Over a Century of Economics Research Collaboration

Willy Chen* Xiao Qiao† Hanzhe Zhang‡

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Abstract

We study collaboration patterns among 100,000+ academic economists using bibliographic information on nearly 500,000 economics publications and working papers since 1886. To enable this analysis, we construct a complete panel of author affiliations over time by chaining publication records—a contribution that overcomes well-known deficiencies in existing bibliographic data. We document several new patterns. First, inter-institutional collaboration was U-shaped: declining through the 20th century and rising in the 21st. Second, the experience composition of research teams—the mix of junior and senior economists—has remained stable. Third, returns to collaboration have shifted in waves: solo-author papers were most likely to be highly cited in the 1950s, two-author papers in the 1960s–1980s, three-author papers in the 1990s–2000s, and four-plus-author papers in the 2010s. Researchers respond to these changing returns primarily at the four-plus-author margin. Using COVID as a natural experiment that shifts collaboration costs, we find a polarizing effect: some researchers retreated to solo work while others formed larger teams. We develop a parsimonious theoretical framework of skill complementarity, coordination costs, and heterogeneous responses to cost shocks to rationalize all empirical findings.

Keywords: collaboration, academic economists, homerun papers, working papers, COVID

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*Department of Economics, Michigan State University, willyc@msu.edu.

†Department of Data Science, City University of Hong Kong, xiaoqiao@cityu.edu.hk.

‡Department of Economics, Michigan State University, hanzhe@msu.edu.

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1 Introduction

It is now well-established that research collaboration among academic economists has increased dramatically over the past century. Existing studies have documented the rise in the average number of authors per paper (McDowell and Melvin, 1983; Barnett, Ault, and Kaserman, 1988; Hudson, 1996; Hamermesh, 2013; Jones, 2021), but limited data quality has constrained the investigation of deeper dimensions of collaboration. What remains poorly understood is the composition of research teams–who works with whom, across which institutions, and at what career stages, as well as the economic forces that shape these choices. Author affiliations in commonly used databases such as Research Papers in Economics (RePEc), Web of Science (WoS), and Scopus are frequently outdated, overwritten, or missing entirely. This is a problem that is especially acute for working papers, where repositories such as SSRN retain only the most recent affiliation and overwrite historical records. Without knowing where a researcher was located at the time a paper was written, questions about inter-institutional collaboration, geographic scope, and the relationship between institutional prestige and research impact cannot be answered reliably.

This paper studies granular collaboration patterns and their drivers, enabled by a unique dataset. We construct a novel panel of author–institution affiliations over time by chaining together over 240,000 publication records from 64 of the most prominent economics journals. By linking successive publications of the same author, we recover a near-complete time series of institutional affiliations for approximately 110,000 academic economists, achieving a 98% coverage rate. We validate this panel against hand-collected career histories of MIT faculty (85.6% match) and award-winning economists (76.3% match). Combined with bibliographic data on nearly 500,000 economics publications and working papers from 1886 to 2023, this dataset provides a uniquely comprehensive and accurate foundation for studying collaboration.

Enabled by more granular data, we document several new patterns in academic collaboration. Inter-institutional collaboration, measured by the fraction of multi-author papers whose authors span different institutions, followed a U-shaped trajectory: declining from approximately 90% in 1950 to 60% in 2000, then rising to 75% by 2023. This nonmonotonic pattern challenges the simple narrative that improvements in communication technology have steadily reduced the costs of long-distance collaboration. During the very decades when telephone, email, and the internet became widespread, economists increasingly collaborated with colleagues at their own institutions. Only in the 21st century did the trend reverse. Meanwhile, the experience composition of research teams has been remarkably stable: conditional on team size, the mix of junior and senior economists on a paper has changed little over seven decades. The economics profession has also become more global, with the share of EC64 papers authored exclusively by US-based researchers falling from over 90% in the 1950s to roughly 30% today.

We investigate the drivers of collaboration by examining both the benefits and costs of teamwork. Our empirical analysis is organized around a simple trade-off: a researcher collaborates when the marginal benefit of adding a team member (e.g., improved paper quality and impact) exceeds the marginal cost of coordination. On the benefit side, we study how the returns to different team sizes have evolved over time and whether researchers respond to these changing returns. We find that the type of paper most likely to become highly cited has shifted in waves: solo-author papers dominated in the 1950s, two-author papers in the 1960s through the 1980s, three-author papers in the 1990s and 2000s, and four-plus-author papers in the 2010s. Using a seemingly unrelated regression framework, we find that researchers respond to rising returns most strongly at the four-plus-author margin, assembling into larger teams when such teams have recently produced a disproportionate share of highly cited work, with weaker evidence of a response at the two- or three-author margin. On the cost side, we exploit the COVID-19 pandemic as a natural experiment that shifted the costs of collaboration while leaving the return structure approximately unchanged. We find a polarizing effect: the pandemic simultaneously increased the share of solo-author papers and papers with four-plus authors, while reducing the share of two- and three-author papers. This is consistent with heterogeneous responses to cost shocks—some researchers found collaboration more difficult under lockdown and retreated to solo work, while others leveraged digital tools and normalized remote workflows to scale up their teams. Inter-institutional collaboration and experience composition remained largely unchanged during the pandemic, suggesting that the cost shock operated primarily on the team-size margin rather than through team composition.

To provide conceptual coherence, we develop a parsimonious model of team size choice with increasing productive complementarity and convex coordination costs. Despite its simplicity, this framework rationalizes all five main empirical patterns: wave-like growth in team sizes, the U-shaped trajectory of inter-institutional collaboration, stable experience composition, differential responsiveness at the four-plus-author margin, and COVID-era polarization. The model demonstrates that a unified set of assumptions can qualitatively account for the disparate empirical patterns we document.

Our paper contributes to three strands of literature. The first documents facts about research collaboration. Wuchty, Jones, and Uzzi (2007) illustrate rising team sizes across both the natural and social sciences. Uzzi et al. (2013) find that teams generate more creative ideas than individuals. Jones (2009, 2010) documents that researchers train longer and specialize more as fields advance. Within economics specifically, several studies examine collaboration trends over relatively short windows using a small number of journals (McDowell and Melvin, 1983; Barnett, Ault, and Kaserman, 1988; Hudson, 1996; Nowell and Grijalva, 2011; Hamermesh, 2013; Andrikopoulos, Samitas, and Kostaris, 2016; Ji and Jin, 2016; Seltzer and Hamermesh, 2018; Schwert, 2021). Jones (2021) provides a broad overview using over 3,000 journals classified as economics. Compared with prior work, we offer more comprehensive documentation spanning nearly 140 years of publication data. Importantly, our detailed affiliation panel enables us to study inter-institutional collaboration and the role of institutional prestige at a level of granularity that was previously infeasible.

The second strand seeks to identify the mechanisms behind collaboration. Sheng (2020) empirically investigates a pairwise coauthor formation model of Jackson and Wolinsky (1996). Ahmadpoor and Jones (2019) find positive assortative matching among authors with similar citation levels in the physical sciences. Liu et al. (2023) surveys the empirical literature and notes that when split into two categories, far more papers document regularities than identify mechanisms. Our paper adds to both categories, with an emphasis on making progress on the latter through our analysis of time-varying returns and cost shocks.

The third strand examines the effects of COVID on research productivity and collaboration (Butler and Jaffe, 2021; Bayhan et al., 2022; Ford et al., 2021; Yang et al., 2022). Survey-based research highlights differential impacts by gender (King and Frederickson, 2021; Liu et al., 2022; Sinatra et al., 2023). Heo et al. (2022) documents delays in lab-based STEM research and reduced informal collaboration due to virtual conferences. Whereas this literature tends to focus on COVID itself as the outcome of interest, we treat the pandemic as a laboratory for understanding how cost shocks affect collaboration patterns, using working papers to capture real-time adjustments.

The rest of the paper is organized as follows. Section 2 describes the construction of our unique database of author and paper information. Section 3 documents patterns of collaboration. Section 4 conducts empirical tests of possible channels. Section 5 provides a theoretical framework to rationalize the empirical findings. Section 6 concludes.

2 Data

We obtain paper-level information from the bibliometric database OpenAlex, which includes publications from 1886 to 2024 and working papers from the Social Science Research Network (SSRN) from its inception in 1994 to 2024. We also collect working papers posted on the National Bureau of Economic Research (NBER) website from the beginning of the working paper series in 1973 to 2023. For publications, we consider papers published in 64 journals commonly regarded as the most prominent economics research outlets. These include general-interest journals (e.g., *Journal of Political Economy*, *Economic Journal*, and *European Economic Review*) and field journals (e.g., *Journal of Development Economics*, *Games and Economic Behavior*, and *Social Choice and Welfare*). Table 1 lists the 64 journals by field.[1] Publications have been available since 1886, when the

[1]The list of journals comes from the School of Economics at Shanghai University of Finance and Economics (SUFE) and is consistent with top journals in various ranking lists (Kalaitzidakis, Mamuneas, and Stengos, 2003; Heckman

Quarterly Journal of Economics was founded. We refer to all 64 journals as "EC64" and the T5 general interest journals (*American Economic Review*, *Econometrica*, *Journal of Political Economy*, *Quarterly Journal of Economics*, and *Review of Economic Studies*) as "T5." Any author who has published an EC64 paper is considered an "academic economist." Given that SSRN covers social science research in general, we include only papers in which 33% or more of the authors are academic economists, defined by having published a paper in EC64.

We record the year papers are published or posted to working paper repositories. Since the dating is precise only up to the year, we define the pre-COVID period as all years through 2019 and the COVID period as 2020 and beyond. To ensure that our focus is on economics research and to provide a valid comparison before and after COVID, we exclude papers that primarily concern the pandemic by filtering out any papers whose titles include "COVID," "coronavirus," or "sars-cov-2." We distinguish between papers in which all authors share a single institutional affiliation—indicating intra-institutional collaboration—and those with multiple affiliations, which indicate inter-institutional collaboration. A paper's major affiliation is defined as the most frequently occurring affiliation among its authors.

2.1 Author Affiliation Records

Accurate, time-varying author affiliations are essential for studying collaboration across institutions. This information is typically unavailable in existing datasets. Affiliations in bibliographic catalogs may be incorrect or outdated, a problem that is particularly pronounced for working papers: repositories such as SSRN often retain only the latest affiliation and overwrite past positions, even for works posted while the author held a previous position. For example, if an author moved from institution I to institution J in 2011, a working paper posted on SSRN in 2008 (while at institution I) may now show institution J as the affiliation.

To overcome this problem, we construct author–affiliation records using published papers, which contain the affiliation as of the date of publication. By chaining together multiple publications, we build a panel of author affiliations over time. Our approach follows the framework proposed by Lin et al. (2023) for completing institutional data from the Microsoft Academic Graph (MAG). Since MAG stopped updates in December 2021, we use its successor, OpenAlex (OA) — an open-access bibliographic database maintained by OurResearch. As of March 2024, OA includes metadata for over 200 million papers and books, 13 million authors, and over 100,000 institutions.

A further challenge is author identity fragmentation: the same researcher may appear under

and Moktan, 2020; Ham, Wright, and Ye, 2026). We base our selection of journals on the SUFE list because it is more comprehensive than the lists maintained by other institutions—e.g., New York University Stern Business School (Cabral, 2020) and Tilburg University (Tilburg University, 2025).

multiple identifiers across publications. To address this, we query the Web of Science for the same EC64 publications, match papers across sources by title, and within matched papers link authors by name. This generates a crosswalk that consolidates fragmented records into unified author identifiers, ensuring each economist's full publication and affiliation history is attributed to a single identity. As a further quality check, we drop single-year affiliation stints, which are most likely attributable to parsing errors in the underlying bibliographic data.

