Tier A Field" in table O-A9 presents the top two journals by field). Second, publication volume-weighted proportions of outgoing citations from the top 2 field journals are calculated for each journal that received citations from articles published by the top two field journals in 2017, where the volume adjustment is made with respect to the yearly publication volume of the journals that received citations from the top two field journals. The proportions only use citations to articles published between 1996–2017 due to data unavailability for the pre-1996 period. Third, journals are ranked within a field based on field-specific outgoing proportions constructed in step 2. This table uses field-specific proportions constructed in steps 1–3 to present the ten journals that received the largest proportion of citations from the top two journals of each field.

Definition of journal abbreviations, alphabetical: *AEJae–American Economic Journal: Applied Economics*; *AEJep–American Economic Journal: Economic Policy*; *AEJma–American Economic Journal: Macroeconomics*; *AER–American Economic Review*; *AnnStat–Annals of Statistics*; *BPEA–Brookings Papers on Economic Activity*; *ECMA–Econometrica*; *EcT–Economic Theory*; *EctJ–Econometrics Journal*; *EctRev–Econometric Reviews*; *EctT–Econometric Theory*; *ExpEc–Experimental Economics*; *FoundTrFin–Foundations and Trends in Finance*; *GAMES–Games and Economic Behavior*; *HE–Health Economics*; *HtlhServRes–Health Services Research*; *IJGT–International Journal of Game Theory*; *IJIO–International Journal of Industrial Organization*; *JAE–Journal of Applied Econometrics*; *JASA–Journal of the American Statistical Association*; *JAccEc–Journal of Accounting and Economics*; *JBES–Journal of Business and Economic Statistics*; *JDE–Journal of Development Economics*; *JEG–Journal of Economic Growth*; *JEL–Journal of Economic Literature*; *JEMS–Journal of Economics and Management Strategy*; *JEP–Journal of Economic Perspectives*; *JET–Journal of Economic Theory*; *JFE–Journal of Financial Economics*; *JFQA–Journal of Financial and Quantitative Analysis*; *JFinInterm–Journal of Financial Intermediation*; *JFinMkt–Journal of Financial Markets*; *JHE–Journal of Health Economics*; *JHR–Journal of Human Resources*; *JInE–Journal of Industrial Economics*; *JLawEcon–Journal of Law and Economics*; *JMCB–Journal of Money, Credit and Banking*; *JME–Journal of Monetary Economics*; *JOE–Journal of Econometrics*; *JOF–Journal of Finance*; *JOLE–Journal of Labor Economics*; *JPE–Journal of Political Economy*; *JPub–Journal of Public Economics*; *QJE–Quarterly Journal of Economics*; *RAND–RAND Journal of Economics*; *RED–Review of Economic Dynamics*; *ReFin–Review of Financial Studies*; *ReStat–Review of Economics and Statistics*; *ReStud–Review of Economic Studies*; *SocChWelf–Social Choice and Welfare*; *WBER–World Bank Economic Review.*

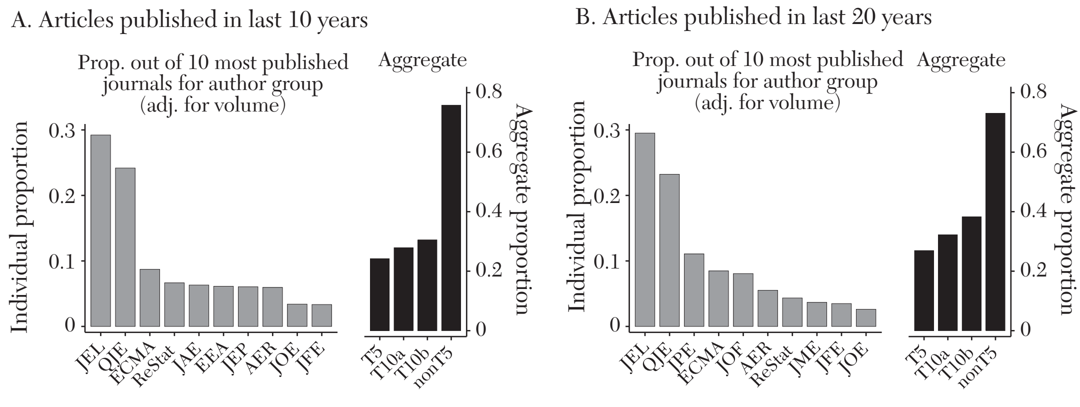

Figure 15. Proportion of RePEc's Most Cited Articles Published in Different Journals in the Last 10 and 20 Years (Adjusted for Publication Volume)

Source: RePEc.
Notes: The plot uses RePEc rankings for the top 1 percent of all economics articles over time to present the proportion of top cited articles that were published in different journals. Each subfigure is divided into an individual and aggregate journal section. The aggregate section presents the volume-adjusted proportions accounted for by (i) the T5, (ii) the T10a—the T10 according to Kalaitzidakis, Mamuneas, and Stengos (2003), (iii) the T10b—the T10 according to Kodrzycki and Yu (2006), and (iv) non-T5 journals. T10a includes the T5 and the *Journal of Economic Theory*, *Journal of Econometrics*, *Econometric Theory*, *Journal of Business and Economic Statistics*, and the *Journal of Monetary Economics*. T10b includes the T5 and the *Journal of Economic Theory*, *Journal of Econometrics*, *Journal of Finance*, *Journal of Financial Economics*, and the *Review of Financial Studies*. The labels in the horizontal axis correspond to: *JEL—Journal of Economic Literature*, *QJE—Quarterly Journal of Economics*, *ECMA—Econometrica*, *ReStat—Review of Economics and Statistics*, *JAE—Journal of Applied Econometrics*, *EEA—Journal of the European Economic Association*, *JEP—Journal of Economic Perspectives*, *AER—American Economic Review*, *JOE—Journal of Econometrics*, *JFE—Journal of Financial Economics*, and *JME—Journal of Monetary Economics*.

lished in non-T5 journals account for more than 70 percent of RePEcs most-cited articles in the past ten and 20 years, respectively. Among the 20 most cited articles by RePEc, 35 percent were not published in the T5 (see table O-A49). The most cited non-T5 papers reads like an honor roll of economic analysis (see table 7, and tables O-A47–O-A48). Many classics have appeared outside the T5. The T5 ignores publication of books. Becker's *Human Capital* (1964) has more than four times the number of citations of any paper listed on RePEc.[62] The exclusion of books from citation warps incentives against broad and integrated research and toward writing bite-sized fragments.

