Tenure and Research Trajectories

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Tenure is a cornerstone of the US academic system, yet its relationship to faculty research trajectories remains poorly understood. Conceptually, tenure systems may act as a selection mechanism, screening in high-output researchers; a dynamic incentive mechanism, encouraging high output prior to tenure but low output after tenure; and a creative search mechanism, encouraging tenured individuals to undertake high-risk work. Here, we integrate data from seven different sources to trace US tenure-line faculty and their research outputs at an unprecedented scale and scope, covering over 12,000 researchers across 15 disciplines. Our analysis reveals that faculty publication rates typically increase sharply during the tenure track and peak just before obtaining tenure. Post-tenure trends, however, vary across disciplines: in lab-based fields, such as biology and chemistry, research output typically remains high post-tenure, whereas in non-lab-based fields, such as mathematics and sociology, research output typically declines substantially post-tenure. Turning to creative search, faculty increasingly produce novel, high-risk research after securing tenure. However, this shift toward novelty and risk-taking comes with a decline in impact, with post-tenure research yielding fewer highly cited papers. Comparing outcomes across common career ages but different tenure years or comparing research trajectories in tenure-based and non-tenure-based research settings underscores that breaks in the research trajectories are sharply tied to the individual's tenure year. Overall, these findings provide a new empirical basis for understanding the tenure system, individual research trajectories, and the shape of scientific output.

Introduction

Few labor contracts are as distinctive or consequential as academic tenure in the United States[1], which combines a fixed-term probationary period, a high-stakes "up-or-out" decision, and lifetime job security. Despite its central role in the US academic system and its widespread use, we lack a systematic understanding of how tenure shapes scientists' productivity, impact, and research agendas. Understanding the relationship between tenure and research trajectories is important not only for academic institutions and individual researchers, but also for the broader public, given the role of public funding in supporting university research and the role of scientific advances in propelling technological developments, rising standards of living, and improved human health, among other benefits[2–10].

Tenure, as a lifetime labor contract, may have a strong influence on researcher incentives, choices, and performance[11–14]. On one dimension, tenure operates as an "up-or-out" contract, creating powerful incentives to produce substantial, high-impact research within a fixed probationary period[15–18]. This high-stakes timeline may drive researchers to focus on achievable projects that demonstrate their productivity and potential. However, upon receiving tenure and its job security, the incentives to continue to produce high-quantity or high-impact research may weaken. This "moral hazard" problem may lead to reduced output or a shift toward incremental work. On the other hand, moral hazard considerations may be offset or overcome by a "screening" function of tenure[19–23]. Here the tenure process can be thought of as a difficult test that identifies individuals who, regardless of incentives, are willing and able to maintain high levels of research success throughout their careers. Further, despite the job security of tenure, scientific norms and incentives may encourage persistent effort as researchers seek continued achievements, funding, and status, whether through grant money, prizes, or the respect of their peers[9,13,24]. These contrasting forces raise important questions about the overall effects of tenure on research productivity across disciplines and career stages.

Beyond the rate of research production, tenure may also influence the direction of research. Specifically, research projects are steps into the unknown, where failure is common[25–27], especially in more "exploratory" work where researchers investigate novel terrain and payoffs are highly uncertain[28–36]. Indeed, even ultimately successful, breakthrough ideas, from mRNA vaccines to artificial intelligence, often follow years of failure or stagnation[25–27]. Tenure, by offering job security, creates a rare contractual arrangement that may encourage researchers to take bigger bets in their creative search[12,13], attempting relatively novel inquiries in pursuit of transformative discoveries. However, while tenure's role in encouraging risk-taking and exploration is often assumed, its actual effects on research trajectories remain unclear. Does tenure consistently foster exploratory work, or does it depend on disciplinary norms or institutional contexts? Do researchers across different

disciplines respond differently to tenure? And how do the patterns observed in the US tenure system compare to other institutional settings, such as national laboratories or European universities, where different employment structures prevail?

Amidst ongoing debates about tenure's advantages and drawbacks[11,37–39], existing empirical studies have mainly focused on specific disciplines and selected faculty groups[40–43], with systematic assessments limited by the lack of comprehensive longitudinal faculty data across scientific disciplines. In this paper, we integrate seven different data sources to assemble the largest and most comprehensive database of faculty rosters and research outputs to date. The core of this data is sourced from the Academic Analytics Research Center (AARC) [D1], which captures a census of about 300K faculty from 362 Ph.D.-granting institutions in the US. The dataset covers the time period between 2011 and 2020 and spans all scientific disciplines, allowing us to systematically identify tenure-line faculty members and examine how an individual's research evolves before and after tenure. We focus on faculty members who experience a transition from a tenure-track to a tenured position between 2012 and 2015, allowing us to follow their careers for at least five years before and after their promotion. In addition, this time window ensures that our results are not affected by the COVID-19 pandemic, which had a significant impact on scientific careers, tenure clocks, and research production[44–46]. We complement AARC data [D1] with two additional databases [D2 and D3] that trace the entire faculty rosters of two different large research universities in the US, covering all faculty members who were promoted over the past 25 years. These data allow us to test the generalizability of the findings from the first dataset [D1] over longer time spans. We further integrate D1-D3 with large-scale datasets that offer information related to publications, citations, funding, and other relevant research measures, including SciSciNet [D4][47], Scopus [D5], and Dimensions [D6]. Lastly, we integrate dissertation data from ProQuest [D7] with D1-D6, allowing us to develop a peer group of researchers who graduated from similar PhD programs in the same years as the faculty members we study. Overall, we trace the research outputs of 12,611 faculty members across the sciences, engineering, and social sciences (see SI for further details on the descriptions of the datasets and additional validations).

Results

Tenure and Research Output

We first focus on the relationship between tenure and publication rates. We evaluate outcomes over an eleven-year span, including the five years before and after tenure. We find that, on average, the publication rate rises steeply and steadily through the tenure track, typically peaking the year before tenure (Fig. 1A). After tenure, the average publication rate shows remarkable stability, settling near the peak achieved right before tenure (Fig. 1A). We further test whether this pattern may be influenced by the research environment, such as university rank[48–50], finding the same

distinctive patterns at different university ranks (Fig. 1B). Overall, publications feature a rise-and-stabilize pattern, with the transition occurring around the tenure year, suggesting that the timing of tenure substantially conditions individual output, irrespective of university rank (Fig. 1B).

However, this pattern might also be a function of career age, as output rates shift over the life cycle[51–57]. To test this, we separate our analyses by grouping scientists with different career ages when attaining tenure. More specifically, we measure the number of years elapsed between the doctoral degree and tenure (i.e., "career age at tenure") for each scientist and then consider the publication pattern around tenure for researchers with different career ages (Fig. 1C). Strikingly, regardless of career age, average publication rate follows the same rise-and-stabilize pattern. The tenure transition manifests itself whether the researchers are as few as 6 years past their PhD or as many as 14 years past their PhD. The sharp transitions in publication rates thus do not appear related to career age but rather closely follow the specific tenure timing.

The rise-and-stabilize pattern documented in Fig. 1 is rather unexpected, considering two lines of evidence in prior literature. First, research on the lifecycle of creative output consistently shows a smooth, curvilinear relationship, with no sharp breaks in publication growth[51–56]. By contrast, when lining publication rates up against individual-specific tenure timing, our analysis instead reveals a sharp transition in output growth, timed to the individual's change in the labor contract. Second, research on economics and finance professors indicates falling publication counts after tenure[43]. By contrast, our results show sustained output levels post-tenure when looking at all fields together. This suggests potentially substantial disciplinary differences in how researchers behave after tenure, which we explore next.

Field-level heterogeneity

We classify scientists into 15 different disciplines based on their publications (see SI and Fig. S2). This discipline-level analysis reveals heterogeneity, with two broad patterns (Fig. 2). For business, economics, mathematics, sociology, and political science, the average trend in research output follows a rise-and-fall pattern[51–54]. Yet for all other disciplines, publication rates sustain after tenure rather than decline. In sum, publication rates rise sharply during the tenure track for all disciplines and peak around the year of tenure. Following the peak, disciplines diverge, with some showing declining publication rates while others show rates that stabilize at high levels. While tenure is a universal feature across disciplines, these results unveil great disciplinary variation in output patterns after tenure.

Amidst the many factors that may underpin such disciplinary variations, one notable distinction lies in laboratory approaches to research[58,59]. Disciplines that follow the rise-and-stabilize patterns are

generally organized through a laboratory model of scientific production, whereas the rise-and-fall disciplines—business, economics, mathematics, sociology, and political science—do not traditionally use this laboratory model. The laboratory model is characterized by reliance on grant funding and substantial teamwork, often in a hierarchy where the principal investigator recruits and collaborates extensively with PhD students and post-doctoral researchers. To quantify these distinctions, we measure the median team size per paper for each discipline (SI Section S4 and Fig. S3), the fraction of solo-authored papers (SI Section S4 and Fig. S4), the share of papers co-authored with early career researchers (SI Section S4 and Fig. S5), and the amount of funding garnered by each faculty (SI Section S4 and Fig. S6). Across all these measures, we consistently see the split between the two classes of disciplines (SI Section S4). We further confirm that the rise-and-stabilize patterns persist when considering only the lead-author papers by faculty in laboratory disciplines (Fig. S7).

Individual-level heterogeneity

Individual scientists may follow varied research trajectories[60,61] or respond differently to incentives such as tenure[62,63]. To examine individual-level heterogeneity, we compare publications per year before and after tenure for each scientist and calculate the share of faculty members whose publication rate increases or decreases. Specifically, we group individual researchers into four categories according to their average publication rate after tenure: (i) *zero* (the individual stops producing papers after tenure); (ii) *lower* (the annual publication rate declines); (iii) *higher* (the annual publication rate grows between 0 and 100%); and (iv) *more than double* (the annual publication rate grows more than 100%). Figure 3 summarizes these results. We find that across all disciplines, only a tiny fraction of faculty ceases production entirely after tenure. Further, a substantial fraction of faculty significantly increases their average publication rate after tenure, with many even doubling their research output. The two classes of disciplines in Fig. 2 prove germane again when considering individual heterogeneity. In the rise-and-stabilize disciplines, the majority of researchers see increased publication rates post-tenure. In the rise-and-fall disciplines, the majority of faculty see decreased publication rates post-tenure.

We further quantify differences in publication rates across individual researchers using the Gini index and examine how this evolves pre- and post-tenure (Fig. S9, S10). We find the publication rate differences across faculty members decrease as junior faculty approach tenure, reaching their lowest point in the year before tenure before rising again after tenure. We repeat our analyses by measuring the coefficient of variation in publication rates, observing similar patterns (Fig. S11). Notably, this convergence-then-divergence pattern applies to all disciplines, with the transition occurring in the year right before tenure. The tenure timing again marks a sharp shift in behavior.

Research impact

Publication impact, beyond publication counts, is also central to understanding researcher output, prompting us to examine the production of high-impact papers before and after tenure. Since the impact of papers is time- and field-dependent[64], we measure hit papers, defined as those in the top 5% of the distribution of citations across all papers in the same publication year and subfield (SI Section S6). Figure 4A shows the pooled hit rate, computed as the ratio of the total number of hit papers over the total number of articles in the given year before or after tenure. The hit rate is found to be higher before tenure than after tenure, with a downward trend that generalizes across the diverse disciplines we consider. We also investigate the timing of the highest-impact paper each researcher produces in the 11-year span and compare the position with a null model where impacts are distributed randomly within a career (SI Section S7). At this individual level, researchers tend to produce their most cited paper (again, normalized according to the field and year) during the tenure track rather than after tenure (Fig. 4B). To ensure that the exceptional impact in pre-tenure years is not driven by collaborations, especially those with prior advisors, we repeat the analysis by considering papers published as the last author, and we arrive at the same conclusions (Fig. S12).

Overall, these results are consistent with conceptualizations where tenure, as an "up-or-out" contract design, brings out an individual's peak performance during the tenure track. At the same time, while researchers from many disciplines see sustained publication rates post-tenure, and these sustained publication rates continue to include many high-impact papers, the proportion of papers that are high-impact generally declines after tenure.

Tenure and Exploration

A perceived advantage of tenure is that job security encourages professors to take bigger risks in their research projects and explore novel ideas. This pursuit of novelty can take two distinct forms.

In one form, scholars try directions that are new to them personally—a new agenda that extends their focus and skills. In the second form, scholars try directions that are novel for science as a whole—research orientations that appear unusual within the scope of prior science. Here we operationalize measures for both types of novelty and explore the nature of pre- to post-tenure transitions.

We first group the papers of each faculty member into topics, applying a community detection method to the co-reference network of these papers (see SI Section S8 for detailed methods)[28,65]. Figure 5A shows an illustrative example, where nodes represent the faculty member's papers and two papers are connected if they share common references. To explore linkages with tenure, we

further categorize each detected community according to whether it appears both before and after tenure (i.e., a continued topic), only after tenure (i.e., a new topic), only before tenure (i.e., an abandoned topic), or whether the paper is disconnected from all other papers (i.e., an isolated topic). Fig. 5B continues the example in Fig. 5A, but with the publication year for each paper lined up against the faculty member's tenure timing. In this example, the faculty member abandoned one topic (red), explored one new topic (gold), and continued one pre-tenure research topic (black).

Applying these methods to each individual in our data, Fig. 5C investigates whether and how faculty members reorganize their research portfolio after tenure. Our analysis indicates that faculty do tend to shift their directions: approximately two-thirds of faculty engage with at least one new topic in the five years after tenure, and approximately one-third of faculty members abandon at least one topic, depending on the discipline. Notably, virtually all faculty continue working on at least one topic they focused on before tenure. In other words, faculty almost never exhibit a complete switch in research directions following tenure but rather exhibit a portfolio approach in creative search. Faculty members balance ongoing connections with their established research agenda (exploitation) with the pursuit of new directions (exploration), which is consistent with the "ambidexterity" literature on organizations[66], but here applied to individual behavior.

To understand the relative focus on exploration and exploitation, we divide faculty members' research outputs into continuations of pre-tenure topics versus investigations of a new topic that was not studied before tenure. Whereas the average publication rate tends to follow two broad classes across the disciplines, here we find that when we only count papers that continue the pre-tenure agenda (black dashed line), all disciplines follow the rise-and-fall pattern (Fig. 6). This suggests that new agendas post-tenure (shaded areas in Fig. 6) are a key feature sustaining output rates for the rise-and-stabilize patterns observed in Fig. 2 (see also Fig. S27).

The second form of novelty we consider is whether faculty increasingly engage in novel research, not compared to their own work, but compared to prior science as a whole. Specifically, and following prior literature[6,67,68], we measure novelty as capturing atypical combinations of prior work[33] (SI Section S6). As we did for impact, we compute the pooled novelty rate and the position of the most novel paper in the 11-year sequence compared with a null model. Figure 7A shows that the pooled novelty rate tends to increase, indicating a higher propensity of faculty to be involved in novel-to-science projects after tenure. Further, the most novel paper within the period tends to appear after tenure (Fig. 7B). Notably, these findings contrast with the impact results (Fig. 4): Whereas the share of hit papers goes down with time, the novelty of the papers tends to go up. These patterns are consistent with more exploratory work post tenure. While there is no obvious

sharp break at tenure, we do see a shift toward more novelty and lower success rates, largely consistent with a key motivating idea of tenure in encouraging higher-risk search.

To quantify the balance between exploration and exploitation in the context of creative search behavior, we further compute the hit and novelty rates by research agenda (i.e., new vs. continuing) before and after tenure. These comparisons are only feasible for faculty who start a new agenda after tenure (~5k scholars); hence, the results should be interpreted as conditional on successfully starting a new agenda post-tenure. We find that papers published before tenure in the "old" agenda (i.e., the topics faculty members keep after tenure) show the highest hit rate (Fig. 8A). However, post-tenure papers within this pre-existing agenda are substantially less impactful than pre-tenure papers. Interestingly, papers that belong to the new agenda (i.e., exploration) have a greater impact than new papers that continue the pre-tenure agenda (i.e., exploitation). Taken together, we see that new agendas for a faculty member tend to outperform continuations of the old agendas. This is consistent with faculty expanding into new areas as their prior areas deliver diminishing returns.

Turning to novelty, we indeed find that papers on new topics post-tenure are also more novel in science as a whole (Fig. 8B). We confirm these trends by considering continuous outcome variables (avg. citation and avg. novelty, SI Section S6 and Fig. S14) and fields with and without the laboratory model (SI Section S4 and Fig. S15). In sum, these results indicate that in the post-tenure period, faculty tend to undertake agendas that are both new to them and relatively novel in science, a potentially riskier behavior that extends the reach of science as a whole but produces fewer hits. This shift appears in comparisons of post-tenure with pre-tenure periods, highlighting evolving research directions over time.

Institutional Comparisons

One key question is whether the patterns we observe are specific to tenure, given that other factors may be at play. To further interrogate the role of tenure, we compare patterns between individual researchers in the tenure-line context with alternative "control groups" of researchers in different institutional contexts. First, we use dissertation data to identify graduates who were in similar US PhD programs and graduated in the same year but were not tenured by the end of our time window (Fig. S16). Second, using a similar matching strategy, we identify individuals from the same PhD program and graduation year who moved to Europe upon graduation (where labor contracts are organized differently than in the US tenure system, Fig. S17A). Third, we identify the graduates of these similar US PhD programs who joined government organizations in the US, such as National Labs, and we compare their research trajectories with our tenure-line faculty sample (Fig. S17B). Fourth, leveraging the internal HR data from two large R1 universities (D2 and D3), we identify

faculty members employed in the same university in the same period but separate them based on tenure eligibility, comparing their research trajectories (Fig. S18-S19).

Across all these control groups, we find that the control researchers do not exhibit the characteristic publication rate shifts that we observe at tenure for the tenure sample. Rather, output measures tend to move in a smooth manner when studying research trajectories among these various control groups. Note that these controls do not imply causal relationships between tenure and research trajectories, especially to the extent that researchers who enter the US tenure track are a selected sample, and in general it is difficult to deploy experimental or quasi-experimental approaches to the tenure system. Nevertheless, the results from these numerous control exercises further inform the distinctiveness of the shifts we see in research trajectories across tenure within US academic institutions. Overall, the sharp break in output appears unique to tenure timing, whether in comparisons among US tenure-line academics (Fig. 1) or in comparison to individual research trajectories in different institutional contexts (Fig. S16-19).

Tests with Alternative Data

We further examine the main analyses using alternative data and additional regression methods. Specifically, while our main analyses use publication data via Microsoft Academic Graph and SciSciNet [D4], we reconsider the main findings with Scopus [D5], using that database's publication records and field encodings. The results prove robust to these alternative data (SI Section S1, S3, S6 and Figs. S20-32). Further, we consider the main findings for publication rate, hit rate, and novelty rate in regressions that include individual researcher fixed effects and numerous paper-level controls, finding consistent results (SI Section S11 and Figs. S33-37).

Discussion

Integrating seven different large-scale data sources, this work reveals central facts about research trajectories before and after tenure, demonstrating widespread turning points for individual scientists. On average, receipt of tenure is associated with sustained high rates of research output and a shift toward more novel but less impactful work. The results prove robust across different datasets, controls, and assumptions. The distinctiveness of tenure patterns also appears when comparing tenure-line researchers with individual researchers working under different incentive contracts or in different types of research institutions.

The findings speak to conceptual views of tenure's potential effects, both in the rate and direction of research activities, while also revealing important heterogeneity across disciplines and individuals. Viewed as a screening mechanism, tenure does tend to select on individuals who maintain robust research agendas. Viewed as a moral hazard problem, theories that emphasize

weak incentives to sustain research output post-tenure do not appear to describe the sciences or researchers on average. Publication rates tend to stabilize at high levels. Further, the cessation of publishing upon tenure is exceedingly rare, whereas individuals doubling their pre-tenure rate of research output is far more common. At the same time, outside the laboratory sciences, we do see a tendency for declining publication rates after tenure. The disciplinary heterogeneity suggests the incentive aspects of tenure may be important yet are overcome by other forces in many fields. Unpacking the forces that support continued research output beyond tenure is an important area for future work.

Other theoretical viewpoints emphasize that tenure, through the job security it provides, encourages exploratory, higher-risk research. The empirical evidence indicates that faculty do indeed tend to shift toward more novel research after tenure, but with declining hit rates, consistent with higher-risk research allocations. Digging deeper into research portfolios, nearly all faculty continue at least one pre-tenure research agenda, while more than half of faculty add a new agenda. The new agendas further exhibit greater novelty for science. It is thus common to see shifts toward research that is not just new to the individual but new to science as a whole.

Overall, given the central role of tenure in the US academic system, this paper establishes a new empirical basis for understanding faculty research trajectories both before and after tenure. While the focus of this paper is on research outputs, tenure is a pivotal point of a career that often marks shifts in many other dimensions, including service, mentoring, administrative duties, and more. Weighing the broader activities of scientists is a key area for future work. Moreover, while our analyses examined changes in individual research trajectories before and after tenure, future work may include those who did not attain tenure, examine later career outcomes, and further investigate research trajectories in alternative institutional contexts, enabling researchers to answer a range of new questions. Given the prominence of research universities in generating fundamental knowledge and innovations that drive human progress, understanding how tenure systems influence research outcomes is important not only for the academic community but also for advancing discoveries that benefit the broader society.

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Data and code availability

Data and code necessary to reproduce results will be made available upon publication.

Data sources

[D1] https://aarcresearch.com/

[D2, D3] HR internal data

[D4] https://doi.org/10.6084/m9.figshare.c.6076908.v1

[D5] https://www.scopus.com

[D6] https://www.dimensions.ai/

[D7] https://www.proquest.com

References

1. 1940 Statement of Principles on Academic Freedom and Tenure. *AAUP* https://www.aaup.org/report/1940-statement-principles-academic-freedom-and-tenure (2006).

2. Disraeli, B. *Inaugural Address Delivered to the University of Glasgow Nov. 19, 1873; by Benjamin Disraeli. 2d Ed., Including the Occasional Speeches at Glasgow, Authorised Ed., Corr. by the Author*. (London Longmans, Green, 1873).

3. Bush, V. & Holt, R. D. *Science, the Endless Frontier*. (Princeton University Press, 2021). doi:10.2307/j.ctv15r5879.

4. Wang, D. & Barabási, A.-L. *The Science of Science*. (Cambridge University Press, 2021).

5. Jones, B. F. Science and Innovation: The Under-Fueled Engine of Prosperity • The Aspen Institute Economic Strategy Group. *The Aspen Institute Economic Strategy Group* https://www.economicstrategygroup.org/publication/jones/ (2021).

6. Fortunato, S. *et al.* Science of science. *Science* **359**, eaao0185 (2018).

7. Nelson, R. R. The Simple Economics of Basic Scientific Research. *J. Polit. Econ.* **67**, 297–306 (1959).

8. Mokyr, J. *The Gifts of Athena*. (Princeton University Press, 2002).

9. Merton, R. K. *The Sociology of Science: Theoretical and Empirical Investigations*. (University of Chicago Press, Chicago, IL, 1979).

10. Wang, Y., Qian, Y., Qi, X., Cao, N. & Wang, D. InnovationInsights: A Visual Analytics Approach for Understanding the Dual Frontiers of Science and Technology. *IEEE Trans. Vis. Comput. Graph.* **30**, 518–528 (2024).

11. McPherson, M. S. & Schapiro, M. O. Tenure Issues in Higher Education. *J. Econ. Perspect.* **13**, 85–98 (1999).

12. Manso, G. Motivating Innovation. *J. Finance* **66**, 1823–1860 (2011).

13. Azoulay, P., Graff Zivin, J. S. & Manso, G. Incentives and creativity: evidence from the academic life sciences. *RAND J. Econ.* **42**, 527–554 (2011).

14. MacLeod, W. B. & Urquiola, M. Why Does the United States Have the Best Research Universities? Incentives, Resources, and Virtuous Circles. *J. Econ. Perspect.* **35**, 185–206 (2021).

15. Kahn, C. & Huberman, G. Two-Sided Uncertainty and 'Up-or-Out' Contracts. *J. Labor Econ.* **6**, 423–444 (1988).

16. Waldman, M. Up-or-Out Contracts: A Signaling Perspective. *J. Labor Econ.* **8**, 230–250 (1990).

17. Carmichael, H. L. Incentives in Academics: Why is There Tenure? *J. Polit. Econ.* **96**, 453–472 (1988).

18. Siow, A. Tenure and Other Unusual Personnel Practices in Academia. *J. Law Econ. Organ.* **14**, 152–173 (1998).

19. O'Flaherty, B. & Siow, A. On the Job Screening, up or Out Rules, and Firm Growth. *Can. J. Econ. Rev. Can. Econ.* **25**, 346–368 (1992).