To construct the affiliation panel, we extract author-affiliation records from all EC64 publications and apply the unified author identifiers from the crosswalk. We then fill gaps using the following procedure. First, for each author-affiliation pair, we identify the range of years with observed records. Second, we forward fill any missing years between the first and last recorded years, replacing missing values with the last observed non-missing value to ensure continuity. Third, for years that contain only forward-filled values, we retain the most recent entry. For authors whose last observed publication is in 2018 or later, we extend their affiliation forward through 2024. As a data quality check, we remove single-year affiliation stints that arise from isolated records inconsistent with an author's broader career history, as these are most likely attributable to parsing errors in the underlying bibliographic data. We exclude affiliation records for NBER and IZA in the first step due to the inter-institutional nature of these organizations. Our approach yields a 98% complete panel of author affiliation records. 70% of the unique papers in the data are fully matched with author-affiliation information. In EC64, 70% of papers have fully matched author information from the panel; another 8% of papers were recovered using a combination of the panel and the originally attached author information; and 18% of papers have no affiliation information at all.[2]

To verify quality, we cross-check against manually collected information on the education and career history of tenure-track faculty at MIT. For years with an affiliation present, our construction yields an 85.6% match rate. We also validate against the education and career histories of 200 award-winning economists collected by Freeman et al. (2024), finding a 76.3% match rate. The main sources of mismatches are the lack of publications in certain years and the lag between institutional moves and subsequent publications, which can result in erroneous institutional assignments during transition years.

2.2 Paper-Year Records

Our dataset includes paper and author information organized at the paper-year level. Each record contains the title, publication year, journal or repository, authors, and their affiliations. For a paper

[2] The only authors who do not have affiliations from this construction are those who have missing affiliation information from their publications.

i published in the year t in the journal/repository j, we construct the following outcome variables: the number of authors on the paper (Num_{ijt}); an intra-institutional collaboration indicator ($Intra_{ijt}$) equal to 1 if all authors share a common institution; the fraction of authors from the major institution (pct_maj_{ijt}); the fraction of junior economists (pct_jun_{ijt}), defined as authors whose first EC64 paper was published 0 to 9 years ago; and the fraction of senior economists (pct_sen_{ijt}), defined as authors whose first EC64 paper was published 10 or more years ago.

Authors of NBER working papers must be linked to author profiles from OpenAlex to populate the author affiliation records we construct from EC64 papers. In lieu of unique identifiers, we adopt a fuzzy matching algorithm similar to that used by Bremer (2023) and retain pairs of names with a Jaro–Winkler distance of $p = 0.1$ smaller than 0.05 (Cohen et al., 2021). When applied to 31,356 working papers from 1973 to 2023, 25,448 papers (81.2%) have fully matched author identifiers, 5,407 papers (17.2%) have partial matches, and 501 papers (1.6%) are unmatched. However, because many authors posted NBER papers before their first EC64 publication with non-missing affiliations, the affiliation match rate is lower: 11,931 papers (38.1%) have fully matched author affiliations, 15,182 papers (48.4%) have partial matches, and 4,243 papers (13.5%) are missing all affiliation information.

Table 2 presents summary statistics for each of the samples. The average number of authors per paper is higher for working papers than for publications, reflecting the more recent nature of repositories. There is substantial collaboration across institutions in all samples: at the lowest, 77.4% of multi-author NBER working papers are written by teams spanning multiple institutions.

3 Stylized Facts in Economics Research Collaboration

We document a set of stylized facts characterizing research collaboration among academic economists. Since the COVID pandemic began in 2020 and had a significant impact on collaboration patterns, we first focus on data through 2019 to study secular trends, reserving 2020 onward for the COVID analysis in Section 4.3.

Before assessing co-authorship structures directly, we establish a foundational baseline regarding the sheer scale of the discipline. The long-run trajectory of economics is characterized by a massive secular expansion in both research infrastructure and the academic workforce. Figure 1 documents the steady accumulation of active EC64 journals alongside an exponential acceleration in annual publication volume across the T5, EC64, SSRN, and NBER series from 1886 through 2024. Parallel to this institutional deepening, Figure 2 tracks the corresponding demographic explosion of the discipline, illustrating a stark rise in new, active, publishing, and cumulative economists over the same century-plus horizon. Together, these trends highlight a transition from a small, centralized field into a vast, dense research ecosystem—a structural shift that underpins the evolving collaborative dynamics we document below.

3.1 Rising Collaboration

The broad trend toward larger research teams is well documented in prior work, and our data confirm it across a longer time horizon and a wider set of papers. Before 1950, more than 95% of economics publications were solo-authored. Multi-author papers then rose in waves: two-author papers became common in the 1950s and 1960s, three-author papers in the 1970s and 1980s, and papers with four or more authors in the 2000s. We quantify these changes using a linear trend specification:

$$100 \cdot \mathbb{1}\{Num_{ist} = n\} = \beta_0 + \beta_{1,n} t + \alpha_s + \varepsilon_{ist}, \tag{1}$$

where $\mathbb{1}\{Num_{ist} = n\}$ is an indicator variable for whether the number of authors on paper i from source s (journal or repository) at time t is $n \in \{1, 2, 3, 4+\}$, and α_s captures the differences across outlets.

Between 2001 and 2019, all examined paper repositories experienced a significant shift away from single- and dual-authorship toward larger research teams. As shown in Table 3, the share of solo- and two-author papers declined by roughly 1 percentage point annually across all four samples from 2001 to 2019, with EC64 seeing the steepest drop in single authors at -1.13 percentage points. Conversely, three-author and four-plus-author papers grew by averages of roughly 0.95 and 0.69 percentage points per year, respectively. These patterns, further detailed in Appendix Figure B3-B5, align with prior literature and establish the baseline for the new affiliation-based results that follow.

3.2 Collaboration across Institutions

As research teams have grown, has their institutional composition changed? On the one hand, if rising collaboration is primarily driven by improved communication and lower coordination costs, we would expect more collaboration across institutions over time. On the other hand, if collaboration increases because of a more competitive publication environment that rewards teamwork per se, changes in institutional composition are not assured.

Our affiliation panel allows us to address this question with precision. We compute two variables: the proportion of inter-institutional papers—those with at least one author affiliated with a different institution—among all multi-author papers, and the share of authors at the major institution among inter-institutional papers.

Figure 3 panel (a) plots the fraction of inter-institutional papers over time in both working papers and publications. The pattern is striking and nonmonotonic. From 1950 to 2000, the fraction of multi-author papers involving inter-institutional collaboration declined from approximately 90% to 70%. This trend then reversed, rising to 80% by 2024. The decline is notable because it occurred during precisely the decades when communication technology was transforming academic life. Rather than enabling more inter-institutional teamwork, these tools appear to have coincided with—or perhaps facilitated—a period of intensified intra-institutional collaboration, possibly as departments grew larger and more specialized. Only in the 21st century did the trend reverse, consistent with the maturation of digital collaboration tools and the normalization of remote work. In Section 5, we show that this U-shaped pattern is consistent with a net benefit of inter-institutional collaboration that first declined as intra-departmental opportunities expanded, then rose with later-generation communication technologies.

Working papers from NBER and SSRN exhibit higher levels of inter-institutional collaboration than published papers, measured by the share of multi-author papers with at least one author from a different institution. The fraction of inter-institutional SSRN papers hovers around 80% throughout the sample, and the share of inter-institutional NBER papers increases over time.

Figure 3 panel (b) shows that among inter-institutional papers, the fraction of authors from the majority institution has decreased over time, particularly for EC64 and T5 publications. Working papers show little change in this measure. This pattern suggests that growing collaboration is not simply driven by former colleagues who have moved to new institutions, but rather by deeper partnerships across multiple institutions.

We quantify these patterns by estimating trend models:

$$100 \cdot Inter_{ist} = \beta_0 + \beta_1 t + \alpha_s + \varepsilon_{ist}, \tag{2}$$

$$pct\_maj_{ist} = \beta_0 + \beta_1 t + \alpha_s + \varepsilon_{ist}, \tag{3}$$

where $Inter_{ist}$ is an indicator variable that is 1 if at least one author does not share an affiliation with another author, and pct_maj_{ist} is the share of authors from the major institution on an inter-institutional paper. Independent variables are defined in the same way as those in Equation (1).

Table 4 documents a general rise in inter-institutional collaboration from 2001 through 2019. Panel A shows that within EC64 publications, multi-institution coauthorship grew across all team sizes, increasing by 0.27 to 0.33 percentage points annually. We find similar upward trends among Top 5 (T5) journals for two- and three-author papers, while NBER working papers display the sharpest increases among larger teams (1.03 percentage points). Conversely, SSRN exhibits modest declines for smaller teams. Consistent with these patterns, Panel B reveals a steady decline in institutional concentration for teams with three or more authors, with the primary institution's author share decreasing by 0.19 to 0.28 percentage points annually across the journal and NBER working paper samples.

In Table 5, we introduce field fixed effects to evaluate whether these patterns are driven by compositional shifts across subfields. The documented decline in institutional concentration remains remarkably stable. For inter-institutional collaboration, however, the upward trend becomes primarily concentrated within three-author teams, while the estimates for other team sizes lose statistical significance. Overall, the persistent drop in institutional assortativity suggests an intra-market shift rather than an artifact of sorting across fields.

3.3 Collaboration across Experience Levels

Research teams can also be characterized by the experience composition of their members. We classify authors into three groups: *junior* (first EC64 publication within the preceding nine years), *senior* (first EC64 publication ten or more years prior), and *non-economist* (never published in EC64). A partnership between researchers of similar experience levels may indicate a horizontal relationship, such as a combination of distinct expertise, while teamwork across experience levels may suggest a vertical one, such as mentorship.

Figure 4 panel (a) presents the shares of two-author EC64 publications by collaboration type: two juniors, one junior and one senior, and two seniors. Despite the dramatic changes in team sizes documented above, the split among these three categories has remained remarkably stable over time. The share of junior–senior papers has consistently hovered around 35%, and the fraction of senior–senior papers grew and stabilized at approximately 20% beginning in the 1980s. The share of junior–junior papers rose into the 1970s before declining and stabilizing around 35%.

Figure 4 panel (b) shows analogous patterns for SSRN working papers, where we can also identify collaborations involving non-economists. The trends are similar: stable shares of junior–senior and senior–senior collaboration, with a decreasing share of junior–junior papers and a growing proportion of papers by an economist and a non-economist, suggesting increased interdisciplinary collaboration. Figure 5 extends the analysis to papers with three and four-plus authors and continue to show relatively stable experience composition conditional on team size.

We estimate trend models for experience-level assortativity:

$$100 \cdot \mathbb{1}\{pct\_jun = 100\}_{ist} = \beta_0 + \beta_1 t + \alpha_s + \varepsilon_{ist}, \tag{4}$$

$$100 \cdot \mathbb{1}\{pct\_sen = 100\}_{ist} = \beta_0 + \beta_1 t + \alpha_s + \varepsilon_{ist}, \tag{5}$$

where $\mathbb{1}\{pct\_jun = 100\}_{ist}$ and $\mathbb{1}\{pct\_sen = 100\}_{ist}$ are indicator variables for a paper written entirely by junior economists and entirely by senior economists, respectively.

Table 6 quantifies these patterns for two- and three-author papers from 2001 to 2019. All-junior papers decline significantly across all samples, by 0.65 percentage points per year for SSRN, 0.67

for NBER, and 0.31 for EC64. All-senior papers fall far less—0.13 percentage points per year for SSRN and 0.07 for EC64—with insignificant trends for NBER and T5 journals. These unconditional declines in all-junior papers reflect the broader compositional shift toward larger, more experience-diverse teams: as team sizes have grown, purely junior collaborations have given way to mixed arrangements. The key finding remains: The stability of experience composition conditional on team size; the junior–senior mix within each team size category has changed little over time, placing an important constraint on theories of collaboration that we return to in Section 5.

3.4 Collaboration across the Globe

The geographic composition of economics research has undergone a profound transformation, as illustrated in Figure 6. In the 1950s and 1960s, papers written exclusively by US-based researchers dominated the EC64 journals, regularly accounting for 90% or more of published output. Beginning in the late 1970s and accelerating through the 1990s and 2000s, this dominance declined steadily. By the 2020s, solely US-based papers fell to approximately 30–35% of all publications. This decline was matched by a dramatic rise in international collaboration; papers with at least one US author and one non-US author grew from near zero in the 1950s to roughly 35–40% today. Papers authored entirely by researchers based outside the US also expanded substantially, comprising roughly 30% of the literature in recent years. The economics profession has become a genuinely global enterprise.

