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IZA DP No. 11868

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

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ABSTRACT

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

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 U.S. 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 Classification: A14, I23, J44, O31

Keywords: tenure and promotion practices, career concerns, economics publishing, citations

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* This research was supported by a grant from the Institute for New Economic Thinking to the Center for the Economics of Human Development. An early version of this analysis was presented in a round table, "The Curse of the Top Five," at the AEA meetings on January 7th, 2017. Participants included the authors, George Akerlof, Angus Deaton, Drew Fudenberg, and Lars Peter Hansen. For a video of the session, see https://www.aeaweb.org/webcasts/2017/curse. James Heckman receives compensation for his role as Editor at the Journal of Political Economy, which is one of the "Top Five" journals discussed in this paper. A conflict of interest management plan is in place in accordance with University of Chicago conflict of interest policies. We thank George Akerlof, Dan Black, Tom Ferguson, Jorge Luis García, Rob Johnson, Ganesh Karapakula, Rasmus Landersø, Meera Mody, Magne Mogstad, Tanya Rajan, and Harald Uhlig for comments. We thank Patrick Chen and Aakash Rao for outstanding research assistance.

Contents

1 Introduction

This paper examines how academic economics incentivizes young scholars and thereby shapes the values and goals of future generations of professional economists. Anyone who talks with young economists entering academia about their career prospects and those of their peers 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 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*, *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies*. These "general interest" journals publish papers on a broad range of topics. They are classified in the T5 based on aggregate proxies for 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 assesses 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

[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)

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 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.

At some level the case for relying on the T5 signal is strong. The profession has grown in size and has become more specialized. There is a demand for certification of quality which publication in the T5 is used to meet. Publication in a highly-rated general interest journal is considered a proxy for the likelihood that a candidate publishes highly cited general interest papers, although readership of a paper and subscribership of a journal are not the same. We establish in this paper that citation and publication in T5 journals are very different things.

The T5 standard has become increasingly difficult to attain. Card and DellaVigna (2013) document that the amount of space available in T5s 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 increased[5] with concomitant growth in rejection rates and delays in the refereeing process.[6] Editors now tend to use more referees than in the past. The acceptance rates at T5 journals declined from 15% in 1980 to 6% in 2012.[7]

Economists at highly ranked departments with established reputations are increasingly not publishing in T5 or field journals[8] and more often post papers online in influential working paper series, which are highly cited, but not counted as T5s. This 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

[3] See Table 7 of Gibson et al. (2014). Economics faculty in the University of California system experience salary penalties for not publishing in the T5.

[4] See Online Appendix Figure O-A30 for a summary of Card and DellaVigna (2013)'s data.

[5] Card and DellaVigna (2013)

[6] Ellison (2002)

[7] Card and DellaVigna (2013).

[8] Ellison (2011)

also raises some potentially worrisome problems, which this paper addresses.

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 U.S. between the years 1996-2010.[9] 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 370% 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 90% and 260% respectively, compared to those with the same number of non-T5 publications. The estimated effects of publication in non-T5 journals pale in comparison.

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. Faculty in lower ranked departments are able to achieve higher rates of tenure with the same number of T5 publications. Despite this heterogeneity, publishing in the T5 is the most effective means of improving one's chances of obtaining tenure regardless of department quality. The promotion and advancement power of the T5 in the top 35 U.S. economics departments is unquestionable.

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% or higher probability of attaining tenure in the first spell. It takes three for a

[9] The top 35 is assessed based on an average of the US News rankings assigned to economics departments during the years 2008, 2010, and 2015.

woman, but this is only a point estimate and standard errors are large.

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.[10] 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.[11] A substantial fraction of the 20 most cited RePEc papers were not published in the T5.[12] Controlling for citation counts measured ten or more years after tenure decisions were made, publication in the Top 5 remains a strong determinant of tenure probabilities and transition rates to tenure.

In principle, insisting that scholars publish in general interest journals works against the growing trend in academic economics toward specialization and Balkanization. However, the practice is organized hypocrisy. 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 received from 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 appraisers do not practice what they preach.

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. It is well-

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

[11] Akerlof (2018) 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`.

[12] 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."

documented that journals in economics tend to publish work by authors who are connected with the journal's editors (see Brogaard et al., 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.[13]

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.[14] The evidence on this issue is not conclusive, but it appears to favor the story of net benefits to insider knowledge. 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.[15]

The plan of the rest of this paper is as follows. Section 2 documents the power of the T5 in determining tenure and the time-to-tenure. Section 3 reports responses to a survey of junior faculty about current tenure and promotion practices. They confirm 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[16] to present background information and to report sensitivity analyses. We attach a within-text-Appendix to provide essential methodological details.

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

[14] 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 et al. (2014) estimate that authors publish 100% 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% more citations than unconnected articles on average.

[15] See Kapeller et al. (2017)

[16] See `http://heckman.uchicago.edu/publishing-and-promotion/appendix.pdf`

2 Empirical Evidence on the Potency of the Top Five

This section presents an extensive analysis of the empirical basis for the fears and expectations of young economists. We find that their expectations are generally correct and 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 4 conducts a parallel analysis excluding papers in finance. Our point estimates are barely affected. Under either allocation rule, 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 U.S. economics departments between the years 1996 and 2010. Panel data are constructed in four steps.[17] Online Appendix Section 1 describes the data construction in detail.

Tenure rates by the end of the first spell vary between 26% and 31% across the department groupings, and do not exhibit systematic differences with respect to department ranking.[18] Not surprisingly, substantial portions of junior faculty move downwards.[19] The incidence of lateral movement is highest among the top five departments with a rate of 21% and is lowest for departments ranked 26 to 35 with a rate of 6%. Conversely, upward

[17] 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 WayBackMachine; (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.

[18] See Online Appendix Table O-A4.

[19] The top 5 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 5 departments are unable to move upwards by definition, thereby restricting their outcome destinations to 4 options instead of 5.

movement and exits to industry are more common among lower ranked departments, and become less frequent for higher-ranked departments.[20] Tenure rates are considerably higher at the end of the second spell across all department rank groupings, with tenure rates ranging from 34% to 54%.[21,22]

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

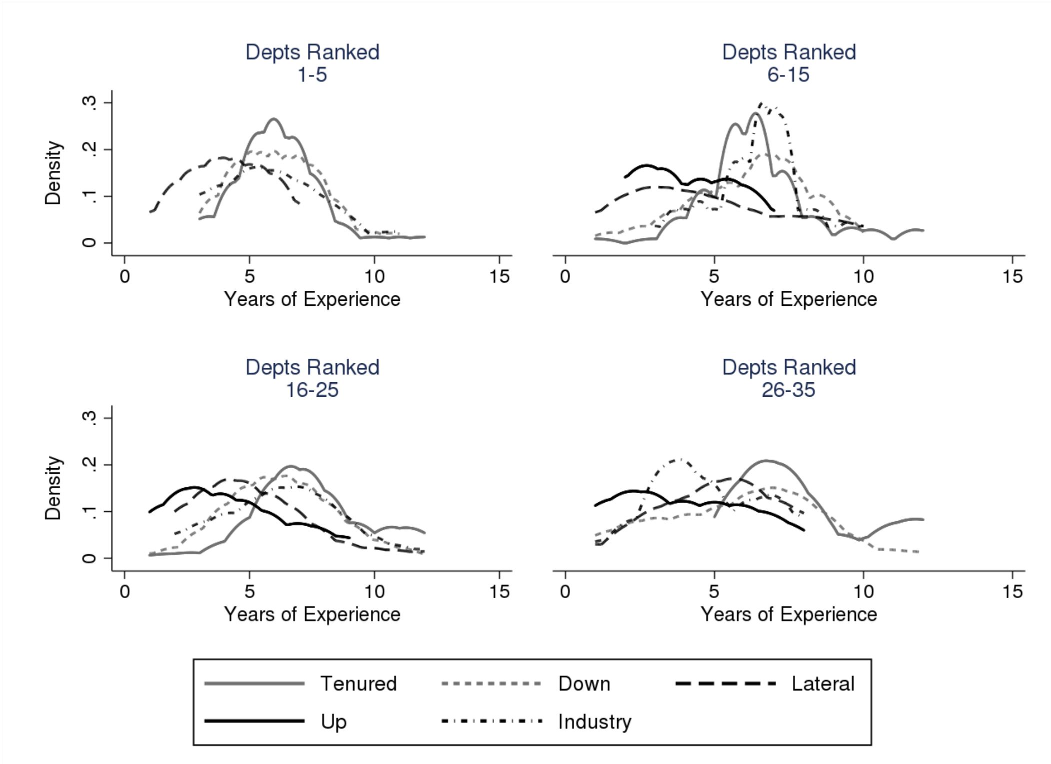


Figure 1 plots department rank-specific distributions for the length of first tenure-track employment for individuals who received tenure or moved to other opportunities following the first spell of tenure-track employment. The distributions for tenure recipients have means between 5.4 and 7.0 years and standard deviations between 2.0 and 3.0 years.[23,24] The distributions for upward and lateral departmental movements are left-shifted relative to the

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

[21]See Online Appendix Table O-A6 for tenure rates during the second spell.

[22]Online Appendix Table O-A7 gives estimates for rates of tenure conferral for the top 35 departments.

[23]See Online Appendix Table O-A5 for means and standard deviations corresponding to each group

[24]The right tails for the tenured distributions extend beyond 10 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.

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 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 Section 2.4.

2.1.1 Categorizing the Journals

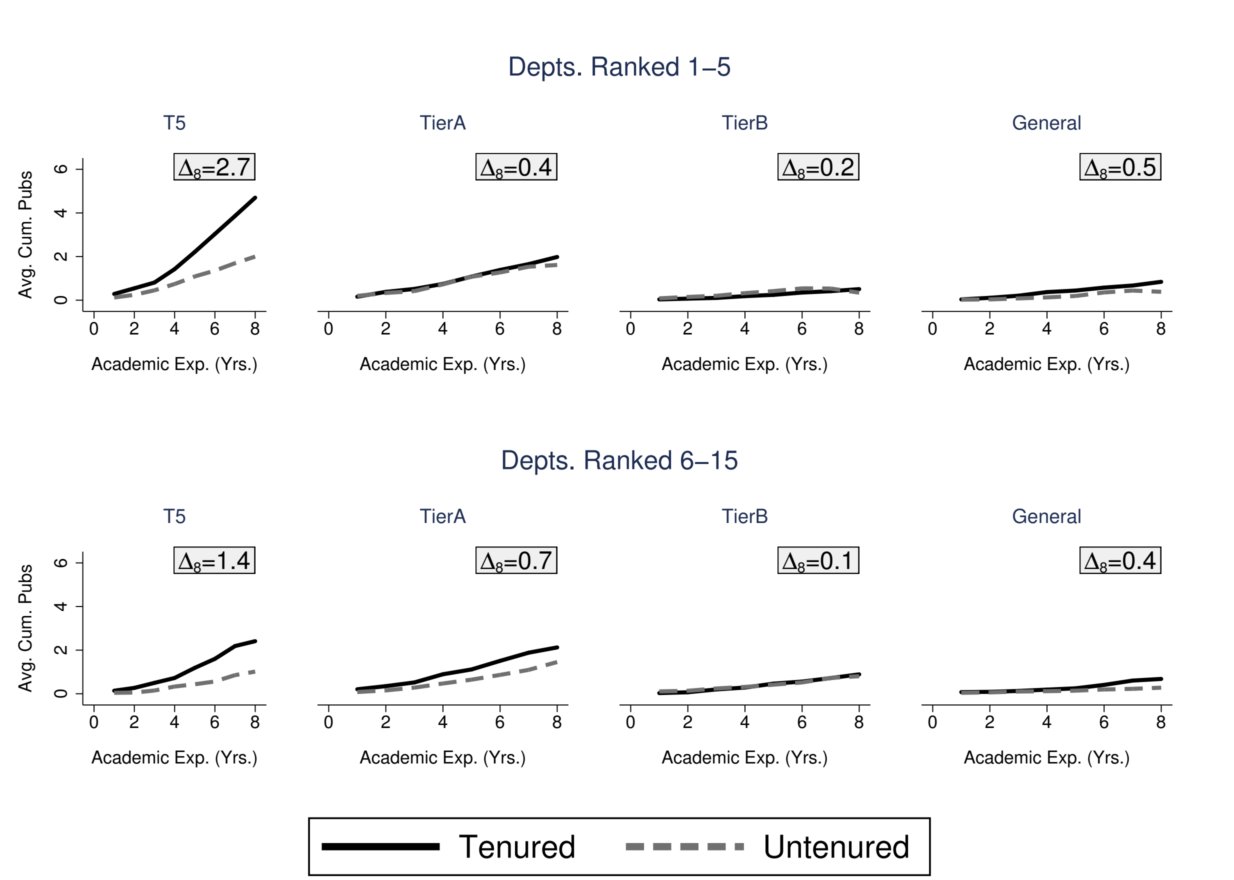
To compare the relationships between tenure decisions and publications in T5 and non-T5 journals, we categorize non-T5 journals into quality-based categories. Such categorization allows us to estimate the influence on tenure of publishing in non-T5 journals of similar standing. We use the field-specific rankings of Combes and Linnemer (2010) to categorize journals into the following groups: Tier A Field, Tier B Field, and non-T5 general interest.[25] Online Appendix Table O-A9 presents this journal categorization.