20. O'Flaherty, B. & Siow, A. Up-or-Out Rules in the Market for Lawyers. *J. Labor Econ.* **13**, 709–735 (1995).

21. Malcomson, J. M. Work Incentives, Hierarchy, and Internal Labor Markets. *J. Polit. Econ.* **92**, 486–507 (1984).

22. Carmichael, L. Firm-Specific Human Capital and Promotion Ladders. *Bell J. Econ.* **14**, 251–258 (1983).

23. Lazear, E. P. & Rosen, S. Rank-Order Tournaments as Optimum Labor Contracts. *J. Polit. Econ.* **89**, 841–864 (1981).

24. MacLeod, W. B., Riehl, E., Saavedra, J. E. & Urquiola, M. The Big Sort: College Reputation and Labor Market Outcomes. *Am. Econ. J. Appl. Econ.* **9**, 223–261 (2017).

25. Sitkin, S. Learning Through Failure : The Strategy of Small Losses. *Res. Organ. Behav.* (1992).

26. Wang, Y., Jones, B. F. & Wang, D. Early-career setback and future career impact. *Nat. Commun.* **10**, 4331 (2019).

27. Yin, Y., Wang, Y., Evans, J. A. & Wang, D. Quantifying the dynamics of failure across science, startups and security. *Nature* **575**, 190–194 (2019).

28. Liu, L., Dehmamy, N., Chown, J., Giles, C. L. & Wang, D. Understanding the onset of hot streaks across artistic, cultural, and scientific careers. *Nat. Commun.* **12**, 5392 (2021).

29. Hill, R., Yin, Y., Stein, C., Wang, D. & Jones, B. F. Adaptability and the Pivot Penalty in Science. Preprint at https://doi.org/10.48550/arXiv.2107.06476 (2021).

30. Ke, Q., Ferrara, E., Radicchi, F. & Flammini, A. Defining and identifying Sleeping Beauties in science. *Proc. Natl. Acad. Sci.* **112**, 7426–7431 (2015).

31. Ahmadpoor, M. & Jones, B. F. The dual frontier: Patented inventions and prior scientific advance. *Science* **357**, 583–587 (2017).

32. Merton, R. K. Singletons and Multiples in Scientific Discovery: A Chapter in the Sociology

of Science. *Proc. Am. Philos. Soc.* **105**, 470–486 (1961).

33. Uzzi, B., Mukherjee, S., Stringer, M. & Jones, B. Atypical Combinations and Scientific Impact. *Science* **342**, 468–472 (2013).

34. Wang, J., Veugelers, R. & Stephan, P. Bias against novelty in science: A cautionary tale for users of bibliometric indicators. *Res. Policy* **46**, 1416–1436 (2017).

35. Lane, J. N. *et al.* Conservatism Gets Funded? A Field Experiment on the Role of Negative Information in Novel Project Evaluation. *Manag. Sci.* **68**, 4478–4495 (2022).

36. Arts, S. & Fleming, L. Paradise of Novelty—Or Loss of Human Capital? Exploring New Fields and Inventive Output. *Organ. Sci.* **29**, 1074–1092 (2018).

37. How can we reform the STEM tenure system for the 21st Century? https://www.pnas.org/doi/10.1073/pnas.2207098119 doi:10.1073/pnas.2207098119.

38. Carter, R. G. *et al.* Innovation, entrepreneurship, promotion, and tenure. *Science* **373**, 1312–1314 (2021).

39. Dance, A. Is it time for tenure to evolve? *Nature* **620**, 453–455 (2023).

40. Holley, J. W. Tenure and Research Productivity. *Res. High. Educ.* **6**, 181–192 (1977).

41. Li, S. & Ou-Yang, H. Explicit Incentives, Implicit Incentives, and Performance: Evidence from Academic Tenure. SSRN Scholarly Paper at https://doi.org/10.2139/ssrn.399240 (2010).

42. Yoon, A. H. Academic Tenure. *J. Empir. Leg. Stud.* **13**, 428–453 (2016).

43. Brogaard, J., Engelberg, J. & Van Wesep, E. Do Economists Swing for the Fences after Tenure? *J. Econ. Perspect.* **32**, 179–194 (2018).

44. Myers, K. R. *et al.* Unequal effects of the COVID-19 pandemic on scientists. *Nat. Hum. Behav.* **4**, 880–883 (2020).

45. Htun, M. Tenure and promotion after the pandemic. *Science* **368**, 1075–1075 (2020).

46. Gao, J., Yin, Y., Myers, K. R., Lakhani, K. R. & Wang, D. Potentially long-lasting effects of the pandemic on scientists. *Nat. Commun.* **12**, 6188 (2021).

47. Lin, Z., Yin, Y., Liu, L. & Wang, D. SciSciNet: A large-scale open data lake for the science of science research. *Sci. Data* **10**, 315 (2023).

48. Wapman, K. H., Zhang, S., Clauset, A. & Larremore, D. B. Quantifying hierarchy and dynamics in US faculty hiring and retention. *Nature* 1–8 (2022) doi:10.1038/s41586-022-05222-x.

49. Clauset, A., Arbesman, S. & Larremore, D. B. Systematic inequality and hierarchy in faculty hiring networks. *Sci. Adv.* **1**, e1400005 (2015).

50. Lee, E., Clauset, A. & Larremore, D. B. The dynamics of faculty hiring networks. *EPJ Data Sci.* **10**, 1–25 (2021).

51. Dennis, W. Age and Productivity among Scientists. *Science* **123**, 724–725 (1956).

52. Oster, S. M. & Hamermesh, D. S. Aging and Productivity Among Economists. *Rev. Econ. Stat.* **80**, 154–156 (1998).

53. Levin, S. G. & Stephan, P. E. Research Productivity Over the Life Cycle: Evidence for Academic Scientists. *Am. Econ. Rev.* **81**, 114–132 (1991).

54. Gingras, Y., Larivière, V., Macaluso, B. & Robitaille, J.-P. The Effects of Aging on Researchers' Publication and Citation Patterns. *PLOS ONE* **3**, e4048 (2008).

55. Jones, B. F. The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder? *Rev. Econ. Stud.* **76**, 283–317 (2009).

56. Sinatra, R., Wang, D., Deville, P., Song, C. & Barabási, A.-L. Quantifying the evolution of individual scientific impact. *Science* **354**, aaf5239 (2016).

57. Liu, L. *et al.* Hot streaks in artistic, cultural, and scientific careers. *Nature* **559**, 396–399 (2018).

58. Zhang, S., Wapman, K. H., Larremore, D. B. & Clauset, A. Labor advantages drive the greater productivity of faculty at elite universities. *Sci. Adv.* **8**, eabq7056 (2022).

59. Andalón, M., de Fontenay, C., Ginther, D. K. & Lim, K. The rise of teamwork and career prospects in academic science. *Nat. Biotechnol.* **42**, 1314–1319 (2024).

60. Way, S. F., Morgan, A. C., Clauset, A. & Larremore, D. B. The misleading narrative of the canonical faculty productivity trajectory. *Proc. Natl. Acad. Sci.* **114**, E9216–E9223 (2017).

61. Zhang, S., LaBerge, N., Way, S. F., Larremore, D. B. & Clauset, A. Scientific productivity as a random walk. Preprint at http://arxiv.org/abs/2309.04414 (2023).

62. Gneezy, U., Meier, S. & Rey-Biel, P. When and Why Incentives (Don't) Work to Modify Behavior. *J. Econ. Perspect.* **25**, 191–210 (2011).

63. Checchi, D., De Fraja, G. & Verzillo, S. Incentives and Careers in Academia: Theory and Empirical Analysis. *Rev. Econ. Stat.* **103**, 786–802 (2021).

64. Radicchi, F., Fortunato, S. & Castellano, C. Universality of citation distributions: Toward an objective measure of scientific impact. *Proc. Natl. Acad. Sci.* **105**, 17268–17272 (2008).

65. Zeng, A. *et al.* Increasing trend of scientists to switch between topics. *Nat. Commun.* **10**, 3439 (2019).

66. Kassotaki, O. Review of Organizational Ambidexterity Research. *Sage Open* **12**, 21582440221082127 (2022).

67. Liu, L., Jones, B. F., Uzzi, B. & Wang, D. Data, measurement and empirical methods in the science of science. *Nat. Hum. Behav.* **7**, 1046–1058 (2023).

68. Yang, Y., Tian, T. Y., Woodruff, T. K., Jones, B. F. & Uzzi, B. Gender-diverse teams produce more novel and higher-impact scientific ideas. *Proc. Natl. Acad. Sci.* **119**, e2200841119 (2022).

Figures and Tables

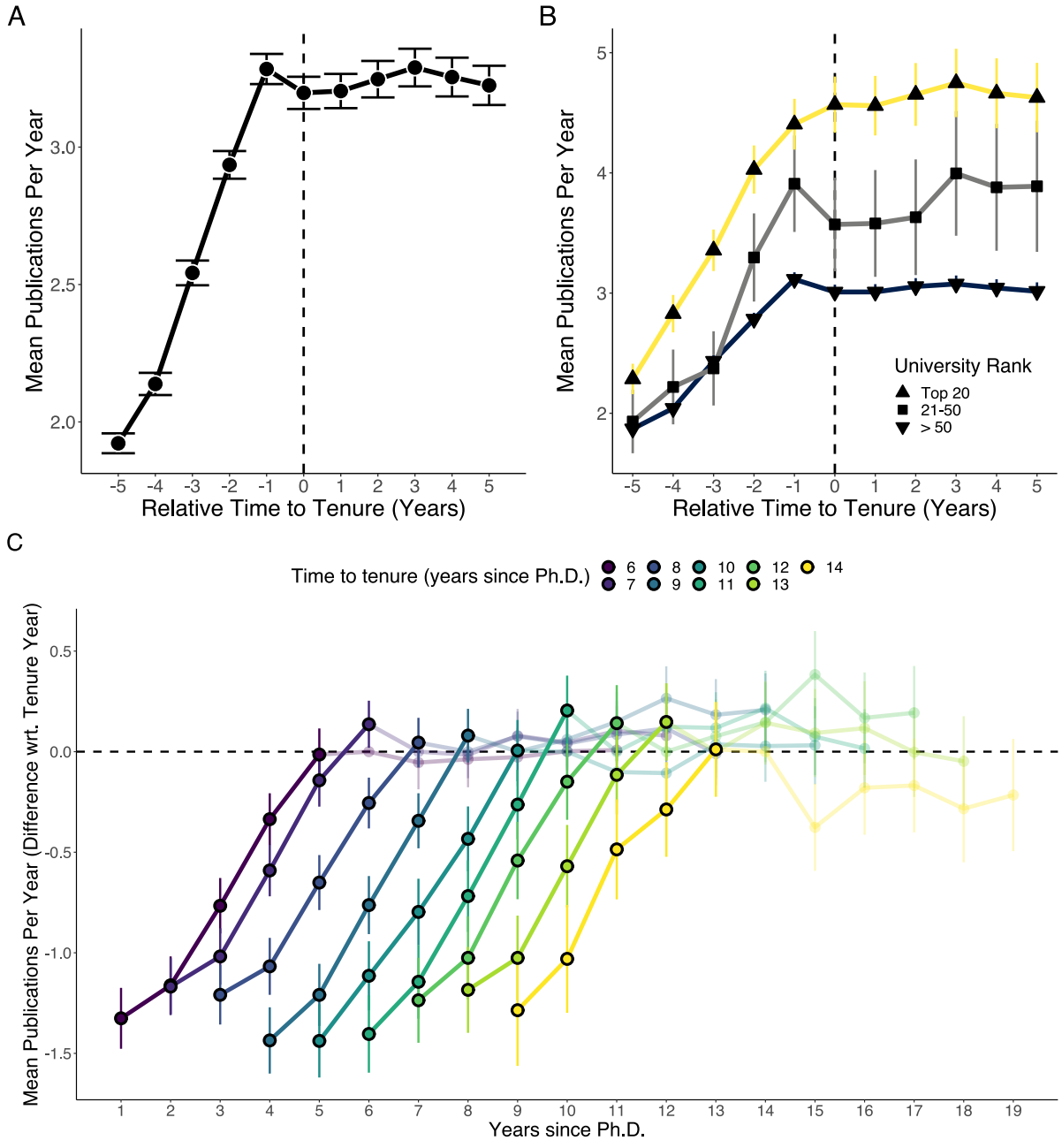
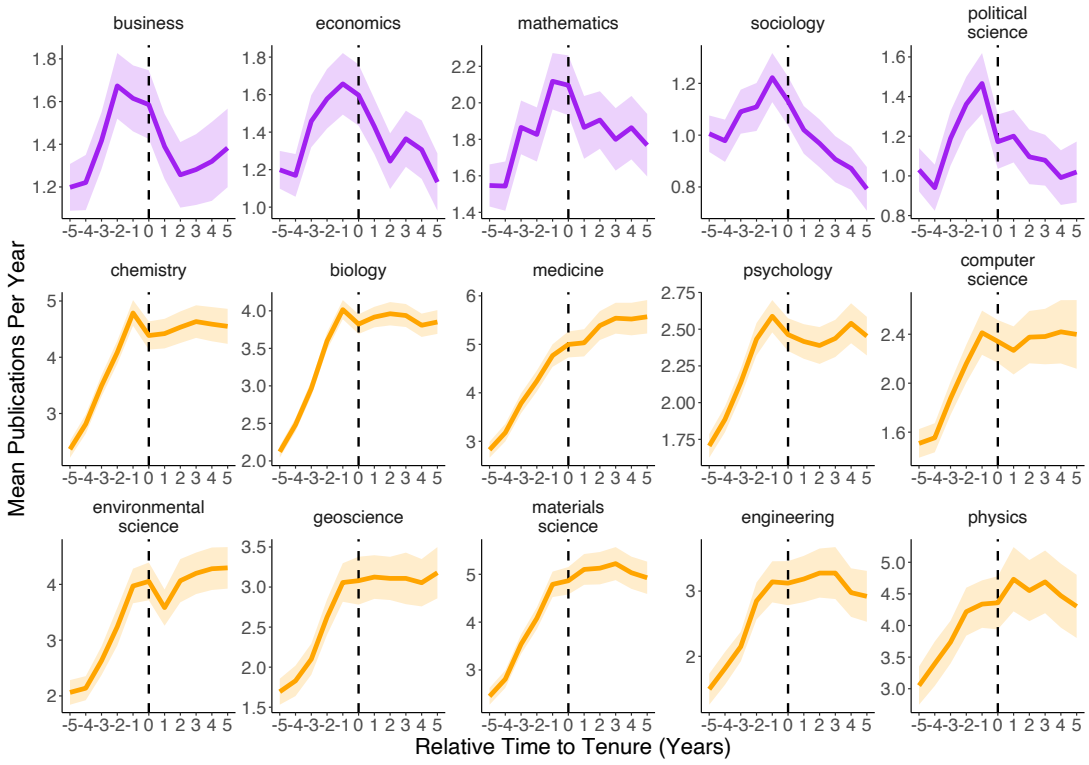


Figure 1: Tenure and publication rates. (A) Articles published per year, averaged across researchers for each year before and after tenure. (**B**) Articles published per year, averaged across researchers, by university rank. (**C**) Articles published with respect to tenure year, by career age. Career age is defined as the number of years from Ph.D. to tenure; 85% of the academics in the total sample reach tenure between 6 and 14 years after completing a Ph.D. (see Fig. S1). Error bars are 95% CIs. This figure is based on datasets D1 and D4.



504

505 **Figure 2: Cross-disciplinary variations in publication patterns.** Each panel shows the average
506 number of papers published by authors in a particular discipline. Disciplines are colored to
507 distinguish two types of trends: those where publications rise and decline (purple), and those where
508 they rise and stabilize (orange). These trends roughly correspond to non-lab-based and lab-based
509 disciplines, respectively. Shaded areas represent 95% CIs. This figure is based on datasets D1
510 and D4.

511

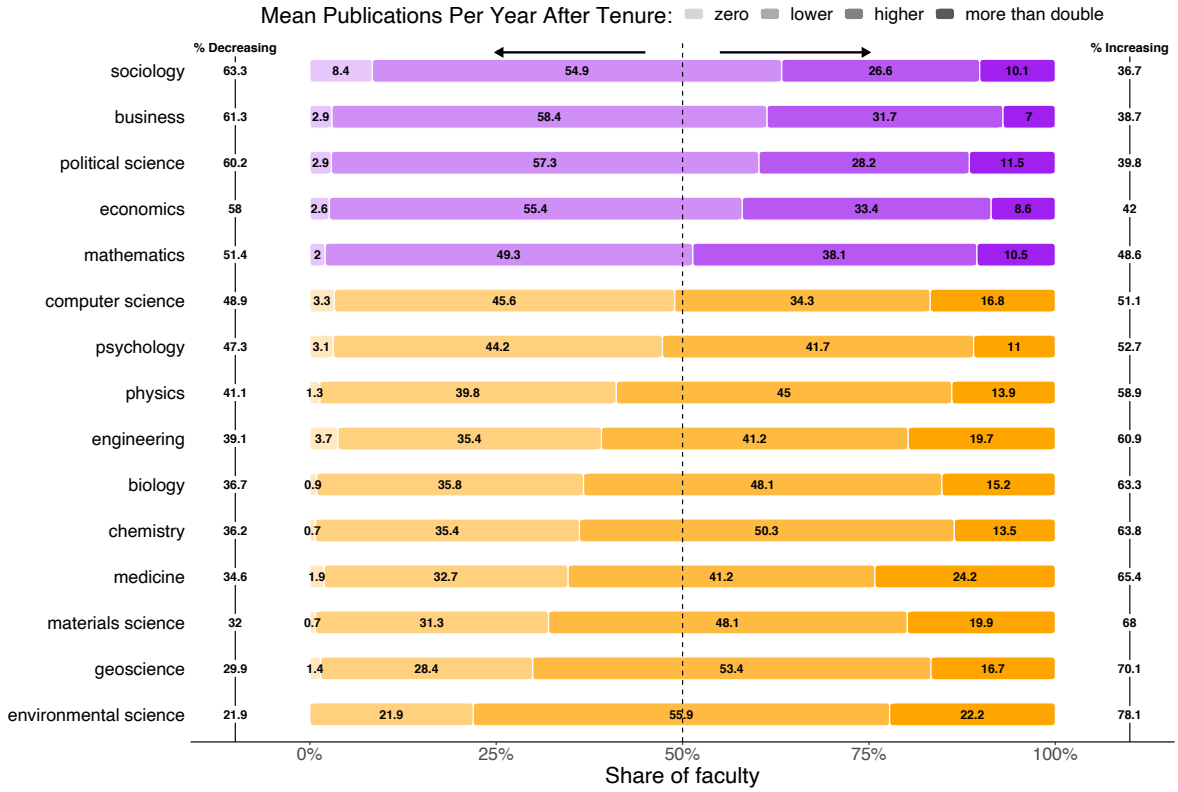
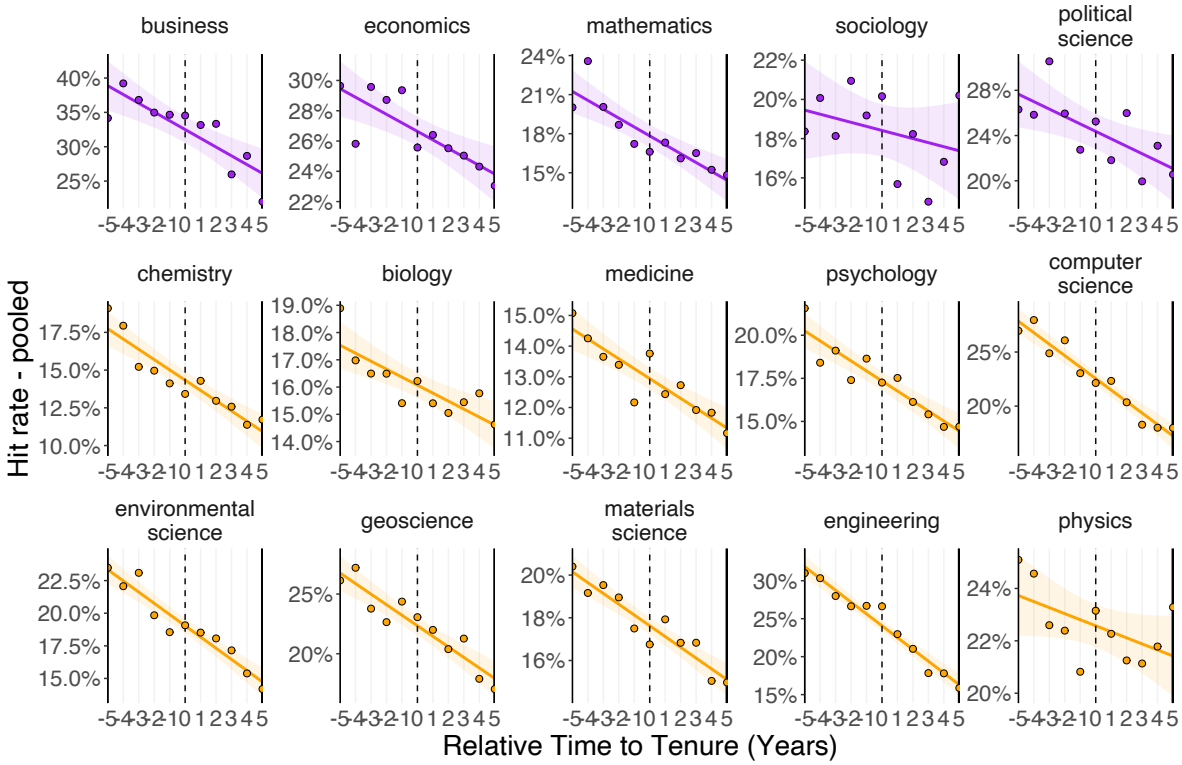


Figure 3: Fields and individual heterogeneity. Share of faculty who increase or decrease their average number of publications per year after tenure by field. Note that we exclude a negligible fraction of faculty who did not publish any paper in the five years before tenure. This figure is based on datasets D1 and D4.

A


business
economics
mathematics
sociology
political science
chemistry
biology
medicine
psychology
computer science
environmental science
geoscience
materials science
engineering
physics
Hit rate - pooled
Relative Time to Tenure (Years)

B

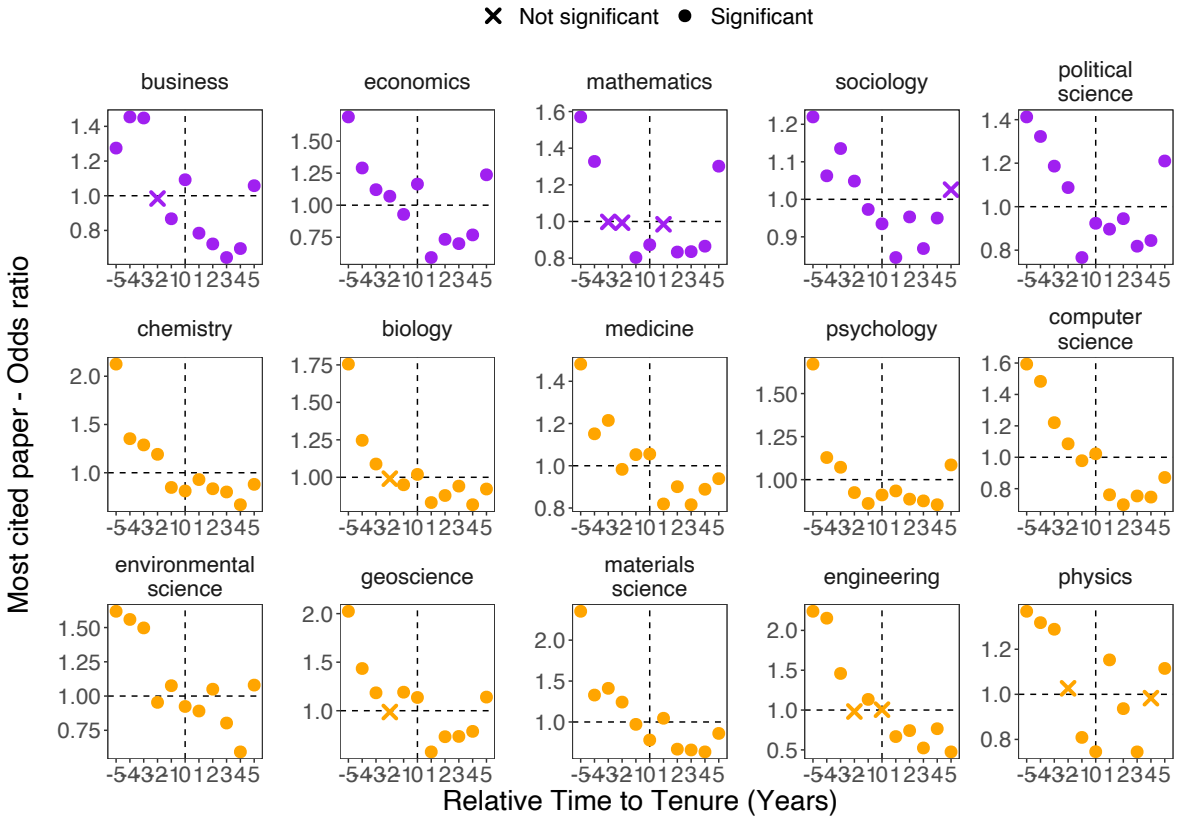

Not significant
Significant
business
economics
mathematics
sociology
political science
chemistry
biology
medicine
psychology
computer science
environmental science
geoscience
materials science
engineering
physics
Most cited paper - Odds ratio
Relative Time to Tenure (Years)

Figure 4: Impact. (**A**) Pooled hit rate (number of hit papers over the total number of articles published by faculty in each year before and after tenure). Different versions of the hit rates, confirming the same trends, can be found in Fig. S13A. (**B**) Share of faculty who produce their most cited paper over our time window (ratio with respect to null model) by field. Significance at 0.95 C.I. This figure is based on datasets D1 and D4.