4 Drivers of Collaboration

We now investigate the forces behind these patterns. Our conceptual starting point is a simple economic trade-off: a researcher collaborates when the marginal benefit of teamwork, such as higher paper quality and impact, exceeds the marginal cost of coordination, such as time, communication frictions, and opportunity costs. Changes in either benefits or costs can shift collaboration patterns. We examine the benefits by studying how the returns to different team sizes have evolved over time and whether researchers respond to these changing returns. We then examine the costs by exploiting the COVID-19 pandemic as an exogenous shock to collaboration costs.

4.1 Increasing Complexity of Papers

A likely driver of increased collaboration is the growing complexity of economics research, which we interpret as raising the benefit of teamwork. Figure 7 shows the trends of the number of pages per paper and per author over time for T5 and non-T5 papers. Paper length provides a rough proxy:

over the past century, the number of pages per paper has grown dramatically. In T5 journals, average paper length rose from fewer than 10 pages before 1990 to over 35 pages by 2020. Non-T5 EC64 journals also saw steady increases to roughly 20 pages. However, the number of pages per author has followed a more restrained trajectory. In T5 journals, pages per author peaked at just under 20 around 2010 and have since plateaued or slightly declined. This divergence between total paper length and pages per author suggests that as the demands of frontier economics research have intensified—incorporating more sophisticated empirical methods, larger datasets, and complex theoretical frameworks—researchers have relied on expanded co-authorship to share the burden. In the organizing framework of Section 5, this increasing complexity is captured by a rising return parameter β_t that scales the benefit of teamwork.

4.2 Changes in Returns to Collaboration

We measure a research paper's return by its professional impact, using citation counts as our proxy. Following Jones (2021), we focus on highly cited papers across teams of varying sizes. Crucially, we deviate from his approach by utilizing trailing five-year citation windows rather than cumulative counts. This design choice carries two immediate implications. First, it restricts our analysis to papers published in or before 2019 to ensure a complete five-year post-publication window. Second, it naturally highlights papers that achieve rapid professional recognition—a desirable trait in academia, where promotions and prestige are often tied to recent impact.

4.2.1 Predicting a Homerun Paper

To measure the relative success of different team sizes, we construct a citation percentile measure for each paper. This object measures the average position in the citation distribution attained by papers with n authors in a particular time period. Importantly, these returns should be interpreted as equilibrium success outcomes that reflect the realized influence of different organizational forms. We also consider an alternative measure following Jones (2021), which uses the likelihood of being highly cited as the outcome. Formally, paper i from journal j in year t is a *homerun paper* if its trailing 5-year citation count is among the top decile of all EC64 papers published in the same year.

We estimate the returns to multiple authorship using:

$$Y_{nijt} = \alpha + \sum_{n} \beta_n \mathbb{1}\{Num_{ist} = n\} + \gamma X_{ijt} + \kappa_t + \phi_j^F + \phi_j^J + \varepsilon_{nijt}, \tag{6}$$

where Y_{ijt} is the citation outcome of paper i published in journal j in the year t. The primary variables of interest are a set of indicator functions, $\mathbb{1}\{\mathrm{Num}_{ijt} = n\}$, equaling one if a paper has n authors, with solo-author papers serving as the omitted baseline category. The vector X_{ijt} contains paper- and author-level characteristics, including indicators for inter-institutional and international collaborations, maximum author experience, and institutional prestige (e.g., affiliations with US or top-tier institutions). To account for heterogeneous secular trends and sorting patterns across fields, we sequentially introduce year (κ_t), broad field (ϕ_j^F), and narrow journal (ϕ_j^J) fixed effects. This non-parametric approach absorbs common macro trends alongside time-invariant, discipline-specific characteristics.

Table 7 presents our baseline estimates where the dependent variable is the paper's citation percentile. Across specifications, the returns to co-authorship exhibit an inverted U-shape that peaks at three authors. We find highly consistent patterns in Table 8, which uses an indicator for a "homerun" paper as the outcome variable. In column 4, our most demanding specification containing both year and journal fixed effects, two-author papers are 3.81 percentage points more likely to become homerun papers than solo-author papers. This premium rises to 4.76 percentage points for three-author papers before tapering slightly for larger teams, at 3.49 percentage points more likely than solo-author papers.

Beyond team size, institutional prestige remains the strongest predictor of high citation counts: having a coauthor from a top-10 institution yields the largest marginal effect, followed closely by affiliations with top 11–30 institutions. This pattern holds whether citation outcomes are measured continuously via percentiles or discretely via the homerun threshold. Our core findings are robust to alternative sample restrictions and specification choices.

4.2.2 Time-varying Returns to Multi-author Papers

The preceding results pool across decades. To evaluate how the returns to team size have evolved over time, we re-estimate Equation (6) across rolling ten-year intervals. Figure 8 plots the aggregate multi-author premium, while Figure 9 decomposes these returns by specific team sizes alongside 95 percent confidence intervals.

The estimates reveal a stark structural shift in the returns to collaboration over the last seven decades. In the 1950s, solo-authored papers held a nominal—though statistically insignificant—advantage. By the 1960s and 1970s, a pronounced coauthorship premium emerged, rendering two- and three-author papers 3 to 6 percentage points more likely to achieve top-decile citation status than solo works. The most striking secular trend, however, is the long-run trajectory of larger scale collaborations. The premium for four-plus-author papers was volatile and statistically negligible through the 1980s, but escalated sharply beginning in the 1990s. By the 2010s, these large teams yielded the highest marginal returns in our sample, eclipsing all other configurations with an approximate 9 percentage point premium over solo authors.

The returns structurally shift starting in the 1990s. Two-author papers become significantly less likely to be highly cited, and three-author papers plateau. Meanwhile, four-plus-author papers become precisely estimated and increasingly likely to become homerun papers. They statistically overtake two-author papers in the 1990s, eclipse three-author papers in the 2000s, and establish clear dominance in the 2010s, averaging a highly significant 9 percentage points higher than solo-author papers.

The timing of these waves is revealing. Each increase in the citation advantage of larger teams appears to coincide with the increase in the prevalence of that team size. Figure B7 plots the fraction of n-author papers alongside the fraction of homerun papers written by n-author teams. For teams of all sizes, popularity and success track each other closely. This correlation raises the question of whether rising returns drive rising collaboration, or whether the causality runs in the opposite direction.

4.2.3 Do Returns Drive Popularity?

We investigate whether economists collaborate more in response to increasing returns to collaborative work. The relationship of interest is:

$$S_{n,t} = \alpha_n + \beta_{0,n}t + \beta_{1,n}HRS_{n,t-5} + \gamma_n S_{n,t-5} + e_{n,t}, \tag{7}$$

where $S_{n,t}$ is the share of n-author papers in year t, and $HRS_{n,t-5}$ is the share of n-author papers in the top decile of trailing 5-year citations in year $t-5$. The 5-year lag aligns with our citation window.[3]

Because $\sum_n S_{n,t} = 1.$, information in one regression may be related to coefficients in another. We thus follow Tomz, Tucker, and Wittenberg (2002) and use the ratio of these variables for multi-author papers over solo-author papers instead. Let M_{njt} denote the number of n-author papers in journal j in year t. We construct two measures:

Relative n-author impact is the ratio between the homerun rate of n-author papers and the homerun rate of solo-author papers:

$$RI_t(n) = \frac{\sum_i HR_{nijt} / \sum_j M_{njt}}{\sum_i HR_{1ijt} / \sum_j M_{1jt}}.$$

Relative n-author returns is the ratio of the number of n-author homerun papers to the number of solo-author homerun papers:

$$RR_t(n) = \frac{\sum_i HR_{nijt}}{\sum_i HR_{1ijt}}.$$

[3]We estimate the same models with a 6-year, 7-year, or 10-year lag, and the results do not change.

Using these two measures, we compute relative shares: $LRS_{n,t} = \ln(S_{n,t}/S_{1,t})$, $LRI_{n,t} = \ln(RI_t(n))$, and $LRR_{n,t} = \ln(RR_t(n))$. Following the seemingly unrelated regression (SUR) framework of Tomz, Tucker, and Wittenberg (2002), we take the logarithms of ratios relative to the solo-author share, breaking the adding-up constraint. To examine whether specific team sizes exhibit this relationship, we estimate the following system:

$$\begin{cases} \Delta LRS_{2,t} = \alpha_2 + \beta_{0,2}t + \beta_{1,2}LRI_{2,t-5} + \gamma_2 LRS_{2,t-5} + e_{2,t}, \\ \Delta LRS_{3,t} = \alpha_3 + \beta_{0,3}t + \beta_{1,3}LRI_{3,t-5} + \gamma_3 LRS_{3,t-5} + e_{3,t}, \\ \Delta LRS_{4,t} = \alpha_4 + \beta_{0,4}t + \beta_{1,4}LRI_{4,t-5} + \gamma_4 LRS_{4,t-5} + e_{4,t}. \end{cases} \tag{8}$$

We are interested in $\beta_{1,n}$. A positive coefficient indicates that researchers tend to assemble teams of size n following periods of higher relative impact for that team size.

In Table 9, the SUR system reveals a clear asymmetry. For four-plus-author papers, the coefficient on $LRI_{4,t-5}$ is positive and statistically significant across all four specifications. For two-author papers, coefficients are positive across all models and marginally significant in columns 2 and 3, suggesting a weaker but directionally consistent response at the entry margin of collaboration. For three-author papers, the coefficient is near zero in column 1 and negative, though statistically insignificant, in all remaining specifications.

Four-plus-author teams are a relatively new and costly organizational form whose adoption requires crossing a coordination threshold; researchers appear to do so selectively when recent returns justify the cost. The null result for three-author papers is consistent with their long-established prevalence: a form that has been common for decades responds less to short-run return signals than to institutional norms. In the organizing framework of Section 5, this pattern reflects the additional fixed organizational cost for large teams that raises their activation threshold. The coefficients on $LRS_{n,t-5}$ are small and mostly insignificant, offering little support for an imitation mechanism. Table A4 confirms that results are similar when using relative returns LRR in place of relative impact LRI.

In Table 10, we re-estimate Table 9 with added decade fixed-effects to non-parametrically control for time trends. The results for four-plus-author papers are consistent with those of Table 9, while the negative coefficient of $LRS_{3,t-5}$ is larger and statistically significant. These changes reflect the trend of the returns of four-plus-author papers superseding those of three-plus-author papers after the 2000s.

4.3 COVID as a Natural Experiment

The COVID-19 pandemic provides a plausibly exogenous shock to the cost of research collaboration, though we acknowledge that working papers are self-selected into submission, and the primary channel through which COVID affected collaboration may have operated through both costs and benefits rather than costs alone. The pandemic simultaneously introduced significant frictions to traditional in-person collaboration, namely lockdowns, travel bans, and canceled conferences, while accelerating the adoption of video conferencing, cloud-based workflows, and remote collaboration tools. We treat this episode as a natural experiment that shifted the costs of teamwork while leaving the underlying return structure approximately unchanged: the distribution of research questions, methodological demands, and citation patterns are slow-moving and unlikely to have shifted discontinuously in March 2020.

Our identification strategy rests on two assumptions. First, the pandemic was unanticipated, so pre-existing collaboration decisions were not contaminated by expectations of the shock. Second, the primary channel through which COVID affected collaboration was through costs (coordination frictions, disrupted routines, differential access to technology) rather than through benefits (the inherent value of teamwork for paper quality). We strengthen this assumption by excluding papers about COVID itself, which would conflate a change in research topics with a change in collaboration technology.

Given the rapid nature of these developments and the inherent lags in formal journal publication, we focus our analysis on SSRN and NBER working papers to capture real-time adjustments in research production. Figure 1 shows that the economics profession experienced a positive shock to the number of working papers in 2020, followed by negative growth in 2021.