In subfield after subfield this pattern is repeated. Truly innovative papers often do not survive the gauntlet of mainstream refereeing and editing that feature "normal science" and not "novel science."

5. *Openness and Incest*

Monopolies restrict welfare. Oligopolies do little better. Openness and entry promote productivity, innovation, and the introduction of new ideas. Card and DellaVigna (2013) document the decline in the number

[62] See table O-A50 for a sample of these neglected classics.

TABLE 7
20 Most Cited Non-T5 Articles in RePEc's Ranking of Most Cited Articles

	Author	Article name *Journal*	Pub Year	RePEc Rank	RePEc Cites
1.	Lucas, R. J.	"On the Mechanics of Economic Development" *Journal of Monetary Economics*	1988	5	4,249
2.	Blundell, R. Bond, S.	"Initial Conditions and Moment Restrictions in Dynamic Panel Data Models" *Journal of Econometrics*	1998	6	4,195
3.	Jensen, M. Meckling, W.	"Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure" *Journal of Financial Economics*	1976	7	4,145
4.	Johansen, S.	"Statistical Analysis of Cointegration Vectors" *Journal of Economic Dynamics and Control*	1988	8	3,939
5.	Bollerslev, T.	"Generalized Autoregressive Conditional Heteroskedasticity" *Journal of Econometrics*	1986	9	3,876
6.	Arellano, M. Bover, O.	"Another Look at the Instrumental Variable Estimation of Error-Components Models" *Journal of Econometrics*	1995	15	3,087
7.	Fama, E. French, K.	"Common Risk Factors in the Returns on Stocks and Bonds" *Journal of Financial Economics*	1993	19	2,760
8.	Calvo, G.	"Staggered Prices in a Utility-Maximizing Framework" *Journal of Monetary Economics*	1983	23	2,576
9.	Im, K. S. Pesaran, H. Shin, Y.	"Testing for Unit Roots in Heterogeneous Panels" *Journal of Econometrics*	2003	25	2,487
10.	Charnes, A. Cooper, W. Rhodes, E.	"Measuring the Efficiency of Decision Making Units" *European Journal of Operations Research*	1978	28	2,438

Source: RePEc. Accessed on May 19, 2017.

of T5 papers published because T5 journal space is fixed in supply and papers have become longer. They show that demand for journal space has increased greatly in the face of fixed supply.[63] This has created a more competitive environment. Thus, it is likely that the cost and effort going into getting into the T5 has increased. This might mean that the average quality of papers published has gone up. It might also mean that more valuable resources of time and effort are being devoted to tailoring papers to please a certain group of editors. Although we have no evidence to prove this, the incentives to do so are clear.

One consequence of increased effort required to gain access to T5 is that scholars who have good reputations would avoid the rat race because they can secure a large readership by posting papers in prominent working paper series. Indeed, citation to working papers has become more prominent because of their greater availability and currency.

[63] See online appendix figure O-A31.

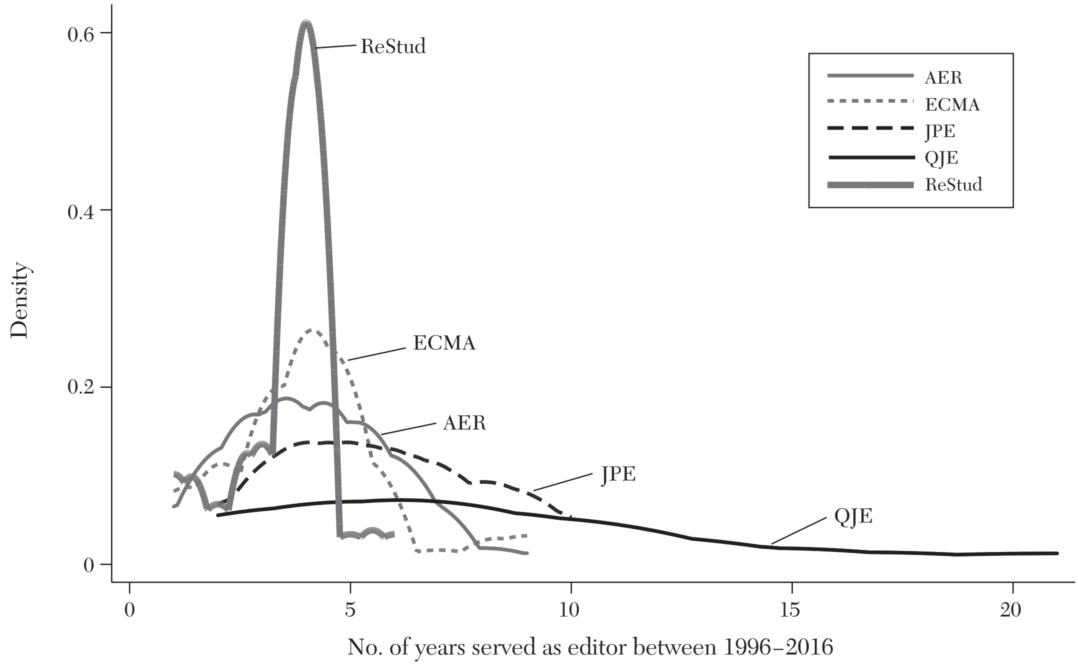

Figure 16. Density Plot for the Number of Years Served by Editors 1996–2016

Source: Brogaard, Engelberg, and Parsons (2014) for data until 2011. Data for subsequent years collected from journal front pages.
Note: The plot presents the density for the number of years served by editors of each journal between the years 1996 and 2016.