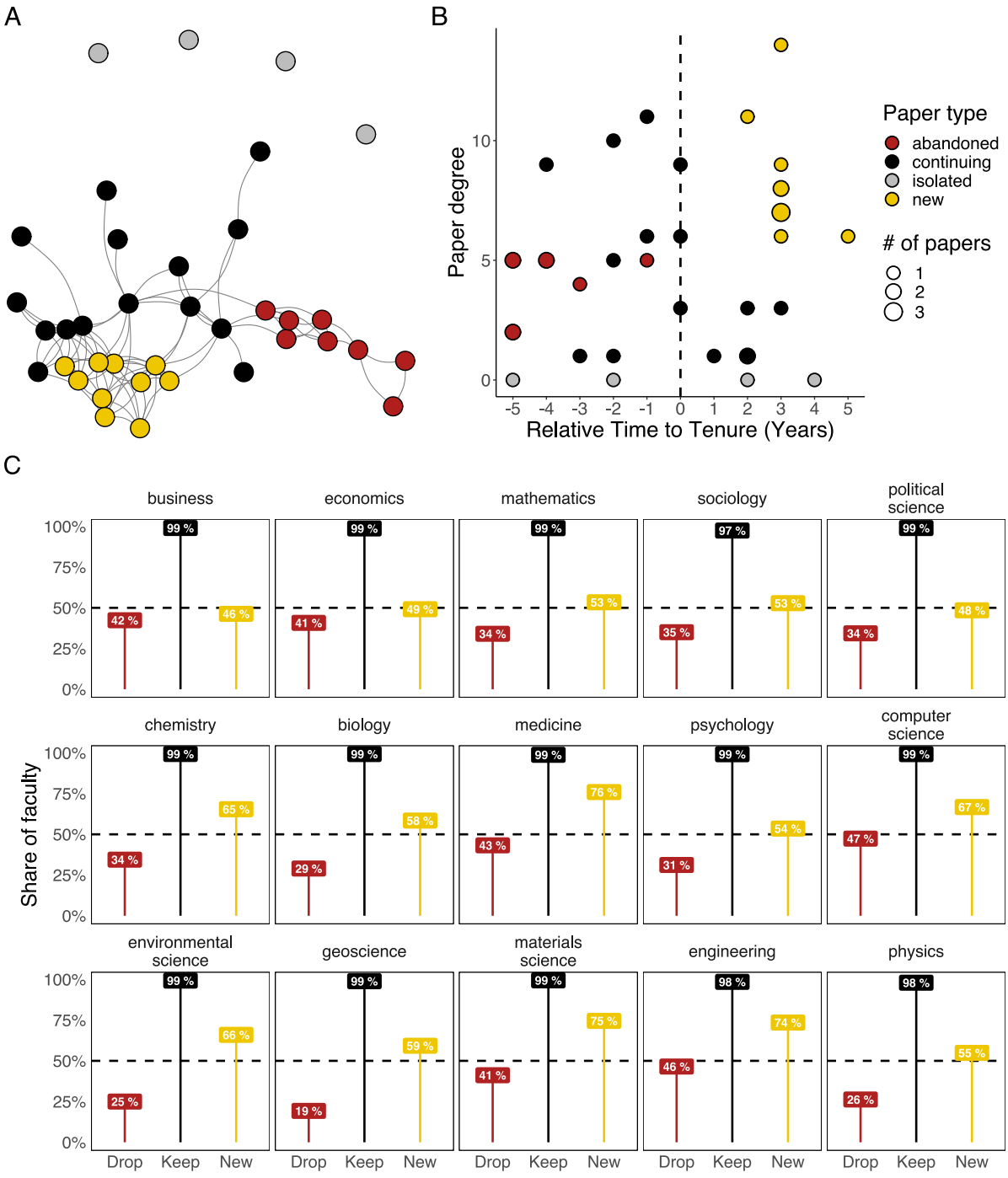
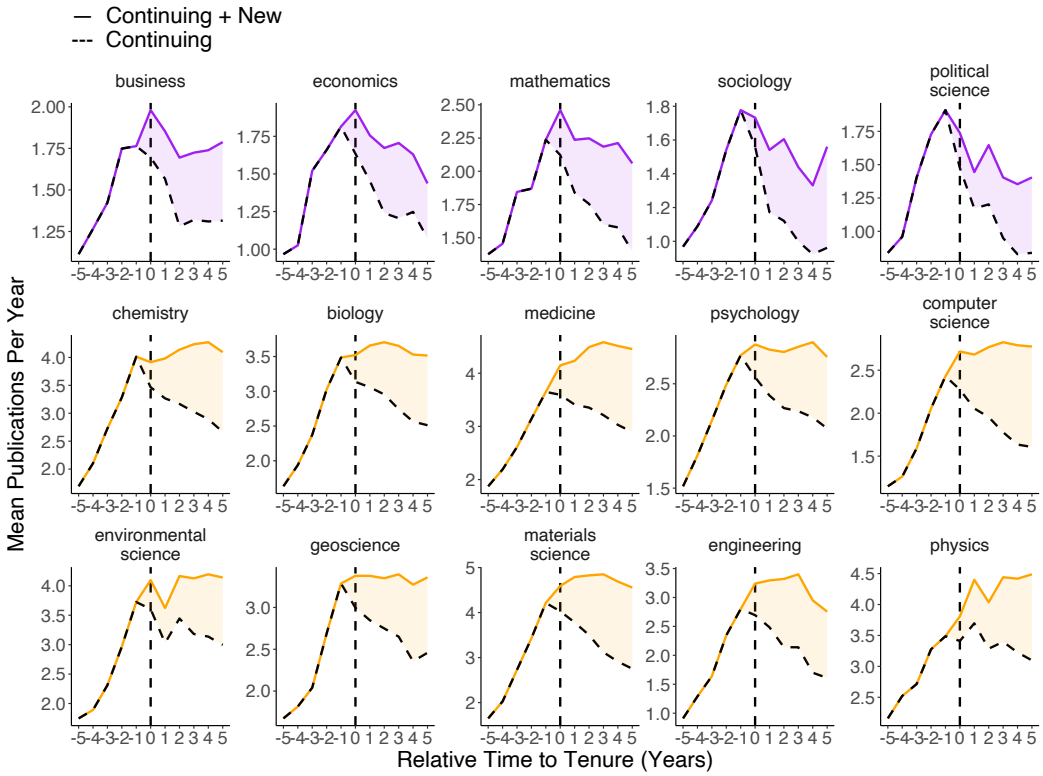


Figure 5: Tenure and research portfolio. (**A**) A stylized example of a co-reference network and community detection for a single scholar. (**B**) Scatter plot of topic exploration before and after tenure for a single faculty member. (**C**) Share of scholars who reorganize their research portfolio after tenure (New = start a new agenda; Keep = maintain parts of the "old" agenda; Abandon = abandon some topics explored before tenure). This figure is based on datasets D1 and D4.

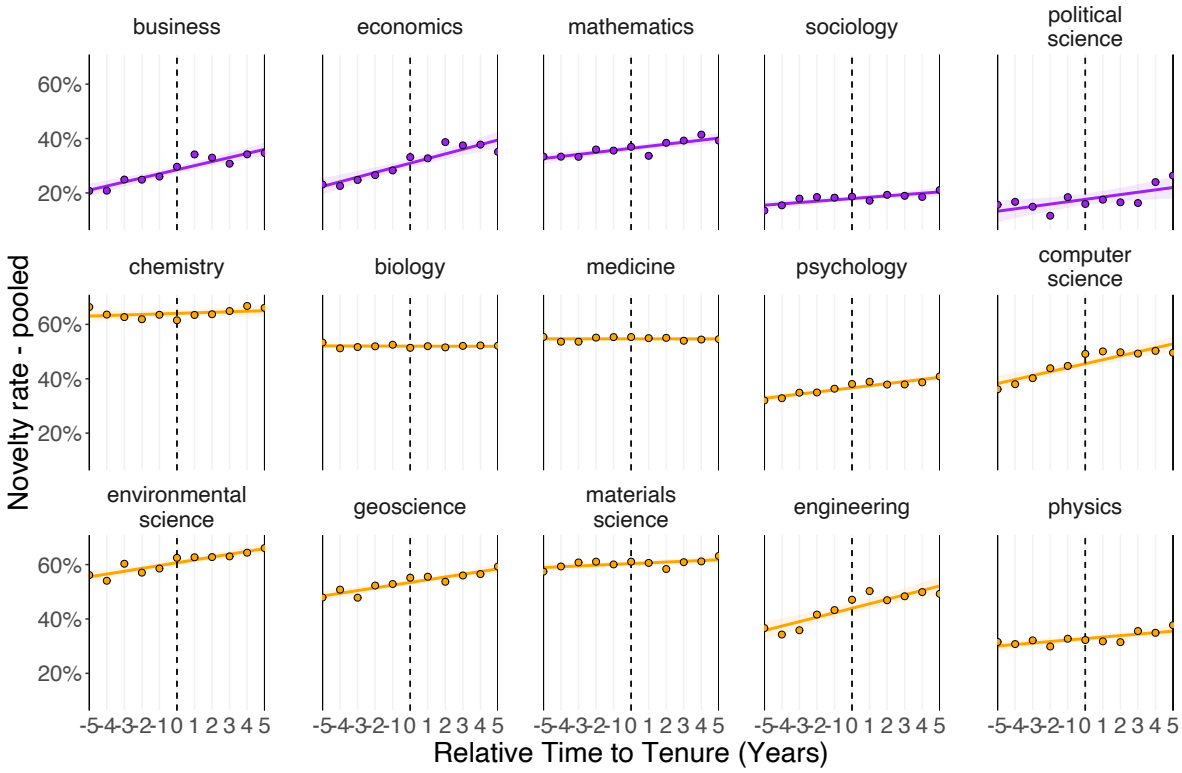


534

535 **Figure 6: Post-tenure diversification and research trajectories.** Average number of papers by
536 type/topic. The black dashed line indicates the average number of papers adhering to the old
537 agenda. The solid line indicates the average number of papers, considering papers that belong to
538 both "continuing" and "new" communities. This figure is based on datasets D1 and D4.

539

A


business
economics
mathematics
sociology
political science
chemistry
biology
medicine
psychology
computer science
environmental science
geoscience
materials science
engineering
physics
Novelty rate - pooled
60%
40%
20%
-5 -4 -3 -2 -1 0 1 2 3 4 5
Relative Time to Tenure (Years)

B

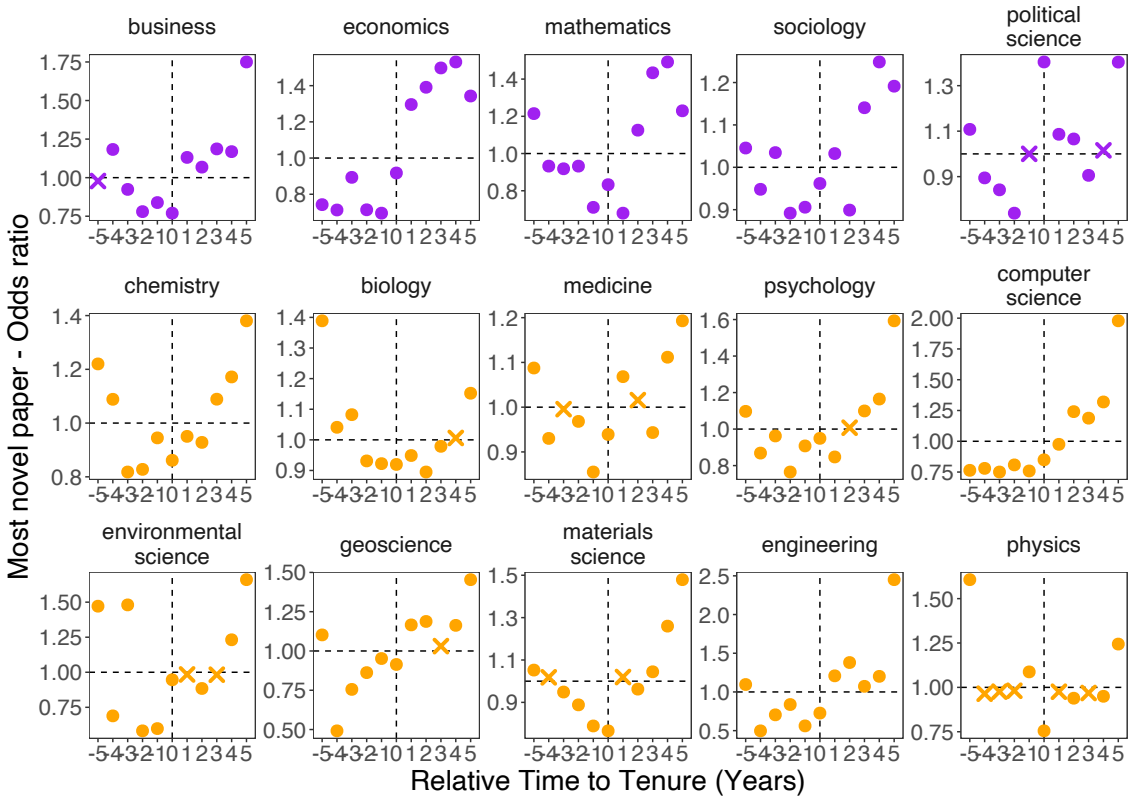

Not significant
Significant
business
economics
mathematics
sociology
political science
chemistry
biology
medicine
psychology
computer science
environmental science
geoscience
materials science
engineering
physics
Most novel paper - Odds ratio
-5 -4 -3 -2 -1 0 1 2 3 4 5
Relative Time to Tenure (Years)

Figure 7: Novelty. (**A**) Pooled novelty rate by field (number of novel papers over the total number of articles published by faculty in our sample each year). A different version of the novelty rates, confirming the same trends, can be found in Fig. S13B. (**B**) Share of faculty who produce their most novel paper over our time window (ratio with respect to null model) by field. Significance at .95 C.I. This figure is based on datasets D1 and D4.

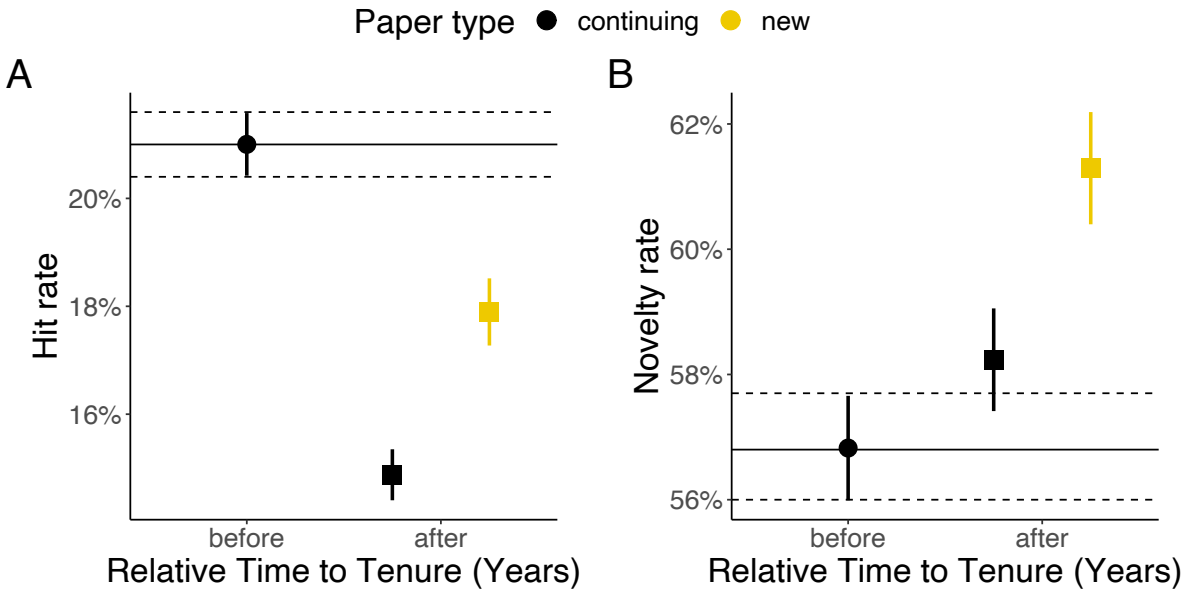


Figure 8: Post-tenure diversification, impact, and novelty. (**A**) Hit rate by paper type for scholars with a new agenda. (**B**) Novelty rate by paper type for scholars with a new agenda. Error bars are 95% CIs. This figure is based on datasets D1 and D4.

Supporting Information for
Tenure and Research Trajectories

Supporting Information Text

S1 Data sources

The data used in the study have been integrated from the seven sources listed below:

1. Academic Analytics Research Center (AARC) US university faculty rosters dataset [D1]. The raw data comprise a census of US universities' employment records for tenured and tenure-track faculty members during the years between 2011 and 2020. The original faculty rosters include information for all Ph.D.-granting institutions in the US (393) and about 314,141 scholars, with links to grants and scientific articles published in this time window. https://aarcresearch.com/

2. Internal human resources (HR) employment records for a large R1 university in the US [D2]. This dataset covers the years 2000-2017.

3. Internal human resources (HR) employment records for a second large R1 university in the US [D3]. This dataset covers the years 2000-2017.

4. SciSciNet[1] [D4], a data lake based on Microsoft Academic Graph data. The data lake is curated by the Center for Science of Science and Innovation (CSSI) at the Kellogg School of Management at Northwestern University and is publicly available. SciSciNet includes information about 134M scientific publications, with a comprehensive list of additional metrics at the article level. https://doi.org/10.6084/m9.figshare.c.6076908.v1

5. Scopus [D5], a large multidisciplinary abstract and citation database for academic research that was developed by Elsevier. Scopus provides detailed bibliographic information on a wide range of sources, including peer-reviewed journals and conference proceedings. Our access to the Scopus database was provided by the ICSR Lab affiliated with Elsevier. https://www.scopus.com

6. Dimensions [D6], an extensive bibliometric database curated by Digital Science and available through subscription. https://www.dimensions.ai/

7. ProQuest [D7], a repository of Ph.D. dissertations that covers all US institutions. https://www.proquest.com/

S2 Main sample construction

We identify faculty members who have experienced a transition from a tenure-track position to a tenured position by following the steps below.

1. We manually clean the raw faculty title strings in AARC [D1], indicating the role of each faculty member employed at a given institution at time *t* (excluding job titles not related to tenure-line jobs, such as "clinical assistant professor" or "research assistant professor").

2. We code the transition as a tenure promotion if a scholar's faculty title changes from "assistant professor" (AP) at time *t* to "associate professor" (ASSP) at time *t+1.* Note that we exclude all cases in which the transition is not observed in two consecutive years. As 2011 is the first year for which we have AARC data, the first possible transition year included in our sample is 2012 (i.e., faculty who are recorded as AP in 2011 and transition to ASSP in 2012).

3. We exclude scholars who obtained tenure in less than four years or more than 25 years since their Ph.D., as their records may represent errors or very atypical career paths. We also exclude faculty members for whom the Ph.D. year is missing.

4. We restrict the sample to scholars who obtained tenure in 2012-2015 to ensure we have five years after tenure for observation and to avoid the possibility that our results are affected by the COVID-19 pandemic[2,3].

5. We link publication records using journal articles listed in D1 and D4, keeping only scholars with at least one publication in the 11 years around tenure (from five years before to five years after the year of the promotion).

6. We classify scholars according to the fields of their published papers and exclude those who could not be classified in a single discipline. We exclude scholars whose primary discipline is art, history, or philosophy since scholars in the humanities often have different

incentives and publication thresholds for tenure (e.g., publishing monographs and books rather than articles). We also exclude scholars whose main field was particle physics because their career trajectories are largely different from those of all other scientists in terms of their number of articles, co-authors, and citations[4]. More details regarding field classification are presented below.

The final sample integrating D1 and D4 includes 12,611 scholars active in 15 disciplines.

S3 Field classification

We assign a single field to each scholar in this sample based on the field that appears most frequently in her publication list. To determine this field, we use the 19 level 0 classifications in SciSciNet [D2] (e.g., physics, computer science, economics). To identify the high-energy physicists for exclusion (as mentioned above), we look at the more granular level 1 classifications in SciSciNet within the physics category, and we eliminate scientists whose main specialization is "particle physics." In addition, we group together scholars whose primary field is geography or geology under a single label: geoscience (see Fig. S2 for a summary). After excluding the humanities (i.e., art, history, and philosophy) and merging geography and geology, we have 15 different disciplines.

When we repeat the analyses using Scopus papers from D5 (Figs. S19-S34), we identify the field of each paper using the Scopus-based classification system developed by Science-Metrix. This system uses journal information to classify each paper in Scopus into 174 subfields. For multidisciplinary journals, the system uses character-based convolutional deep neural networks to classify at the individual paper level. All normalization of paper-level metrics for Scopus is within the subfield level. The sample linked to Scopus includes 12,379 scholars from 342 institutions and 427,498 publications. All of these scholars published at least one paper indexed in Scopus. For consistency, we maintain the same field classification at the author level.

S4 Lab-based disciplines

We further group the 15 disciplines in the sample integrating D1 and D4 into two broad categories based on whether they have standardized collaboration norms, which typically mean larger team sizes, hierarchical team structures, reliance on grants, and organization in research labs[5]. Business, economics, mathematics, sociology, and political science have historically been fields in which individual (or small team) work is most prevalent, although the organization of the scientific workforce is now universally moving toward larger team sizes[6,7]. All other fields in our sample are generally organized in larger teams or laboratories with clear divisions of labor.

Previous literature indicates that field collaboration norms are often correlated with team size, as disciplines that tend to have large teams are also most likely to be characterized by other collaboration norms. To test whether this distinction can be measured empirically, we classify fields using several metrics that help us understand the nature of such differences. First, we compute the median team size per subfield, using a more granular level of subfield classification from AARC that comprises 170 different subfields. Then, we categorize subfields into two groups, one with a median team size larger than three and one with a median team size of three or less. Results confirm that the subfields broadly fall in the same, more general classification categories used above, and the publication rate patterns presented in Fig. 2 hold (see Fig. S3).

Second, a greater number of solo-authored papers in a field is indicative of a field with different collaboration norms. Despite the pervasive decline in the incidence of solo-authored papers, it is still relatively more common for scientists to publish individual works in certain fields. Indeed, the share of solo-authored papers also separates fields into two groups that are broadly consistent with our classification (see Fig. S4).