4.3.1 The Effect on the Number of Authors

Because the fraction of multi-author papers exhibits a time trend, changes during COVID may simply reflect the continuation of secular shifts. To isolate pandemic-specific deviations, we estimate:

$$100 \cdot \mathbb{1}\{Num_{ist} = n\} = \beta_0 + \sum_{c=2020}^{2023} \delta_c \mathbb{1}\{t = c\} + \beta_1 t + \varepsilon_{ist}. \tag{9}$$

Figure 10 visualizes these deviations from the extended linear trends of 2000–2019, and Table 11 provides the estimates. The results reveal a clear shift toward large teams at the expense of mid-sized collaborations. Papers with four or more authors deviated most strongly from the trend in 2021 (6.74 percentage points above trend), with large positive deviations persisting through 2022 and 2023. Three-author papers significantly underperformed their trend across all three pandemic years (2020–2022), and two-author papers showed significant negative deviations throughout the same period. The share of solo-author papers shows no statistically significant deviation from the trend in any year.

This pattern is consistent with heterogeneous responses to the cost shock. Some researchers found collaboration harder under lockdown conditions and retreated to solo work, while others leveraged digital tools and the normalization of remote workflows to scale up their teams. The net effect was a hollowing out of mid-sized teams, with mass shifting toward larger collaborations. Notably, the four-plus-author deviation remains significant in 2023, while the negative deviations for two- and three-author papers lose significance, suggesting an asymmetric return to trend across team sizes.

4.3.2 The Effect on Inter-institutional Collaboration

Did the pandemic alter collaboration across institutions? We estimate COVID-period deviations for inter-institutional collaboration and institutional concentration by revising Equations (2) and (3) to:

$$100 \cdot \mathbb{1}\{Inter_{ist}\} = \alpha_s + \sum_{c=2020}^{2023} \delta_c \mathbb{1}\{t = c\} + \beta_1 t + \varepsilon_{ist}, \tag{10}$$

$$pct\_maj_{ist} = \alpha_s + \sum_{c=2020}^{2023} \delta_c \mathbb{1}\{t = c\} + \beta_1 t + \varepsilon_{ist}. \tag{11}$$

Table 12 reports the results. SSRN working papers experienced a modest, statistically significant increase in inter-institutional collaboration in 2020, but this effect vanished in subsequent years. The NBER sample shows no significant deviation throughout 2020–2023. The share of authors at the primary institution remained largely stable during 2020–2022, with a significant increase in institutional concentration appearing only in 2023. These findings provide limited evidence that the pandemic shifted the propensity for researchers to reach outside their own institutions, even as team sizes changed. This result is consistent with the interpretation that the pandemic operated primarily on the team-size margin—whether to collaborate at all, and if so, with how many people—rather than on the institution-composition margin.

4.3.3 The Effect on Experience Assortativity

Finally, we examine whether COVID altered the experience composition of research teams:

$$100 \cdot \mathbb{1}\{pct\_jun = 100\}_{ist} = \alpha_s + \sum_{c=2020}^{2023} \delta_c \mathbb{1}\{t = c\} + \beta_1 t + \varepsilon_{ist}, \quad (12)$$

$$100 \cdot \mathbb{1}\{pct\_sen = 100\}_{ist} = \alpha_s + \sum_{c=2020}^{2023} \delta_c \mathbb{1}\{t = c\} + \beta_1 t + \varepsilon_{ist}. \quad (13)$$

Table 13 reports the results. In the SSRN sample, the share of all-junior papers rose significantly above trend in each year from 2020 through 2023, peaking at 2.56 percentage points in 2021. This rise in junior-only teams was accompanied by a significant contraction in all-senior collaborations, which fell as much as 7.63 percentage points below trend in 2021 and remained significantly negative through 2023. In contrast, the NBER sample shows no statistically significant deviations in either category throughout the period. Unlike the team-size effects in Section 3.1, the SSRN experience-composition shifts did not dissipate by 2023, suggesting a more persistent realignment in how junior and senior economists sorted into teams during and after the pandemic—at least among the working paper population captured by SSRN.

5 A Theoretical Framework

The preceding sections document five empirical patterns: (i) team sizes grow over time in waves; (ii) inter-institutional collaboration is U-shaped; (iii) experience composition is stable, conditional on team size; (iv) the four-plus-author margin is most responsive to rising returns; and (v) COVID increases polarization in the team size distribution.

This section develops a stylized framework that integrates these findings. The model provides a parsimonious environment in which complementarities in research production, convex coordination costs, and heterogeneous responses to cost shocks generate shifts in both the relative success and prevalence of different organizational forms. The framework highlights the mechanisms linking relative performance to organizational choice and shows how these forces can produce wave-like dynamics and polarization.

5.1 Setup

Consider a researcher in period t who chooses to participate in a team of size $n \in \{1, 2, 3, 4+\}$. The researcher's per capita payoff from a size-n team is

$$\pi_t(n) = \beta_t h(n) - c(n),$$

where $h(n)$ captures the productive complementarity from combining specialized inputs, and $c(n)$ captures coordination costs. We normalize $h(1) = c(1) = 0$ so that $\pi_t(1) = 0$ is the baseline payoff from working alone. The payoff can be interpreted as the expected distributional position (e.g., citation percentile or top 10% of all citations) of a project, net of coordination costs, rather than as a literal production function.

We impose two natural restrictions on these functions.

Assumption 1 (Increasing complementarity). Production function h is strictly increasing: $0 = h(1) < h(2) < h(3) < h(4)$.

Assumption 2 (Increasing marginal costs). The marginal coordination cost is strictly increasing in team size: $c(2) - c(1) < c(3) - c(2) < c(4) - c(3)$.

The parameter $\beta_t > 0$ scales the relative performance advantage of collaborative production. An increase in β_t captures shifts in the research environment that raise the expected distribution position of larger teams; for example, increasing project complexity or data requirements. As a result, the value added by additional team members has grown.

The researcher chooses $n^*(t) = \text{argmax}_n \pi_t(n)$. Note that this builds on the implicit assumption of 1 team per period.

5.2 Team Size Grows in Waves

Define the threshold at which size n first dominates $n - 1$:

$$\bar{\beta}(n) = \frac{c(n) - c(n-1)}{h(n) - h(n-1)}.$$

By Assumption 2, these thresholds are ordered: $\bar{\beta}(2) < \bar{\beta}(3) < \bar{\beta}(4)$. As β_t rises over time, the optimal team size increases sequentially, first from 1 to 2, then from 2 to 3, and finally from 3 to 4, generating the "wave" pattern observed in the data.

Proposition 1 (Sequential expansion)**.** Under Assumptions 1 and 2, if β_t is increasing over time, then $n^*(t)$ weakly increases and does so sequentially: the optimal team size moves from 1 to 2 when β_t crosses $\bar{\beta}(2)$, from 2 to 3 when it crosses $\bar{\beta}(3)$, and from 3 to 4 when it crosses $\bar{\beta}(4)$.

Proof. For adjacent sizes $n-1$ and n, size n is preferred when $\beta_t[h(n)-h(n-1)] > c(n)-c(n-1)$, i.e., when $\beta_t > \bar{\beta}(n)$. Since $\bar{\beta}(2) < \bar{\beta}(3) < \bar{\beta}(4)$, these switches occur in order. □

Note that if there is an additional fixed organizational cost $F > 0$ required to form teams of size 4, which reflects the need for explicit project management, data infrastructure, or coordinated division of labor, then the effective threshold becomes $\bar{\beta}(4) + F/[h(4) - h(3)]$. This raises the bar for large teams relative to medium-sized ones. A moderate increase in β_t may therefore smoothly shift mass from two- to three-author teams while leaving the four-author margin inactive. Only a sufficiently large increase in β_t triggers discrete entry into large-team production, consistent with the finding in Section 4.2.3 that only the four-plus-author margin responds significantly to rising returns.

5.3 Team Composition

Conditional on team size $n \geq 2$, the researcher also chooses the composition of the team along two dimensions: institutional diversity and experience mix. We model these as additive bonuses to the payoff:

$$\pi_t(n, d, m) = \beta_t h(n) - c(n) + g_t^I \cdot d + g_t^X \cdot m,$$

where $d = 1$ if the team spans multiple institutions and $m = 1$ if the team mixes junior and senior researchers. The terms g_t^I and g_t^X are reduced-form net benefits that absorb both the gains (e.g., idea diversity, mentorship) and the costs (e.g., coordination frictions, communication barriers) of each type of heterogeneity.

Proposition 2 (Inter-institutional collaboration)**.** Fix team size n. The share of inter-institutional teams is weakly increasing in g_t^I.

The empirical finding of a U-shaped pattern in inter-institutional collaboration is consistent with a path of g_t^I that first declines as the profession expands and intra-departmental collaboration becomes easier; and later rises as improvements in communication technology and the normalization of remote work increase the net value of inter-institution teamwork.

Proposition 3 (Stable experience composition)**.** Fix team size n. If g_t^X is approximately constant over time, then the share of mixed-experience teams, conditional on size n, is approximately constant.

This result is consistent with the stability documented in Section 3.3 and implies that large changes in team size need not be accompanied by changes in experience assortativity. Who works with *how many* coauthors can change even if who works with *juniors versus seniors* does not.

5.4 COVID as a Heterogeneous Cost Shock

We model the COVID pandemic as a temporary disruption to coordination costs that affects researchers heterogeneously. Let researchers differ in exposure $\theta_i \geq 0$, with continuous support.

During the pandemic, researcher i's payoff from team size n is

$$\pi_{it}(n) = \beta_t h(n) - c(n) - \tau_t \theta_i \psi(n), \tag{14}$$

where $\tau_t > 0$ during the pandemic and $\tau_t = 0$ otherwise. We assume $\psi(1) = 0$, $\psi(n) > 0$ for $n \geq 2$, and disruption is largest for medium-sized teams:

$$\psi(2), \psi(3) > \psi(4).$$

This condition reflects that small teams may be particularly sensitive to disruptions to informal coordination, while solo work and fully institutionalized large-team production are relatively less exposed. Thus, the pandemic raises coordination costs unevenly across researchers and across team-size margins. It does not alter complementarity $h(n)$ or the secular return parameter β_t.

Proposition 4 (Pandemic Polarization)**.** Suppose coordination costs are convex, as in Assumption 2. If the pandemic introduces a temporary heterogeneous disruption $\tau_t > 0$, $\psi(2) > \psi(4)$, and $\psi(3) > \psi(4)$, then:

1. Researchers with sufficiently high θ_i weakly reduce team size, with some switching from $n \geq 2$ to $n = 1$;

2. Researchers with sufficiently low θ_i weakly increase team size, with some switching from $n = 2, 3$ to $n = 4$;

3. The combined share of two- and three-author teams decreases.

Hence, the team-size distribution becomes more polarized, with simultaneous expansion at both extremes.

Proof. The pandemic shifts adjacent-size thresholds by

$$\tau_t \theta_i \big[\psi(n) - \psi(n-1)\big].$$

Convex coordination costs imply ordered baseline thresholds. Because disruption is greatest for medium-sized teams, sufficiently exposed researchers cross thresholds toward smaller teams, while less exposed researchers cross thresholds toward larger teams. Interior margins contract. □

Corollary 1 (Reversion)**.** If $\tau_t \to 0$, team-size shares revert to their pre-pandemic configuration.

The model predicts simultaneous expansion at both extremes of the team-size distribution under heterogeneous cost shocks, a pattern consistent with the temporary polarization observed in 2020-2022 and a return to trend by 2023 as τ_t recedes. The polarization result does not rely on technological improvement. It arises from the interaction of convex coordination costs and heterogeneous exposure to disruption.

Corollary 2 (Limited compositional change)**.** Because the pandemic shock operates through τ_t alone and does not alter g_t^I or g_t^X, the institutional and experiential composition of teams, conditional on size, remains approximately unchanged during COVID.

This is consistent with the findings in Table 12 and Table 13. There is limited evidence of pandemic-induced changes in inter-institutional collaboration or experience assortativity.

5.5 Discussion

This parsimonious model maps each comparative static to a single empirical margin: β_t governs the long-run growth in team size, g_t^I governs institutional composition, g_t^X governs experience composition, and τ_t governs transitory cost shocks. Its parsimony is intentional. The framework is designed to clarify the mechanisms linking relative performance to organizational choice and to show how a unified set of forces can generate the secular wave-like expansion of team sizes, the stability of experience composition, the U-shape in institutional collaboration, the differential responsiveness across team-size margins, concentrated at the four-plus-author level, and the polarizing effect of COVID, all without requiring ad hoc assumptions tailored to individual findings.