Publication lags documented by Card and DellaVigna (2013) diminish readership of published papers. Ellison (2011) documents that highly ranked scholars are placing fewer of their papers in the T5 journals.

Compounding the privately rational incentive to curry favor with editors is the phenomenon of longevity of editorial terms, especially at house journals. Professional associations generally limit the terms of editors. House journals have much looser limits. They retain editors with their special preferences for years. See figure 16. Long tenure for editors inevitably creates a culture around them, their interests, and their research styles. The basic economics of incentives suggests that prospective authors cultivate these editors and cater to their whims. Such clientele effects are an inevitable feature of any journal. Turnover of editors limits the harm in non-house journals. House journals are much less likely to foster turnover. Journals published by professional associations generally have more rapid turnover, although some of the journals published by the American Economic Association are exceptions to this rule.

Long term lengths inevitably incentivize incest and inbreeding. Table 8 estimates "incest coefficients" for the T5 journals.[64]

[64] Colussi (2018) conducts a similar analysis for the "top four" journals (T5 excluding *ReStud*) using citations data for the period 2000–2006. His estimates of inbreeding

TABLE 8
INCEST COEFFICIENTS: PUBLICATIONS IN TOP 5 BETWEEN 2000–2016 BY AUTHOR AFFILIATION LISTED DURING PUBLICATION

	AER			ECMA			JPE			QJE			ReStud		
	Count	%	% All	Count	%	% All	Count	%	% All	Count	%	% All	Count	%	% All
Universities:															
Chicago	266	14.7	7.7	70	12.8	6.8	90	23.8	14.3	103	20.8	15.4	25	7.4	3.5
Columbia	169	9.4	4.9	28	5.1	2.7	27	7.1	4.3	43	8.7	6.4	33	9.8	4.6
Harvard	412	22.8	11.9	58	10.6	5.7	55	14.6	8.7	165	33.3	24.7	26	7.7	3.7
MIT	255	14.1	7.3	75	13.7	7.3	47	12.4	7.5	93	18.8	13.9	33	9.8	4.6
NYU	153	8.5	4.4	53	9.7	5.2	37	9.8	5.9	39	7.9	5.8	52	15.4	7.3
Northwestern	135	7.5	3.9	94	17.2	9.2	36	9.5	5.7	33	6.7	4.9	50	14.8	7.0
Princeton	166	9.2	4.8	54	9.9	5.3	24	6.3	3.8	39	7.9	5.8	34	10.1	4.8
Stanford	245	13.6	7.1	75	13.7	7.3	42	11.1	6.7	62	12.5	9.3	33	9.8	4.6
UC, Berkeley	230	12.7	6.6	47	8.6	4.6	28	7.4	4.4	65	13.1	9.7	33	9.8	4.6
UPenn	162	9.0	4.7	48	8.8	4.7	38	10.1	6.0	26	5.3	3.9	46	13.6	6.5
Yale	134	7.4	3.9	88	16.1	8.6	23	6.1	3.7	33	6.7	4.9	22	6.5	3.1
UCL	53	2.9	1.5	39	7.1	3.8	15	4.0	2.4	11	2.2	1.6	32	9.5	4.5
University combination:															
Harvard/MIT	597	33.0	17.2	122	22.3	11.9	94	24.9	14.9	225	45.5	33.7	53	15.7	7.5
Total (Top Afil.)	1,807	100.0	52.0	546	100.0	53.4	378	100.0	60.0	495	100.0	74.2	337	100.0	47.5
Total (Non-Top Afil.)	1,667	n/a	48.0	476	n/a	46.6	252	n/a	40.0	172	n/a	25.8	373	n/a	52.5
Total (Top and Non-Top)	3,474	n/a	n/a	1,022	n/a	n/a	630	n/a	n/a	667	n/a	n/a	710	n/a	n/a

Source: Elsevier, Scopus.com.
Note: This table reports three columns for each T5 journal. The left-most columns report the number of articles that were affiliated to each university. The middle columns present the percentage of articles published in the journal that were affiliated to the university out of all articles affiliated to the listed top universities. The right-most columns present the percentage of articles published in the journal that were affiliated to the university out of all articles published in the journal. An author is defined as being affiliated with a university during a given year if he/she listed the university as an affiliation in any publication that was made during that specific year. An article is defined as being affiliated with a university during a specific year if at least one author was affiliated to the university during the year.

The table documents the percentage of publications in the period 2000–2016 made by the top ten US departments as assessed by the US News rankings of economics departments,[65] plus New York University (ranked thirteenth) and University College London (not ranked by the US News). The percentages shown are those attributed to scholars affiliated with a particular university for each T5 journal. The *JPE* has a high incest coefficient—14.3 percent for Chicago affiliates; the non-house-affiliated *AER* has a relatively high incest coefficient for Harvard faculty who account for 11.9 percent of its publications.[66] Most conspicuous is the *QJE* with a 24.7 percent incest coefficient for Harvard affiliates and a 13.9 percent coefficient for MIT affiliates (the combined incest coefficient is over 33 percent).[67,68]

Tenure committees abdicate their responsibilities if they rely too strongly on T5 publications in making their decisions. They effectively delegate the task of candidate evaluation to editors of the T5. This leads to a potentially dangerous concentration of power in the hands of a few editors and leaves the discipline vulnerable to potential bias and corruption within T5 editorial systems.