Although a larger team size is an explicit proxy for distinguishing fields characterized by labs and collaboration norms, the organization of scientific work can differ in other critical dimensions and entail field-dependent trade-offs[8]. For instance, if organizational differences result in alternative hierarchical structures, fields with collaboration norms will be distinguished by a larger share of articles co-authored with early-career researchers (e.g., Ph.D. students and postdocs). To test this metric, we determine the number of articles that have at least one author with less than two years of experience since their first publication, and we compare the share across the 15 fields. Results confirm a clear separation of the fields into two groups (see Fig. S5).

Some disciplines organized through labs rely significantly more on grants. Therefore, as an additional measure to quantify collaboration norms and lab structure, we look at the share of scholars who received at least one grant after tenure. Once again, this analysis allows us to capture the difference between fields with and without collaboration norms. Mathematics is a notable exception in this analysis, as individual grants (especially from the National Science Foundation) are particularly common in this field (see Fig. S6).

S5 Collaboration and university rank

The evidence presented in Fig. 2 shows that publication trajectories are characterized by two different patterns. To verify the robustness of our results and the distinction between fields with and without collaboration norms, we recompute the mean publications per year, only counting researchers' articles for which they are lead authors (Fig. S7). In other words, for all scholars active

in fields with collaboration norms, we only consider articles they published as the last author. We do not, however, apply this correction to fields without collaboration norms, as alphabetical listings of authors are common in these disciplines. Figure S7 confirms the distinction between the two broad classes.

Differences among the institutions where faculty work could also affect their incentives and publication rates, and these differences may not be evident in these average trends. To address this concern, we group scientists according to the rank of the institution where they attained tenure, using university rankings to classify institutions as in Wapman et al.[9] Figure S8 shows that the pattern in research output is consistent, irrespective of the institution's rank.

S6 Impact measures

We approximate the quality of scientific articles by looking at the number of citations, as is standard in the literature. However, citations are both time- and field-dependent. Therefore, we define "hit papers" as papers in the top 5% of the citation distribution for a given subfield (based on level 1 classifications in SciSciNet) in a given year (Fig. 5A). Note that these rates are still relatively high compared with the baseline of 5%. Two reasons for these high levels are that, first, our sample only includes faculty who eventually received tenure during our observation period, and, second, we only consider US universities, which tend to have higher hit paper rates on average.

We define "novel papers" as papers with an atypicality score lower than zero. The atypicality score, introduced by Uzzi et al.[10], is based on pairwise combinations of journals in each paper's bibliography and normalized against a randomized citation network. Novelty rates are computed as for hit rates: the number of novel papers over the total number of papers published by scholars in our sample (Fig. 7A). We use a different definition of hit rate and novelty rate in Fig. S13, in which we compute the average hit/novelty rate per person per year instead of considering a pooled version. In this analysis, we only include scholars who publish at least one paper each year to avoid missing data imputation. Results for this smaller sample (N=4,051) confirm the trends presented in the main text (downward for hit, Fig. S13A; upward for novelty, Fig. S13B).

As an alternative to hit and novelty rates, we consider the continuous versions of these measures. Specifically, in Fig. S14A, we consider the average natural logarithm of CF (normalized citations for subfield and year) and the average novelty score (Fig. S14B) measured as in Yang et al.[11]

When we further validate the novelty results using papers in Scopus [D5], we adopt the novelty measure proposed by Lee et al.[12], which is less computationally intensive. Specifically, to calculate a paper p's novelty, we first extract its reference list comprising n publications in academic journals or conferences. We then create a set of C_n^2 non-sequential pairwise combinations of the n

publications and count the number of times each venue pair appears in this set. We repeat these steps for all Scopus publications in the same subfield and year as p. We then aggregate the total number of times each venue pair occurs in these publications' references. A venue pair (i, j)'s commonness C_{ij} in this subfield-year set is defined as:

$$C_{ij} = \frac{N_{ij}N}{N_i N_j}$$

where N_{ij} is the number of venue pairs (i, j), N is the total number of all venue pairs, and N_i is the number of venue pairs including venue i. We select the 10th percentile of p's reference venue pairs' commonness values to represent p's novelty. We calculate such novelty values for over 30 million Scopus-indexed research papers published between 2006 and 2020, sort the novelty values for publications in the same subfield and year in descending order, and normalize the novelty values into a percentile. Thus, unlike the original novelty metric, a higher percentile for this measure represents higher novelty. We define novel publications as the top 10% of publications (Figs. S28-S31) by this measure.

S7 Null model

For each scientist in our sample, we rank papers according to the number of normalized citations by subfield and year (CF) or the atypicality score to investigate the relative position of the most impactful and novel works within the 11-year period in individual careers. Next, we count the share of faculty members who produced their most cited or most novel paper in a given year relative to the year they received tenure. To control for individual publication patterns, we construct a null model by reshuffling (100 times) the measure of interest (CF or atypicality) within each individual career, and we compute the expected share of faculty who produce their most cited (or novel) paper in any given year (Fig. 4B, Fig. 7B).

S8 Community detection

To investigate the exploratory behaviors of faculty members pre- and post-tenure, we employ Louvain[13], a widely used community detection method in network science, on the co-citing network for the 11-year period for each faculty member. Specifically, we construct weighted undirected networks for individual faculty members, with papers serving as nodes, and links connecting papers that share at least one common reference. The number of shared references between the connected papers determines the weights of these links. It is worth noting that the networks may contain isolated nodes, representing papers that do not share any common references with other papers in the network. Following the community detection process and prior literature[14,15], each paper is assigned to a community representing a specific topic, while isolated papers are not

assigned any topics. In order to detect meaningful communities, we only consider scholars who published at least five papers before tenure and five papers after tenure. The resulting sample [D1+D4] comprises 8,963 scholars. When we repeat the analysis using Scopus [D1+D5], the sample comprises 9,318 scholars and 405,522 publications.

S9 Continuous variable for topic exploration

To quantify the exploration of new topics that diverge from prior work, we also measure the topic dissimilarity of a paper, which shows the extent to which a scholar's paper topic deviates from the topics explored in their previous five years of research papers (Fig. S32). Topic dissimilarity directly measures the distinctiveness of a paper's topic from the topics of the author's previous works. For each scholar, we first collect all papers authored by the scholar in the previous five years. Then, for a paper p in this set, we concatenate its title and abstract into a text string that represents *p*'s topic. We ignore papers with too little text (word count <= 5). We convert the text to lowercase, remove special characters and numbers, lemmatize each word, and remove common English stop words, as well as short words (length < 3 letters) and generic words that are commonly used in various disciplines. The generic word list contains words that are ranked in the top 3% for highest inverse document frequency (IDF) (e.g., conclusion, level, and improve). We train a Word2Vec model based on these processed texts and convert each text into a 128-dimensional vector. The topic dissimilarity of a paper is defined as the average cosine distance between each paper in our sample and its predecessor paper:

$$D_{topic} = 1 - \frac{v \cdot V}{|v| \cdot |V|}.$$

S10 Control groups and additional validations

To isolate the effect of tenure on scientific production, we move beyond the career age comparison (Fig. 1B), and we construct a first control group by looking at faculty members who did not get tenure in our time frame. More specifically, we combine three different datasets: AARC [D1], Dimensions [D6], and ProQuest [D7]. AARC [D1] allows us to identify faculty members who attain tenure in the period under consideration, Dimensions [D6] enables us to retrieve their publications lists, and ProQuest [D7] allows us to find individuals with the same Ph.D. year and subfield who did not receive tenure during our time frame. Then, we match observations one-to-one on the Ph.D. year and subfield to compare treated faculty (those who obtained tenure) with control individuals who were not tenured by the end of our time window. Our final sample for this analysis includes ~1,500 faculty members for each group. Figure S16A shows the difference in publication patterns

between faculty who received tenure in the time window and the matched faculty who did not attain tenure in the same period. Figure S16B shows that tenure also represents a great divide in terms of output differences among individual scholars, as we note a V-shaped pattern around the actual tenure year for those who received tenure. We do not find this behavior in the control group. These results confirm the critical impact of tenure on both the mean and variance of scientific production over time.

We use a similar matching strategy to construct two additional control groups. First, for each individual we study in the U.S. tenure system, we identify scholars who received a Ph.D. in the US in the same year and field but moved to Europe—the UK, Germany, or France, where the tenure-track system is not as strong or as common as in the US. And second, we identify scholars who received a Ph.D. in the US in the same year and field but now work for a government agency within the US. Fig. S17 presents a comparison of faculty who received tenure in the US and these two control groups, providing additional evidence that tenure presents distinctive shapes in publication trajectories.

We also use internal HR data [D2 and D3], including faculty rosters and employment records, from two large R1 universities in the US to validate the trends described in Fig. 1. We gather information on all faculty members who obtained tenure in the last 20 years and evaluate the average publication trajectory, finding a turning point around tenure (Fig. S18A, Fig. S19A). Note that we do not have to rely on faculty titles to determine tenure status in these data because the employment records for this sample make it clear if a position is tenured or not.

Using these internal employment records, we further refine our analysis to evaluate the difference in publication trajectories between tenure-track and non-tenure-eligible positions over time. In particular, we compare the publication trajectory of scholars in tenure-line positions who are tenured at year 6 or 7 with non-tenure-track employees during their first 11 years of employment at the institution. Figure S18B-C and Fig. S19B-C show the average patterns for these two groups, [D2] and [D3], respectively.

S11 Regression models

We estimate the following models to further control for individual heterogeneity in publication rates and other potentially relevant factors for hit and novelty rates. In particular, for publication rates, we estimate the following model:

$$y_{i\tau} = \beta_0 + \sum_{t\neq 0} \beta_t I_{\tau=t} + \sigma_i + \epsilon_{ij},$$

where $y_{i\tau}$ represents the number of publications for scholar i in year τ. t is a specific year relative to tenure ranging from -5 to 5, excluding the base year 0. β_t is the coefficient representing the effect of being in year t relative to the tenure year. $I_{\tau=t}$ is an indicator function equal to 1 if $\tau = t$ and 0 otherwise. σ_i is the scholar fixed effect to control for different publication rates across scholars. We use a Poisson regression since the dependent variable is a count (i.e., number of publications). Standard errors are clustered at the individual level (Fig. S33).

In addition, we estimate variations of the following model for hit (novelty) rates:

$$y_{ij\tau} = \beta_0 + \sum_{t\neq 0} \beta_t I_{\tau=t} + \Gamma X_j + \sigma_i + \epsilon_{ij\tau},$$

where $y_{ij\tau}$ is an indicator equal to 1 if paper j written by scholar i at time τ is a hit (top novel) paper, and 0 otherwise. Hit and novel papers are normalized by year and subfield as described in section S6. X_j is a series of paper-level covariates including the number of authors, number of references, leading authors' previous average number of publications, whether the scholar is the leading author, and the publication type (e.g., journal/conference). Dealing with binary dependent variables, we use a logistic regression approach (Fig. S34-S35). However, as an alternative specification, we also estimate an OLS with citation or novelty percentile as dependent variables (Fig. S36-S37).

Supporting Figures and Tables

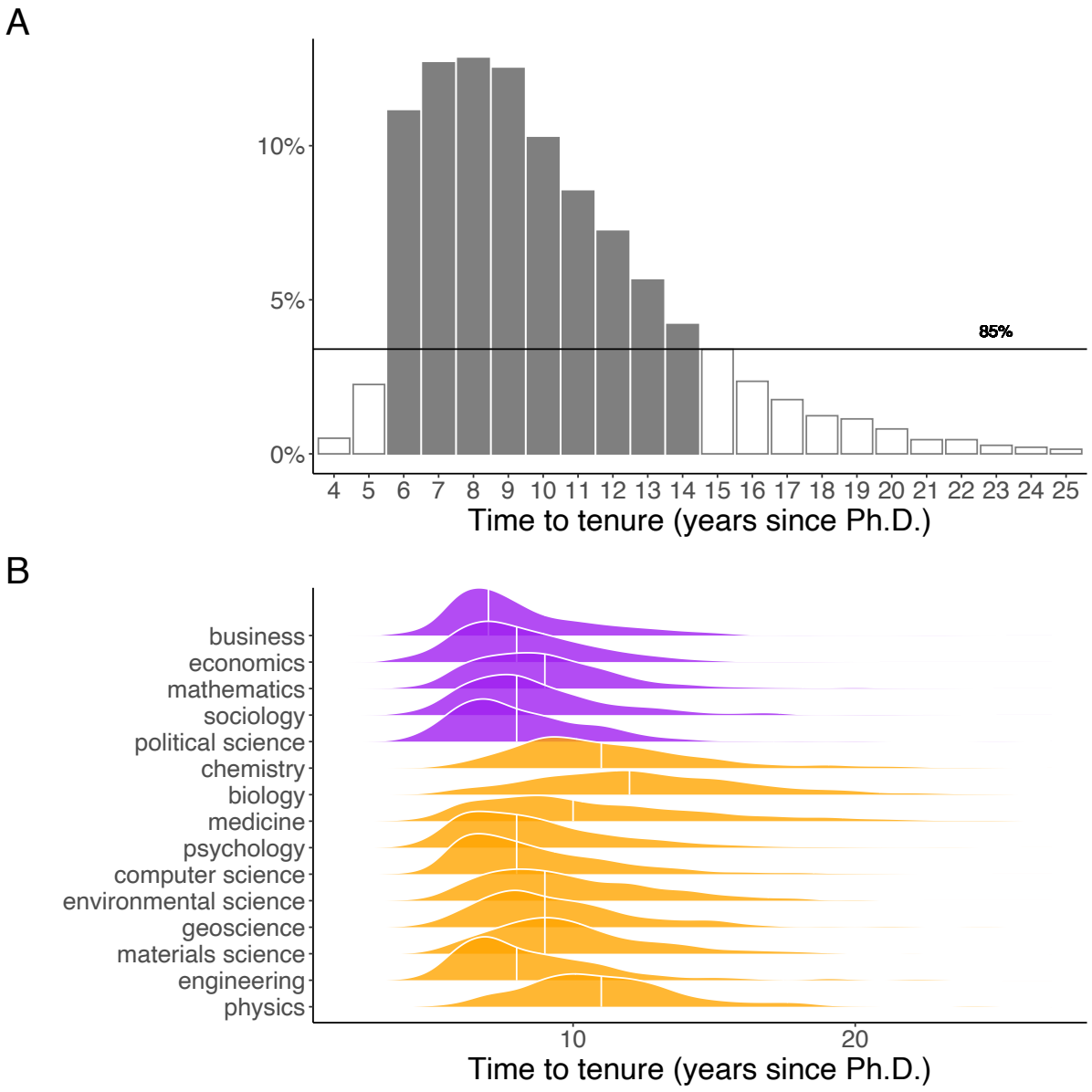
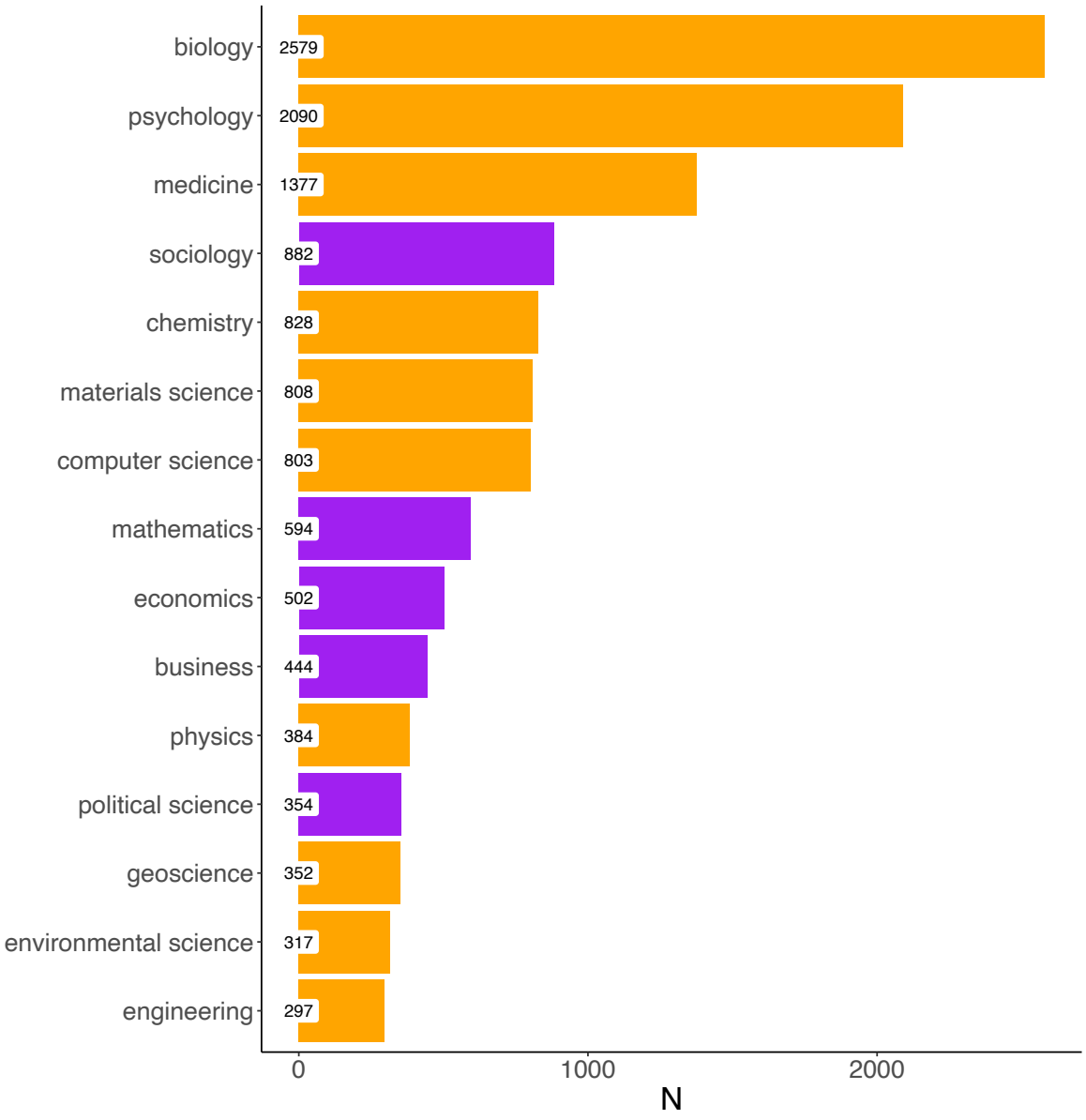


Figure S1: Time to tenure. (A) Distribution of time to tenure, measured in years from Ph.D. to tenure. In Fig. 1B (main text), we show average publication patterns for faculty who received tenure between 6 and 14 years after receiving their Ph.D. (85% of the sample). (**B**) Distribution of time to tenure by field. Purple indicates fields that are non-lab-based; orange indicates lab-based fields. This figure is based on datasets D1 and D4.



832

833 **Figure S2: Field distribution.** Number of faculty members in each field. Scholars are classified
834 into a single field according to their publications' most common field code. Field classification
835 follows level 0 classifications in SciSciNet. Geoscience is the combination of geology and
836 geography. Purple indicates fields that are non-lab-based; orange indicates lab-based fields. This
837 figure is based on datasets D1 and D4.

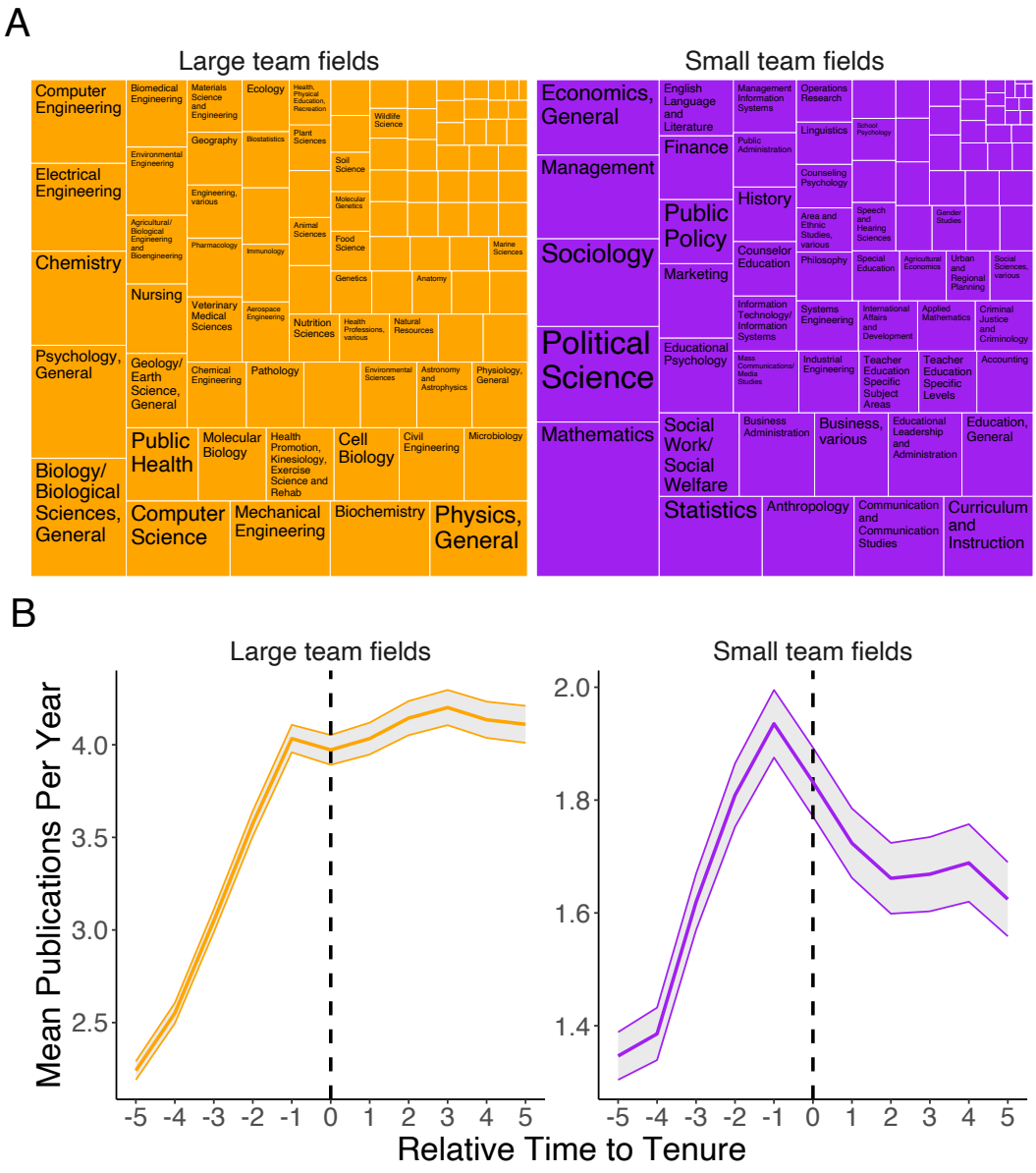
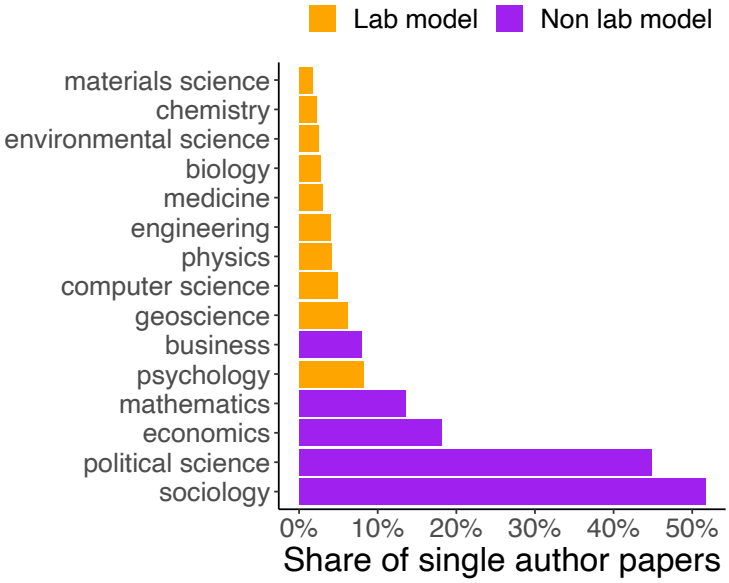


Figure S3: Alternative field classification and team size. (**A**) Alternative field classification (170 subfields) based on the median team size (large teams have more than 3 people, and small teams have 3 people or fewer than 3 people). (**B**) Average number of papers published per year by field category (large team fields vs. small team fields). Shaded areas represent 95% CIs. This figure is based on datasets D1 and D4.