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.[26] The plots reveal a striking pattern. In terms of research productivity in peer-reviewed journals, tenured faculty at the top 5 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 3 publications by the 8^{th} 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.

[25] 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 give highest ranked non-T5 general interest journals.

[26] 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 8 between the tenured and untenured groups.

The degree of T5 separation falls among departments ranked 6 to 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 8^{th} year increasing from 0.4 for the top 5 departments to 0.7 for departments ranked 6 to 15. Despite these changes, the T5 continues to serve as the main differentiator between tenured and tenure-denied faculty among departments ranked 6 to 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 to 25.

The observed pattern of publication behavior suggests that expectations for the number of T5 publications 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 decrease in 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 using a logit specification.[27,28] Controlling for the total number of publications in all specifications, we isolate a composition effect from a scale effect. We further control for gender, number of co-authors, quality of graduate alma mater, and the quality of authors' publication portfolios as proxied by the total number of citations received by each author across all relevant journal articles[29].

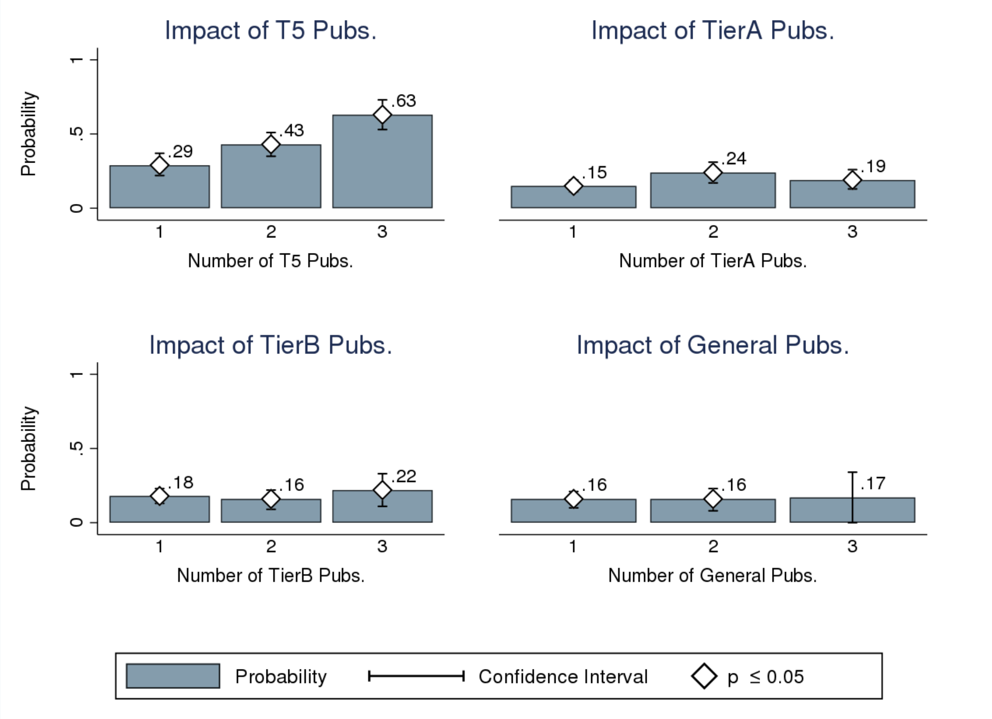
Figure 3 shows that publishing in T5 journals is associated with the largest increases in probabilities of receiving tenure. An individual with a single T5 publication is predicted to have a 0.29 probability of receiving tenure. The predicted probability increases to 0.43 and 0.63 for individuals with two and three T5 publications respectively. Although publishing in non-T5 outlets is associated with non-zero probabilities of receiving tenure that are statistically significant at the 5% 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 0.24 and it is associated with publishing two articles in Tier A journals. This probability is lower than the probability of

[27] See Text-Appendix Section 1.1 for the exact specification used in our Logit estimations.

[28] 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.

[29] Relevance of an article varies by analysis. The current estimates of tenure by the first spell utilize citations for all articles published during the first spell. Estimates for tenure by the 7^{th} year utilize citations to articles published by the 7^{th} year of tenure-track experience.

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



Note: This figure plots the predicted probabilities associated with different levels of publications in different journal categories. The predicted probability is defined in Equation TA-2 (Equation TA-2 uses parameter estimates from Equation TA-1). White diamonds on the bars indicate that the prediction is significantly different than zero at the 5% level.

0.29 associated with publishing a single T5 article. The probability of 0.63 associated with three or more T5 publications is approximately 160% 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 7^{th} year of tenure-track employment.[30]

2.2.1 The Power of the T5 by Department Rank

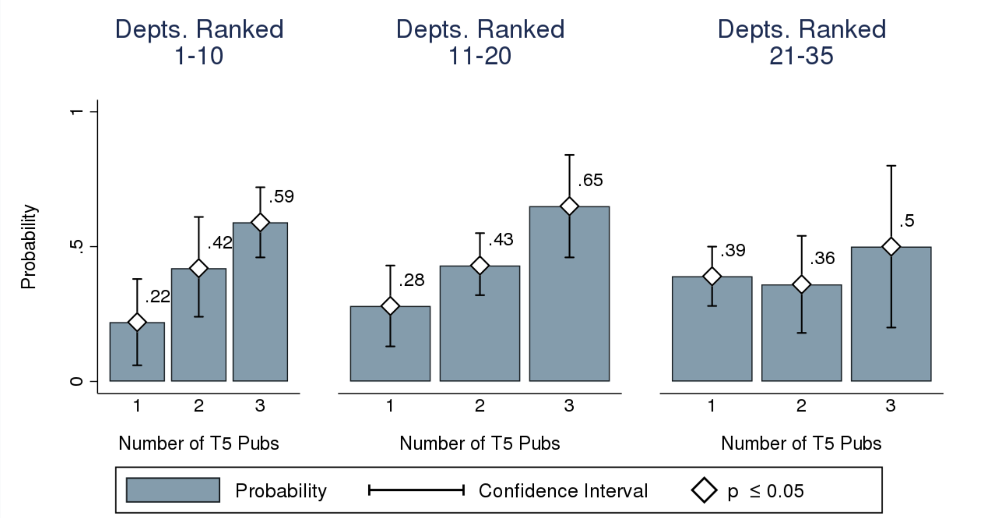
Figure 4 plots department rank-specific predicted probabilities for receipt of tenure during the first spell of tenure-track experience associated with different levels of T5 publications.[31]

[30] See Online Appendix Section 2.3 for results and details on specification used.

[31] The corresponding marginal effects are presented under the department rank-specific columns of Online Appendix Table O-A13.

The length of first spell varies by individual.[32] The results of that analysis are qualitatively similar to the analysis in the main text. Department rank-specific estimates for tenure by the 7^{th} year are presented in Online Appendix Figures O-A6–O-A8. Predictions for each rank group is obtained by restrictively estimating logit models over subsamples of faculty who had their first spell of tenure-track experience at a department within the rank group in question. For all empirical models estimated in this paper we include departmental fixed effects and adjust standard errors for clustering at the department level.

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



Note: This figure plots the predicted probabilities associated with different levels of publications in different journal categories. The predicted probability is defined in Equation TA-2 (Equation TA-2 uses parameter estimates from Equation TA-1). Department rank-specific estimates are obtained by restrictively estimating Equation TA-1 over subsamples of faculty belonging to the department rank group in question. White diamonds on the bars indicate that the prediction is significantly different than zero at the 5% level.

The figure reveals heterogeneity in the associated impact of each T5 publication in the probability of receiving tenure. Faculty at lower ranked departments attain 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 0.22 in a top 10 department,

[32]We also estimate models that fix duration to 7 years of tenure-track experience. Pooled estimates are presented in Online Appendix Figure O-A5.

but the same individual experiences probabilities of 0.28 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 10 departments who have published the same number of T5 articles.[33]

2.2.2 The Power of the T5 By Quality of T5 Publications [34]

This section investigates the staying power of the T5. Results from previous sections show that T5 publications have a powerful impact on tenure decisions, after controlling for differences in the quality of authors' 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 alone. Figure 5 presents compelling 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. Probabilities of tenure associated with different levels of T5 publications are presented within each quartile.[35] 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.[36] The analysis in this section 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.

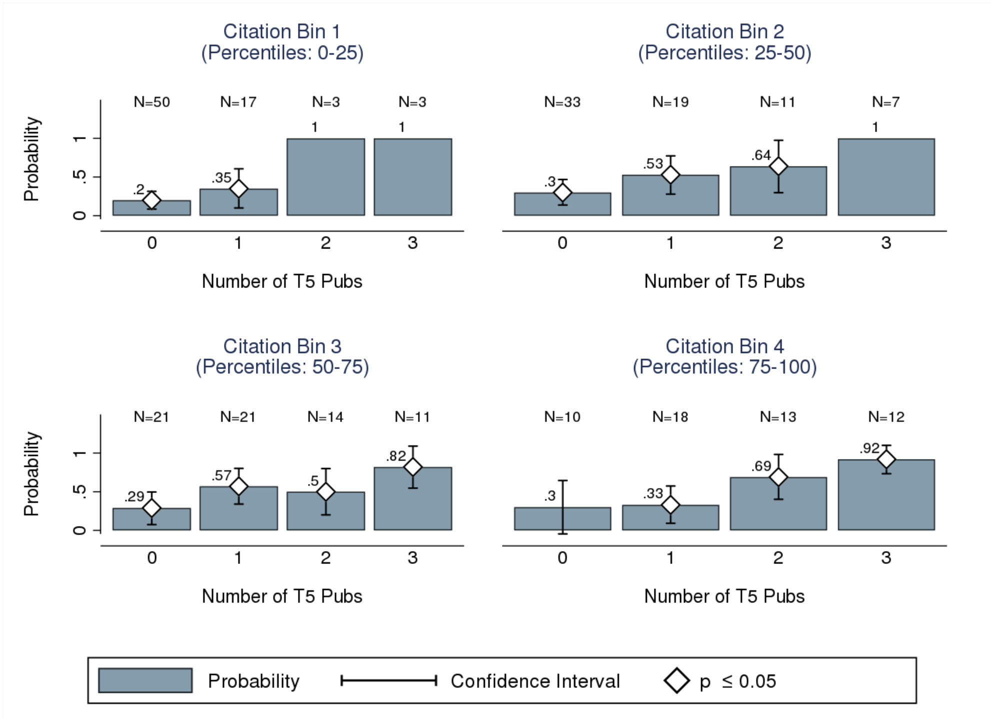
[33] While differences are evident, one cannot reject the null of equalities of the probabilities across department rank groups. See Online Appendix Table O-A14.