5.1 *Corruption or Inside Information?*

A number of studies have attempted to determine if there is corruption in the editorial process of economics journals by examining the extent to which an article's chances of publication are affected by the presence of connections between the article's authors and journal editors. Analyzing data on 1,051 articles published in 1984 by 28 leading economics journals (T5 included), Laband and Piette (1994) find that articles with author–editor connections are indeed more likely to be published. However, on average, these articles also tend to attract higher citations. Brogaard, Engelberg, and Parsons (2014) find qualitatively similar results from their analysis of a more comprehensive sample of 50,000 articles published since 1955 by 30 top economics and finance journals. They estimate that authors publish twice as many papers in a journal when the journal is edited by a colleague, compared to periods when such department–editor networks do not exist. They also find that connected articles generate 5–25 percent

are lower than ours: Colussi (2018) finds that Harvard faculty account for 15 percent of *QJE* publications during the period 2000–2006, and Chicago faculty account for 10 percent of *JPE* publications. The differences in the magnitude of the estimates are due to: (i) differences in the publication periods considered (2000–2016 in our analysis versus 2000–2006 in Colussi 2018); and (ii) differences in strategies for assigning author affiliation (we assign affiliation based on institutional affiliation reported by the authors in their publications, whereas Colussi (2018) assigns affiliation based on employment data reported in authors' curriculum vitaes). The two assignment strategies can yield differing outcomes because the institution that a researcher is affiliated with when they complete their research (the affiliation picked up by our strategy) may be different from the institution where the researcher was hired when the work was eventually published (the affiliation picked up by matching date of publication with yearly employment data from CVs).

Despite differences in the magnitude of estimates, Colussi's (2018) results lead to the same conclusion: "*ECA* and the *AER* seem to be more open than the *QJE* and *JPE*, which show a bias toward authors appointed at their host institutions." The two sets of results thus complement each other by using different strategies, data sets, and time periods to arrive at the same mutually confirmed conclusion.

[65] The top ten departments are determined based on an average of US News department rankings for the years 2008, 2010, and 2015.

[66] Chicago faculty account for only 7.7 percent.

[67] Some papers have multiple authors at MIT and Harvard. Thus, some percentages do not sum up. Except for Harvard faculty at the *AER*, the percentages for the non-house journals show little evidence of favoritism.

[68] The relative high proportion of *AER* publications by Harvard faculty cannot be attributed to incest. Harvard faculty did not serve in the *AER* editorial board during the period being analyzed (see online appendix table O-A59). Indeed, the 11.9 percent figure might serve as a quality benchmark to down-weight the *QJE* incest coefficient.

more citations than unconnected articles on average. The authors of both studies conclude that their findings are suggestive of an underlying phenomenon whereby uncorrupt, article-impact-maximizing editors exploit their author connections to identify high-potential papers. They conjecture that heterogeneous access to information for connected and unconnected papers makes it less expensive for editors to identify high-potential papers written by authors within their network, which in turn has the effect of simultaneously increasing both the number and quality of published articles authored by individuals within their network.

While indicative of the overall fairness of the editorial process within the top journals of economics, the aggregate nature of these analyses prevent the studies from shedding light on the prevalence of editorial corruption within the T5—a small subsample of the journals analyzed by these studies. We are therefore none the wiser about corruption within the T5 and must continue to allow for its possible existence when evaluating the consequences of relying on the T5 to judge quality.

Despite the ambiguity regarding the prevalence and importance of corruption in T5 publishing, these results have important implications. If the explanations in the literature hold for the T5 journals, tenure-track faculty with connections to T5 editorial boards gain an advantage over colleagues who lack such networks. While this may be a fair practice from the perspective of an editor seeking to maximize article impact conditional on his/her information set, it would be unfair from the perspective of an unconnected author whose tenure outcome is closely tied to the T5 editor's decision which, if correctly conjectured, is biased against unconnected authors. Therefore, given the available evidence, one must allow for the possibility of strong network bias against tenure-track faculty who lack connections with T5 editors, regardless of whether such bias stems from blatant editorial corruption or from the above conjectured impact-maximizing behavior of editors who seek quality papers.[69]

Biases stemming from informational efficiencies associated with author-editor networks are inevitable. Out of sight, out of mind. Also relevant are the effects that an editor's ideological and methodological biases might have on editorial decisions. Such biases could operate both directly through the editor by affecting the manner in which the editor assesses and overrules referee reports, and indirectly by influencing the referees that editors select. In the presence of strong policy and/or methodology preferences, a journal will tend to disproportionately publish papers that exhibit the editor's preferred papers. Such biases could have profound effects on the health and future of the discipline, given the large dependence of tenure decisions on T5 publications.

First, any biases have a direct effect on the composition of tenured scholars by decreasing the chances of publishing in the T5 for tenure-track faculty who do not cater to editorial preferences. This will cause access to the T5 to be more limited for scholars outside the network, which mechanically decreases their tenure rates.

Second, strong editorial preferences might also have an additional indirect effect by inducing future tenure-track faculty to only pursue those types of research that have been known to be published by an editor's journal. Pursuing this strategy is individually

[69] Bertsimas et al. (2015) study the power of (short term) network connections in predicting future citations in operations research and management science. Their analysis implicitly documents the power of membership in networks. Membership in a network fosters more citations, but may also transmit knowledge. The evidence by Ellison (2011) that top scholars are relying more on internet posts suggests the power of incumbency and points to the value of a PLOS system. See Eisen (2013).

rational but socially irrational. Reliance on the T5 influences the course of future research.