844

845 **Figure S4: Solo-author papers.** Share of single-author papers by field. This figure is based on
846 datasets D1 and D4.

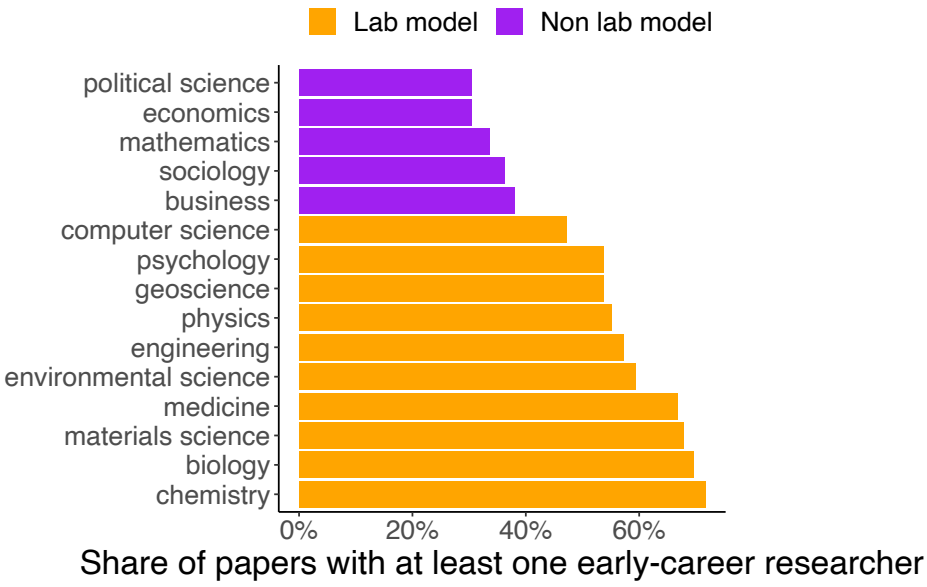


Figure S5: Collaboration with early-career researchers. Share of papers co-authored with early-career researchers by field (i.e., authors with less than two years of experience since their first publication). This figure is based on datasets D1 and D4.

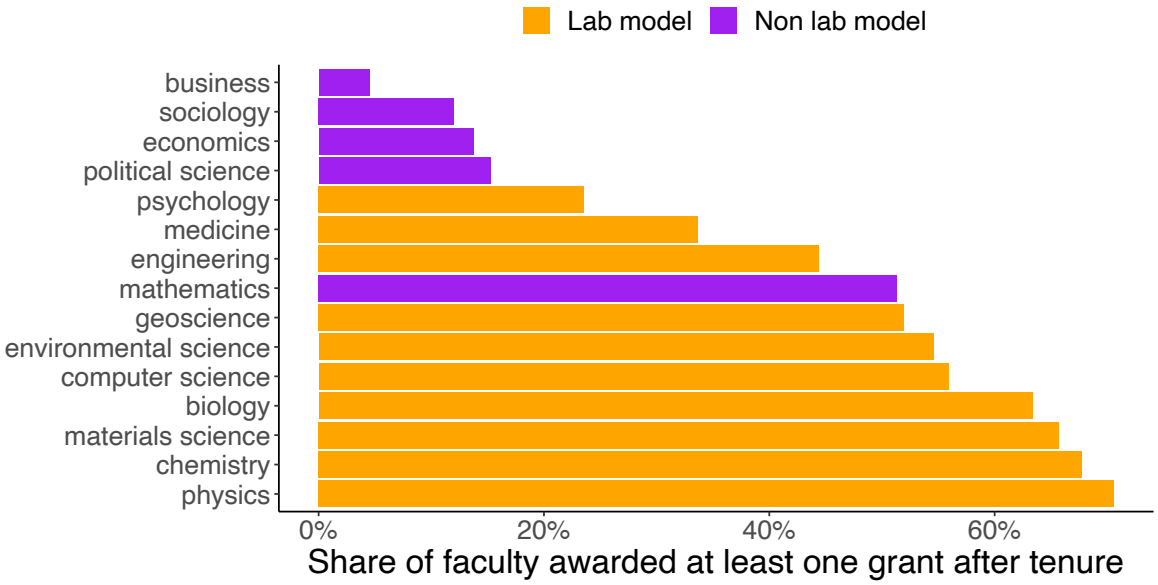


Figure S6: Reliance on grants. Share of faculty awarded at least one grant after tenure by field. This figure is based on datasets D1 and D4.

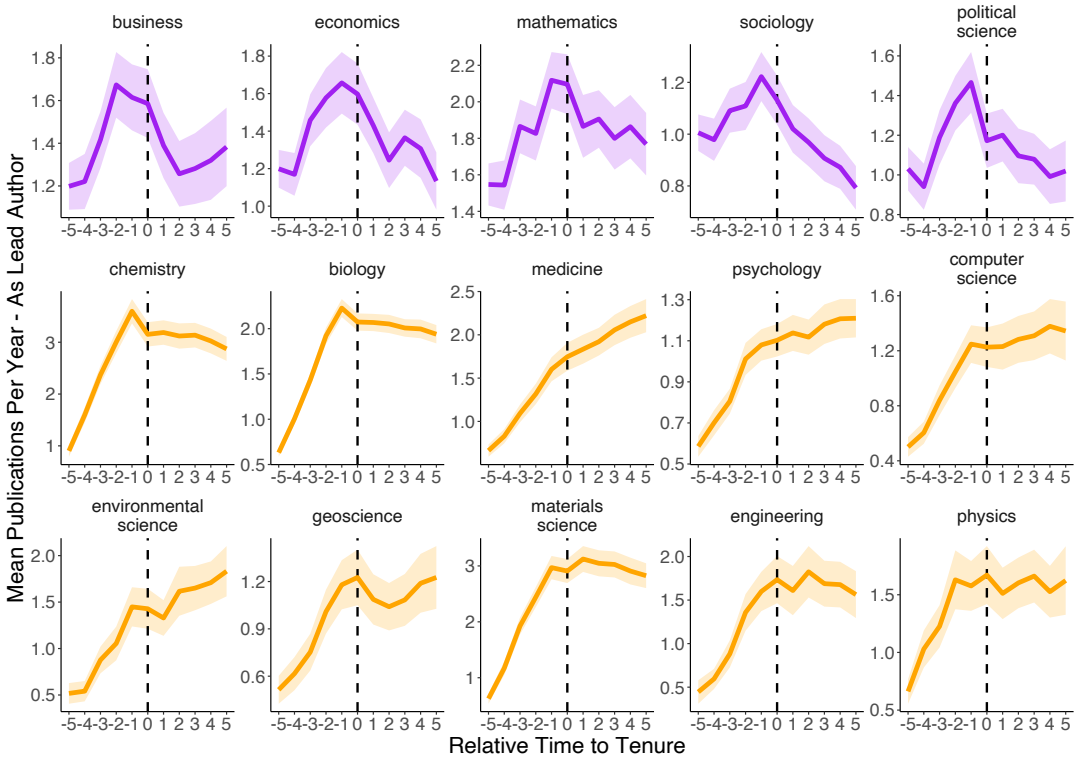


Figure S7: Mean publications per year as lead author. Each panel shows the average number of papers a scholar published as lead (i.e., last) author per year by field. We only consider the lead (last) authors for fields characterized by collaboration norms because alphabetical listings of authors are common in fields in which collaboration norms are not the standard. For these fields (first row), we tally all papers as in Fig. 2 (main text). Shaded areas represent 95% CIs. This figure is based on datasets D1 and D4.

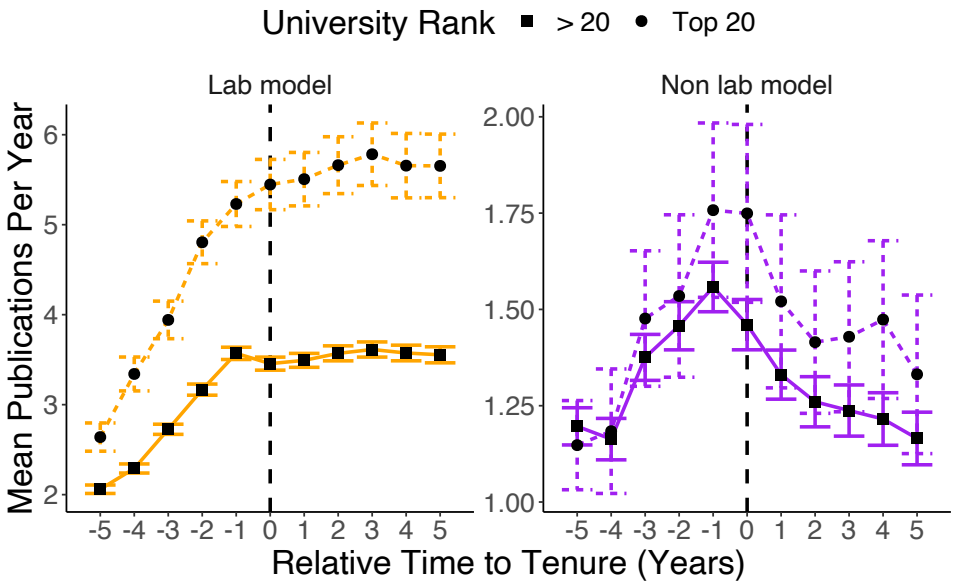


Figure S8: Mean publications per year by university rank. Average number of papers per year by university rank. Top 20 (dot and dashed lines) vs. all other institutions (square and solid lines). As in Wapman et al., we use university rankings to classify institutions[9]. We exclude scholars with multiple affiliations at the time of tenure. Error bars are 95% CIs. This figure is based on datasets D1 and D4.

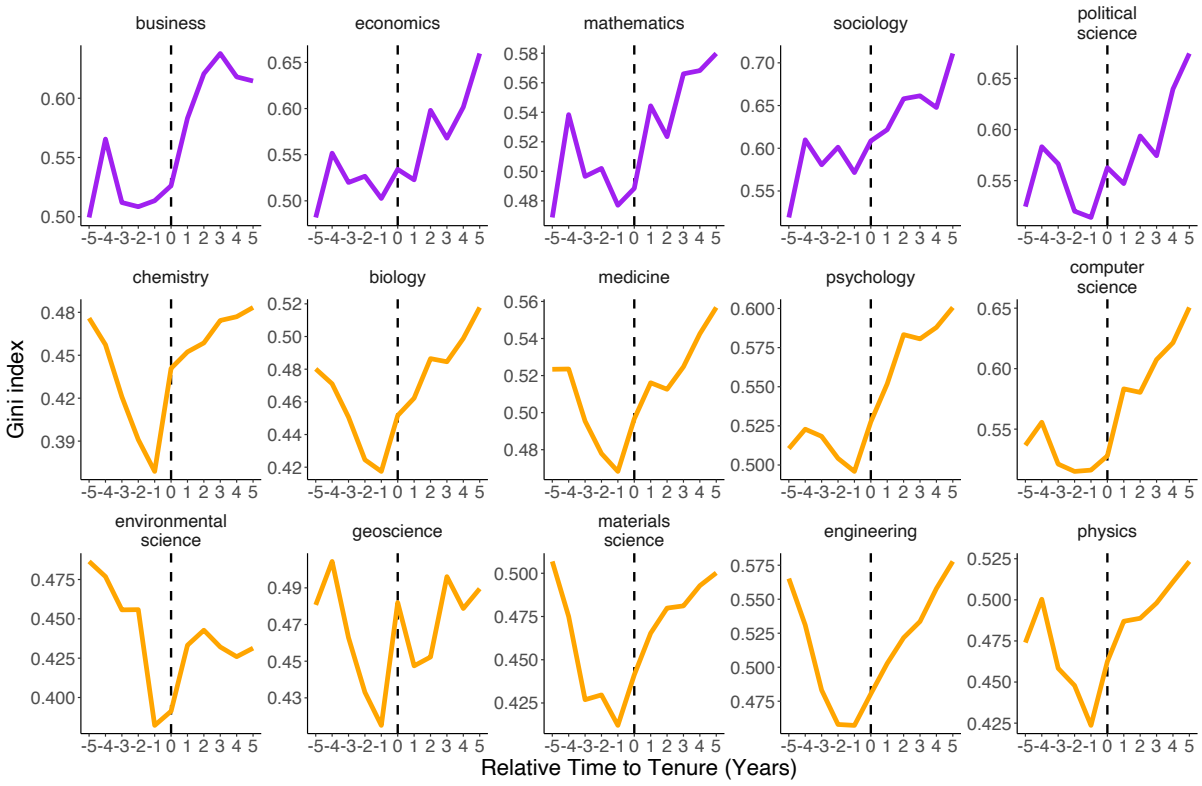
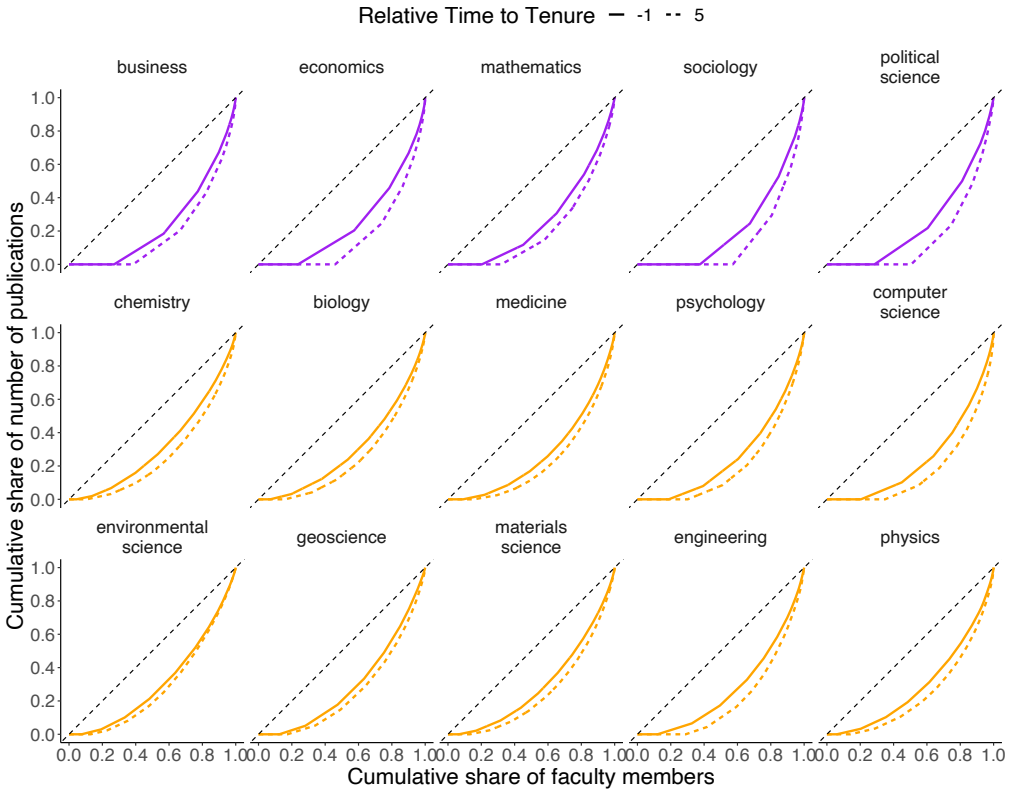


Figure S9: Dispersion in publication rates over time. Gini index of the number of papers per year by individual researchers over the 11-year time window, by field. This figure is based on datasets D1 and D4.



881

882 **Figure S10: Lorenz curve before tenure vs. after tenure.** Lorenz curve of the number of papers
883 for year -1 and year 5 (relative to tenure) by field. This figure is based on datasets D1 and D4.

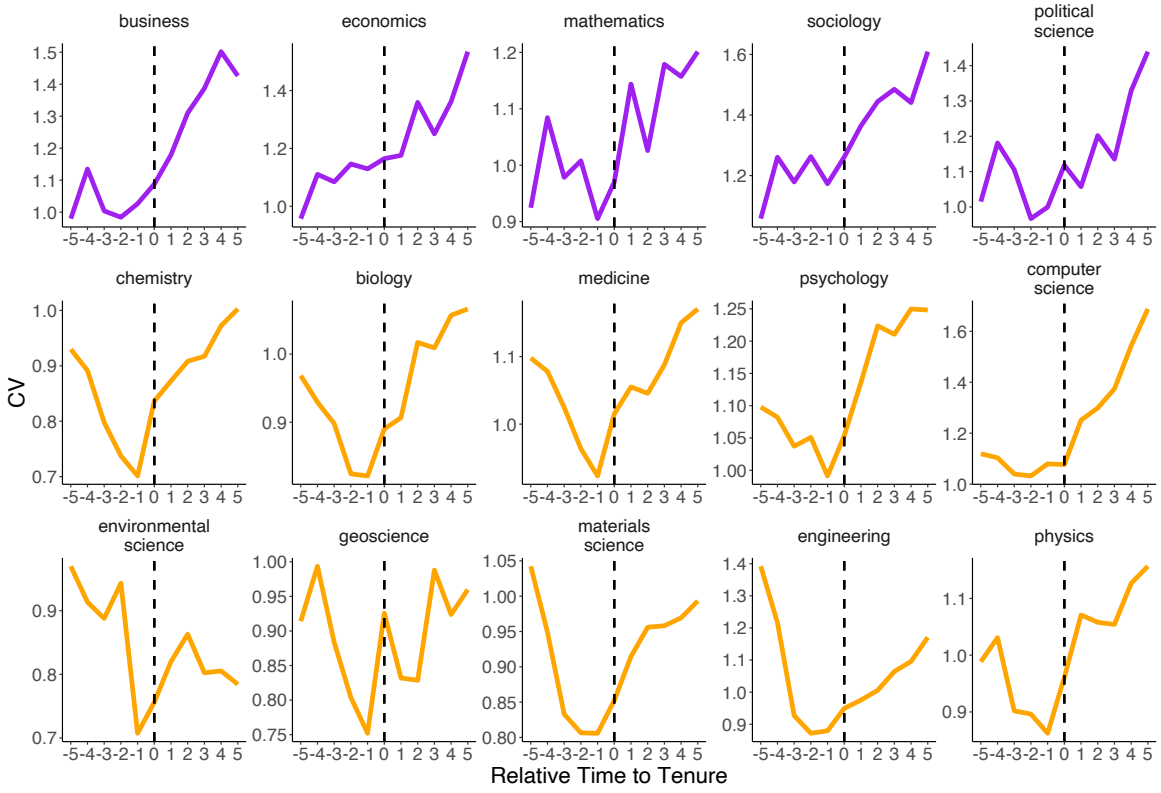
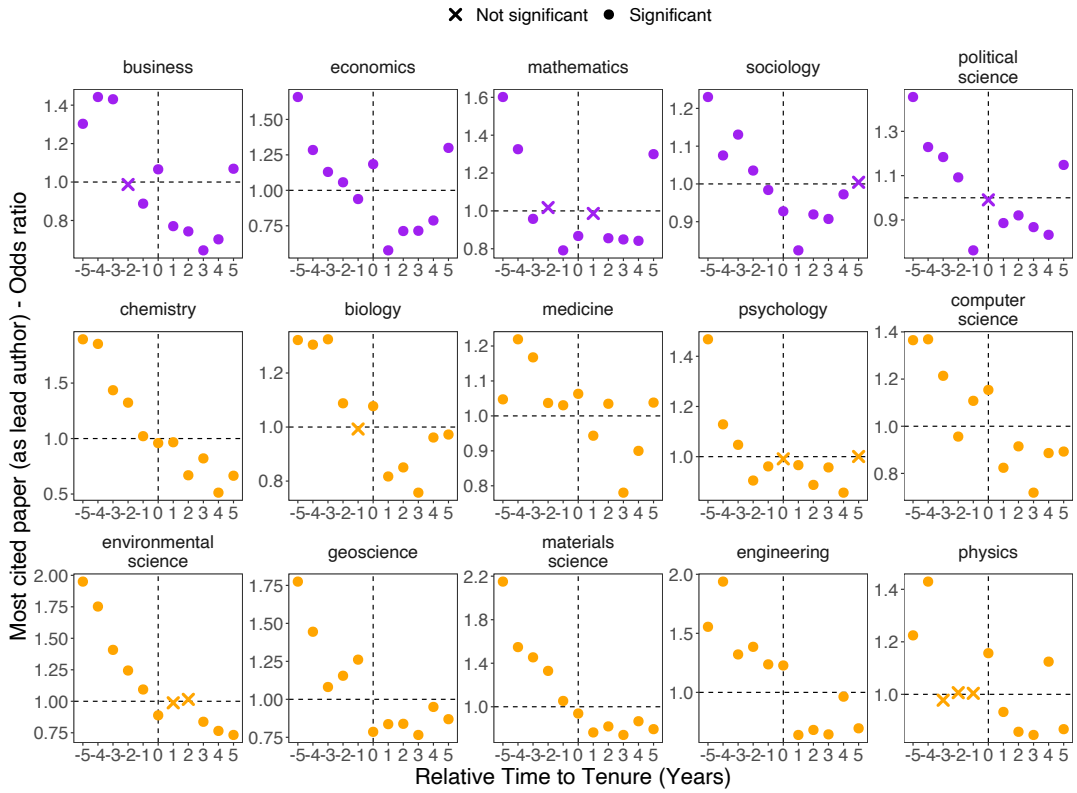


Figure S11: Dispersion over time - alternative to Gini. Coefficient of variation (CV) of the number of papers over the 11-year time window by field. This figure is based on datasets D1 and D4.



890

891 **Figure S12: Most cited paper as lead author.** Share of faculty who produce their most cited paper
892 during our time window (ratio with respect to null model) by field. Significance at .95 C.I. This figure
893 is based on datasets D1 and D2.

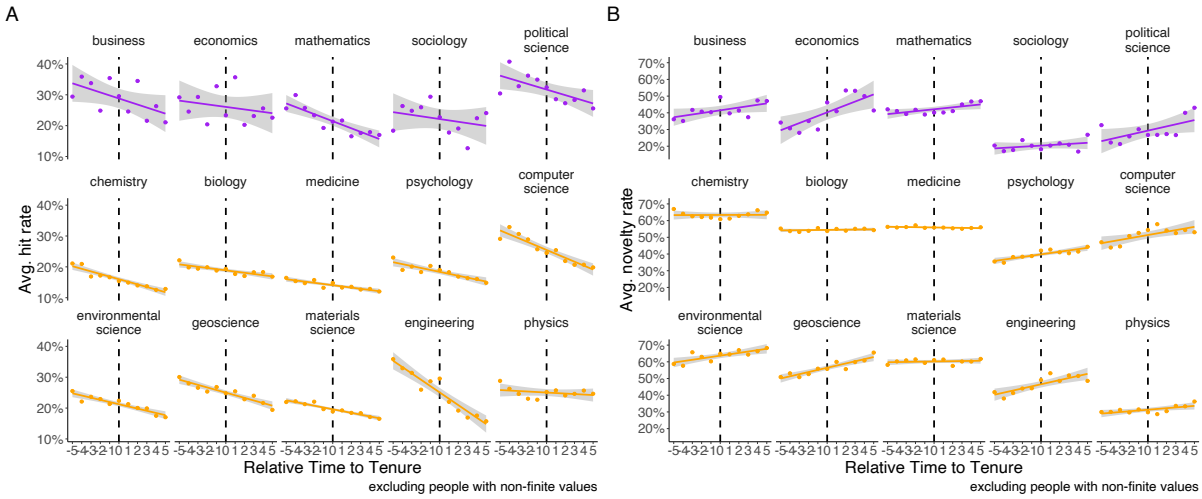


Figure S13: Average hit and novelty rate. (A) Average hit rate by field for faculty who publish at least one paper per year (i.e., excluding faculty with non-finite values). (**B**) Average novelty rate by field for faculty who publish at least one paper per year (i.e., excluding faculty with non-finite values). Lines represent linear fits with 95% CIs. This figure is based on datasets D1 and D4.