The key insight is that gradual changes in the relative performance advantage of collaboration, combined with convex coordination costs and heterogeneous responses to shocks, are sufficient to reproduce the qualitative features of the data. A richer quantitative model could build on this structure to deliver sharper predictions, but the central comparative statics emerge transparently in this minimal environment.

6 Conclusion

This paper studies how the organization of economics research has evolved over nearly 140 years and what economic forces may underlie those changes. Using a newly constructed panel linking publications from 64 leading journals with working papers and time-varying author affiliations, we document five regularities that characterize modern research collaboration.

First, team sizes expand in waves, with the profession moving sequentially from solo-authored work to two-, three-, and eventually four-plus-author teams. Second, inter-institutional collaboration follows a U-shaped pattern—declining through much of the 20th century and rising in the 21st. Third, conditional on team size, the experience composition of teams remains remarkably stable. Fourth, the relative likelihood that papers become highly cited shifts across team sizes over time, and researchers respond most strongly at the four-plus-author margin. Fifth, the COVID-19 pandemic temporarily polarized the team-size distribution, increasing both solo and large-team projects while reducing mid-sized collaborations.

Taken together, these findings are consistent with a changing trade-off between productive complementarity and coordination costs. Increasing research complexity appears to raise the benefits of collaboration, while technological and institutional changes alter its costs. A parsimonious framework with increasing complementarity, convex coordination costs, and heterogeneous cost shocks can qualitatively account for the patterns we document.

More broadly, the paper provides new evidence on how knowledge production adapts as fields mature, technologies evolve, and the profession becomes more global. Understanding these dynamics helps clarify how economists allocate effort, form teams, and respond to changing research environments. Although our investigation imposes minimal structure and relies on reduced-form evidence, we hope the empirical patterns documented and the comprehensive dataset that enables them will serve as building blocks for future theoretical and structural work on the economics of research collaboration.

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Tables

Table 1: Journals by Field

* Numbers in parentheses indicate the ranks in Ham, Wright, and Ye (2026).

General Interest	*Quarterly Journal of Economics* (1) *American Economic Review* (2) *Econometrica* (3) *Review of Economic Studies* (4) *Journal of Political Economy* (5) *Journal of the European Economic Association* (8) *Economic Journal* (18) *International Economic Review* (23) *European Economic Review* (34) *Canadian Journal of Economics* (61) *Journal of Economic Literature* (nonstandard) *Journal of Economic Perspectives* (nonstandard) *American Economic Review: Insights* (new)
Applied Microeconomics	*American Economic Journal: Applied Economics* (7) *American Economic Journal: Economic Policy* (9) *Journal of Labor Economics* (10) *Review of Economics and Statistics* (12) *Journal of Human Resources* (15) *Journal of International Economics* (22) *Journal of Public Economics* (25) *Journal of Development Economics* (29) *Journal of Applied Econometrics* (30) *Journal of Urban Economics* (39) *Journal of Law and Economics* (40) *Journal of Health Economics* (42) *Journal of Environmental Economics and Management* (49) *Journal of Population Economics* (56) *Journal of Economic Education* (nonstandard) *American Journal of Agricultural Economics* *Journal of Real Estate Finance and Economics*

Finance	*Journal of Finance* *Journal of Financial Economics* *Review of Financial Studies*
Microeconomic Theory	*Theoretical Economics* (11) *American Economic Journal: Microeconomics* (14) *RAND Journal of Economics* (19) *Journal of Economic Theory* (24) *Experimental Economics* (27) *Games and Economic Behavior* (33) *Economic Theory* (36) *Journal of Industrial Economics* (38) *Journal of Risk and Uncertainty* (41) *International Journal of Industrial Organization* (52) *Journal of Economic Behavior and Organization* (53) *Journal of Economics and Management Strategy* (64) *Journal of Mathematical Economics* (66) *Social Choice and Welfare* (71) *Journal of Comparative Economics* (94) *Journal of Regulatory Economics*
Macroeconomics	*American Economic Journal: Macroeconomics* (6) *Journal of Monetary Economics* (13) *Journal of Economic Growth* (17) *Review of Economic Dynamics* (20) *Journal of Money, Credit and Banking* (37) *Journal of Economic Dynamics and Control* (59) *Macroeconomic Dynamics* (75)
Econometrics	*Quantitative Economics* (16) *Journal of Business and Economic Statistics* (21) *Journal of Econometrics* (26) *Econometric Theory* (28)
Economic History	*Journal of Economic History* (48) *Explorations in Economic History* (62) *Economic History Review* (85) *History of Political Economy*

Table 2: Summary Statistics

	SSRN	NBER	Top Five	EC64
Coverage Years	1994-2024	1973-2023	1886-2024	1886-2024
Number of Papers	133,273	11,931	34,835	241,917
Number of Authors per Paper	2.4	2.4	1.5	1.8
Number of Unique Authors	110,890	4,978	23,616	134,619
% Inter-Institutional in Multi-Authored Papers	79.5%	77.4%	82.3%	80.1%
Avg % Junior in Multi-Authored Papers	62.8%	70.5%	86.9%	88.3%

Note: SSRN papers exclude those with fewer than 33% economist authors (about 5.7% of SSRN papers with at least one economist author). NBER papers only include those for which we could recover full author-affiliation information. The 64 journals in EC64 are listed in Table 1. A paper is inter-institutional if at least one author does not share an affiliation with another author. For inter-institutional analysis, NBER papers only include papers for which we successfully recover affiliation information of all authors for the year they are posted. An economist is a junior in the year of publication if their first EC64 publication was within 9 years.

Table 3: Estimated Linear Yearly Trends in the Number of Authors from 2001 to 2019

	(1)	(2)	(3)	(4)
	% 1 Author	% 2 Authors	% 3 Authors	% 4+ Authors
Panel A: *SSRN*				
Yearly Trend	-0.78***	-0.81***	1.01***	0.57***
	(0.02)	(0.03)	(0.03)	(0.02)
Number of Papers	101,016	101,016	101,016	101,016
Panel B: *NBER*				
Yearly Trend	-0.97***	-1.01***	1.01***	0.96***
	(0.06)	(0.07)	(0.07)	(0.04)
Number of Papers	15,030	15,030	15,030	15,030
Panel C: *Top 5*				
Yearly Trend	-0.94***	-0.77***	0.93***	0.78***
	(0.10)	(0.11)	(0.09)	(0.06)
Number of Papers	6,319	6,319	6,319	6,319
Panel D: *EC64*				
Yearly Trend	-1.13***	-0.16***	0.84***	0.46***
	(0.03)	(0.03)	(0.03)	(0.02)
Number of Papers	80,812	80,812	80,812	80,812

Note: SSRN papers only include papers with at least 33% of economist authors. NBER papers only include those for which we could recover full author-affiliation information. We also estimated a version with a quadratic specification for trend; the results are not qualitatively different. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Estimated Yearly Trend in Institutional Assortativity in Collaboration from 2001 to 2019

	(1) SSRN	(2) NBER	(3) EC64	(4) T5
Panel A		% Papers Inter-Institutional		
3 Authors	15.30***	12.86***	16.37***	22.92***
	(0.58)	(2.20)	(0.70)	(2.27)
4+ Authors	22.30***	19.52***	20.76***	21.83***
	(0.69)	(3.07)	(0.89)	(2.75)
Yearly Trend				
2 Authors	-0.15***	0.59***	0.33***	0.47***
	(0.04)	(0.15)	(0.05)	(0.16)
3 Authors	-0.12***	0.29	0.28***	0.62***
	(0.04)	(0.18)	(0.06)	(0.17)
4+ Authors	0.03	1.03**	0.27***	-0.10
	(0.06)	(0.48)	(0.09)	(0.28)
Number of Papers	83,041	4,433	52,901	4,629
Panel B		% Authors in Major Institution		
3 Authors	-1.36***	-3.33***	-1.59***	-3.32***
	(0.19)	(0.88)	(0.36)	(1.10)
4+ Authors	-4.34***	-8.87***	-5.44***	-7.72***
	(0.38)	(1.84)	(0.57)	(1.57)
Yearly Trend				
2 Authors	0.00	0.00	-0.01	-0.06
	(0.00)	(.)	(0.02)	(0.05)
	(0.02)	(0.08)	(0.02)	(0.08)
3 Authors	-0.04*	-0.28***	-0.19***	-0.28**
	(0.02)	(0.10)	(0.03)	(0.11)
4+ Authors	-0.11**	-0.41	-0.20***	-0.09
	(0.05)	(0.28)	(0.07)	(0.21)
Number of Papers	65,730	3,435	35,104	3,113

Note: SSRN papers exclude those with fewer than 33% economist authors (about 5.7% of SSRN papers with at least one economist author). NBER papers only include those for which we could recover full author-affiliation information. The 64 journals in EC64 are listed in Table 1. A paper is inter-institutional if at least one author does not share an affiliation with another author. For inter-institutional analysis, NBER papers only include papers for which we successfully recover affiliation information of all authors for the year they are posted.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Estimated Yearly Trend in Institutional Assortativity in Collaboration from 2001 to 2019

	(1) EC64	(2) T5	(3) EC64	(4) T5
	% Papers Inter-Institutional		% Authors in Major Institution	
3 Authors	30.68***	35.81***	-1.66***	-3.32***
	(0.73)	(2.39)	(0.36)	(1.10)
4+ Authors	30.26***	33.76***	-5.42***	-7.72***
	(0.98)	(3.04)	(0.57)	(1.57)
Yearly Trend				
2 Authors	-0.05	-0.05	-0.01	-0.06
	(0.05)	(0.17)	(0.02)	(0.05)
3 Authors	0.23***	0.53***	-0.18***	-0.28**
	(0.06)	(0.17)	(0.03)	(0.11)
4+ Authors	0.11	0.18	-0.20***	-0.09
	(0.10)	(0.34)	(0.07)	(0.21)
Field FE	×	×	×	×
Number of Papers	52,901	4,629	35,104	3,113

Note: SSRN papers exclude those with fewer than 33% economist authors (about 5.7% of SSRN papers with at least one economist author). NBER papers only include those for which we could recover full author-affiliation information. The 64 journals in EC64 are listed in Table 1. A paper is inter-institutional if at least one author does not share an affiliation with another author. For inter-institutional analysis, NBER papers only include papers for which we successfully recover affiliation information of all authors for the year they are posted.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Estimated Yearly Trend in Experience Assortativity in Multi-Authored Papers from 2001 to 2019

	(1) SSRN	(2) NBER	(3) EC64	(4) Top 5
	% Papers with All Junior Authors			
Yearly Trend	-0.65***	-0.67***	-0.31***	-0.51***
	(0.02)	(0.11)	(0.04)	(0.11)
	% Papers with All Senior Authors			
Yearly Trend	-0.13***	-0.10	-0.07**	-0.07
	(0.01)	(0.13)	(0.03)	(0.10)
Number of Papers	130,126	4,433	53,159	4,626

Note: SSRN papers include those with at least 33% economist authors. NBER papers only include those for which we could recover full author-affiliation information. An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior. All models are estimated with only two- and three-authored papers. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Predictors of EC64 Citation Percentile among Papers Published in the Same Year, 1900-2020