6. *Summary and Discussion*

Without doubt, publication in the top five is a powerful determinant of tenure in academic economics that influences the choices of topics on which young economists work, and squeezes papers into bite-sized journal-friendly fragments. One of us (Heckman) has had numerous conversations over the years with first-rate graduate students, postdoctoral fellows, and assistant professors about scientifically interesting research projects, only to be told:

> *"That is a great idea, but it will not lead to a top five."*

An emphasis on publishing in the T5 discourages large-scale, data-intensive empirical projects that explore and report the sensitivity of estimates to alternative assumptions. The fruits of such projects are often too long and do not easily fit into the format of the 40-page limit imposed by most of the T5 journals.

Reliance on the T5 centralizes power to shape the profession into the hands of a select group of editors. Relying on the T5 to screen the next generation of economists incentivizes professional incest and creates incentives for clientele effects, whereby career-oriented authors appeal to the tastes of editors and the various biases of journals. It raises entry costs for new ideas and persons outside the orbits of the journals and their editors.[70]

The current practice has weak empirical support if judged by its ability to produce papers that last in terms of citation counts. Publication in the T5 is claimed to demonstrate the appeal of a paper to a broad base of professional economists assuming (without evidence) that subscribers read issues of journals cover to cover. The argument also ignores the fact that T5 referees are themselves field specialists, and field journals are highly influential outlets. Moreover, the T5 journals do not have the highest impact factors even among economics journals, never mind general interest journals. Many non-T5 journals have citation counts that rival T5 journals, especially the lower-cited ones, such as the *Review of Economic Studies* or *Econometrica*. Academics who impose the T5 standard impose a standard that they themselves do not follow. They primarily publish in, read, and cite non-T5 journals, as will the candidates who survive the T5 filter and become tenured faculty.

Reliance on the T5 as a screening device raises serious concerns. First, an overemphasis on T5 publications perversely incentivizes scholars to pursue follow-up and replication work at the expense of creative pioneering research, since follow-up work is easy to judge, is more likely to result in clean publishable results, and hence is more likely to be published.[71] This behavior is consistent with basic common sense: you get what you incentivize.

In light of the many adverse and potentially severe consequences associated with reliance on the T5, we believe it unwise for the discipline to continue using publication in the T5 as a measure of research achievement and as a predictor of future scholarly

[70] Many readers of earlier drafts of this paper have remarked to us that the empirical results in this paper do not strictly prove these factors are operative. We grant this point. At the same time, we ask readers to apply the standard analysis of incentives to the "market" we have described. To deny the power and direction of these incentives is to assume an unlikely level of saintliness among journal editors and the scholars seeking to publish in their journals.

[71] See the discussion at https://www.aeaweb.org/webcasts/2017/curse.

potential. The need for change is made ever more apparent by the T5's inadequacy as a predictor of individual article quality, much less the quality of a person. It also has an apparent gender tilt.

Our findings should spark a serious conversation in the profession about how to develop implementable alternatives to judge quality research. Such solutions would necessarily need to de-emphasize the role of the T5 in tenure and promotion decisions, and redistribute the signalling function among more high-quality journals.[72] For example, there is limited evidence that *AEJ: Applied Economics* competes favorably with *ReStat* and *EJ*.

However, a proper solution to the tyranny of the T5 will likely involve much more than a simple redefinition of the T5 to include a handful of additional influential journals. A better solution would address the flaw that is inherent in the practice of judging a scholar's potential for innovative work based on a track record of publications in a handful of journals selected by their impact factors.

In this issue, Akerlof (2020) sounds the alarm about the practice of relying on external rankings rather than individual reading of papers. The appropriate solution to the problem will require a significant shift from the current publications-based system of deciding tenure, to a system that emphasizes departmental peer review of a candidate's work. Such a system would give serious consideration to unpublished working papers and the quality and integrity of a scholar's work. By closely reading published and unpublished papers rather than counting placements of publications, departments would signal that they both acknowledge and adequately account for the greater risk associated with serious scholars working at the frontiers of the discipline—an endeavor that is more likely to result in unpublished working papers chock-full of good ideas rather than T5 publications, compared to other more conventional and safer forms of research.[73]

A more radical proposal is to shift publication away from the current fixed format journals and toward an open source arXiv or PLOS ONE format.[74] Such formats facilitate dissemination of new ideas and provide online realtime peer review for them. Discussion sessions would vet criticisms and provide both authors and their readers with different perspectives. Shorter, more focused papers would stimulate dialogue and break editorial and journal monopolies. An open source system would also allow authors to test new ideas in an arena of serious professional discussion and enable entry into the profession of creative out-of-network scholars. Networks and network-referential-citation circles are powerful barriers to entry into the profession that screen out new entrants with "oddball" ideas and isolates those not acculturated in T5 values. Citing Ellison (2011) again, online publication is already being practiced by senior scholars. Why not broaden the practice and encourage spirited dialogue and rapid dissemination of new ideas?

In any event, the profession should deemphasize crass careerism and promote creative activity. Short tenure clocks and

[72] Due to their limited time in operation, we excluded the four new journals created by the American Economic Association in many of our analyses: *American Economic Journal: Microeconomics*; *American Economic Journal: Macroeconomics*; *American Economic Journal: Economic Policy*; and *American Economic Journal: Applied Economics*.

[73] Some readers have objected that such a procedure would be too time intensive and would require many to read out of their subfields. Others say that "quality" is a subjective thing. These objections go to the core of why economics departments exist if evaluating the work of a colleague is an onerous task. It is a symptom of departments that are collections of isolated scholars rather than a group that learns from fellow members.

[74] See Vale (2015) for a discussion of the use of arXiv in physics. See Eisen (2013) for remarks on PLOS ONE by Michael Eisen, its cofounder.

reliance on the T5 to certify quality do just the opposite.