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

[35] The probabilities are constructed in three steps: (i) the sample is restricted to only include faculty with 3 or more journal publications by the end of the first spell (3 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

[36] 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 Tenure Receipt 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



Note: 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.

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 pays more 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 vastly greater tenure probabilities than faculty with top quartile portfolios that lack T5 publications. This quality-independent influence of T5 publications persists when we restrict the sample to include faculty who published at least 4 or 5 journal articles during their first job spell (see Online Appendix Figures O-A14–O-A15).

The results presented in this section 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 U.S. 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 non-T5 publications (with the same quantity and quality of publications).

2.3 Duration Analysis of Time-to-Tenure

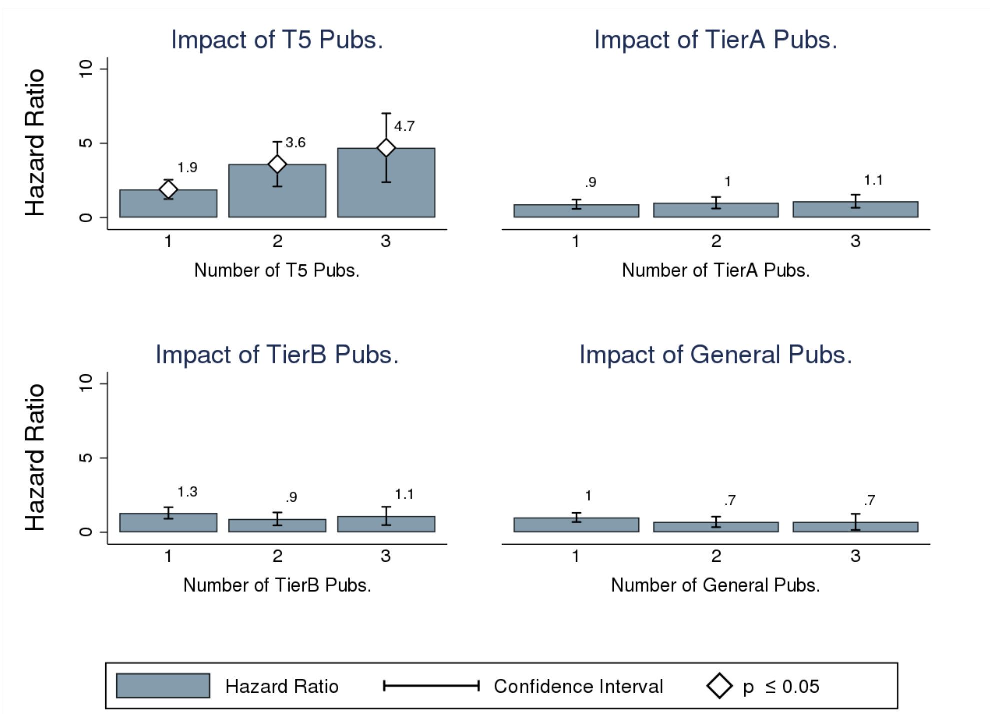
Table 1: Potential States of Employment for Untenured Tenure-Track Faculty

state = s	**Description**
0	Untenured tenure-track in a T35 department
1	Tenured in a T35 department
2	Not employed as a tenure-track faculty in a T35 department

This section 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. To proceed, consider a single-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 their first spell of tenure-track employment is 1. In subsequent periods, individuals can either remain in an untenured tenure-track position in a top 35 department, receive tenure in a top 35 department, or cease to be employed as a tenure-track faculty in a top 35 department.[37] Untenured tenure-track faculty can transition to two mutually exclusive but collectively exhaustive states of employment, relative to their current state of untenured tenure track employment in a top 35 department. We use a standard competing risks duration framework with the states given in Table 1.[38] We condition on the number of publications.

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

Figure 6: Relative Hazard Rates of Tenure Receipt Associated With Publications in Different Outlets



Note: This figure plots hazard ratios associated with different levels of publications in different outlets. Hazard ratios are obtained by estimating Text-Appendix Equation TA-13. White diamonds on the bars indicate that the prediction is statistically significantly different than 1 at the 5% level.

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.[39] Estimates for

[37] 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.

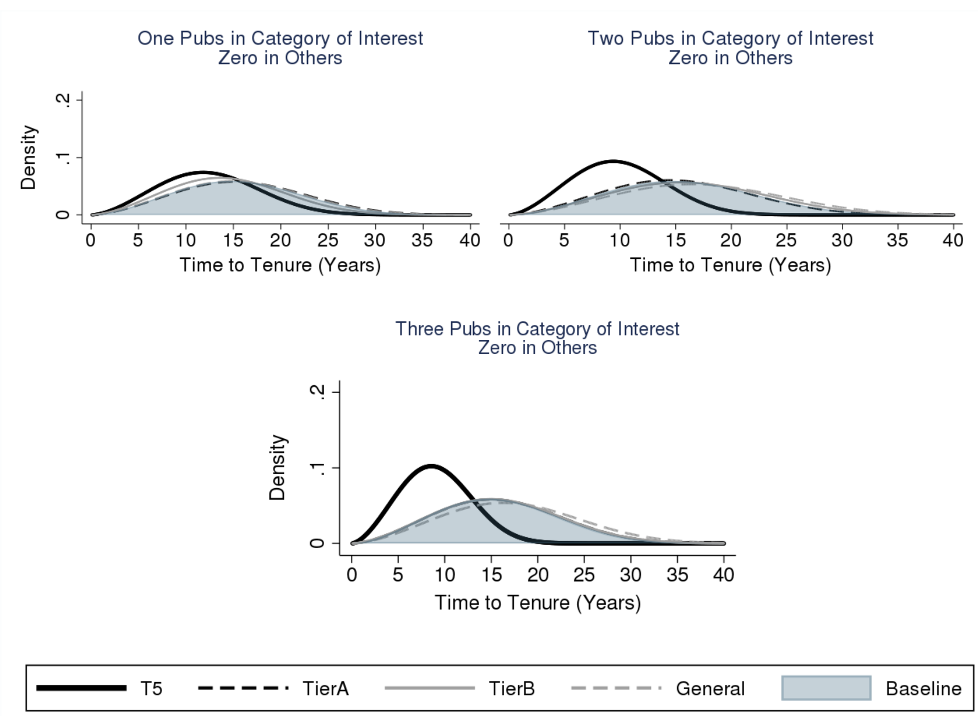
[38] See Text-Appendix Section 2 for details.

[39] See Text-Appendix Section 2.3 for department rank-specific estimates.

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 3.6 and 4.7 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 1.3 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% level.

There are large differences between T5 and non-T5 journals in terms of the improvement in tenure rates that one can expect from publishing in these outlets. The rates of transition to tenure associated with individuals who have published one, two and three T5 articles is 73%, 227%, and 327% greater respectively, than the transition rates associated with individuals who have published three Tier A publications. The differences in hazard

Figure 7: Densities of time-to-tenure (Weibull Distribution)



Note: 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 TA-13. The blue shaded region in each plot represents the distribution of time-to-tenure associated with not having any publications in any journal.[40]

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.[41] Publishing in the 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.

2.4 Heterogeneity in the Probability and Rate of Receiving Tenure By Gender

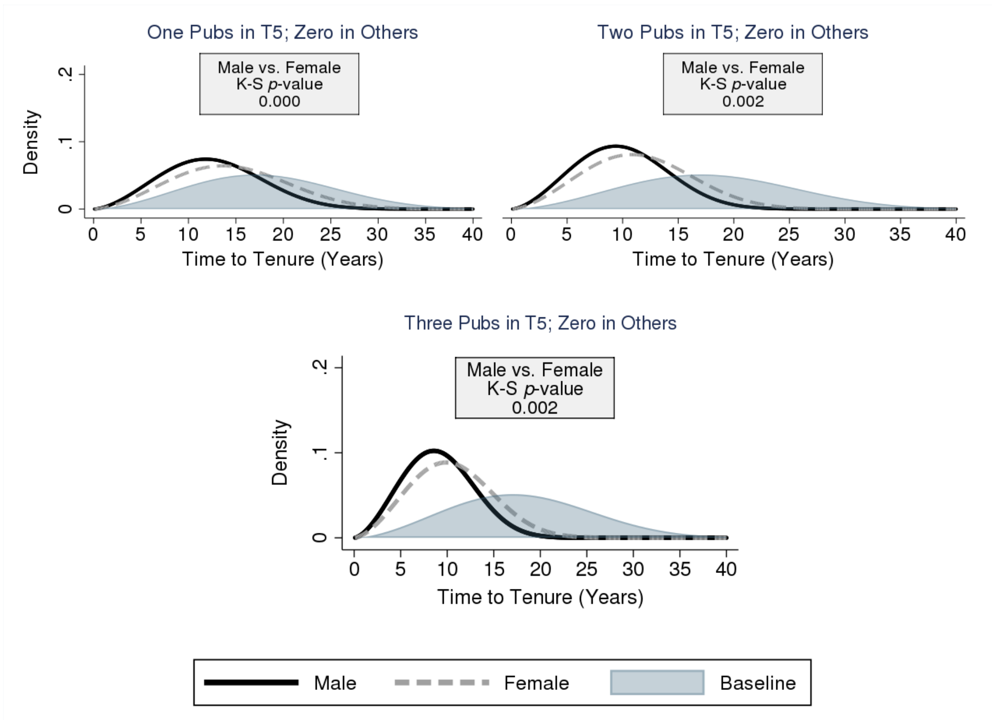
2.4.1 Heterogeneity in Time-to-Tenure

This section 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 1.46 and 1.47 depending on the assumption made about unobserved heterogeneity (see Online Appendix Table O-A17). The ratio of 1.47 for men indicates that male faculty have a rate of time to tenure that is 47% greater than those faced by their female colleagues, once differences in the number of publications and the vector of time-variant and -invariant controls $\boldsymbol{X}$ are accounted for. The difference in hazard rates translates into differences in time-to-tenure. Figure 8 plots gender-specific densities of time-to-tenure associated with publishing one to three T5 publications (see Online Appendix Figure O-A23 for non-parametric Kaplan Meier plots of survival probabilities by gender and number of T5 publications). The densities for females exhibit a rightward shift

[41]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.

[41]Online Appendix Table O-A18 compares Weibull estimates with estimates from an exponential model. T5 is estimated to be relatively more influential (compared to non-T5) in the Weibull model (significance for T5 is comparable across Weibull and exponential, but non-T5s are more significant in exponential than in the Weibull). However, the Weibull model has better fit than the exponential model. Log likelihood is greater for the Weibull compared to the exponentia model. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are also both minimized for the Weibull specification.

Figure 8: Densities of Time-to-Tenure (Weibull Distribution), by Gender (Publication Rewards Held Constant across Genders)



Note: 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 TA-13 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: $f(t \mid \#\text{T5} = x, \#\text{nonT5} = 0, \text{Gender} = g, \boldsymbol{X}) = h(t \mid \#\text{T5} = x, \#\text{nonT5} = 0, \text{Gender} = g, \boldsymbol{X}) \times S(t \mid \#\text{T5} = x, \#\text{nonT5} = 0, \text{Gender} = g, \boldsymbol{X})$ where $h(t \mid \cdot)$ and $S(t \mid \cdot)$ give the conditional hazard and survivor rates at t respectively. The titles for the 3 subplots in Figure 8 lists the conditioning used for the publication variables. "2 Pubs in T5; 0 in Others" gives the condition: $\#\text{T5} = 2, \#\text{nonT5} = 0$. The conditioning on gender is given by the legend which denotes whether the plot is associated with males or females. The conditioning on X is left implicit. Taken together, the black density for the plot labelled "2 Pubs in T5; 0 in Others" plots the following density function: $f(t \mid \#\text{T5} = 2, \#\text{nonT5} = 0, \text{Gender} = Male, \boldsymbol{X})$. 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 journal. Each plot also presents p-values obtained from Kolmogorov-Smirnov tests between the Male and Female distributions.

relative to their male counterparts. Kolmogorov-Smirnov tests reported in the figure reject the null hypothesis of distributional equality across genders at the 5% level for each level of T5 publication.