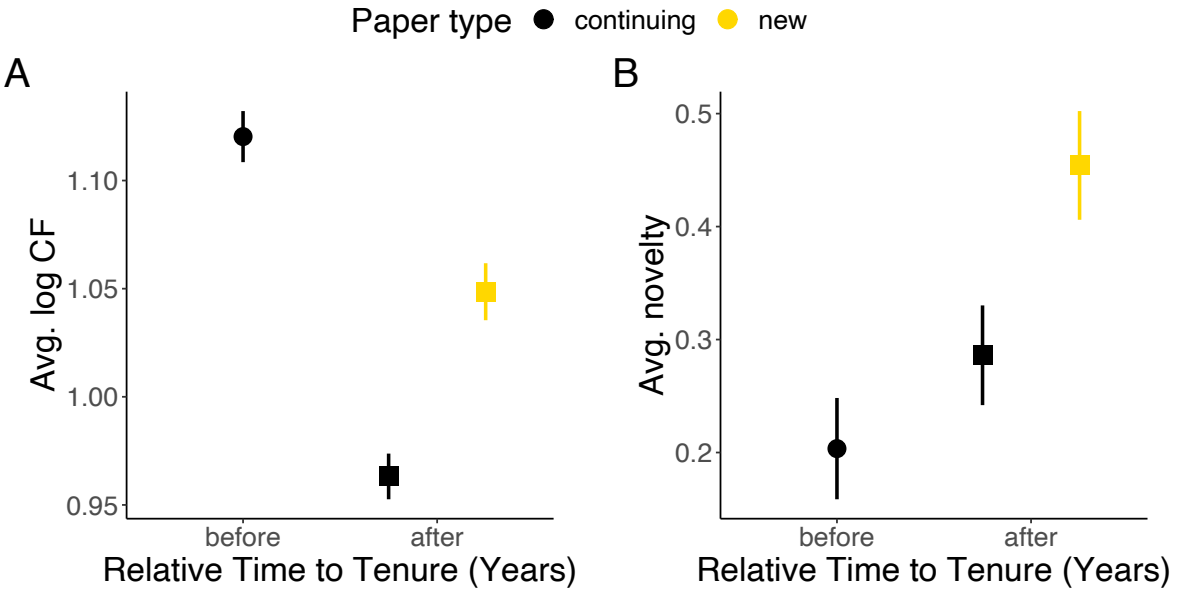
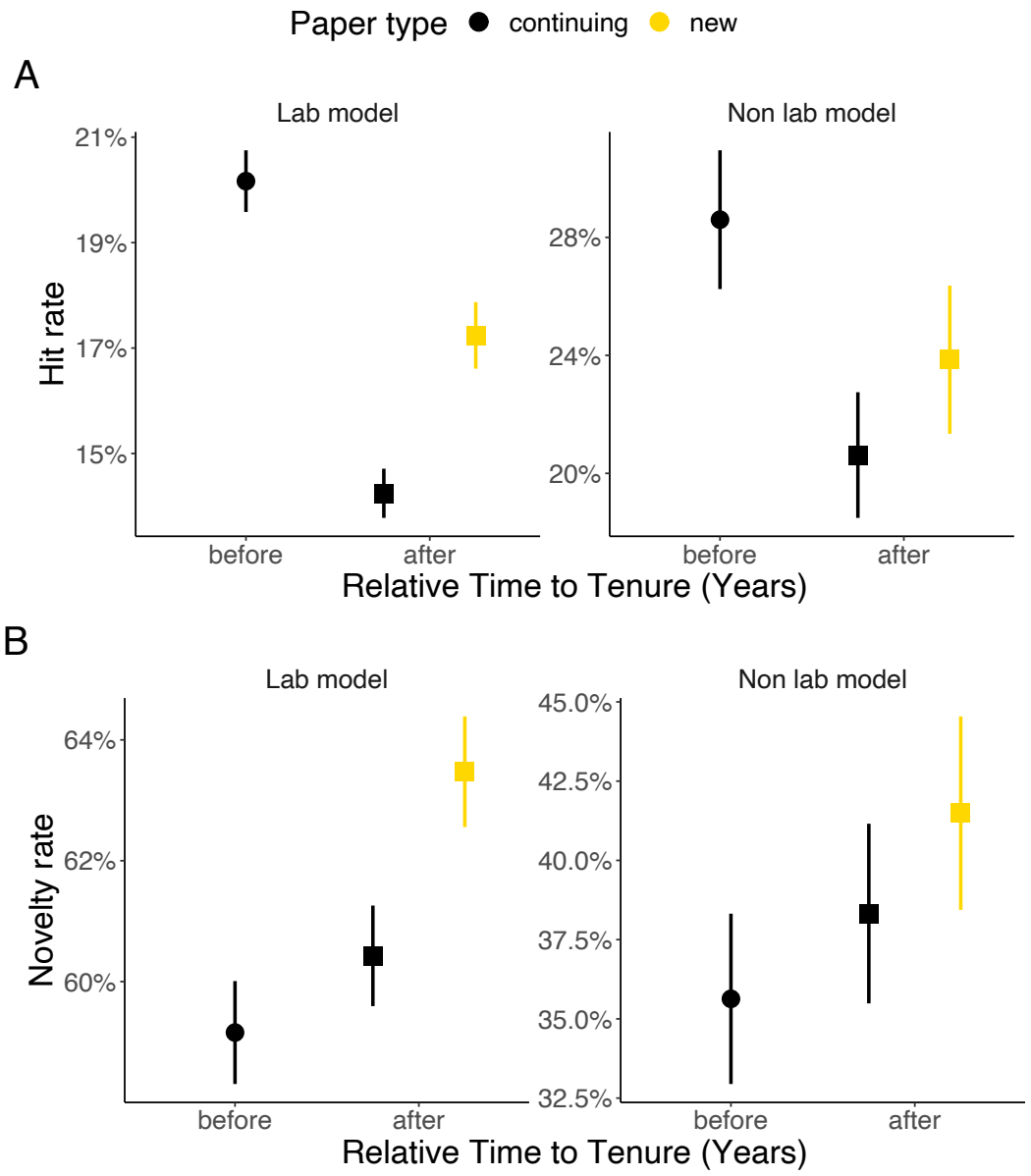


Figure S14: Post-tenure diversification, impact, and novelty – continuous outcomes. (**A**) Average citations by paper type for scholars with a new agenda. (**B**) Average novelty score per paper type for scholars with a new agenda. Error bars are 95% CIs. This figure is based on datasets D1 and D4.



907

908 **Figure S15: Post-tenure diversification, impact, and novelty by lab model.** (**A**) Hit rate by
909 paper type for scholars with a new agenda in fields with and without lab models. (**B**) Novelty rate
910 by paper type for scholars with a new agenda in fields with and without collaboration norms. Error
911 bars are 95% CIs. This figure is based on datasets D1 and D4.

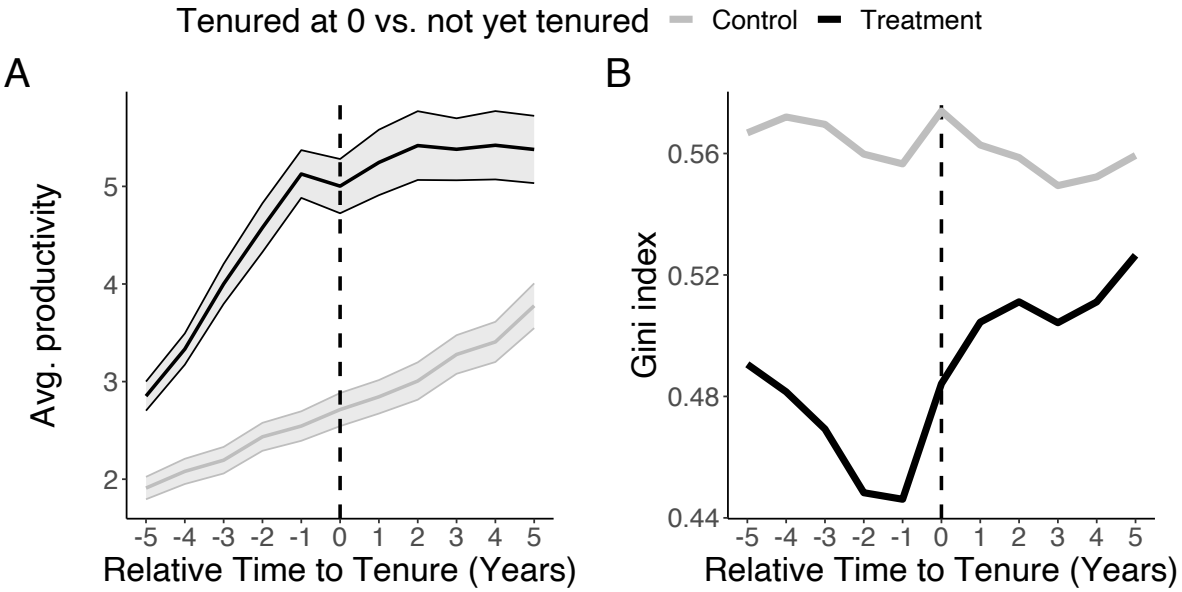


Figure S16: Control group. (**A**) Average number of papers per year by treatment group. Shaded areas represent 95% CIs. (**B**) Gini index of the number of papers by treatment group over the 11-year time window. This figure is based on datasets D1, D6, and D7.

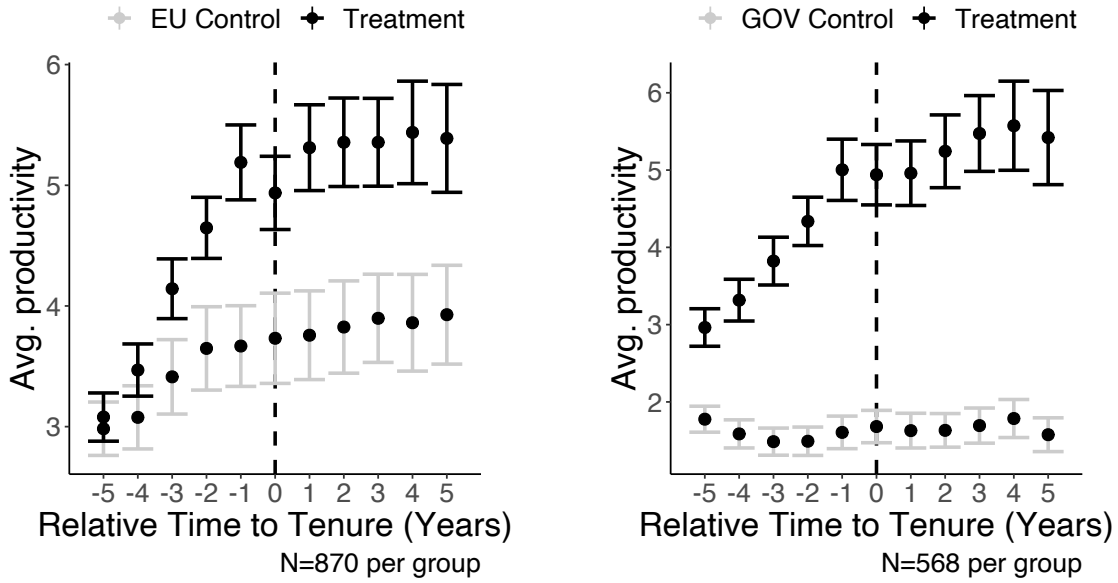


Figure S17: Additional control groups. (**A**) Average number of papers per year over the 11-year time window by treatment group (EU affiliated-scholars). (**B**) Average number of papers over the 11-year time window by treatment group (scholars affiliated with government agencies). Error bars are 95% CIs. This figure is based on datasets D1, D6, and D7.

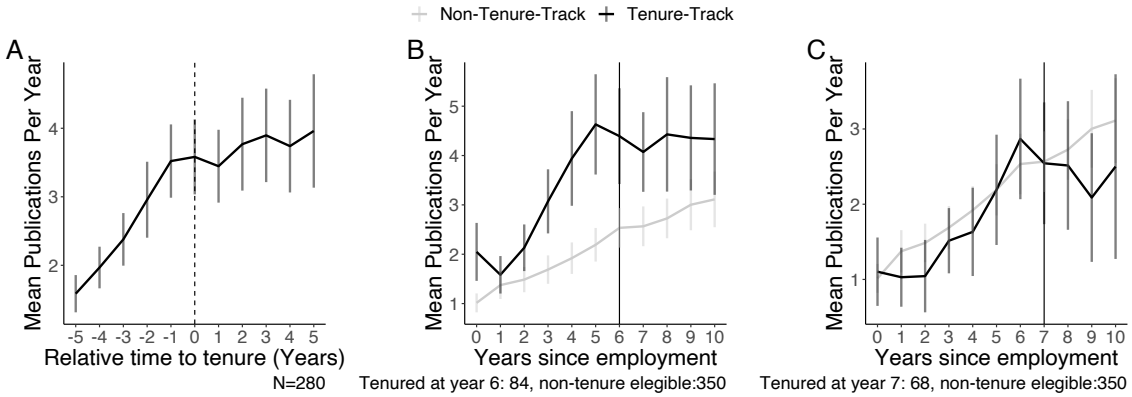


Figure S18: HR records [D2] analysis. (**A**) Average number of papers per year over the 11-year time window for all faculty members who obtained tenure between 2000 and 2017. (**B**) Average number of papers by treatment group (tenure at year 6 – modal year) over the first 11 years of employment. (**C**) Average number of papers by treatment group (tenure at year 7 – second modal year) over the first 11 years of employment. Error bars are 95% CIs. This figure is based on dataset D2.

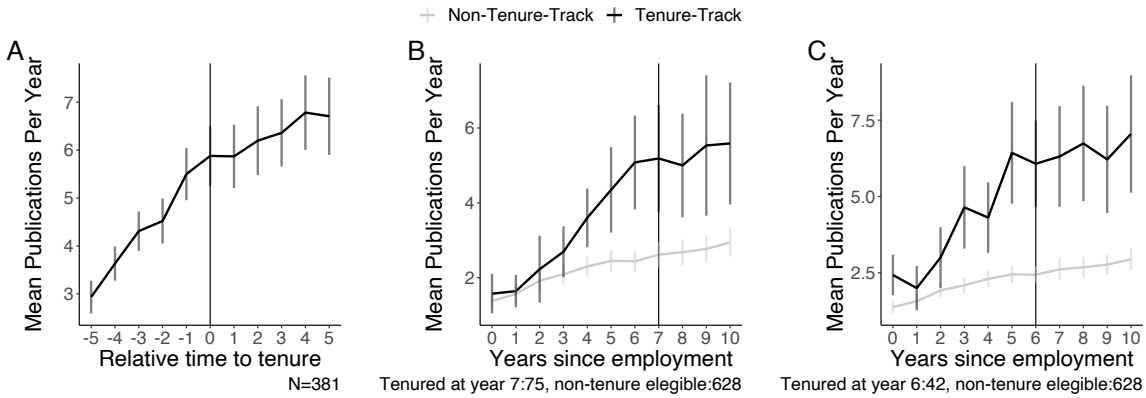


Figure S19: HR records [D3] analysis. (**A**) Average number of papers per year over the 11-year time window for all faculty members who obtained tenure between 2000 and 2017. (**B**) Average number of papers by treatment group (tenure at year 7 – modal year) over the first 11 years of employment. (**C**) Average number of papers by treatment group (tenure at year 6 – second modal year) over the first 11 years of employment. Error bars are 95% CIs. This figure is based on dataset D3.

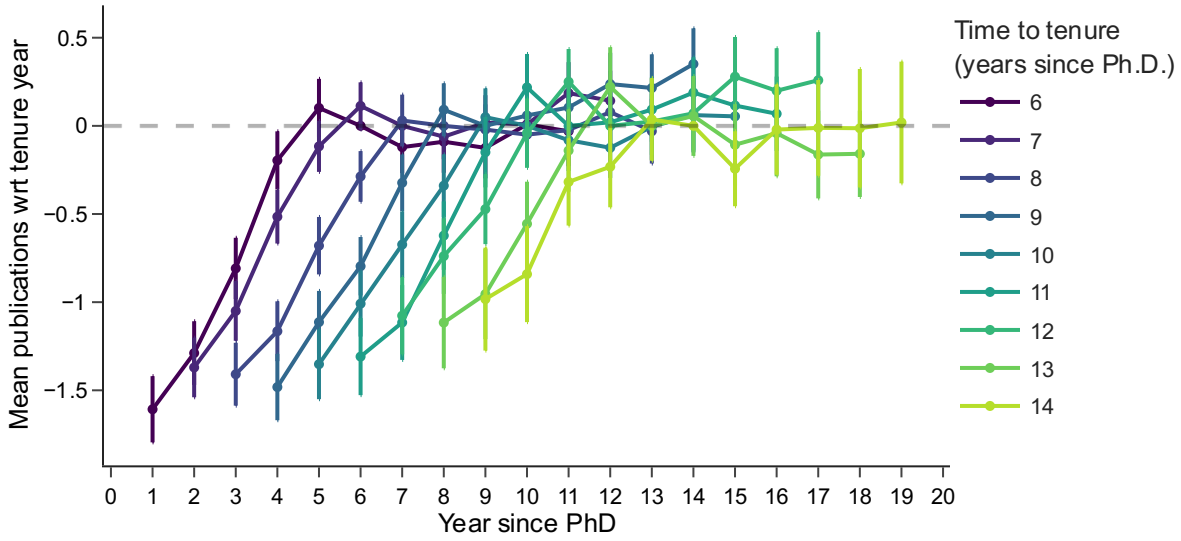
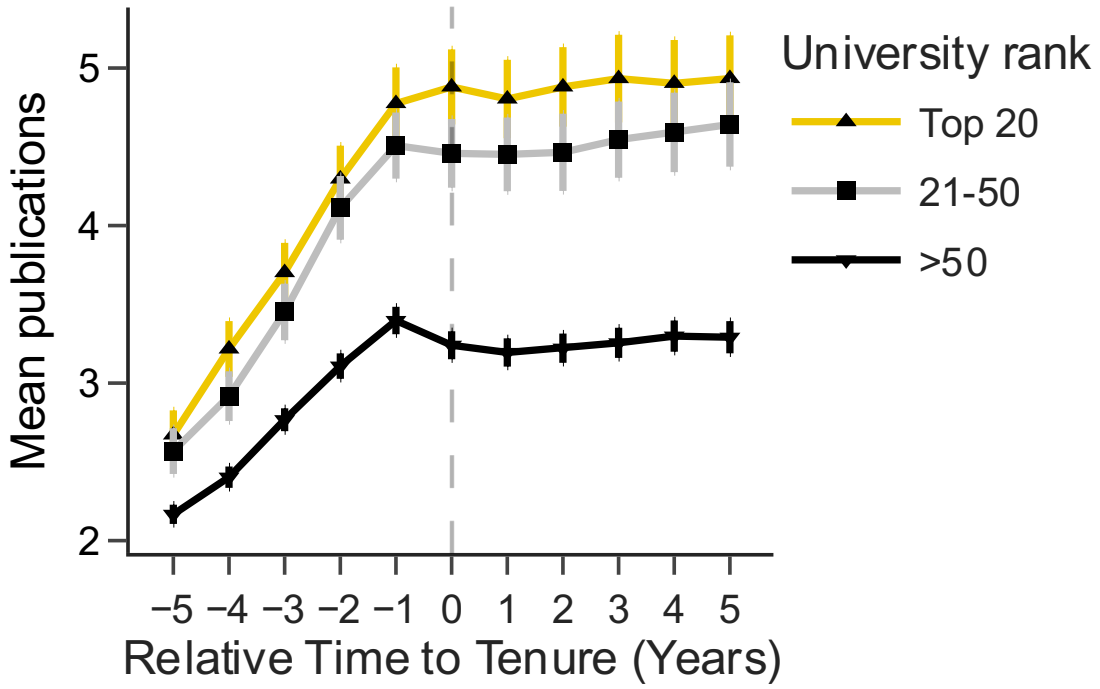


Figure S20: Publication rates (based on Scopus) with respect to tenure year by career age. Career age is defined as the number of years from Ph.D. to tenure. Replication of Fig. 1C. This figure is based on datasets D1 and D5.



953

954 **Figure S21: Publication rates (based on Scopus), averaged across researchers, by**
955 **university rank.** Replication of Fig. 1B. This figure is based on datasets D1 and D5.

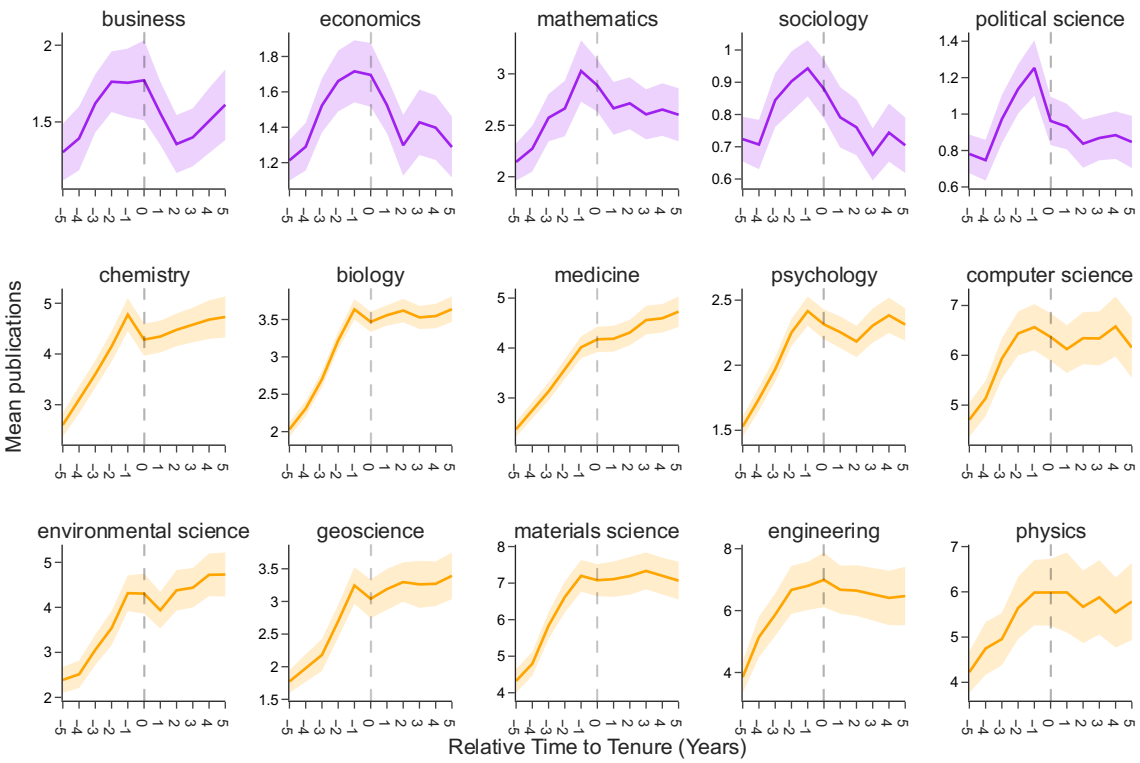


Figure S22: Cross-disciplinary variations in publication patterns based on Scopus. Each panel shows the average number of papers per year by discipline, distinguishing two broad classes. Replication of Fig. 2. This figure is based on datasets D1 and D5.