The importance of tolerating early failure and accounting for both the end product and the path to production is illustrated in the analysis of Manso (2011), who studied optimal incentive schemes for motivating innovation. Distinguishing between activities that *explore* new untested actions and those that *exploit* well-known actions, Manso (2011) shows that schemes aiming to promote *exploratory* activities should design reward structures to adjust for the higher variation associated with payoffs from such activities. Azoulay, Graff Zifin, and Manso (2011) test this hypothesis on a sample of high-ability biomedical researchers by comparing the publication outcomes of HHMI (Howard Hughes Medical Institute) grantees who enjoy more flexible and tolerant review processes with the publication outcomes of NIH (National Institute of Health) grantees who are subject to "normal science" predefined deliverables, shorter review cycles, and grant renewal policies that are unforgiving of failure. They find that, controlling for selection bias, HHMI grantees published high-impact articles at a higher rate than NIH grantees. More importantly, HHMI grantees appeared more likely to engage in *exploratory* research, as suggested by a lower degree of overlap between the MeSH (Medical Subject Headers) keywords associated with works published during the pre- and post-grant periods.

In the long run, the profession will benefit from application of more creativity-sensitive screening of its next generation. Otherwise, academic economics risks becoming (or remaining) a group of top five plodders putting one foot in front of the other. Emphasis on the T5 in sorting talent creates a culture where vitae length and publication speed in select journals rather than the development of a body of coherent and original ideas is most valued. It incentivizes careerism rather than creative scholarship.

APPENDIX

1. *Estimating Probability of Receiving Tenure*

1.1 *Logit Analysis*

This subsection estimates logit models to predict the probability of tenure associated with publications in the four journal categories previously considered. We estimate logit models of the following form:[75]

$$\log\left(\frac{\Pr(Tenure_i = 1)}{1-\Pr(Tenure_i = 1)}\right) = \alpha_0 + \sum_{j\in\mathcal{J}}\left(\sum_{n=1}^{3}\alpha_j^n \cdot \mathbf{1}(\#j_i \geq n)\right) + \mathbf{X}\boldsymbol{\beta} + \overline{\mathbf{C}}\boldsymbol{\eta} + \varepsilon_i, \tag{4}$$

[75] For comparison, we also estimate linear probability models (LPM) that employ variable specifications that are identical to the specifications used in the logit estimations presented in this subsection. The logit and LPM estimates lead to qualitatively similar conclusions. The reader is referred to online appendix subsection 3.1 for LPM estimates.

where $Tenure_i$ is an indicator for receiving tenure by the end of the first spell of tenure-track employment; $\mathcal{J} = \{T5, TierA, TierB, General\}$; $\mathbf{1}(\#j_i \geq n)$ is an indicator for having n or more publications in journals of type j by the end of the first spell, where $j \in \mathcal{J}$; $\mathbf{X}$ is a vector of controls that includes a third degree polynomial for years of tenure-track experience, as well as controls for gender, quality of alma mater, department fixed effects, total number of unique coauthors across all articles published in the first spell, and a control for total volume of publications ln(#Total Publications + 1); and $\overline{\mathbf{C}}$ is a vector of statistics that summarizes the distribution of field-adjusted citations received by each author.[76]

Figure 3 plots average predicted probabilities of tenure associated with different numbers of publications in the four journal categories. The corresponding marginal effects are presented under the "Pooled" columns of the online appendix table O-A13.[77,78]

See online appendix subsection 3.3 for an analysis of the relationship between publications and the probability of receiving tenure by the seventh year of tenure-track employment.

2. *Duration Model*

2.1 *Tenure as a Single-Spell Multi-State Survival Process*

Let $S = \{0,1,2,3\}$ be the collection of relative employment states (relative to current state) that untenured tenure-track faculty can occupy in subsequent periods, where each state is defined in table 1 of the main text. Then, $S' = \{S\} \setminus \{s = 0\} = \{1,2,3\}$ is the collection of states that untenured tenure-track faculty are at risk of transitioning to in subsequent periods. The density of transition times from $s = 0$ to a state $s = k \in S'$ is governed by:

$$f_{0,k}(t_{0,k}) = h_{0,k}(t_{0,k}) \cdot \exp\left\{-\int_0^t h_{0,k}(u)\,du\right\}, \tag{6}$$

where $f_{0,k}$ is the density of exit times from $s = 0$ to $s = k$, and $h_{0,k}$ is the corresponding hazard function. The hazard $h_{0,k}(t_{0,k})$ is the probability of transitioning from $s = 0$ to $s = k$ in t given that transitions out of the current state $s = 0$ have not occurred prior to t (see equation (12) for formal definition).

The probability of transitioning to a particular state $k \in S'$ is given by:

$$P_{0,k} = \int_0^\infty h_{0,k}(t_{0,k}) \cdot \exp\left\{-\int_0^t \left[\sum_{s' \in S'} h_{0,s'}(u)\right] du\right\} dt, \tag{7}$$

[76] See footnote 29 in the main text for details.

[77] Online appendix table O-A10 presents comparable estimates of partial effects obtained from our LPM estimation. Results are qualitatively the same. The top five remains the most influential category by far. Compared to the LPM estimates, marginal effects from the Logit estimation have fewer significant estimates for non-top five categories.