Given the statistical significance of the gender indicator, we next investigate potential differences in rewards associated with T5 publications by gender. We explore heterogeneity in rewards to publication by interacting the publication variables in Equation TA-13 in the Text-Appendix with an indicator for gender. Online Appendix Figures O-A20–O-A22 present gender-specific tenure hazards associated with different levels of publishing in different journal categories. Figure O-A20 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% 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% higher for males than for females. The hazard rate associated with three T5 publications is 92% 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 Section 6.6 for details). We note that point estimates for female faculty are more imprecisely determined than those for males due to the relatively small sample of female faculty.[42]

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. How much of the slower female rate to tenure is accounted for by parental leave of absence is unclear. We lack the requisite data to make the appropriate adjustment to female exposure sets.

[42]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% of assistant and associate professor positions in the 2017-2018 academic year across 103 PhD-granting institutions in the U.S); and (ii) women who publish 3 or more T5 articles are much fewer in number.

2.4.2 Heterogeneity in the Probability of Receiving Tenure

Figure 9 plots raw probabilities of tenure given gender and number of T5 publications.[43] 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 9 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 $\boldsymbol{X}$.[44] 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% level. Probabilities predicted from this model are comparable between genders (see Online Appendix Figures O-A10–O-A13), with the first spell estimates showing greater inter-gender similarity than the by-7^{th}-year estimates[45].

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 Section 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 sample size issues.[46]

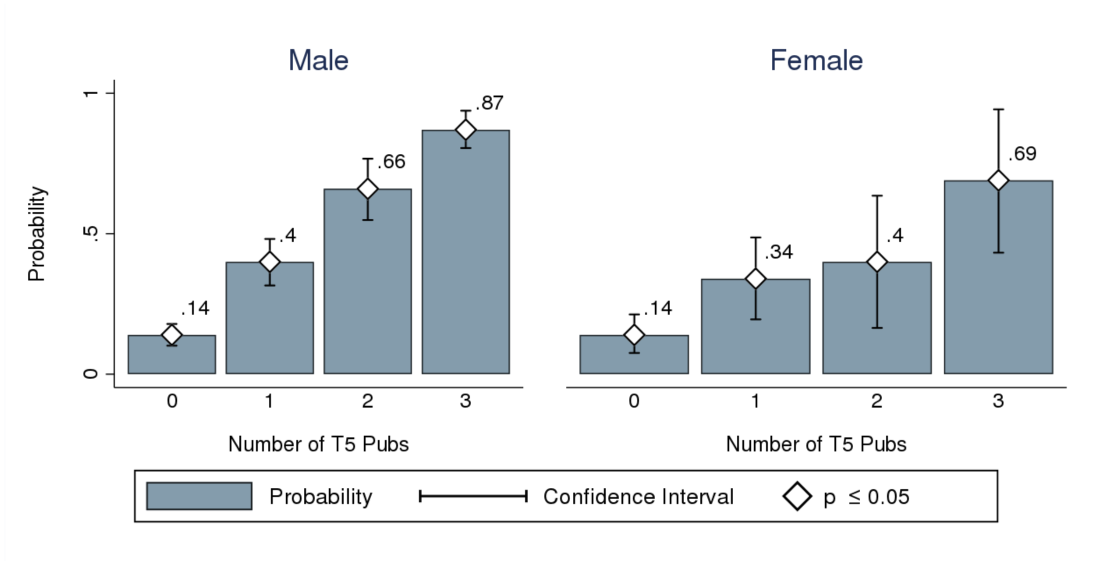
[43] These probabilities are computed as proportions of individuals of a certain gender with a certain number of T5 publications who receive tenure

[44] See Equation TA-1 for exact specification

[45] These probabilities are obtained by adding a gender indicator variable to prediction Equation TA-2 to obtain $Pr(Tenure = 1 \mid \#\widehat{J} = \widehat{N}, \#\widetilde{J} = 0, \text{Gender} = g, \boldsymbol{X})$. The parameters used in these predictions are obtained by estimating Equation TA-1

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

Figure 9: Conditional Probabilities of Receiving Tenure During the First Spell of Tenure-Track Employment Given T5 Publications and Gender



Note: 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.

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

Finance has emerged as a separate field that coexists with, and sometimes overlaps, with mainstream economics. We recognize this reality by conducting separate analyses: (a) pooling economics and finance journals together into combined field journal categories and (b) separating them out. Our results are robust to inclusion or exclusion of finance journals. Online Appendix Section 4 present results that test the sensitivity of logit, Linear Probability Model (LPM), and hazard estimates to alternative variable specifications for finance journals and to the exclusion of finance journals from our samples.[47]

[47]Specifically, we present three sets of results for each estimation (logit, LPM, and hazard) obtained by treating finance journals in three different ways in the model specification. The first set of results excludes finance journals from the Tier A and B field journal categories. The second set of results excludes finance journals from the Tier A and B field journal categories, and introduces a set of publication threshold indicators that measure publication in these finance journals. We refer to this grouping of the five finance journals as the *aggregate* grouping of finance journals. The last set of estimates excludes finance journals from the Tier A and B field journal categories, and introduces two sets of publication threshold indicators that measure publication in two tiers of finance journals–Tier A Finance journals (top 2 finance journals),

Parameter estimates for the impact of T5 and non-T5 non-finance journals on tenure (logit) and time to tenure (duration) are not sensitive to these alternative treatments of finance journals[48]. Estimates by category for Tier A finance journals (obtained from the set of sensitivity tests that employ the *tiered* finance category) are statistically significant. The magnitude of these estimates are large, suggesting that faculty specializing in finance might have access to non-T5 alternatives through which they can signal their research productivity for tenure or promotion. See Online Appendix Section 4 for a more detailed discussion on the sensitivity of the estimates to inclusion or exclusion of finance journals from the model specifications.

We also conduct sensitivity tests of our estimates to alternative treatment of econometrics journals in the field journal categories. Sensitivity results presented in Online Appendix Section 5 reveal that the T5 estimates are robust to the exclusion of econometrics journals as well as to a re-definition of the Tier A field journal category to include the *Annals of Statistics* and the *Journal of the American Statistical Association* (instead of the econometrics journals that were included in our baseline Tier A category). These alternative treatments of econometrics journals leads to a loss of statistical significance for the Tier B field journal estimates obtained from our LPM estimates, suggesting that the positive association observed between tenure outcomes and Tier B publications in our baseline estimates are largely driven by the econometrics journals that originally comprised the Tier B category used in our baseline specification (*Journal of the American Statistical Association* in particular). This loss of statistical significance for the Tier B journals increases the relative importance of T5 publications.

and Tier B Finance journals (finance journals ranked 3–5). We refer to this grouping of the five finance journals as the *tiered* grouping of finance journals.

[48]Tier B journals gain relative prominence in the sensitivity tests that introduce finance journals as separate categories (separate from the field journals). This rise in prominence is only observed in the LPM estimations.

3 Junior Faculty Perceptions of Current Tenure and Promotion Practices

We supplement our analyses of job-history and publications data with findings from a survey of individuals currently employed as assistant and associate professors by the top 50 economics departments in the U.S.[49] 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.[50] The survey responses corroborate and contextualize the evidence in Section 2. Junior faculty have rational expectations about the power of the T5. Appendix Section 7.3 presents our survey instrument.

The survey has an overall response rate of 40% (N=308) across all 50 departments, with response rates of 44% (N=210) for assistant professors and 34% (N=97) for associate professors. The overall response rate was highest for departments ranked 41–50 (43%), and lowest for the top 10 departments (37%). Assistant professors had higher response rates than associate professors across all department rank groups except the top 10 departments, for which the response rate was 37% in both groups. Position- and department rank-specific response rates are reported in Online Appendix Figure O-A28.

The response rate gives rise to concerns about non-response 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

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

[50]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.

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 Section 7.2 presents additional data description for the survey sample.[51]

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 10 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: tenure receipt, promotion to assistant professor, and promotion to associate professor.[52] 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 than the ranking distributions for all of the remaining seven performance areas at the 10% level.[53] In addition to confirming our previous findings of the larger influence of T5 publications relative to publications in non-T5 journals, these survey results reveal that the T5 is also more influential than unobserved measures of performance such as

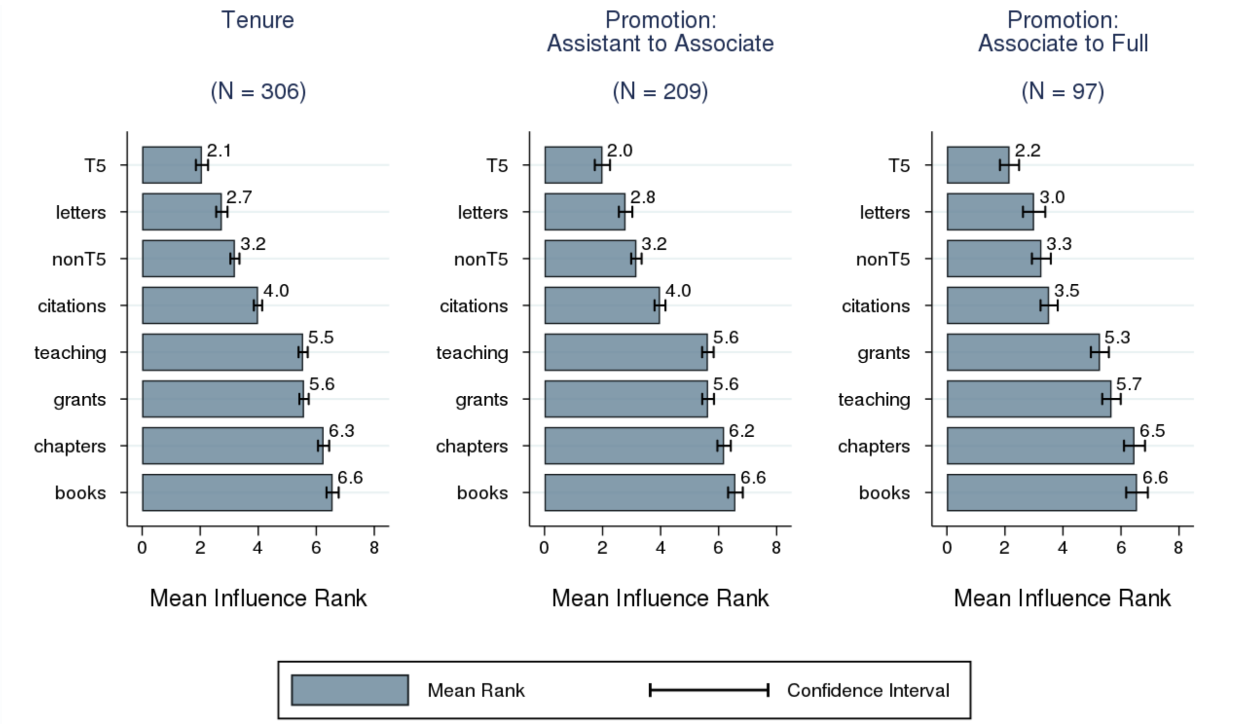
[51] We note that the survey was terminated prematurely because of a complaint to our IRB board by some individuals we attempted to sample. The complainants were concerned that their identity might be determined by our survey protocol despite our efforts to assure anonymity. This source of non-response 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.

[52] 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 towards obtaining. Second, it improves the probability of survey completion by reducing the burden of response for each respondent from 3 to 2 rankings.