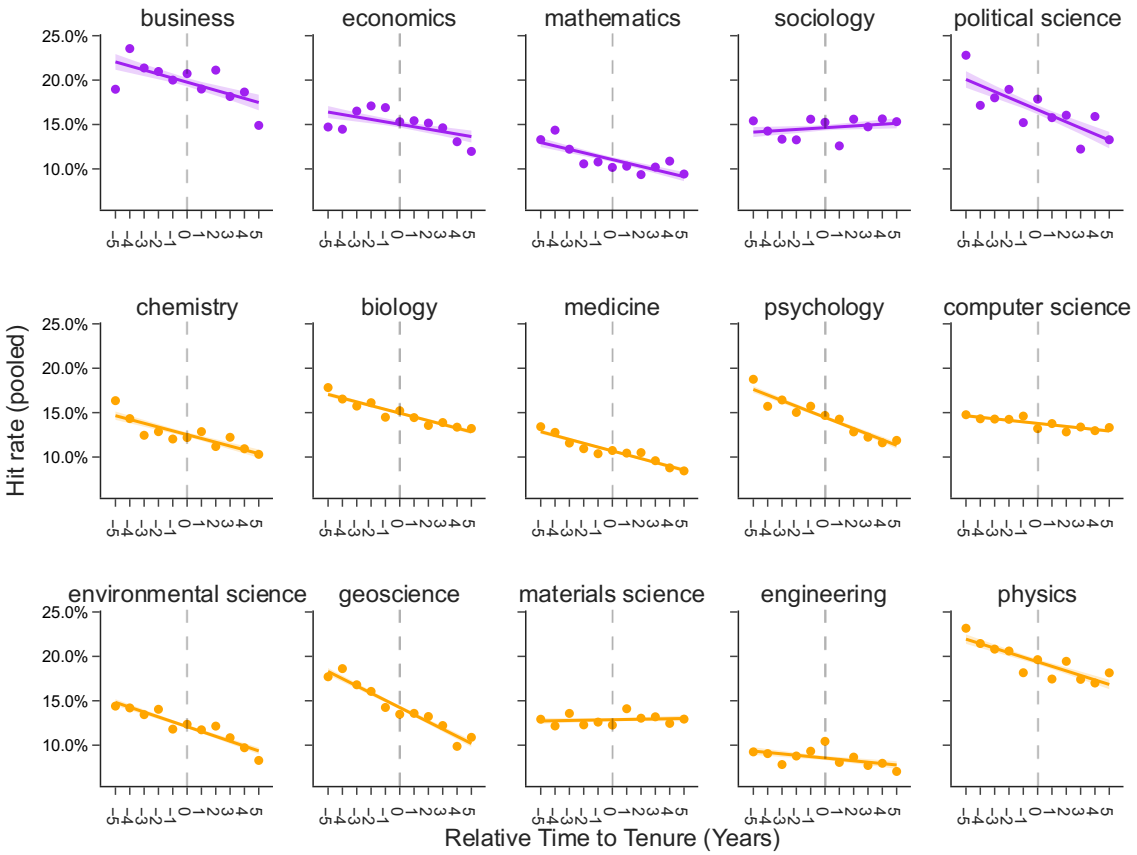


Figure S23: Pooled hit rate based on Scopus. Pooled hit rate is defined as the number of hit papers over the total number of articles published by faculty in each year before and after tenure. Replication of Fig. 4A. This figure is based on datasets D1 and D5.

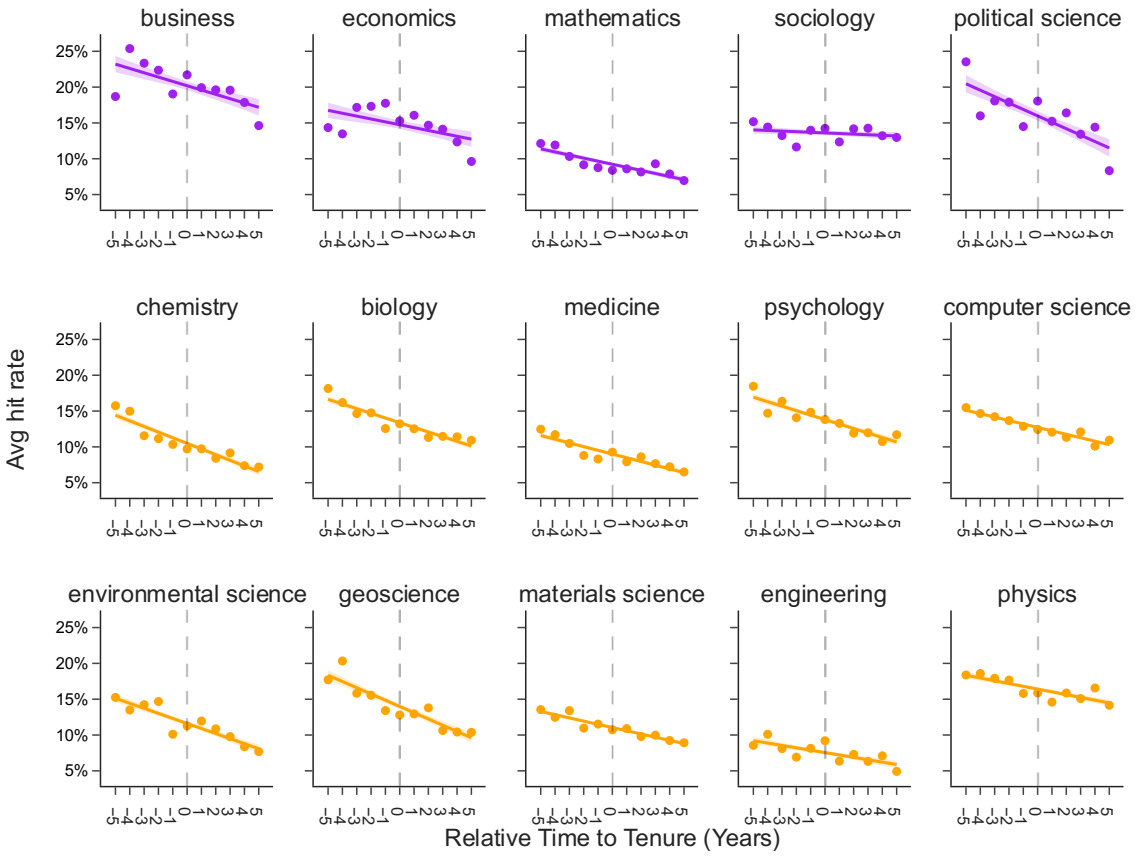
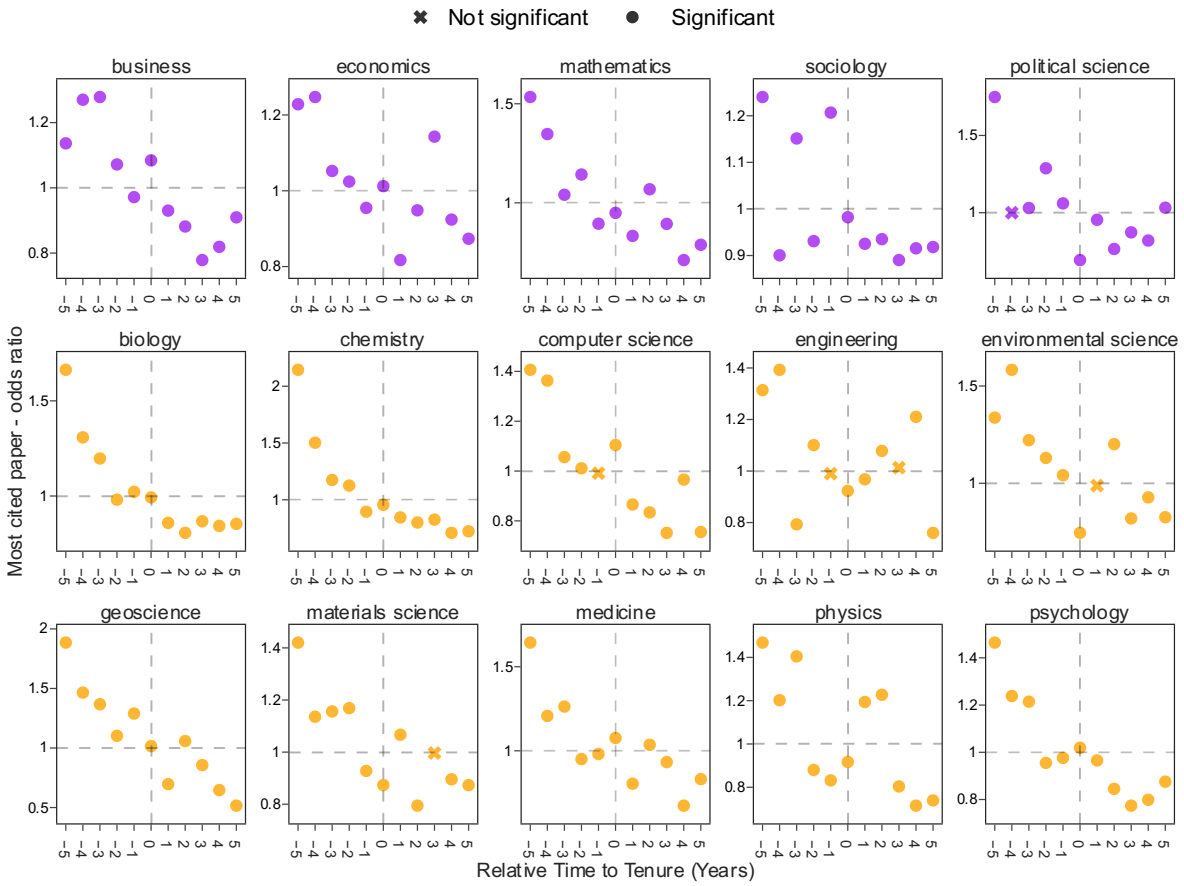


Figure S24: Average hit rate based on Scopus. Average hit rate by field for faculty who publish at least one paper per year. Replication of Fig. S13A. This figure is based on datasets D1 and D5.

971



972

973 **Figure S25: Most cited paper based on Scopus.** Share of faculty who produce their most cited
974 paper during our time window (ratio with respect to null model) by field. Significance at 0.95 C.I.
975 Replication of Fig. 4B. This figure is based on datasets D1 and D5.

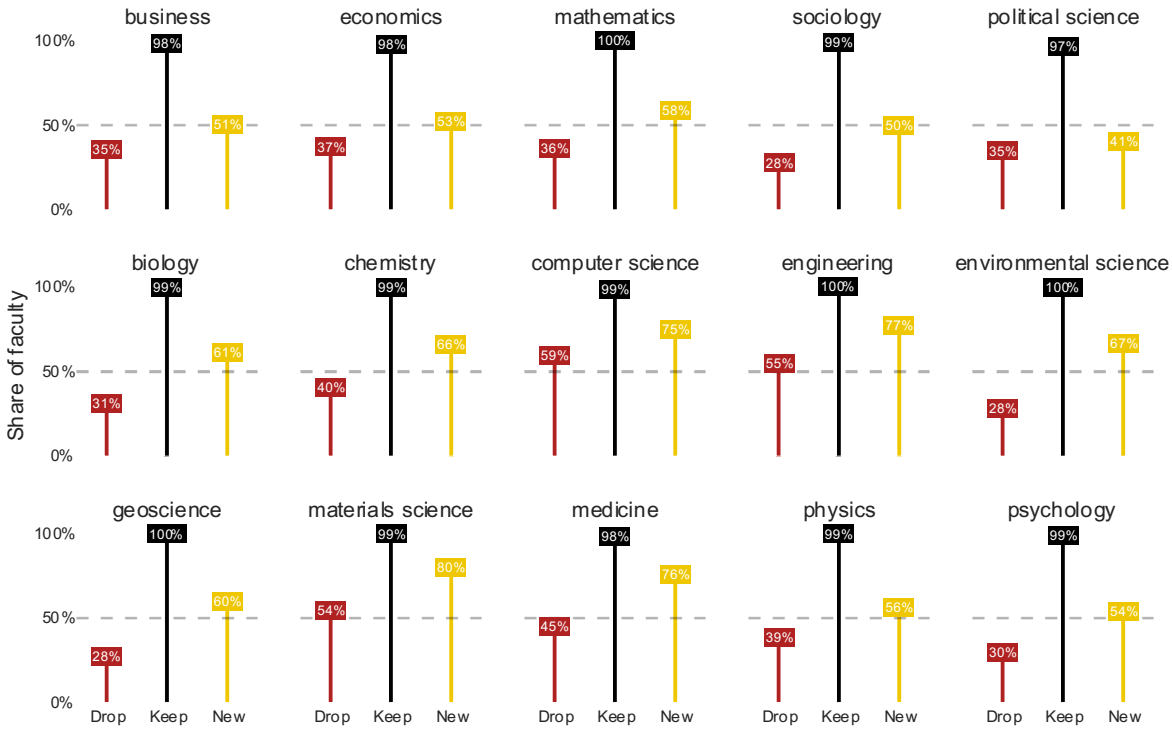


Figure S26: Tenure and research portfolio based on Scopus. Share of scholars who reorganize their research portfolio after tenure. Replication of Fig. 5C. This figure is based on datasets D1 and D5.

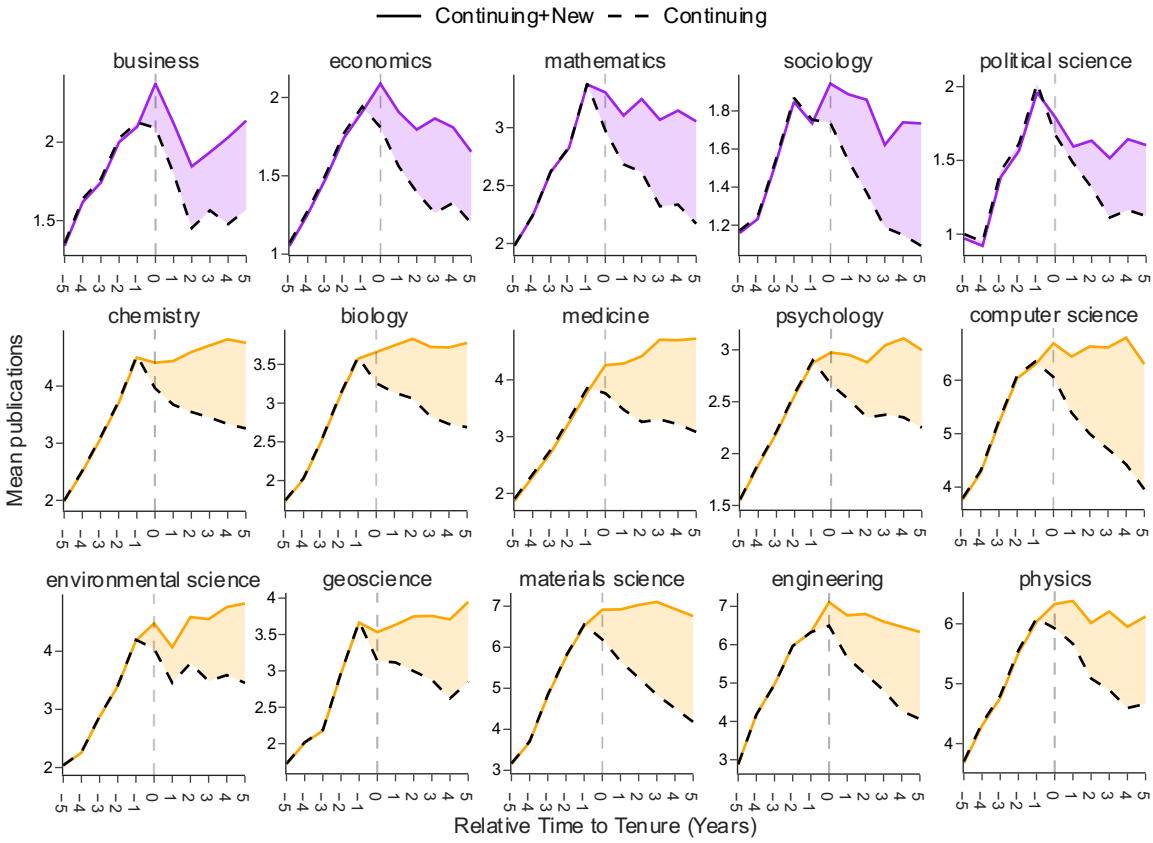


Figure S27: Post-tenure diversification and research trajectories based on Scopus. Average number of papers by type/topic. The black dashed line indicates the average number of papers adhering to the old agenda. The solid line indicates the average number of papers that belong to either the "continuing" or the "new" communities. Replication of Fig. 6. This figure is based on datasets D1 and D5.

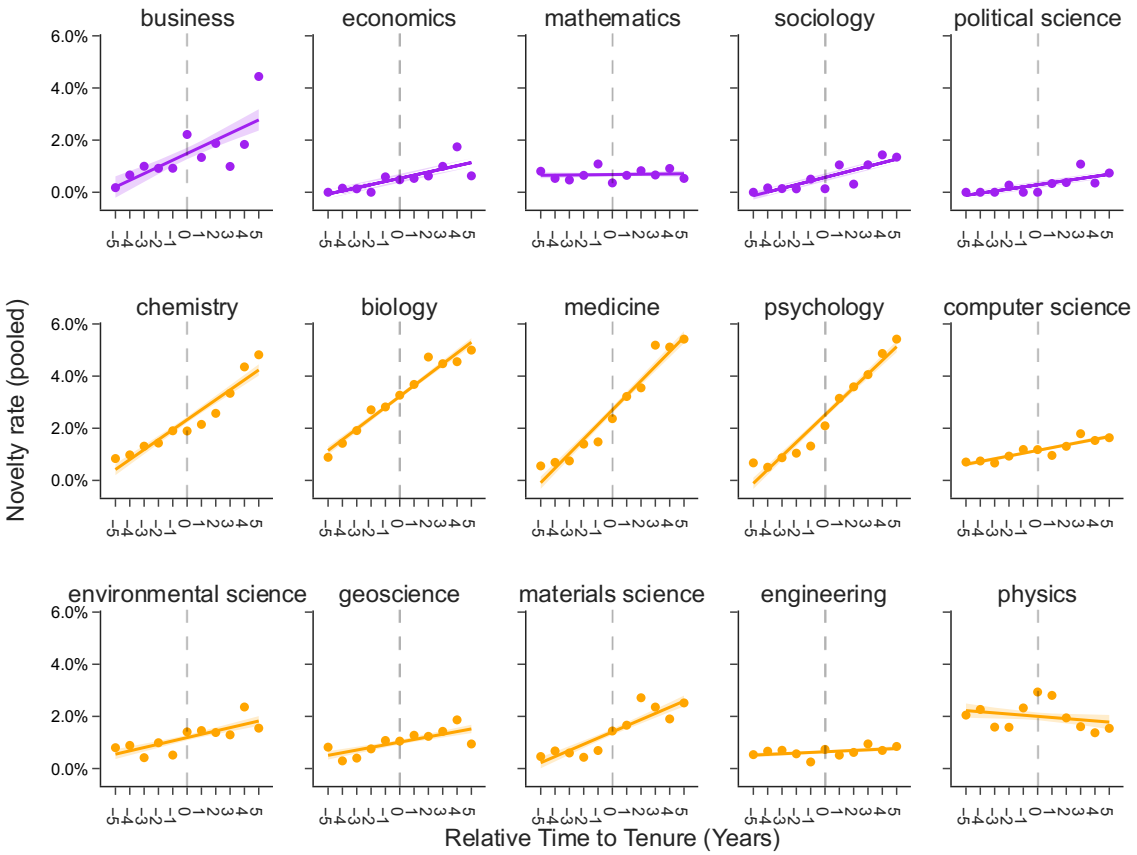


Figure S28: Novelty rate based on Scopus. Pooled novelty rate based on Scopus data by field. The novelty rate is defined as the number of novel papers over the total number of articles published by faculty in our sample each year. Novel papers are defined as the top 10% of papers. This figure is based on datasets D1 and D5.

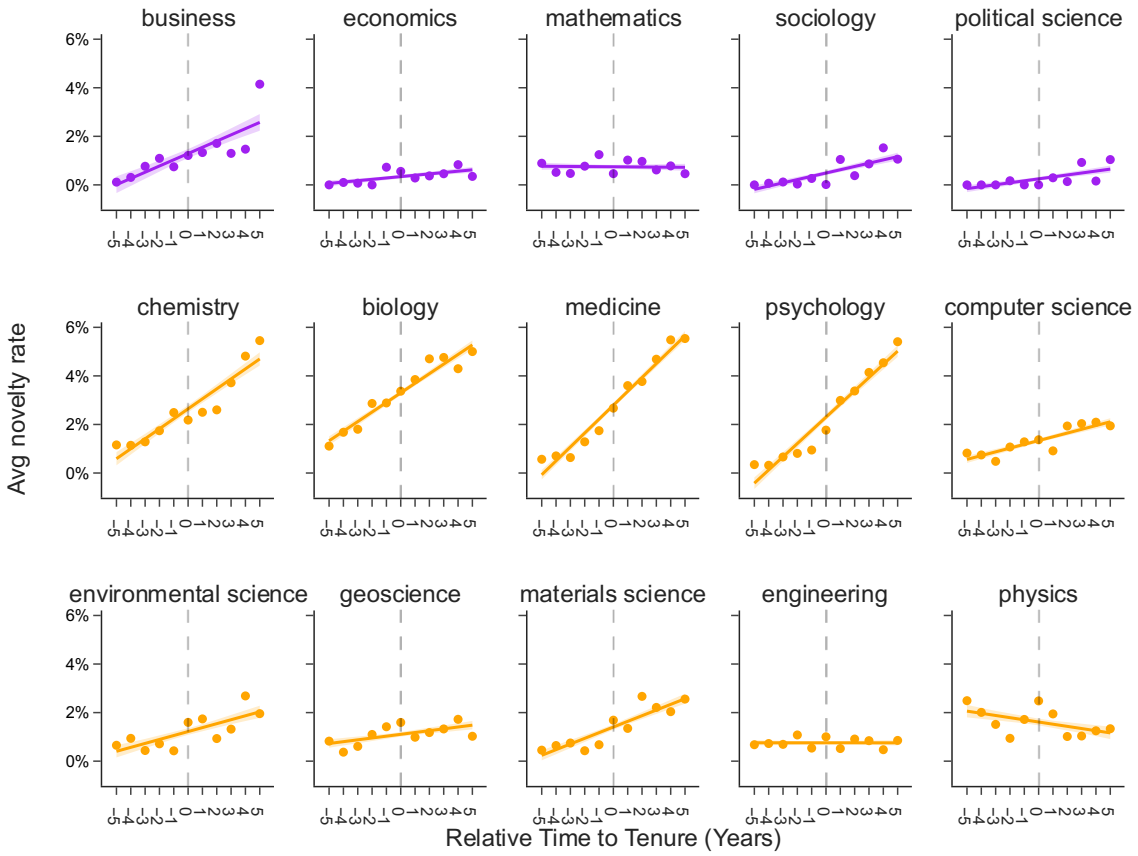


Figure S29: Average novelty rate based on Scopus. Average novelty rate by field for faculty who publish at least one paper per year (i.e., excluding faculty with non-finite values). Replication of Fig. S13B. Novel papers are defined as the top 10% of papers by novelty score. This figure is based on datasets D1 and D5.

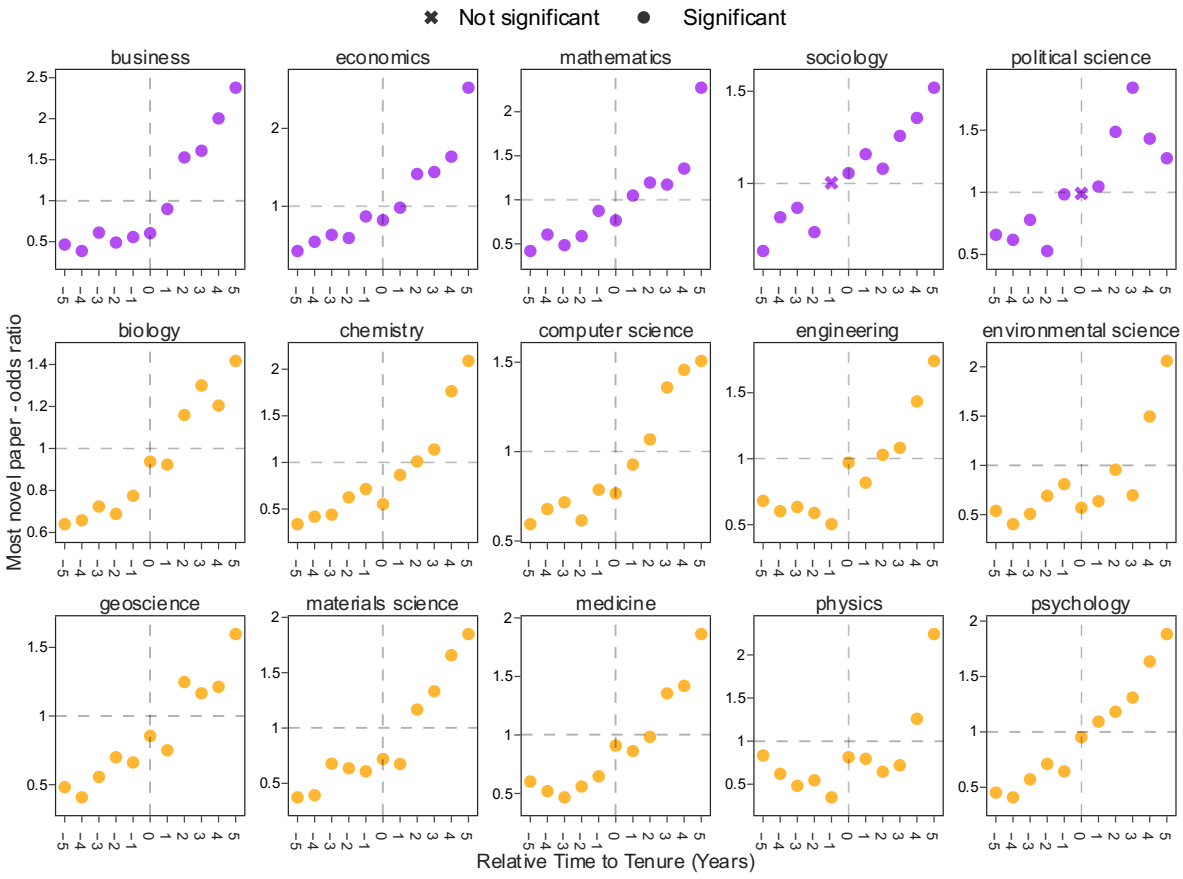


Figure S30: Most novel paper based on Scopus. Share of faculty who produce their most novel paper during our time window (ratio with respect to null model) by field. Significance at .95 C.I. Replication for Fig. 7B. This figure is based on datasets D1 and D5.