	(1)	(2)	(3)	(4)
	Citation Percentile (Higher = More Citations)			
Number of Authors				
2	11.62***	12.15***	9.10***	8.84***
	(0.18)	(0.18)	(0.18)	(0.17)
3	14.57***	15.62***	11.76***	11.78***
	(0.25)	(0.26)	(0.25)	(0.24)
4	14.68***	15.82***	12.18***	12.36***
	(0.37)	(0.37)	(0.36)	(0.35)
$\mathbb{1}$\{Inter-Institutional\}	0.55***	0.38**	-0.22	-0.35**
	(0.17)	(0.17)	(0.17)	(0.16)
$\mathbb{1}$\{Has Senior Author\}	-3.35***	-3.07***	-2.20***	-2.08***
	(0.16)	(0.16)	(0.16)	(0.15)
$\mathbb{1}$\{Has Top 10 Author\}	10.73***	10.47***	8.45***	5.67***
	(0.24)	(0.24)	(0.23)	(0.23)
$\mathbb{1}$\{Has Top 10 Senior\}	-1.61***	-1.56***	-2.05***	-1.57***
	(0.33)	(0.33)	(0.31)	(0.30)
$\mathbb{1}$\{Has 11-30 Author\}	6.05***	5.88***	4.54***	2.94***
	(0.24)	(0.24)	(0.23)	(0.23)
$\mathbb{1}$\{Has 11-30 Senior\}	-1.66***	-1.58***	-1.39***	-0.89***
	(0.33)	(0.33)	(0.32)	(0.31)
$\mathbb{1}$\{US Institution\}	1.14***	1.29***	1.86***	2.16***
	(0.14)	(0.14)	(0.14)	(0.14)
$\mathbb{1}$\{International Collab.\}	-0.81***	0.26	0.90***	0.44**
	(0.20)	(0.21)	(0.20)	(0.20)
Number of Papers	177,549	177,549	177,549	177,549
Year FE		×	×	×
Field FE			×	
Journal FE				×

Note: Top 10 schools are Harvard, MIT, Yale, Stanford, Columbia, Princeton, UChicago, UPenn, Northwestern, and UCBerkeley. Top 11-30 schools are NYU, UCLA, UMich, Cal Tech, Cornell, UCSD, UW Madison, Duke, UMinn, Brown, CMU, BU, Johns Hopkins, UMD, UT Austin, UCDavis, Penn State, Rochester, UNC, UVA, Vanderbilt, and WUSTL. Fields are categorized by journal according to Table 1. A paper is inter-institutional if at least one author does not share an affiliation with another author. An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Predictors of Homerun Papers, 1900-2020

	(1)	(2)	(3)	(4)
	% Likelihood of Becoming a Homerun Paper			
Number of Authors				
2	4.65***	4.90***	3.48***	3.95***
	(0.20)	(0.20)	(0.20)	(0.19)
3	7.66***	8.17***	6.05***	6.69***
	(0.27)	(0.28)	(0.27)	(0.27)
4	8.18***	8.72***	6.91***	7.57***
	(0.40)	(0.41)	(0.40)	(0.39)
$\mathbb{1}${Inter-Institutional}	0.60***	0.51***	-0.16	-0.20
	(0.19)	(0.19)	(0.18)	(0.18)
$\mathbb{1}${Has Senior Author}	-0.46***	-0.27	-0.16	-0.37**
	(0.18)	(0.18)	(0.17)	(0.17)
$\mathbb{1}${Has Top 10 Author}	12.34***	12.23***	9.86***	7.74***
	(0.26)	(0.26)	(0.25)	(0.25)
$\mathbb{1}${Has Top 10 Senior}	-0.06	-0.04	-0.28	-0.31
	(0.35)	(0.35)	(0.35)	(0.34)
$\mathbb{1}${Has 11-30 Author}	5.24***	5.15***	3.63***	2.51***
	(0.26)	(0.26)	(0.26)	(0.25)
$\mathbb{1}${Has 11-30 Senior}	-0.55	-0.51	-0.34	-0.18
	(0.36)	(0.36)	(0.35)	(0.35)
$\mathbb{1}${US Institution}	1.00***	1.11***	2.13***	1.47***
	(0.15)	(0.15)	(0.15)	(0.16)
$\mathbb{1}${International Collab.}	-2.98***	-2.41***	-1.41***	-1.39***
	(0.22)	(0.23)	(0.22)	(0.22)
Number of Papers	177,549	177,549	177,549	177,549
Year FE		×	×	×
Field FE			×	
Journal FE				×

Note: A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year. Top 10 schools are Harvard, MIT, Yale, Stanford, Columbia, Princeton, UChicago, UPenn, Northwestern, and UCBerkeley. Top 11-30 schools are NYU, UCLA, UMich, Cal Tech, Cornell, UCSD, UW Madison, Duke, UMinn, Brown, CMU, BU, Johns Hopkins, UMD, UT Austin, UCDavis, Penn State, Rochester, UNC, UVA, Vanderbilt, and WUSTL. Fields are categorized by journal according to Table 1. A paper is inter-institutional if at least one author does not share an affiliation with another author. An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Estimated Correlations Between Returns and Popularity of Multi-Authored Papers, 1956-2020

		$\Delta LRS_{2,t}$		
$LRI_{2,t-5}$	0.0573	0.0738*	0.0819*	0.0798
	(0.0387)	(0.0434)	(0.0476)	(0.0498)
$LRS_{2,t-5}$		-0.0144		-0.0242
		(0.0300)		(0.0750)
Year			-0.0002	0.0002
			(0.0007)	(0.0016)
		$\Delta LR3S_t$		
$LRI_{3,t-5}$	0.0293	-0.0447	-0.0462	-0.0407
	(0.0453)	(0.0685)	(0.0615)	(0.0681)
$LRS_{3,t-5}$		0.0365		-0.0243
		(0.0313)		(0.0655)
Year			0.0018	0.0027
			(0.0012)	(0.0025)
		$\Delta LRS_{4,t}$		
$LRI_{4,t-5}$	0.1423***	0.1573***	0.1413**	0.1545**
	(0.0499)	(0.0610)	(0.0590)	(0.0618)
$LRS_{4,t-5}$		-0.0189		-0.0504
		(0.0505)		(0.0678)
Year			0.0003	0.0014
			(0.0017)	(0.0023)
Number of Years	64	64	64	64

Note: $LRS_{n,t}$ is the natural log of the ratio between the share of n-author papers and the share of single-authored papers in year t. $LRI_{n,t}$ is the year t natural log of the relative n-author impact, which is the ratio between the share of n-author papers that are homerun and the share of single-authored papers that are homerun. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among all EC64 papers published in the same year. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Estimated Correlations Between Returns and Popularity of Multi-Authored Papers, 1957-2020

	$\Delta LRS_{2,t}$	
$LRI_{2,t-5}$	-0.0084	-0.0143
	(0.0609)	(0.0614)
$LRS_{2,t-5}$		-0.0339
		(0.0936)
	$\Delta LR3S_t$	
$LRI_{3,t-5}$	-0.0733	-0.0464
	(0.0621)	(0.0632)
$LRS_{3,t-5}$		-0.1356*
		(0.0820)
	$\Delta LRS_{4,t}$	
$LRI_{4,t-5}$	0.1463**	0.1443**
	(0.0630)	(0.0646)
$LRS_{4,t-5}$		-0.0489
		(0.1051)
Decade FE	$\times$	$\times$
Number of Years	64	64

Note: $LRS_{n,t}$ is the natural log of the ratio between the share of n-author papers and the share of single-authored papers in year t. $LRI_{n,t}$ is the year t natural log of the relative n-author impact, which is the ratio between the share of n-author papers that are homerun and the share of single-authored papers that are homerun. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among all EC64 papers published in the same year. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Estimated Deviations in the Number of Authors from Linear Yearly Trends During COVID from 2001 to 2023, Working Papers

	(1)	(2)	(3)	(4)
	% 1 Author	% 2 Authors	% 3 Authors	% 4+ Authors
2020	-0.41	-2.31***	-2.83***	5.55***
	(0.46)	(0.68)	(0.69)	(0.52)
2021	0.59	-2.44***	-4.89***	6.74***
	(0.50)	(0.73)	(0.74)	(0.58)
2022	0.22	-2.71***	-3.60***	6.09***
	(0.49)	(0.73)	(0.75)	(0.58)
2023	2.60	-4.76	-4.38	6.54***
	(2.56)	(2.95)	(2.68)	(2.01)
Yearly Trend	-1.12***	-0.16*	1.01***	0.28***
	(0.09)	(0.09)	(0.07)	(0.04)
SSRN	-13.17***	-6.58***	13.33***	6.42***
	(0.78)	(0.90)	(0.78)	(0.50)
SSRN ×	0.34***	-0.65***	0.00	0.30***
Yearly Trend	(0.09)	(0.09)	(0.07)	(0.04)
Number of Papers	125,092	125,092	125,092	125,092

Note: Working papers are SSRN and NBER papers. SSRN papers exclude those with fewer than 33% economist authors (about 5.7% of SSRN papers with at least one economist author). NBER papers only include those for which we could recover full author-affiliation information.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Estimated Deviations in Institutional Concentration of Multi-Author Papers from Yearly Trends During COVID from 2001 to 2023

	(1)	(2)	(3)	(4)
	% Inter-Institutional		% Author in Major Affiliation	
Sample	SSRN	NBER	SSRN	NBER
2020	0.44	0.24	-0.17	-0.09
	(0.60)	(2.25)	(0.25)	(0.78)
2021	-1.08	-1.75	0.31	0.46
	(0.66)	(2.61)	(0.27)	(0.89)
2022	-0.59	1.60	0.08	-1.46
	(0.66)	(2.49)	(0.27)	(0.95)
2023	-1.93***	-3.50	0.96***	2.23**
	(0.70)	(2.77)	(0.29)	(0.99)
2 Authors (Baseline)				
3 Authors	15.27***	14.01***	-1.09***	-3.45***
	(0.41)	(1.43)	(0.13)	(0.56)
4+ Authors	23.64***	19.06***	-4.15***	-6.80***
	(0.43)	(1.54)	(0.20)	(1.00)
Yearly Trend				
2 Authors	-0.16***	0.56***	-0.01*	-0.01
	(0.04)	(0.13)	(0.01)	(0.02)
3 Authors	-0.14***	0.38**	-0.03	-0.30***
	(0.04)	(0.16)	(0.02)	(0.08)
4+ Authors	0.16***	0.92***	-0.11***	-0.17
	(0.05)	(0.33)	(0.03)	(0.19)
Number of Papers	101,768	5,529	80,903	4,366
2019 Mean	80.65	85.28	48.60	47.74

NNote: SSRN papers exclude those with fewer than 33% economist authors (about 5.7% of SSRN papers with at least one economist author). NBER papers only include those for which we could recover full author-affiliation information. The 64 journals in EC64 are listed in Table 1. A paper is inter-institutional if at least one author does not share an affiliation with another author. For inter-institutional analysis, NBER papers only include papers for which we successfully recover affiliation information of all authors for the year they are posted. An economist is a junior in the year of publication if their first EC64 publication was within 9 years.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Estimated Deviations in Experience Assortativity in Multi-Authored Papers from Yearly Trends during COVID from 2001 to 2023

	(1)	(2)	(3)	(4)
	% Papers with All Junior Authors		% Papers with All Senior Authors	
Sample	SSRN	NBER	SSRN	NBER
		% Papers with All Junior Authors		
2020	2.25***	-0.93	-5.79***	2.42
	(0.39)	(2.08)	(0.74)	(2.84)
2021	2.56***	-0.18	-7.63***	4.49
	(0.42)	(2.36)	(0.80)	(3.26)
2022	2.10***	1.50	-6.44***	0.05
	(0.41)	(2.55)	(0.81)	(3.34)
2023	1.62***	0.13	-4.09***	-0.08
	(0.41)	(2.48)	(0.86)	(3.32)
2 Authors (Baseline)				
3 Authors	-6.87***	-5.07***	-6.44***	-18.26***
	(0.26)	(1.39)	(0.49)	(1.84)
4+ Authors	-8.74***	-9.78***	-23.49***	-27.06***
	(0.27)	(1.67)	(0.57)	(2.27)
Yearly Trend				
2 Authors	-0.27***	-0.60***	0.57***	0.26*
	(0.03)	(0.12)	(0.04)	(0.15)
3 Authors	-0.15***	-0.45***	0.49***	0.14
	(0.02)	(0.17)	(0.05)	(0.19)
4+ Authors	-0.18***	-0.06	0.41***	0.35
	(0.03)	(0.26)	(0.07)	(0.35)
Number of Papers	101,768	5,529	101,768	5,529

Note: SSRN papers exclude those with fewer than 33% economist authors (about 5.7% of SSRN papers with at least one economist author). NBER papers only include those for which we could recover full author-affiliation information. The 64 journals in EC64 are listed in Table 1. A paper is inter-institutional if at least one author does not share an affiliation with another author. For inter-institutional analysis, NBER papers only include papers for which we successfully recover affiliation information of all authors for the year they are posted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figures