[53] See Online Appendix Tables O-A56–O-A58 for pair-wise tests on rankings for each type of career advancement.

external letters of recommendation and teaching performance. 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.

Figure 10: Ranking of Performance Areas Based On Their Perceived Influence On Tenure and Promotion Decisions

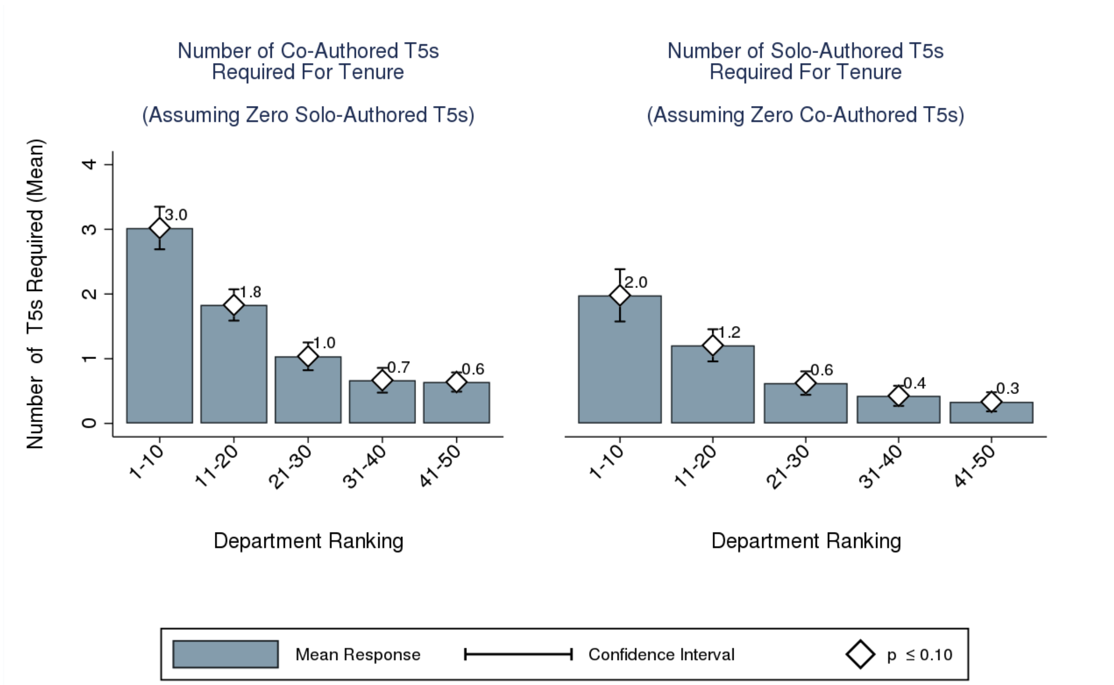


Note: This figure summarizes respondents' rankings of 8 performance areas. Responses are summarized by type of career advancement: tenure receipt, promotion to assistant professor, and promotion to associate professor. The bars present mean responses for each performance area. Respondents were given 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.

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 similar 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 ranked similarly to 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.

Figure 11: Minimum Number of T5 Publications Required for Tenure



Note: 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 than zero at the 10% level.

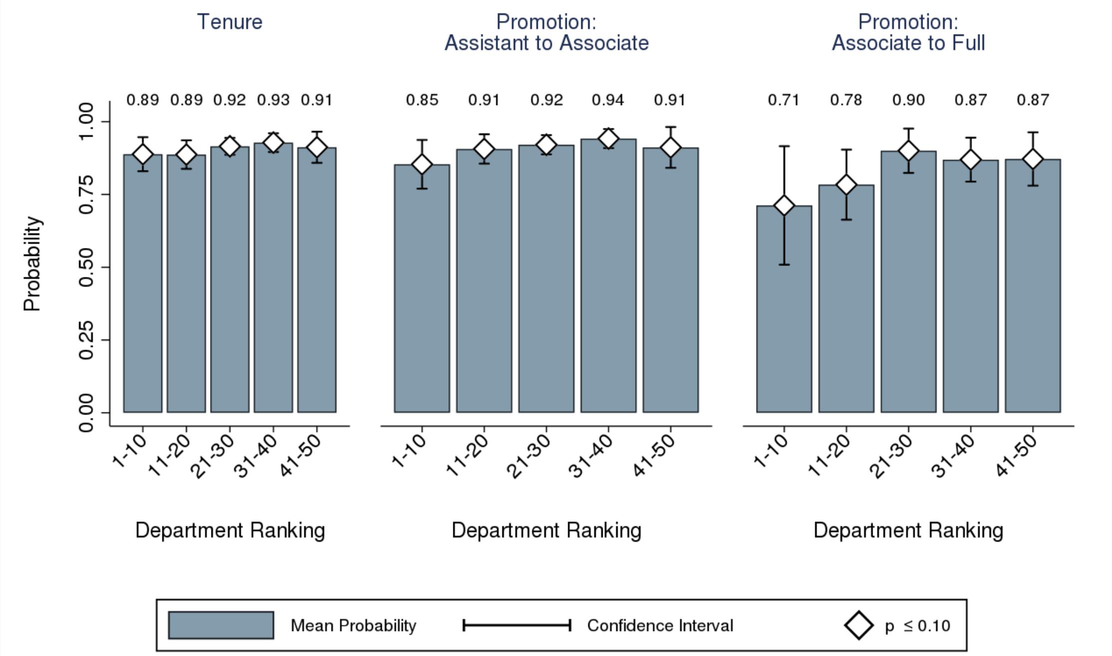
Non-T5 publications receive the third-highest mean rank across all levels of career advancement. However, the rankings for both external letters and non-T5 publications are only significantly different than the rankings for citations when we consider tenure and promotion to associate professor. The Wilcoxon 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 deemed to be of much lower value for tenure 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 12 presents results that answer 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 12 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

Figure 12: Probability That Candidate with T5 Publications Receives Tenure or Promotion Instead of Candidate with non-T5 Publications, *ceteris paribus*



Note: 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 than 50% at the 10% level.

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 than 0.5 at the 10% 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 their articles are published in T5 or non-T5 journals. Faculty form perceptions based on past decisions, and past decisions are clearly biased in favor of T5 publishing (see Figure 5). Today's academic careers are 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, Section 4.1 compares citation distributions of individual journals against the citation distribution of T5 journals as a group. Section 4.2 compares journals with respect to the share of the most influential papers that have been published by T5 and non-T5 journals. Section 4.3 compares T5 and non-T5 journals based on Impact Factors. Section 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 section compares cumulative citation counts (measured as of 2018) of articles published in the T5 and those published in twenty-five other journals over the ten year period 2000–2010. The comparisons in this section build on the analysis of Hamermesh (2018), who compares citations in the T5 journals, with citations in the *Review of Economics and Statistics* and the *Economic Journal*. 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 vs. 1974-75 and 2007-08 in Hamermesh (2018)).[54]

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

Our results confirm his findings. There are large intra-T5 variation in citations and large overlap 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 38^{th} percentile of year-adjusted citations among all T5 publications, but attains a rank of the 58^{th} percentile when compared to *ReStud* alone. These comparisons illustrate the large heterogeneity in influence among the journals that comprise the T5.

For want of a better measure, our comparisons of journal and article quality rely on citations. However, citations likely undervalue the quality of non-T5 articles relative to those published in the T5. Longstanding 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 plausible that T5 articles will attract more citations than non-T5 articles, conditional on article quality. If such biases favor T5 articles, citations will undervalue the quality of non-T5 articles, and thereby understate the degree of comparability between T5 and non-T5 journals[55]. 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.

[55] 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 et al. (1973) show that the AER, ECMA, JPE, and QJE were the four most highly perceived journals in the late 1960's and early 1970's (ReStat was ranked 5th, and ReStud was ranked 6th). The perceived superiority of these four journals have 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 et al. (1973) and show that the AER, ECMA, JPE, and QJE 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 plausible that holding constant both an article's quality and its relevance to the citing author's work, T5 articles receive more citations than non-T5 articles due to longstanding and deeply entrenched perceptions of the superiority of articles published in the T5.

4.1.1 Comparisons Against the Aggregate T5 Distribution

Figure 13 plots distributions of residual $ln(Citations+1)$ for articles published between 2000–2010 in each of the thirty journals considered in our analyses.[56] The journal-specific distributions are overlaid over a shaded distribution that represents the distribution of residual citations for all articles published between 2000–2010 in the T5. 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).[57] presents comparison of median residualized citations (aggregate T5 vs. 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 specification. 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.[58]

The subfigure labelled 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 71^{st} percentile of all T5 publications in terms of residualized citations.[59] In terms of median citations, the *QJE* is followed by *AER*, *JPE*, *ECMA*, and *ReStud*, with the median-cited *ReStud* article reaching the 31^{st} percentile of T5 citations.

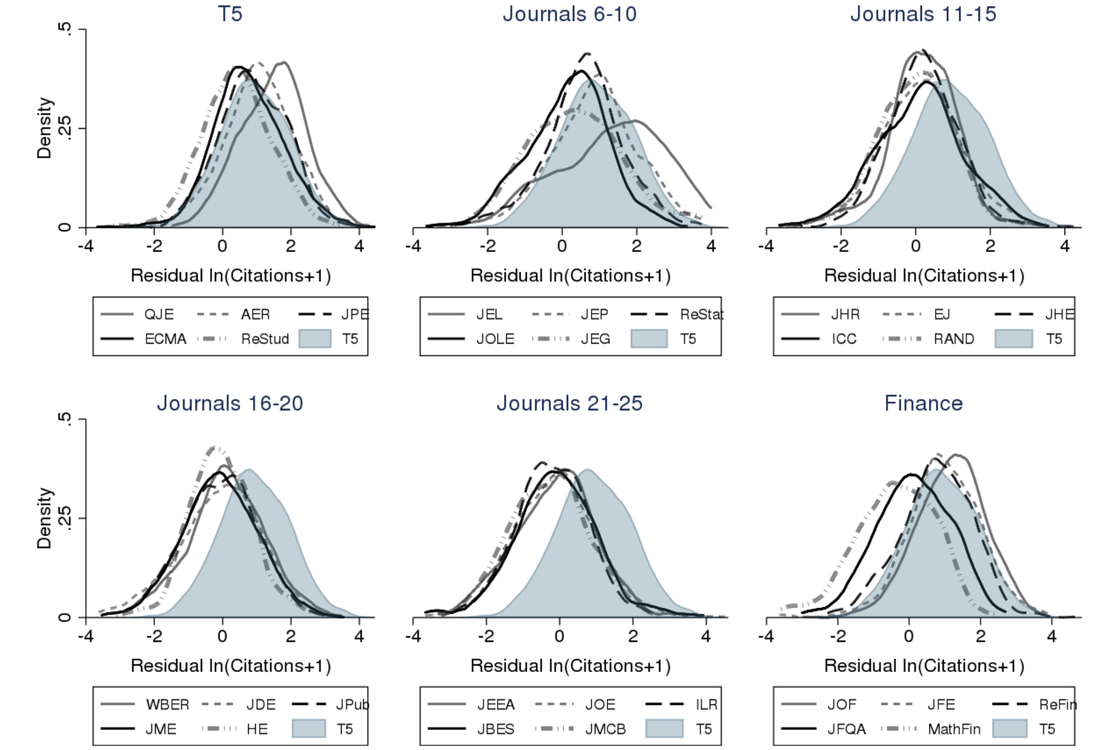
[56] Similar to Hamermesh (2018), we exclude notes, comments, reports of editors, and papers published in the *AER*'s annual issue of *Papers & Proceedings*. We also exclude papers that are less than 10 pages in length.

[57] Online Appendix Table O-A33

[58] The present analysis focuses on comparisons of this year-adjusted measure. The interested reader is referred to Online Appendix Figures O-A24–O-A26 for analogous plots that are specific to articles published in 2000, 2005, and 2010 respectively.