[78] The predicted probability associated with $\hat{N}$ publications in journals of type-$\hat{J}$ is:

$$\Pr\left(Tenure = 1 \mid \#\hat{J} = \hat{N}, \#\tilde{J} = 0, \mathbf{X}\right) = \frac{\exp\left(\alpha_0 + \sum_{n=1}^{\hat{N}} \alpha_{\hat{J}}^n + \mathbf{X}\beta\right)}{1 + \exp\left(\alpha_0 + \sum_{n=1}^{\hat{N}} \alpha_{\hat{J}}^n + \mathbf{X}\beta\right)}, \tag{5}$$

where $\tilde{J} = \mathcal{J} \setminus \hat{J}$ represents the three non-$\hat{J}$ journal categories, and $\#\tilde{J} = 0$ is a condition setting publications in these non-$\hat{J}$ outlets to zero. The estimates represent the predicted probability of an individual receiving tenure with $\hat{N}$ publications in type-$\hat{J}$ journals, assuming that the individual has not published in any other type of journal $\tilde{J}$.

where the exponentiated term represents the probability of surviving from all risks $s' \in S'$ until period t, and $h_{0,k}(\cdot)$ is the transition-k specific hazard. The conditional density of exit times from $s = 0$ to $s = k$ given that no other transitions have occurred in the current spell of untenured tenure-track employment is given by:

$$(8) \qquad g_{0,k}\big(t \,|\, t < t_{0,k'}, \forall k' \in \{S'\} \setminus k\big) = \frac{h_{0,k}(t_{0,k}) \cdot \exp\big\{-\int_0^t \big[\sum_{s' \in S'} h_{0,s'}(u)\big]\,du\big\}}{P_{0,k}}.$$

It follows that the the density of exit times from $s = 0$ to any state $s \in S'$ equals:

$$(9) \qquad f_{0,S'}(t_{0,S'}) = \sum_{s \in S'} P_{0,s} \cdot g_{0,s}\big(t_{0,s} \,|\, t_{0,s} < t_{0,s'}, \forall s' \in \{S'\} \setminus s\big)$$

$$(10) \qquad = \Big[\sum_{s \in S'} h_{0,s}(t_{0,s})\Big] \cdot \exp\Big\{-\int_0^t \Big[\sum_{s \in S'} h_{0,s}(u)\Big]\,du\Big\},$$

where the first term within brackets is the hazard of exiting $s = 0$ to any state in S', and the exponentiated term is the probability that there were no transitions prior to period t in the current spell of untenured tenure-track employment. The probability of surviving from all causes $s \in S'$ up to time period T is given by the survival function:

$$(11) \qquad S_{0,S'}(t_{0,k}) = 1 - F_{0,S'}(t_{0,k}) = 1 - \int_0^T f_{0,S'}(t_{0,k})\,dt,$$

where $F_{0,S'}(t_{0,k})$ is the cumulative density of exit times to any state in S'. The survivor function is a useful quantity that allows us to represent the hazard of transitioning from $s = 0$ to $s = k \in S'$ as:

$$(12) \qquad h_{0,k}(t_{0,k}) = \Pr\big(t = t \,|\, T_{0,k'} > t, \forall k' \in S'\big) = \frac{f_{0,k}(t_{0,k})}{S_{0,S'}(t_{0,k})}.$$

Equation (12) expresses the hazard of transitioning to a new state $k \in S'$ during period t as the conditional probability of the transition occurring at t given that no other transitions having occurred prior to t in the current spell of untenured tenure-track employment.

To proceed, we represent the hazard function with a general Box–Cox parametrization, similar to Flinn and Heckman (1982). Equation (13) specifies the hazard as a function of current-spell duration, observable characteristics and unobserved individual heterogeneity:

$$(13) \qquad h_{0,k}(t_{0,k}) = \exp\Bigg\{\sum_{j \in \mathcal{J}} \Bigg(\sum_{n=1}^{3} \alpha_{0,k}^{j,n} \cdot \mathbf{1}\big(\#j(t_{0,k}) \geq n\big)\Bigg) + \mathbf{X}\boldsymbol{\beta}_{0,k} + \overline{\mathbf{C}}\boldsymbol{\eta}_{0,k}$$
$$+ \gamma_{1,0,k}\frac{\big(t^{\lambda_{1,0,k}} - 1\big)}{\lambda_{1,0,k}} + \gamma_{2,0,k}\frac{\big(t^{\lambda_{2,0,k}} - 1\big)}{\lambda_{2,0,k}} + V_{0,k}\Bigg\},$$

where $\mathbf{1}\big(\#j(t_{0,k}) \geq n\big)$ is an indicator for having n or more publications in journals of type j as of time period t; $\mathbf{X}$ is a vector that includes fixed effects for authors' academic department as well as observable characteristics including co-author characteristics including measures for relative seniority, gender, quality of authors' PhD granting institution as measured by departmental rankings, years since graduation, and a control for total volume of publications ln(#*Total Publications* + 1); $\overline{\mathbf{C}}$ is a vector of statistics that summarizes the distribution of field-adjusted citations received by each author;[79] $\lambda_{1,0,k} < \lambda_{2,0,k}$, $\gamma_{1,0,k}$ and $\gamma_{2,0,k}$ are duration parameters; and $V_{0,k} = \xi_{0,k} V$ is a one-factor specification for individual-level unobserved heterogeneity.

In practice, we estimate the hazard function using two special cases of the Box–Cox parametrization. Specifically, we estimate hazard functions with underlying survivor functions that follow the Weibull and exponential distributions. The Weibull hazard is obtained by setting $\lambda_{1,0,k} = 0$ and $\gamma_{2,0,k} = 0$:

$$(14) \quad h_{0,k}(t_{0,k}) = \exp\left\{\sum_{j\in\mathcal{J}}\left(\sum_{n=1}^{3}\alpha_{0,k}^{j,n}\cdot\mathbf{1}\big(\#j(t_{0,k}) \geq n\big)\right) + \mathbf{X}\boldsymbol{\beta}_{0,k} + \overline{\mathbf{C}}\boldsymbol{\eta}_{0,k} + V_{0,k}\right\} t^{\gamma_{1,0,k}}.$$

The Weibull model allows for monotonic duration dependence, where the sign of dependence is the same as $\gamma_{1,0,k}$. Setting $\gamma_{1,0,k} = 0$ and $\gamma_{2,0,k} = 0$ yields the exponential hazard. The exponential model assumes that there is no duration dependence, and that the baseline hazard is constant over time.