Figure 1: Number of Journals, Published Papers, and Working Papers, 1886-2023

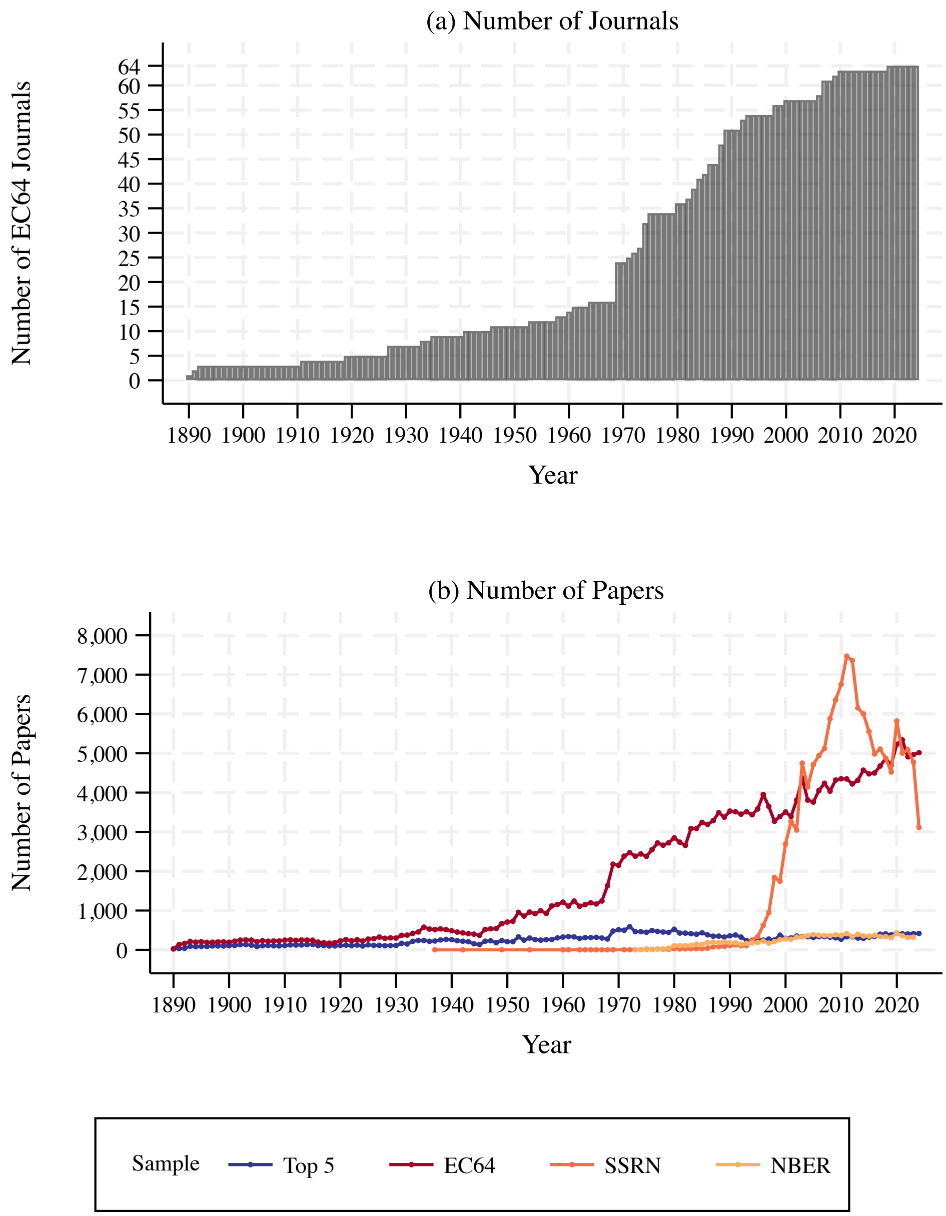
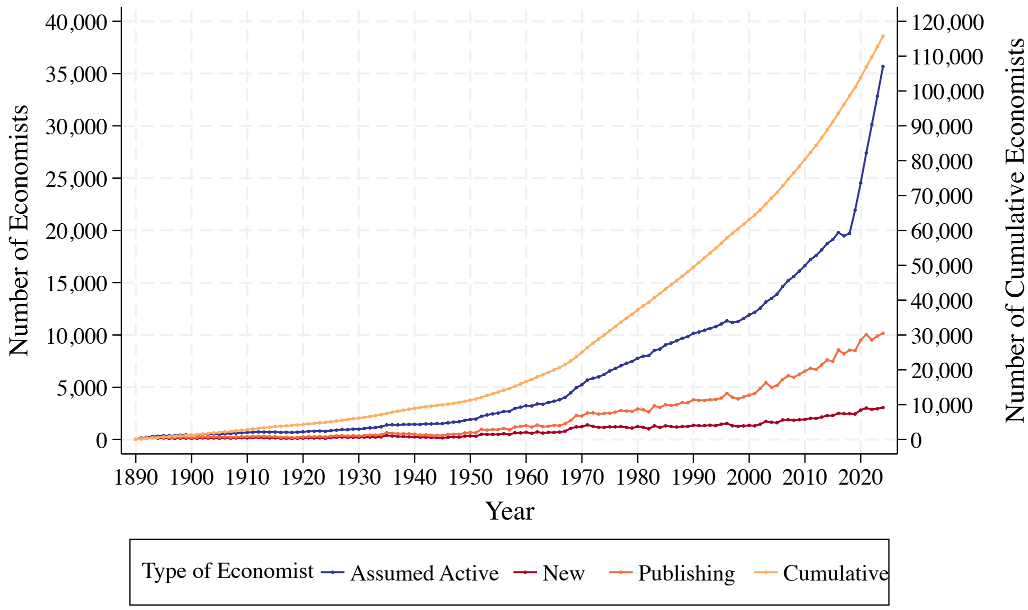


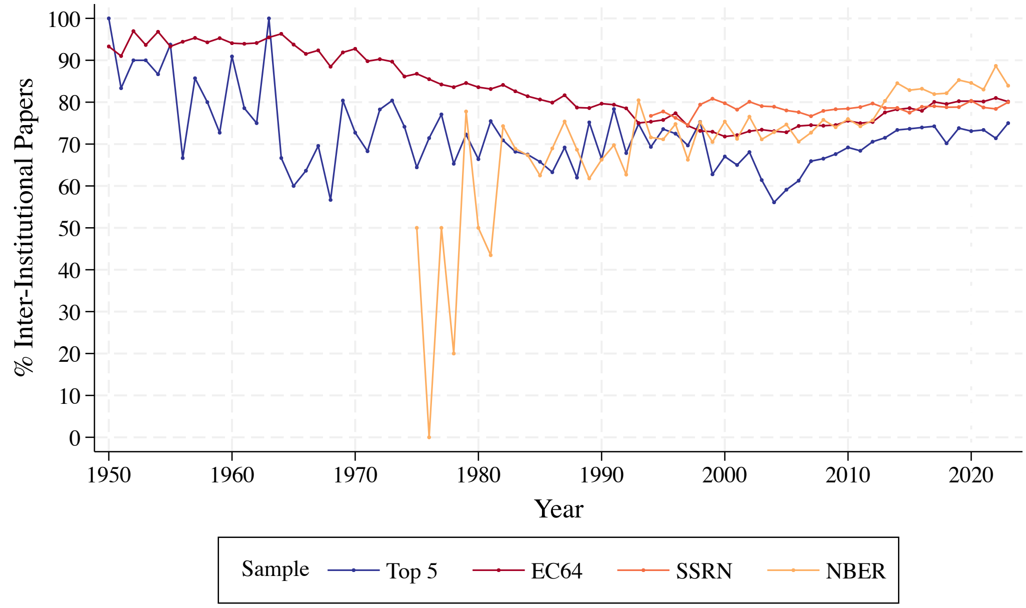
Figure 2: Number of Economists



Note: An economist is assumed to be **active** between their first and last EC64 publication year. A **publishing** economist is one who published in an EC64 journal that year. A **new** economist is one who published in an EC64 journal for the first time in their career that year. Once an economist publishes in EC64, they are counted in the **cumulative** economist category.

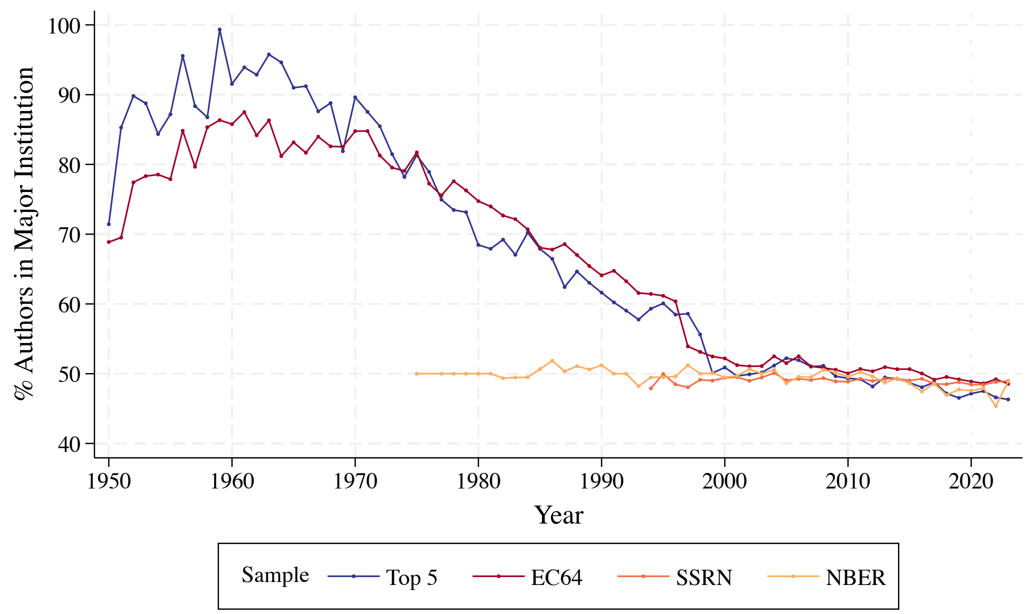
Figure 3: Institutional Collaboration and Concentration Trends

(a) Trends in Inter-Institutional Collaboration



Note: A paper is inter-institutional if at least one author does not share an affiliation with another author.