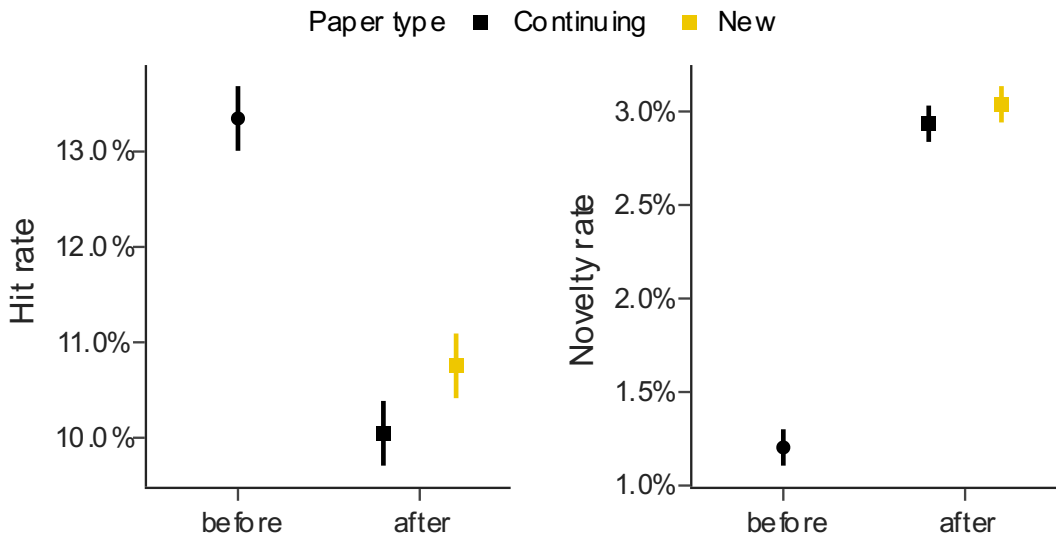


Figure S31: Post-tenure diversification, impact, and novelty based on Scopus. (A) Hit rate by paper type for scholars with a new agenda. (B) Novelty rate by paper type for scholars with a new agenda. Hit papers are defined as the top 5% of papers published the same year in the same field. Novel papers are defined as the top 10% of papers by novelty score. Replication of Fig. 8. This figure is based on datasets D1 and D5.

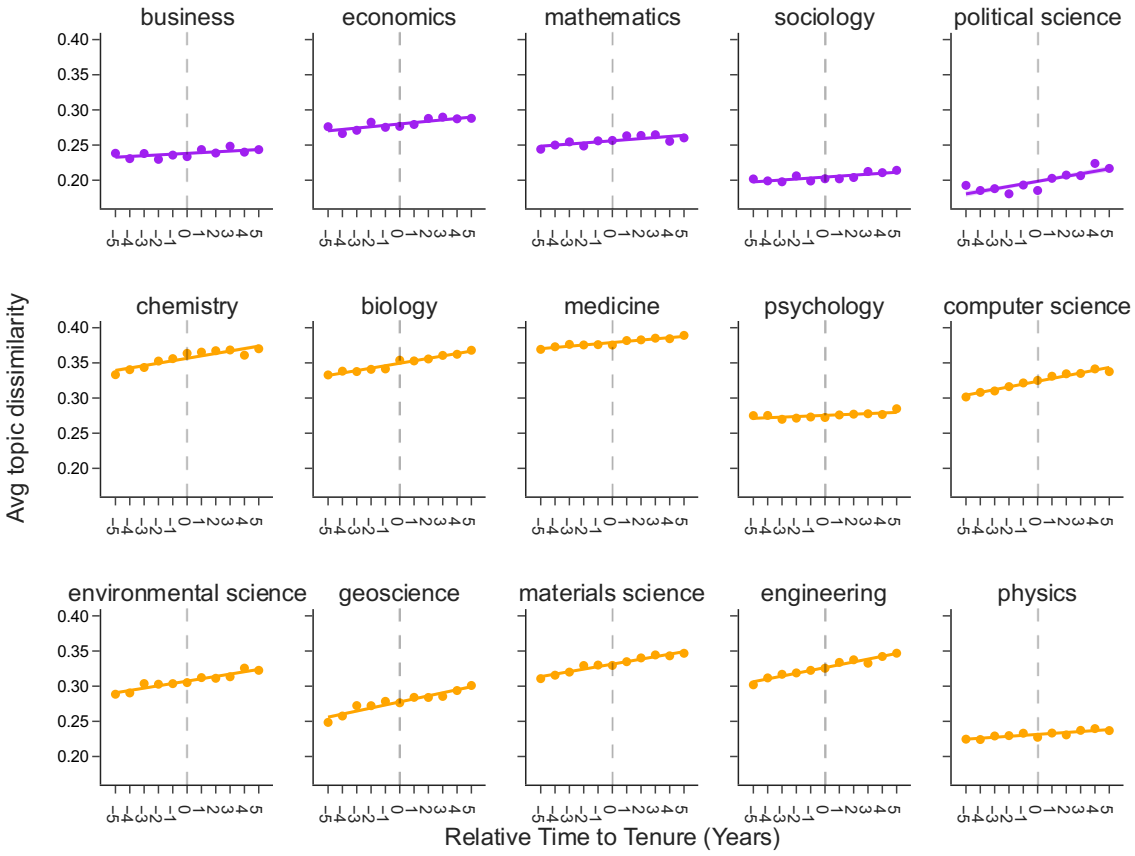


Figure S32: Average topic dissimilarity based on Scopus. This figure is based on datasets D1 and D5.

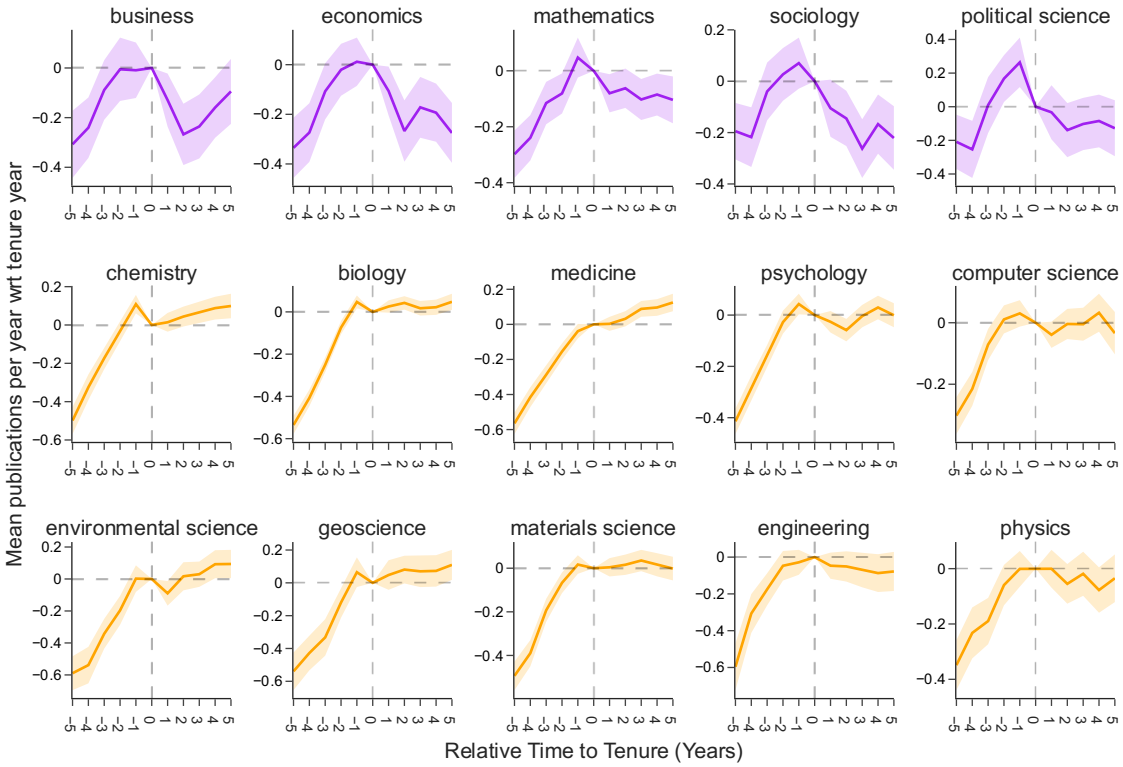


Figure S33: Mean publications per year based on Scopus. The effects are estimated using a Poisson regression and include individual fixed effects. Reference year $t = 0$. This figure is based on datasets D1 and D5.

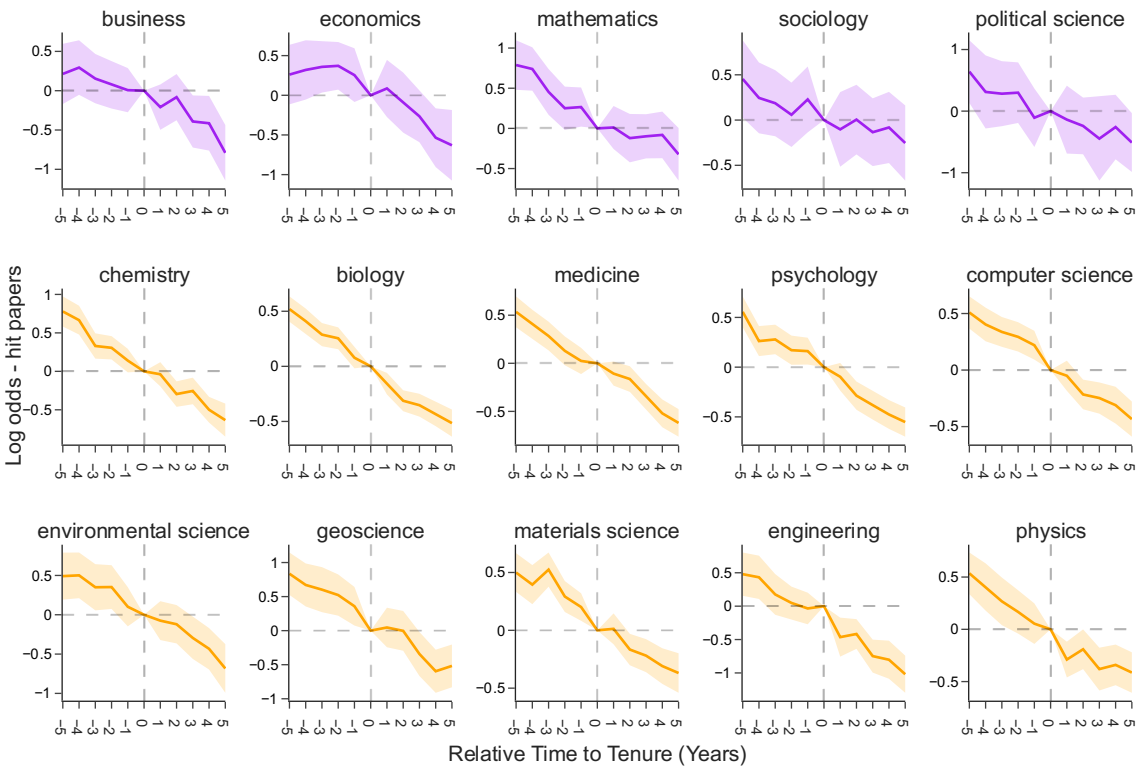


Figure S34: Log odds for hit papers based on Scopus. The effects are estimated using a logistic regression, including individual fixed effects and controls. Reference year $t = 0$. This figure is based on datasets D1 and D5.

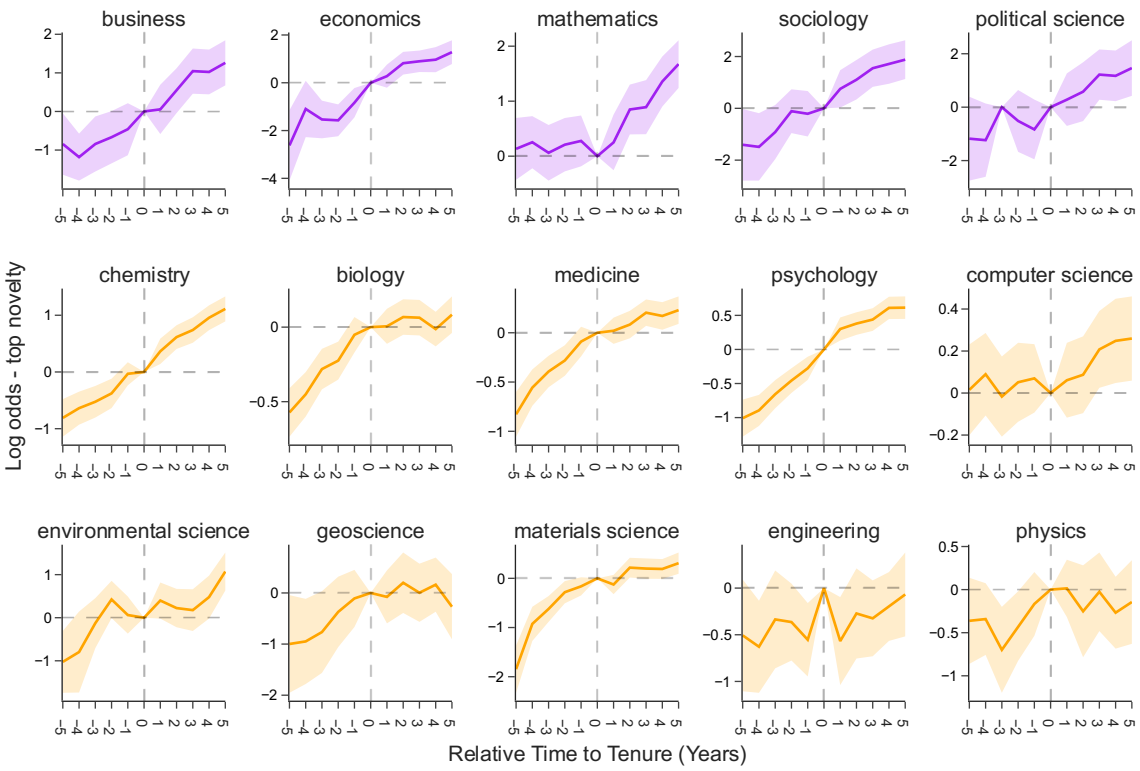


Figure S35: Log odds for novel papers based on Scopus. The effects are estimated using a logistic regression and include individual fixed effects and controls. Reference year $t = 0$. This figure is based on datasets D1 and D5.

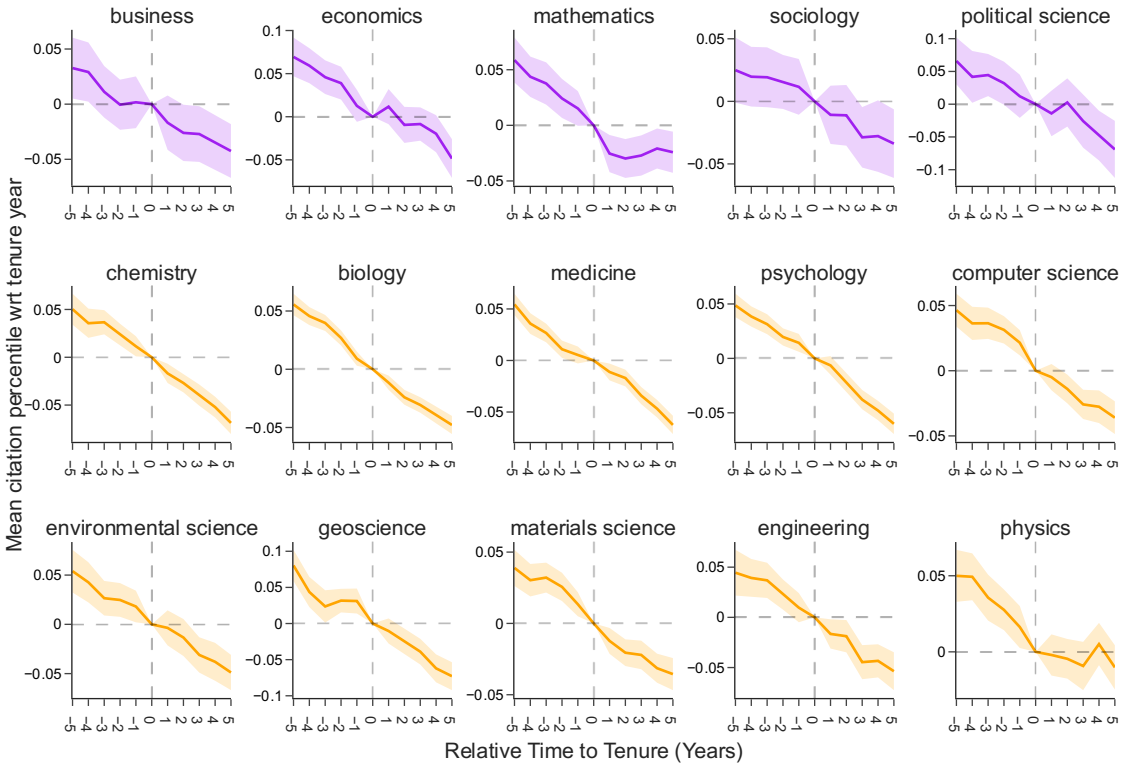


Figure S36: Mean citation percentile based on Scopus. The effects are estimated using an OLS regression, including individual fixed effects and controls. Reference year $t = 0$. This figure is based on datasets D1 and D5.

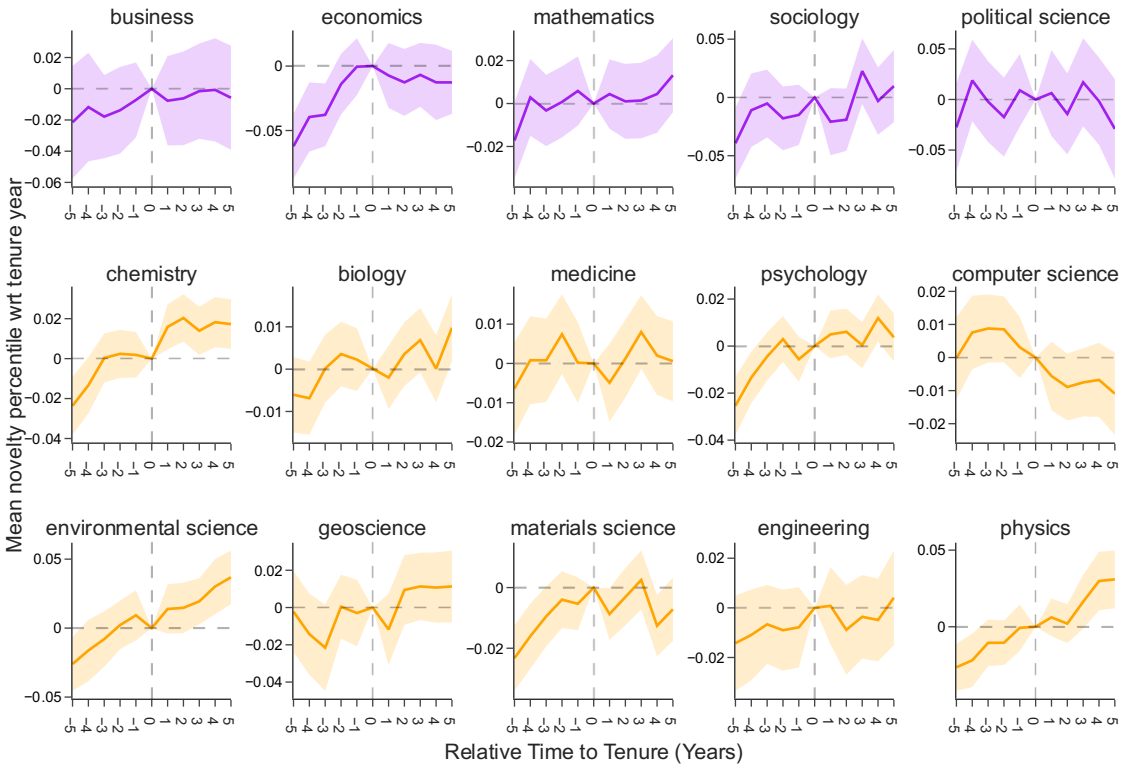


Figure S37: Mean novelty percentile based on Scopus. The effects are estimated using an OLS regression, including individual fixed effects and controls. Reference year $t = 0$. This figure is based on datasets D1 and D5.

SI References

1. Lin, Z., Yin, Y., Liu, L. & Wang, D. SciSciNet: A large-scale open data lake for the science of science research. *Sci. Data* 10, 315 (2023).
2. Myers, K. R. *et al.* Unequal effects of the COVID-19 pandemic on scientists. *Nat. Hum. Behav.* 4, 880–883 (2020).
3. Gao, J., Yin, Y., Myers, K. R., Lakhani, K. R. & Wang, D. Potentially long-lasting effects of the pandemic on scientists. *Nat. Commun.* 12, 6188 (2021).
4. Börner, K., Silva, F. N. & Milojević, S. Visualizing big science projects. *Nat. Rev. Phys.* 3, 753–761 (2021).
5. Zhang, S., Wapman, K. H., Larremore, D. B. & Clauset, A. Labor advantages drive the greater productivity of faculty at elite universities. *Sci. Adv.* 8, eabq7056 (2022).
6. Jones, B. F. The Rise of Research Teams: Benefits and Costs in Economics. *J. Econ. Perspect.* 35, 191–216 (2021).
7. Wuchty, S., Jones, B. F. & Uzzi, B. The Increasing Dominance of Teams in Production of Knowledge. *Science* 316, 1036–1039 (2007).
8. Rahmandad, H. & Vakili, K. Explaining Heterogeneity in the Organization of Scientific Work. *Organ. Sci.* 30, 1125–1145 (2019).
9. Wapman, K. H., Zhang, S., Clauset, A. & Larremore, D. B. Quantifying hierarchy and dynamics in US faculty hiring and retention. *Nature* 1–8 (2022) doi:10.1038/s41586-022-05222-x.
10. Uzzi, B., Mukherjee, S., Stringer, M. & Jones, B. Atypical Combinations and Scientific Impact. *Science* 342, 468–472 (2013).
11. Yang, Y., Tian, T. Y., Woodruff, T. K., Jones, B. F. & Uzzi, B. Gender-diverse teams produce more novel and higher-impact scientific ideas. *Proc. Natl. Acad. Sci.* 119, e2200841119 (2022).
12. Lee, Y.-N., Walsh, J. P. & Wang, J. Creativity in scientific teams: Unpacking novelty and impact. *Res. Policy* 44, 684–697 (2015).
13. Blondel, V. D., Guillaume, J.-L., Lambiotte, R. & Lefebvre, E. Fast unfolding of communities in large networks. *J. Stat. Mech. Theory Exp.* 2008, P10008 (2008).
14. Liu, L., Dehmamy, N., Chown, J., Giles, C. L. & Wang, D. Understanding the onset of hot streaks across artistic, cultural, and scientific careers. *Nat. Commun.* 12, 5392 (2021).
15. Zeng, A. *et al.* Increasing trend of scientists to switch between topics. *Nat. Commun.* 10, 3439 (2019).