2.2 *Extensions to a Multi-Spell Setting*

We have thus far focused on a single-spell model for ease of exposition. In practice, our empirical analysis exploits information on multiple spells of untenured tenure-track employment to estimate a multi-spell version of the duration model. A spell of tenure-track employment is defined as an uninterrupted period of untenured employment in a tenure-track position at a top 35 department. A spell ends either when an individual receives tenure or when the individual exits the department. An individual enters a new spell of untenured tenure-track employment if they do not receive tenure at their initial department and transition to a new untenured tenure-track position in another top 35 department. An individual exits the study if they do not receive tenure at their initial department and exit to a lower-ranked department, move to an industry position, or transition to a non-tenure-track position in a top 35 department.

The extension to a multi-spell setting is straightforward. Equation (15) shows that an immediate generalization is obtained by allowing complete independence among parameters across the l different spells of untenured tenure-track employment:

$$(15) \quad h_{0,k}^{l}(t_{0,k}) = \exp\Bigg\{\sum_{j\in\mathcal{J}}\left(\sum_{n=1}^{3}\alpha_{0,k}^{j,n,l}\cdot\mathbf{1}\big(\#j(t_{0,k}) \geq n\big)\right) + \mathbf{X}\boldsymbol{\beta}_{0,k}^{l} + \overline{\mathbf{C}}\boldsymbol{\eta}_{0,k}^{l}$$
$$+ \gamma_{1,0,k}^{l}\frac{\left(t^{l^{\lambda_{1,0,k}^{l}}} - 1\right)}{\lambda_{1,0,k}^{l}} + \gamma_{2,0,k}^{l}\frac{\left(t^{l^{\lambda_{2,0,k}^{l}}} - 1\right)}{\lambda_{2,0,k}^{l}} + V_{0,k}^{l}\Bigg\}.$$

[79] See footnote 29 in the main text for details.

This model makes the assumption that the parameters associated with duration, observable characteristics, and unobservable heterogeneity are all independent across spells. In our empirical analysis, we impose restrictions on the parameters associated with observed author characteristics and department fixed effects, forcing the parameters $\boldsymbol{\beta}^l$ to be equal across spells. We further restrict the parameters on the publication variables $\alpha_{0,k}^{j,n,l}$ to be constant across spells. This restriction is equivalent to assuming that tenure committees maintain the same publication standards for all untenured faculty regardless of the spell of employment. The term $V_{0,k}^l = C_{0,k}^l V$ is a one-factor spell l-specific specification for unobserved heterogeneity which allows heterogeneity to vary across spells. Lastly, we introduce a parameter $\delta_{0,k}$ that captures potential dependence between survival times and the number of spells that an individual has experienced prior to the current spell. The aforementioned parameter restrictions yield the following hazard function that we use for our estimation:

$$(16)\quad h_{0,k}^l(t_{0,k}) = \exp\Bigg\{\sum_{j\in\mathcal{J}}\left(\sum_{n=1}^{3}\alpha_{0,k}^{j,n}\cdot\mathbf{1}\big(\#j(t_{0,k})\geq n\big)\right) + \mathbf{X}\boldsymbol{\beta}_{0,k} + \overline{\mathbf{C}}\boldsymbol{\eta}_{0,k} + \delta_{0,k}(l-1)$$
$$+ \gamma_{1,0,k}\frac{\left(t^{\lambda_{1,0,k}}-1\right)}{\lambda_{1,0,k}} + \gamma_{2,0,k}\frac{\left(t^{\lambda_{2,0,k}}-1\right)}{\lambda_{2,0,k}} + V_{0,k}^l\Bigg\},$$

where $V_{0,k}^l$ is spell-specific, and the remaining parameters are constant across spells.

2.3 *Heterogeneity in Hazard Rates by Department Rank*

To estimate rank-specific hazard ratios, we interact the publication variables in equation (16) with indicators for being employed by a department in one of the three rank-based groups:

$$(17)\quad h_{0,k}^l(t_{0,k}) = \exp\{\mathbf{Z}\}\times\exp\Bigg\{\left(\sum_{j\in\mathcal{J}}\sum_{n=1}^{3}\alpha_{0,k}^{j,n}\cdot\mathbf{1}\big(\#j(t_{0,k})\geq n\big)\right)$$
$$+\sum_{r=1}^{3}\mathbf{1}(i_t\in r)\times\left(\sum_{j\in\mathcal{J}}\sum_{n=1}^{3}\alpha_{j,r}^{n}\cdot\mathbf{1}\big(\#j(t_{0,k})\geq n\big)\right)\Bigg\},$$

where $\exp\{\mathbf{Z}\}$ represents the components of the hazard that are unrelated to publications, and $\mathbf{1}(i_t \in r)$ is an indicator for whether individual i was employed during t by a department belonging to rank group r.

Rank-specific hazard ratios are estimated by combining the relevant un-interacted publication parameters with the corresponding interacted parameters. The hazard ratio associated with publishing n top five articles in departments ranked 1–10 (rankgroup $r = 1$) is given by:

$$(18)\qquad \frac{h_{0,k}^l(t\,|\,\#T5_t = n, r = 1, \mathbf{X})}{h_{0,k}^l(t\,|\,\#T5_t = 0, r = 1, \mathbf{X})}.$$

Hazard ratios corresponding to other rank groups and journal categories are obtained by an analogous procedure.

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