[59] See Online Appendix Table O-A31 for comparisons of journal-specific median citations against the T5 distribution of citations.

Figure 13: Distribution of Residual Log Citations for Articles Published between 2000–2010 (Measured Through July, 2018)



Source: Scopus.com; accessed 07/2018.
Definition of journal abbreviations: QJE–Quarterly Journal Of Economics, JPE–Journal Of Political Economy, ECMA–Econometrica, AER–American Economic Review, ReStud–Review Of Economic Studies, JEL–Journal Of Economic Literature, JEP–Journal Of Economic Perspectives, ReStat–Review Of Economics And Statistics, JEG–Journal Of Economic Growth, JOLE–Journal Of Labor Economics, JHR–Journal Of Human Resources, EJ–Economic Journal, JHE–Journal Of Health Economics, ICC–Industrial And Corporate Change, WBER–World Bank Economic Review, RAND–Rand Journal Of Economics, JDE–Journal Of Development Economics, JPub–Journal Of Public Economics, JOE–Journal Of Econometrics, HE–Health Economics, ILR–Industrial And Labor Relations Review, JEEA–Journal Of The European Economic Association, JME–Journal Of Monetary Economics, JRU–Journal Of Risk And Uncertainty, JInE–Journal Of Industrial Economics, 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.

The subfigure labeled Journals 6–10 in Figure 13 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 *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 70^{th} percentile of all T5 publications in terms of residual citations, which is one percentile below the ranking for the median-cited *QJE* article. *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-survey economics journals with its median citation reaching the 38^{th} 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 *JEG* whose median-cited article is ranked at the 30^{th} percentile of T5 citations, *JOLE* which has an analagous ranking at the 25^{th} percentile, and *JHR, JHE*, and *ICC* which are all tied at the 24^{th} percentile.[60]

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. *JOF* is most highly cited, with its median-cited article reaching the 61^{st} percentile of all T5 publications. It is followed by *JFE* and *ReFin*, both of which have median citations above that of *ECMA* and *ReStud*.

4.1.2 Comparisons Against Different Subsets of the T5

The comparisons presented in the previous section show that the T5 is composed of journals that vary in terms of the citations they receive: *QJE* receives the highest median citations followed by *AER*, *JPE*, *ECMA*, and *ReStud*. Given the presence of such intra-T5 heterogeneity, this section investigates how the relative performance of non-T5 publications changes as we successively restrict the comparison group to only include the lesser-cited T5 journals.

Online Appendix Table O-A32 presents a table with these comparisons.[61] The results show that the relative performance of non-T5 journals improves considerably when the comparison excludes higher-cited T5 journals. Thus, while the median-cited *ReStat* article ranks in the 38^{th} percentile of the overall T5 distribution, its rank improves to the 48^{th} percentile when the comparison set is restricted to articles in *JPE*, *ECMA*, and *ReStud*. *ReStat*'s performance continues to improve as the comparison group is further restricted, with the median-cited *ReStat* article outranking the median-cited article in the combined *ECMA* and

[60] The next three subfigures in Figure 13 present distributions for fifteen additional economics journals, listed in decreasing order of median citations. The first six of these journals have median-cited articles that are ranked at or above the 20^{th} percentile of all T5 articles.

[61] The first column reports the percentile rank in the aggregate T5 distribution of residualized citations for the median article in each of the thirty journals. Moving from left to right, each additional column successively removes a T5 journal from the comparison set in decreasing order of median citations.

ReStud distribution.

Similar improvements in relative performance are recorded for the other non-T5 journals. In comparisons against the overall T5 distribution, *ReStat* and *JEG* are the only non-T5 non-survey economics journals that attain ranks at or above the 30^{th} percentile of the T5 distribution. The number of journals with a ranking at or above the 30^{th} percentile increases to 8 when the comparison set is restricted to *JPE*, *ECMA*, and *ReStud*; and to 16 when compared solely against *ReStud*.

4.2 Which Journals Publish Influential Research Papers?

This section 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 computed in the previous sections to group articles from the 30 economics journals into four performance-based bins: articles with the Top 25%, Top 10%, Top 5%, and Top 1% 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%. The *QJE* ranks second in the 25%, 10% and 5% bins, and ranks first in the Top 1% bin. With the exception of the Top 25% bin, *AER* and *QJE* account for a combined 30% or more of the articles in each citation bin (they account for 23.5% of the articles in the 25% bin). The other T5 journals contribute fewer influential articles.[62]

The non-T5 non-survey journals publish many influential articles. *JOE*, *ReStat* and *JEG* account for a combined 13.6% of all articles in the Top 1% of residual citations. The

[62] With the exception of the 1% 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 31^{st} percentile of all T5 publications in terms of residual citations.

Table 2: Publication Volume-Unadjusted Proportion of Influential Articles Published By Individual Journals Between 2000–2010

Rank	**Top 25% Citations N=3321**		**Top 10% Citations N=1329**		**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	(4.7%)	ReStat	(4.5%)
					ReStat			
8.	ReStat	(4.8%)	EJ	(4.4%)		(.%)	JEG	(3.8%)
							JPE	
9.	JPub	(4.5%)	JOE	(4.2%)	EJ	(4.5%)		(.%)
10.	JME	(3.8%)	**ReStud**	(3.5%)	JME	(2.6%)	EJ	(3.0%)
					ReStud		JHE	
							RAND	
11.	JDE	(3.8%)	JPub	(3.1%)		(.%)		(.%)
12.	**ReStud**	(3.7%)	ICC	(3.0%)	ICC	(2.4%)		(.%)
					JPub			
13.	JHE	(3.3%)	JDE	(2.7%)		(.%)	JBES	(2.3%)
							JEEA	
							JPub	
14.	JEL	(3.3%)	JME	(2.5%)	JHE	(2.0%)		(.%)
15.	ICC	(2.7%)	JHE	(2.2%)	JBES	(1.4%)		(.%)
					JEG			
16.	HE	(2.5%)	HE	(2.0%)		(.%)	ICC	(1.5%)
							ReStud	
17.	JMCB	(2.4%)	JMCB	(1.5%)	HE	(1.2%)		(.%)
					JDE			
					JOLE			
					RAND			
18.	JHR	(2.1%)	JEG	(1.4%)		(.%)	JME	(0.8%)
			JOLE				JOLE	
							WBER	
19.	RAND	(2.0%)		(.%)		(.%)		(.%)
20.	JOLE	(1.9%)	JEEA	(1.3%)		(.%)		(.%)

Source: Scopus.com; accessed 07/2018
Note: This table presents publication volume-unadjusted proportions of highly cited articles published by different journals.
Definition of journal abbreviations: QJE–Quarterly Journal Of Economics, JPE–Journal Of Political Economy, ECMA–Econometrica, AER–American Economic Review, ReStud–Review Of Economic Studies, JEL–Journal Of Economic Literature, JEP–Journal Of Economic Perspectives, ReStat–Review Of Economics And Statistics, JEG–Journal Of Economic Growth, JOLE–Journal Of Labor Economics, JHR–Journal Of Human Resources, EJ–Economic Journal, JHE–Journal Of Health Economics, ICC–Industrial And Corporate Change, WBER–World Bank Economic Review, RAND–Rand Journal Of Economics, JDE–Journal Of Development Economics, JPub–Journal Of Public Economics, JOE–Journal Of Econometrics, HE–Health Economics, ILR–Industrial And Labor Relations Review, JEEA–Journal Of The European Economic Association, JME–Journal Of Monetary Economics, JRU–Journal Of Risk And Uncertainty, JInE–Journal Of Industrial Economics, 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.

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% articles than *ReStud*, two of the three journals produce more Top 1% articles than *JPE*, and the remaining one produces as many Top 1% articles as the *JPE*. *ReStud* is outranked by six additional non-survey non-T5 journals. These journals contribute a further 16% to the Top 1% bin. The contributions of non-T5 non-survey journals remains significant across the remaining three citation bins. The five most influential non-survey journals in the Top 5% bin produce a combined 20% of the articles in that bin. The Top 10% and Top 25% bins receive 19% and 24% 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. *AER* publishes at least twice as many papers as the next highest publishing T5. It is thus 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.[63] The adjustment discounts the contribution of high-volume journals such as *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 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 proportion of contributions from the *QJE* and *JPE*, reflecting the fact that these

[63] 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:

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

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 $(v_{j,y}/V_y)$ 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=3321**		**Top 10% Citations N=1329**		**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 07/2018
Note: This table presents publication volume-adjusted proportions of highly cited articles published by different journals. Adjusted proportions are calculated according to Equation 1.
Definition of journal abbreviations: QJE–Quarterly Journal Of Economics, JPE–Journal Of Political Economy, ECMA–Econometrica, AER–American Economic Review, ReStud–Review Of Economic Studies, JEL–Journal Of Economic Literature, JEP–Journal Of Economic Perspectives, ReStat–Review Of Economics And Statistics, JEG–Journal Of Economic Growth, JOLE–Journal Of Labor Economics, JHR–Journal Of Human Resources, EJ–Economic Journal, JHE–Journal Of Health Economics, ICC–Industrial And Corporate Change, WBER–World Bank Economic Review, RAND–Rand Journal Of Economics, JDE–Journal Of Development Economics, JPub–Journal Of Public Economics, JOE–Journal Of Econometrics, HE–Health Economics, ILR–Industrial And Labor Relations Review, JEEA–Journal Of The European Economic Association, JME–Journal Of Monetary Economics, JRU–Journal Of Risk And Uncertainty, JInE–Journal Of Industrial Economics, 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.

journals have a lower volume of publication than the *AER*. While the increase in 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%, Top 10%, and Top 5% bins. *ReStud* shows ranking improvements in the Top 25% and Top 10% bins. However, its rankings are not affected in the Top 5% and Top

1% bins despite the volume adjustment.

Among non-T5 non-survey journals, *JEG* experiences the largest upward rise, consistently ranking within the Top 7 across all citation bins. *ReStat* falls in rank. However, it continues to remain influential across the various citation bins. *EJ* and *JOE* both experience downward adjustments.

The major takeaway from the rankings in Tables 1 and 2 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 (2 year; 5 year;$\cdots$; 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 (2 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 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 economics impact factor.

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)	10	(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)	13	(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)	9	(7.67)	11	(7.67)	11	(7.67)
11.	Review Of Economic Studies	20	(3.12)	11	(6.03)	12	(6.42)	13	(7.00)	13	(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)	11	(6.81)	12	(7.62)	12	(7.31)
14.	American Economic Journal: Economic Policy	12	(3.99)	14	(5.51)	16	(5.71)	15	(5.71)	15	(5.71)
15.	Journal Of Human Resources	3	(6.86)	15	(5.11)	14	(5.89)	18	(5.33)	18	(4.90)
16.	American Economic Journal: Macroeconomics	17	(3.45)	16	(4.83)	15	(5.88)	14	(5.88)	14	(5.88)
17.	Journal Of The European Economic Association	21	(3.04)	17	(4.70)	20	(4.82)	21	(4.66)	19	(4.66)
18.	Journal Of Labor Economics	13	(3.88)	18	(4.62)	17	(5.14)	17	(5.33)	16	(5.21)
19.	Economic Journal	19	(3.27)	19	(4.27)	18	(5.01)	16	(5.41)	17	(5.11)
20.	Journal Of Health Economics	16	(3.49)	20	(4.00)	21	(4.32)	23	(4.50)	26	(4.45)
21.	Journal Of Development Economics	23	(2.48)	21	(3.89)	19	(4.90)	19	(4.90)	24	(4.53)
22.	World Development	18	(3.39)	22	(3.60)	27	(3.60)	31	(3.60)	31	(3.60)
23.	Journal Of Monetary Economics	26	(2.24)	23	(3.27)	29	(3.51)	29	(3.86)	30	(3.83)
24.	Journal Of Financial And Quantitative Analysis	27	(2.22)	24	(3.23)	22	(4.25)	22	(4.60)	20	(4.63)
25.	Journal Of Applied Econometrics	24	(2.46)	25	(3.16)	26	(3.83)	27	(4.15)	21	(4.59)

Source: Scopus; Accessed 07/2018.
Note: This table presents 2, 5, 10, 15, and 20 Year Impact Factors for 51 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.
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:

$$IF_{x,j}^{2017} = \sum_{y=2016-x}^{2016} \frac{\text{citations}_{y,j}^{2017}}{\text{volume}_j}$$

where $\text{citations}_{y,j}^{2017}$ 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.

4.4 Where Influential Economists Publish

This section explores where influential economists publish by field of specialization. We use RePEc's field-specific author rankings to compile a list of the 50 most influential authors[64] within 14 fields of specialization[65]. We analyze the publication histories to identify the

[64]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.

[65]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

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[66] . 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 3 for any field, except *ECMA* which ranks 3^{rd} in econometrics and microeconomics. These patterns reveal that the foremost economists working in the major fields of specialization within economics publish most of their specialist 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 publication.[67] The publication volume-adjusted rankings in Table 5 show that once one

[66]We make the following changes to Card and DellaVigna (2013)'s classification scheme:(i) We break out the labor economics category into labor (*JEL* Codes I2 and J except J1), and demographic economics (*JEL* Codes 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).

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

$$\tilde{S}_j^f = \frac{1}{N^f} \sum_{y=1996}^{2017} C_{j,y}^f \; / \left(\frac{v_{j,y}}{V_y} \right) \tag{2}$$

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

Table 5: Journals that Account For Largest Share of **Field-Specific Publications** Between 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

Note: Adjusted proportions are calculated according to Equation 2.
Label Legend: 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, 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
Source: RePEc, EconLit.

Table 6: Journals That Received The Highest Number of Citations From Articles Published Between 2010–2017 In the Top 2 Journals Within Different Fields of Specialization (Rankings Uses Citations to Articles Published Between 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

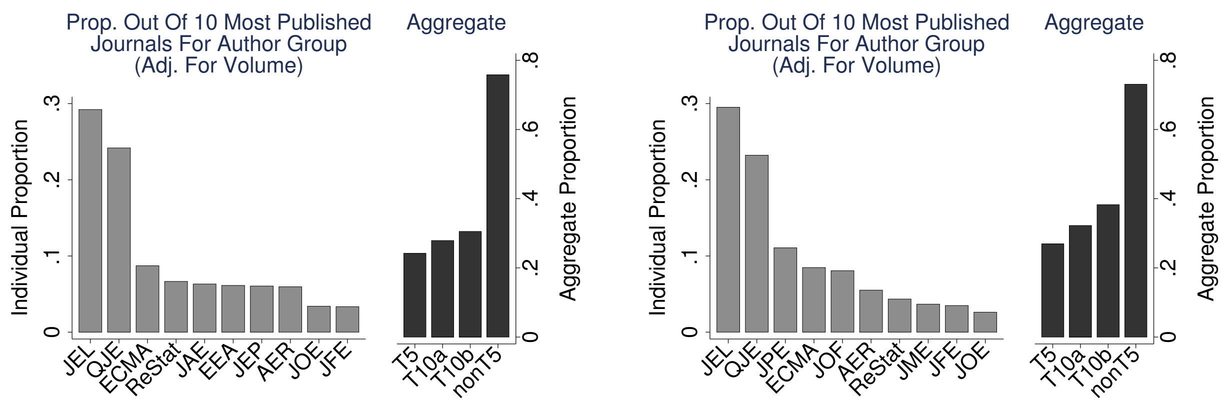
Source: Scopus; Accessed 08/2018.
Note: This table presents a publication volume-adjusted (volume of cited journal) ranking of journals that received the highest citations from the top 2 field journals in nine different fields of specialization. The nine fields used in this table are the same ones used in our analysis of work-history data and categorized in Table O-A9. Construction of the ranking proceeds in three steps. First, the top 2 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 (2010)'s field-specific rankings (the column titled "Tier A Field" in Table O-A9 presents the top 2 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 2 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 2 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 10 journals that received the largest proportion of citations from the top 2 journals of each field.

Label Legend: 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 adjusts for differences in publication volume, the T5 journals account for a considerably smaller share of field-specific articles published by the T50 authors of each field. The difference across ranking methods stems largely from differences in rankings assigned to *AER*. The *AER* experiences substantial negative discounting due to its large publication volume. Rankings for the non-*AER* T5 journals are fairly stable across the ranking methods.

4.5 The Forgotten (by the Top 5) Classics

Figure 14: Proportion of RePEc's Most Cited Articles Published in Different Journals in the Last 10 and 20 Years (Adjusted for Publication Volume)

(a) Articles Published in Last 10 Years (b) Articles Published in Last 20 Years



Source: RePEc.
The plot uses RePEc rankings for the top 1% 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 et al. (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, 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, JME-Journal of Monetary Economics.

The T5 excludes many influential papers. Figures 14a and 14b document that papers published in non-T5 journals account for more than 70% of RePecs most-cited articles in the

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.

past 10 and 20 years, respectively. Among the 20 most cited articles by RePEc, 35% 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 4 times the number of citations of any paper listed on RePEc.[68] The exclusion of books from citation warps incentives against broad and integrated research and towards writing bite-sized fragments of ideas.

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

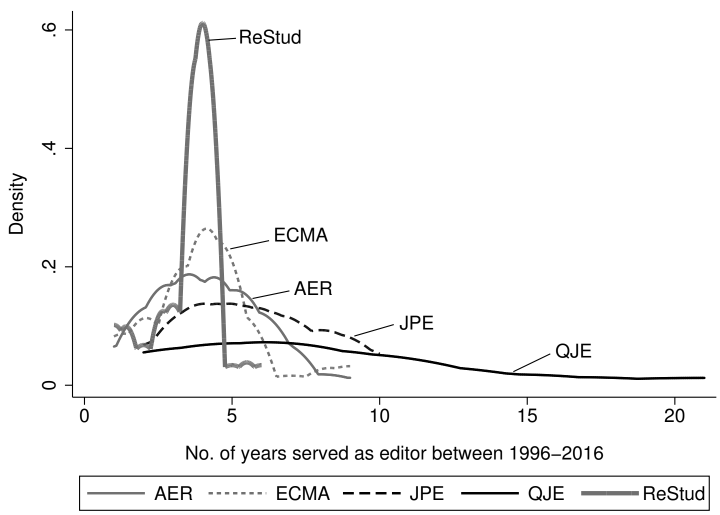
Note: Ranking and Citation Source: RePEc. Accessed on: 05/19/2017

[68] See Table O-A50 for a sample of these neglected classics.

Richard Thaler, the 2017 Nobel Prize winner, is a prominent example of the conservatism of the T5. His work swam against the current and for many years was not published in T5 journals (see Online Appendix Table O-A51). 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

Figure 15: Density Plot for the Number of Years Served by Editors between 1996-2016



Source: Brogaard, Engelberg & 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.

Monopolies restrict welfare. Oligopolies do no better. Openness and entry promote productivity, innovation, and the introduction of new ideas. Card and DellaVigna (2013) document the decline in the number of T5 papers published because T5 journal space is fixed in supply and papers have become longer. Demand for journal space has increased greatly while the supply is fixed.[69] This has created a more competitive environment that – with fixed requirements for tenure – implies that the cost and effort going into T5 publishing has increased

[69]See Online Appendix Figure O-A30

with the decline in the probability of success. This could mean that the average quality of papers published has gone up. It could also mean that more valuable resources of time and effort are being devoted to tailoring papers to please a certain group of editors. Ellison (2011) documents that highly-ranked scholars are placing fewer of their papers in the T5 journals. This phenomenon reduces perceived quality and reputational value of the T5.

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 keep retain editors with their special preferences for years. See Figure 15. 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.

This practice inevitably leads to incest and inbreeding. Table 8 estimates "incest coefficients" for the T5 journals[70]. The table documents the percentage of publications in the period 2000–2016 made by the Top 10 US departments as assessed by the US News rankings of economics departments,[71] plus New York University (ranked 13) and University

[70]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 are lower than ours: Colussi (2018) finds that Harvard faculty account for 15% of *QJE* publications during the period 2000–2006, and Chicago faculty account for 10% 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 vs. 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) assign 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 than 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 (2018)'s 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.

[71]The top 10 departments are determined based on an average of US News department rankings for the years 2008, 2010, and 2015.

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%*
UCBerkeley	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.)	**1807**	***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.)	**1667**	***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 & Non-Top)	**3474**	***n/a***	***n/a***	**1022**	***n/a***	***n/a***	**630**	***n/a***	***n/a***	**667**	***n/a***	***n/a***	**710**	***n/a***	***n/a***

Source: Elsevier, Scopus.com.
Note: The 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 list 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.

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% for Chicago affiliates; the non-house-affiliated *AER* has a relatively high incest coefficient for Harvard faculty who account for 11.9% of its publications[72]. Most conspicuous is the *QJE* with a 24.7% incest coefficient for Harvard affiliates and a 13.9%

[72]Chicago faculty account for only 7.7%

coefficient for MIT affiliates (the combined incest coefficient is over 33%).[73,74]

Tenure committees abdicate their responsibilities if they rely strongly on T5 publications. 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 et al. (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% 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

[73] 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.

[74] 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% figure might serve as a quality benchmark to down-weight the *QJE* incest coefficient.

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 health of the editorial process within the top journals of economics, the aggregate nature of these analyses prevent the studies from shedding light on the prevelance 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 is unfair from the perspective of an unconnected author whose tenure outcome is closely tied to the T5 editor's decision which, as 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.[75]

Biases stemming from informational efficiencies associated with author-editor networks are a reality. Also relevant are the effects that an editor's ideological and methodological biases can 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 ideo-

[75] Bertsimas, Brynjolfsson, Reichman, and Silberholz (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)

logical and/or methodological preferences, a journal will tend to disproportionately publish papers that exhibit the editor's preferred papers. Such biases can have profound effects on the health and future of the discipline, given the large dependence of tenure decisions on T5 publications.

First, such biases will 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 the number of T5 publications to decrease 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. Therefore, reliance on the T5 can catalyze significant realignments of the trajectories of future research, especially given the existence of long editorial tenure.

6 Summary and Discussion

Without doubt, publication in the Top Five is a powerful determinant of tenure in academic economics that influences the choice 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, post-doctoral 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 Top Five discourages large-scale, data-intensive empirical projects that explore and report the sensitivity of estimates to alternative assumptions. The fruits of such projects are too long and do not fit the format of the 40-page limit now widely advocated by the Top Five journals.

Reliance on the T5 centralizes power to shape the profession into the hands of a select group of editors. Relying on the Top Five to screen the next generation of economists incentivizes professional incest and creates clientele effects whereby career-oriented authors appeal to the tastes of editors and biases of journals. It raises entry costs for new ideas and persons outside the orbits of the journals and their editors.[76]

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 Top Five 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. Moreover, the Top Five 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 *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 over-emphasis 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.[77] 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

[76]Many readers of this paper have remarked to us that the empirical results in this paper do not strictly prove all of these claims. 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 unprecedented saintliness among journal editors and the scholars seeking to publish in their journals.

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

the T5 as a measure of research achievement and as a predictor of future scholarly 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 re-distribute the signalling function among more high-quality journals.[78] 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 re-definition of the T5 to include a handful of additional influential journals. A better solution will need to 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 select journals.

In this issue, Akerlof (2018) 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.

[78]Due to their limited time in operation, we excluded the four new journals created by the American Economic Association: American Economic Journal: Microeconomics, American Economic Journal: Macroeconomics, American Economic Journal: Economic Policy, and American Economic Journal: Applied Economics

A more radical proposal is to shift publication away from the current fixed format journals and towards an open source arXiv or PLOS ONE format.[79] Such formats facilitate the dissemination rate 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 into the profession that screen out new entrants with "odd ball" ideas and isolates those not acculturated in T5 values. Ellison (2011) notes that online publication is already being practiced by senior scholars. Why not broaden the practice and encourage spirited dialogue and rapid dissemination of unique thought?

Under any event, the profession should deemphasize crass careerism and promote creative activity. Short tenure clocks and reliance on the Top 5 to certify quality does 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 studies 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 pay-offs from such activities. Azoulay et al. (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 the "normal science" pre-defined deliverables, shorter review cycles and grant renewal policies that are unforgiving of failure. They

[79] 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 co-founder.

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.

Throughout this paper, we have followed the literature in using citation counts as a valid measure of productivity. However, it is well known that citation counts themselves are flawed measures of productivity. It is likely that, following convention, authors are more likely to cite T5 papers even when comparable or superior non-T5 papers are available.

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 rather than the development of a body of coherent and original ideas is most valued. It incentivizes careerism rather than creative scholarship.

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Text-Appendix for Publishing and Promotion in Economics: The Tyranny of the Top Five

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Wednesday 17th October, 2018

Contents

1 Estimating Probability of Receiving Tenure

1.1 Logit Analysis

This section 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:[1]

$$log\left(\frac{Pr(Tenure_i = 1)}{1 - Pr(Tenure_i = 1)}\right) = \alpha_0 + \sum_{j \in \mathcal{J}} \left(\sum_{n=1}^{3} \alpha_j^n \cdot \mathbb{1}(\#j_i \geq n)\right) + \boldsymbol{X\beta} + \varepsilon_i, \qquad \text{(TA-1)}$$

where $Tenure_i$ is an indicator for receiving tenure by the end of the first spell of tenure-track employment; $\mathcal{J} = \{T5, TierA, TierB, General\}$; $\mathbb{1}(\#j_i \geq n)$ is an indicator for having n or more publications in journals of type-j by the end of the first spell, where $j \in J$; and $\boldsymbol{X}$ is a vector of controls that includes a 3^{rd} 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 co-authors across all articles published in the first spell, the total number of citations received by author i across all articles published in the first spell, and a control for total volume of publicaitons $ln(\#\text{Total Publications}+1)$.

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.[2][3]

See Online Appendix Section 2.3 for an analysis of the relationship between publications and the probability of receiving tenure by the 7^{th} year of tenure-track employment.

[1] 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 section. The Logit and LPM estimates lead to qualitatively similar conclusions. The reader is referred to Online Appendix Section 2.1 for LPM estimates.

[2] 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.

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

$$Pr(Tenure = 1 \mid \#\widehat{J} = \widehat{N}, \#\widetilde{J} = 0, \boldsymbol{X}) = \frac{exp\left(\alpha_0 + \sum_{n=1}^{\widehat{N}} \alpha_{\widehat{J}}^n + \boldsymbol{X\beta}\right)}{1 + exp\left(\alpha_0 + \sum_{n=1}^{\widehat{N}} \alpha_{\widehat{J}}^n + \boldsymbol{X\beta}\right)} \qquad \text{(TA-2)}$$

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

2 Duration Model

2.1 Tenure as a single-spell multi-state survival process

Let $S = \{0, 1, 2\}$ be the collection of employment states that untenured tenure-track faculty can occupy in subsequent periods, where each state is defined in Table 1 of the main text. Then, $S' = \{S\} \backslash \{s = 0\} = \{1, 2\}$ 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 $s = j \in S'$ is governed by:

$$f_{0,j}(t_{0,j}) = h_{0,j}(t_{0,j}) \cdot \exp\left\{-\int_0^{t_{0,j}} h_{0,j}(u)du\right\} \tag{TA-3}$$

where $f_{0,j}$ is the density of exit times from $s = 0$ to $s = j$, and $h_{0,j}$ is the corresponding hazard function. The hazard $h_{0,j}(t_{0,j})$ is the probability of transitioning from $s = 0$ to $s = j$ in $t_{0,j}$ given that transitions out of state $s = 0$ have not occurred prior to $t_{0,j}$ (see Equation TA-9 for formal definition).

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

$$P_{0,j} = \int_0^{\infty} h_{0,j}(t_{0,j}) \cdot \exp\left\{-\int_0^{t_{0,j}} \left[\sum_{s' \in S'} h_{0,s'}(u)\right] du\right\} dt_{0,j} \tag{TA-4}$$

where the exponentiated term represents the probability of surviving from all risks $s' \in S'$ until period $t_{0,j}$, and $h_{0,j}(\cdot)$ is the transition-j specific hazard. The conditional density of exit times from $s = 0$ to $s = j$ given that no other transitions have occurred in the current spell of untenured tenure-track employment is given by:

$$g_{0,j}(t_{0,j} \mid t_{0,j} < t_{0,j'} \ \forall j' \in \{S'\} \setminus j) = \frac{h_{0,j}(t_{0,j}) \cdot \exp\left\{-\int_0^{t_{0,j}} \left[\sum_{s' \in S'} h_{0,s'}(u)\right] du\right\}}{P_{0,j}} \tag{TA-5}$$

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

$$f_{0,S'}(t_{0,S'}) = \sum_{s \in S'} P_{0,s} \cdot \ g_{0,s}\left(t_{0,s} \mid t_{0,s} < t_{0,s'} \ \forall s' \in \{S'\} \setminus s\right) \tag{TA-6}$$

$$= \left[\sum_{s \in S'} h_{0,s}(t_{0,s})\right] \cdot \exp\left\{-\int_0^{t_{0,j}} \left[\sum_{s \in S'} h_{0,s}(u)\right] du\right\} \tag{TA-7}$$

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 $t_{0,j}$ 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 survivor function:

$$S_{0,S'}(T) = 1 - F_{0,S'}(T) = 1 - \int_0^T f_{0,S'}(t)dt \tag{TA-8}$$

where $F_{0,S'}(T)$ 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 $s = j \in S'$ as:

$$h_{0,j}(t_{0,j}) = P(T_{0,j} = t_{0,j} \mid T_{0,j'} > t_{0,j}\ \forall j' \in S') = \frac{f_{0,j}(t_{0,j})}{S_{0,S'}(t_{0,j})} \tag{TA-9}$$

Eq. (TA-9) expresses the hazard of transitioning to a new state $j \in S'$ during period $t_{0,j}$ as the conditional probability of the transition occurring at $t_{0,j}$ given that no other transitions having occurred prior to $t_{0,j}$ 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). Eq. (TA-10) specifies the hazard as a function of current-spell duration, observable characteristics and unobserved individual heterogeneity:

$$h_{0,j}(t_{0,j}) = \exp\left\{\sum_{j\in J}\left(\sum_{n=1}^{3}\alpha_j^n \cdot \mathbb{1}(\#j(t_{0,j}) \geq n)\right) + \mathbf{X}_{0,j}\boldsymbol{\beta}_{0,j} + \gamma_{1,0,j}\frac{(t_{0,j}^{\lambda_{1,0,j}} - 1)}{\lambda_{1,0,j}} + \gamma_{2,0,j}\frac{(t_{0,j}^{\lambda_{2,0,j}} - 1)}{\lambda_{2,0,j}} + V_{0,j}\right\} \tag{TA-10}$$

where $\mathbb{1}(\#j(t_{0,j}) \geq n)$ is an indicator for having n or more publications in journals of type-j as of time period $t_{0,j}$; $\mathbf{X}_{0,j}$ is a vector that includes fixed effects for authors' academic department as well as time-varying and time-invariant observable author characteristics including authors' cumulative citation counts, 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); $\boldsymbol{\beta}_{0,j}$ is a vector of parameters associated with $\mathbf{X}_{0,j}$; $\lambda_{1,0,j} < \lambda_{2,0,j}$, $\gamma_{1,0,j}$ and $\gamma_{2,0,j}$ are duration parameters; and $V_{0,j} = C_{0,j}V$ 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 $\lambda_{1,0,j} = 0$ and $\gamma_{2,0,j} = 0$:

$$h_{0,j}(t_{0,j}) = \exp\left\{\sum_{j\in J}\left(\sum_{n=1}^{3}\alpha_j^n \cdot \mathbb{1}(\#j(t_{0,j}) \geq n)\right) + \mathbf{X}_{0,j}\boldsymbol{\beta}_{0,j} + V_{0,j}\right\} t^{\lambda_{1,0,j}} \tag{TA-11}$$

The Weibull model allows for monotonic duration dependence, where the sign of dependence is the same as $\lambda_{1,0,j}$. Setting $\gamma_{1,0,j} = 0$ and $\gamma_{2,0,j} = 0$ 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. Eq. (TA-12) shows that an immediate generalization is obtained by allowing complete independence among parameters across the l different spells of untenured tenure-track employment.

$$h^l_{0,j}(t_{0,j}) = \exp\left\{\sum_{j\in J}\left(\sum_{n=1}^{3}\alpha_j^{n,l}\cdot \mathbb{1}(\#j(t_{0,j})\geq n)\right) + \mathbf{X}_{0,j}\boldsymbol{\beta}^l_{0,j} + \gamma^l_{1,0,j}\frac{(t_{0,j}^{l^{\lambda^l_{1,0,j}}}-1)}{\lambda^l_{1,0,j}} + \gamma^l_{2,0,j}\frac{(t_{0,j}^{l^{\lambda^l_{2,0,j}}}-1)}{\lambda^l_{2,0,j}} + V^l_{0,j}\right\} \tag{TA-12}$$

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 $\alpha_j^{n,l}$ 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. $V^l_{0,j} = C^l_{0,j}V$ is a one-factor spell l-specific specification for unobserved heterogeneity which allows heterogeneity to vary across spells. Lastly, we introduce a parameter $\delta_{0,j}$ which 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:

$$h^l_{0,j}(t_{0,j}) = \exp\Bigg\{ \sum_{j \in J} \left(\sum_{n=1}^{3} \alpha_j^n \cdot \mathbb{1}(\#j(t_{0,j}) \geq n) \right) + \mathbf{X}_{0,j}\boldsymbol{\beta}_{0,j} + \delta_{0,j}(l-1) \; + \\ + \gamma_{1,0,j}\frac{(t_{0,j}^{\lambda_{1,0,j}} - 1)}{\lambda_{1,0,j}} + \gamma_{2,0,j}\frac{(t_{0,j}^{\lambda_{2,0,j}} - 1)}{\lambda_{2,0,j}} + V^l_{0,j} \Bigg\} \quad \text{(TA-13)}$$

where $V^l_{0,j}$ 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 TA-13 with indicators for being employed by a department in one of the three rank-based groups:

$$h^l_{0,j}(t_{0,j}) = \exp\{\boldsymbol{Z}\} \times \exp\Bigg\{ \left(\sum_{j \in J} \sum_{n=1}^{3} \alpha_j^n \cdot \mathbb{1}(\#j(t_{0,j}) \geq n) \right) + \\ + \sum_{r=1}^{3} \mathbb{1}(i_{t_{0,j}} \in r) \times \left(\sum_{j \in J} \sum_{n=1}^{3} \alpha_{j,r}^n \cdot \mathbb{1}(\#j(t_{0,j}) \geq n) \right) \Bigg\} \quad \text{(TA-14)}$$

where $\exp\{\boldsymbol{Z}\}$ represents the components of the hazard that are unrelated to publications, and $\mathbb{1}(i_{t_{0,j}} \in r)$ is an indicator for whether individual i was employed during $t_{0,j}$ 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:

$$\frac{h^l_{0,j}(t_{0,j} \mid \#T5_{t_{0,j}} = n, r = 1, \boldsymbol{X})}{h^l_{0,j}(t_{0,j} \mid \#T5_{t_{0,j}} = 0, r = 1, \boldsymbol{X})} \quad \text{(TA-15)}$$

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

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