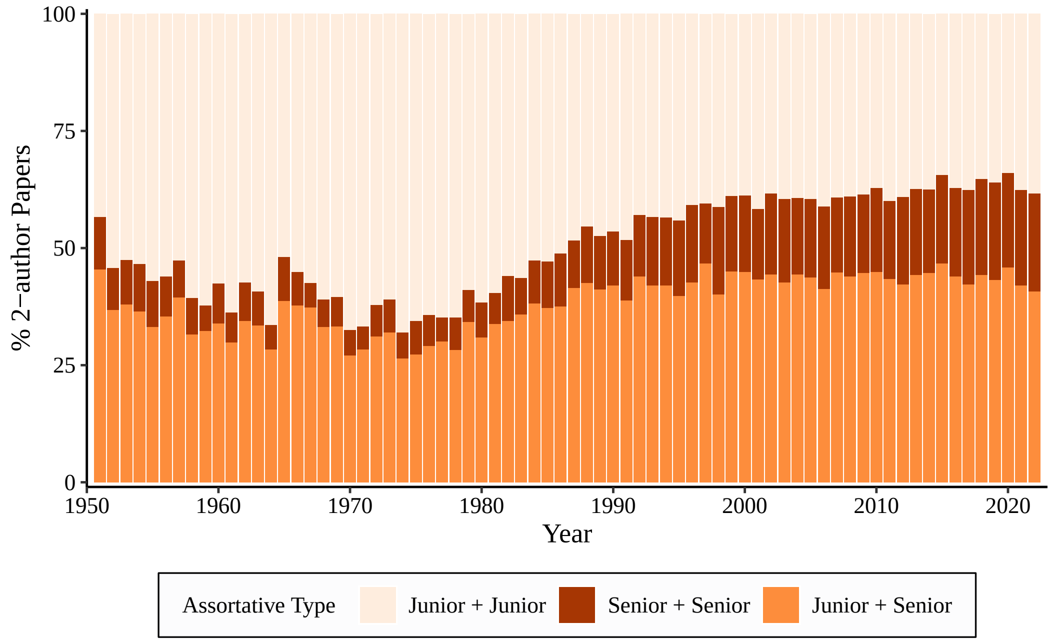
(b) Decrease in Institutional Concentration



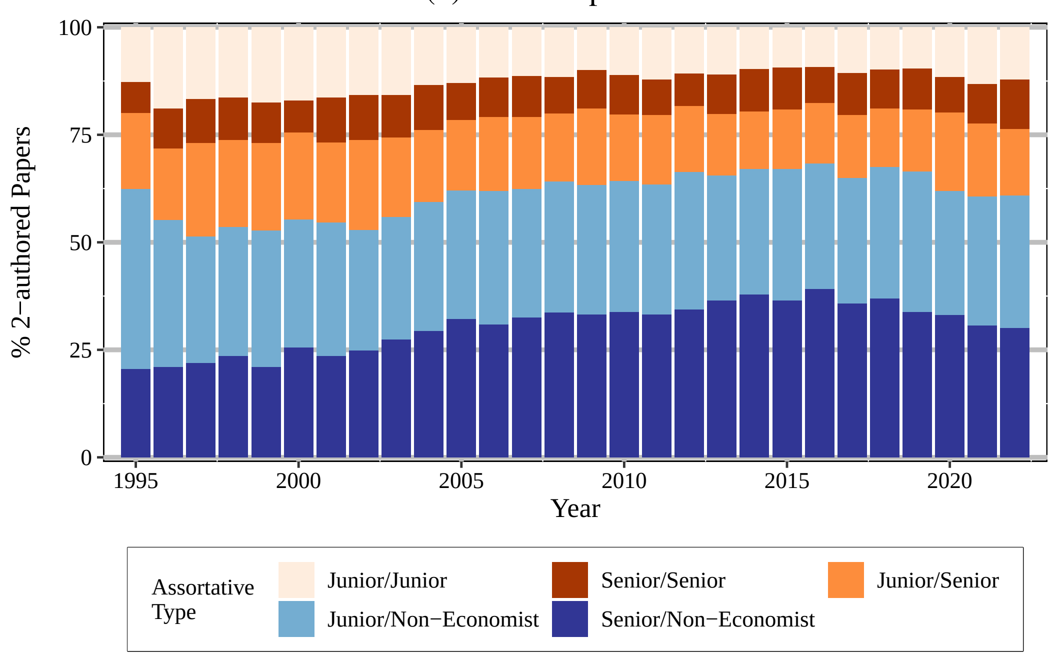
Note: An institution is a major institution if the highest number of authors on the paper are affiliated with said institution. Ties are irrelevant, given that our outcome is the share of authors.

Figure 4: Stable Pattern of Experience Assortativity in 2-Author Papers

(a) EC64 Papers

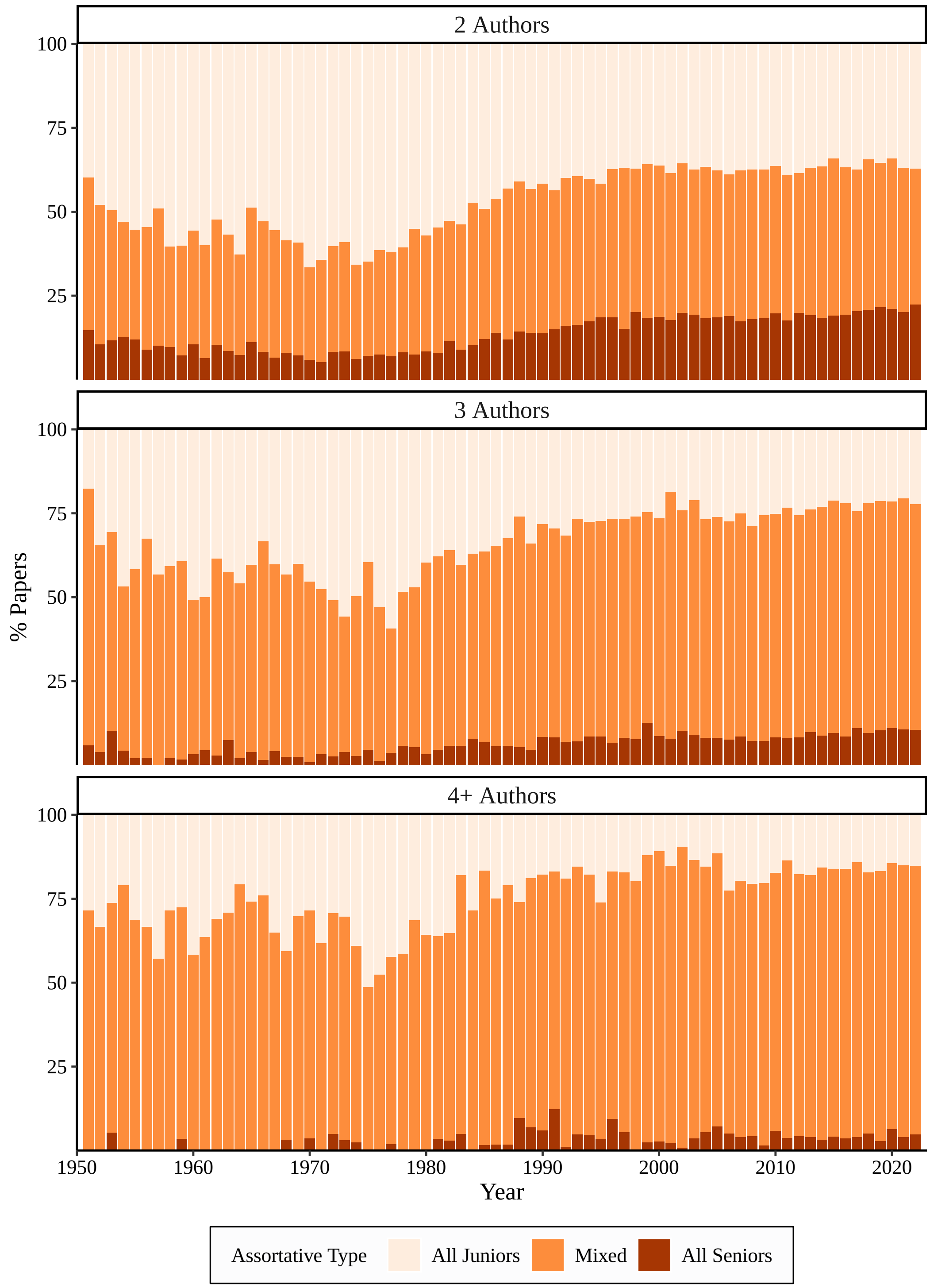


(b) SSRN Papers



Note: An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior.

Figure 5: Experience Assortativity in EC64 Papers Conditional on Number of Authors



Note: An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior.

Figure 6: Growing Trends of International Collaboration

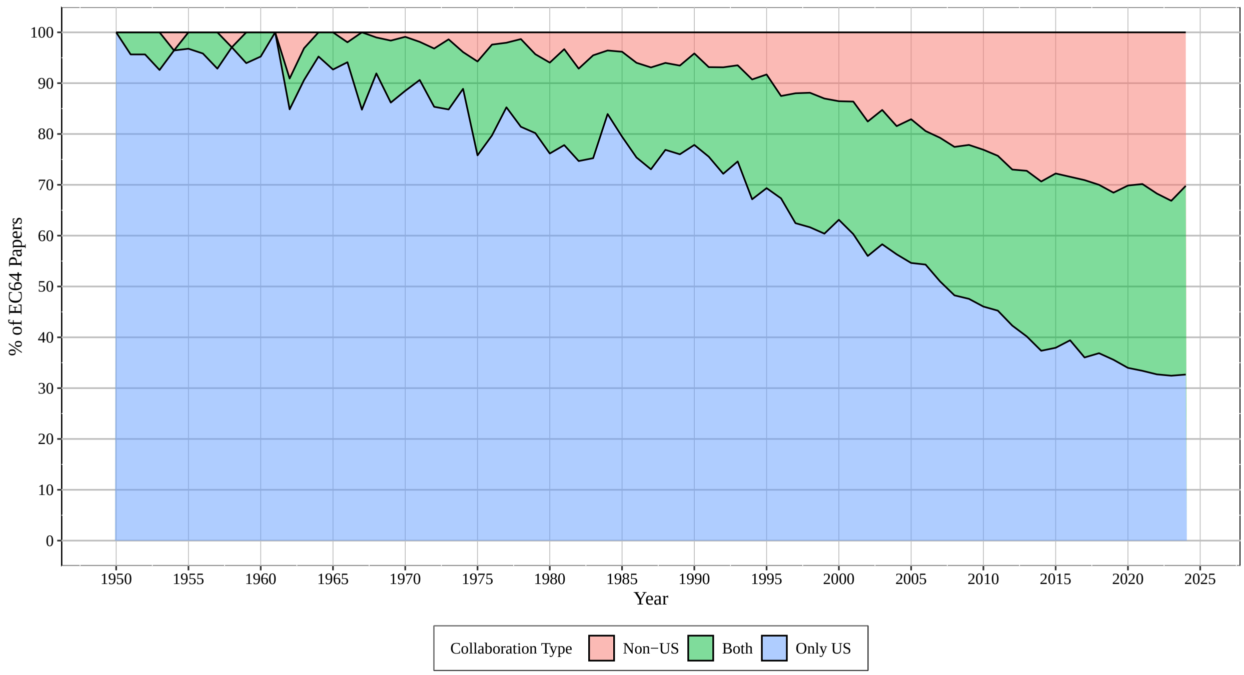


Figure 7: Number of Pages per Paper Increased

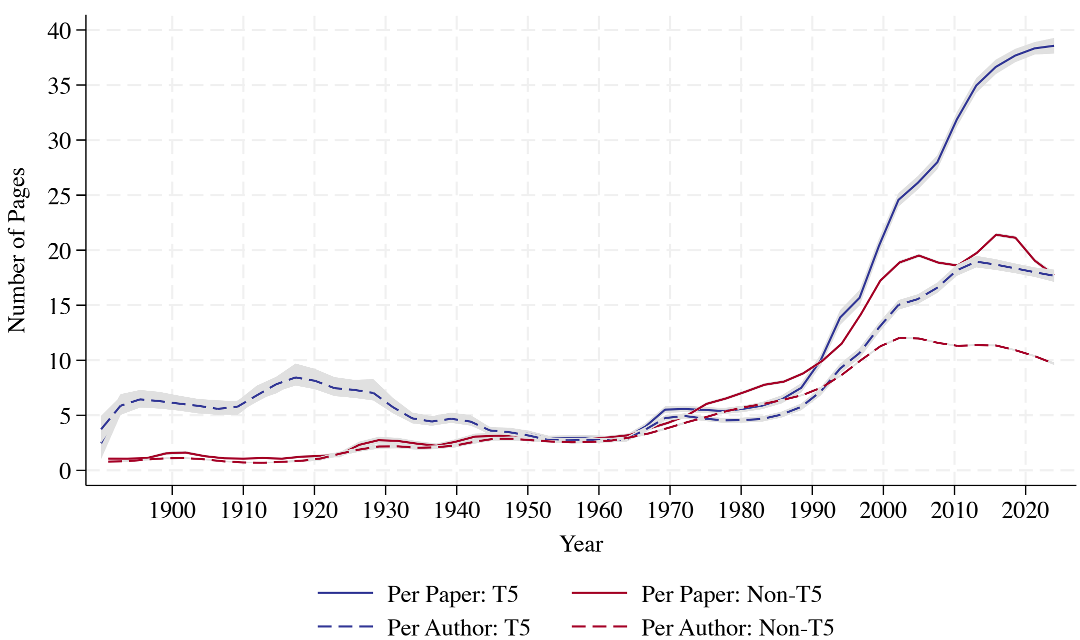
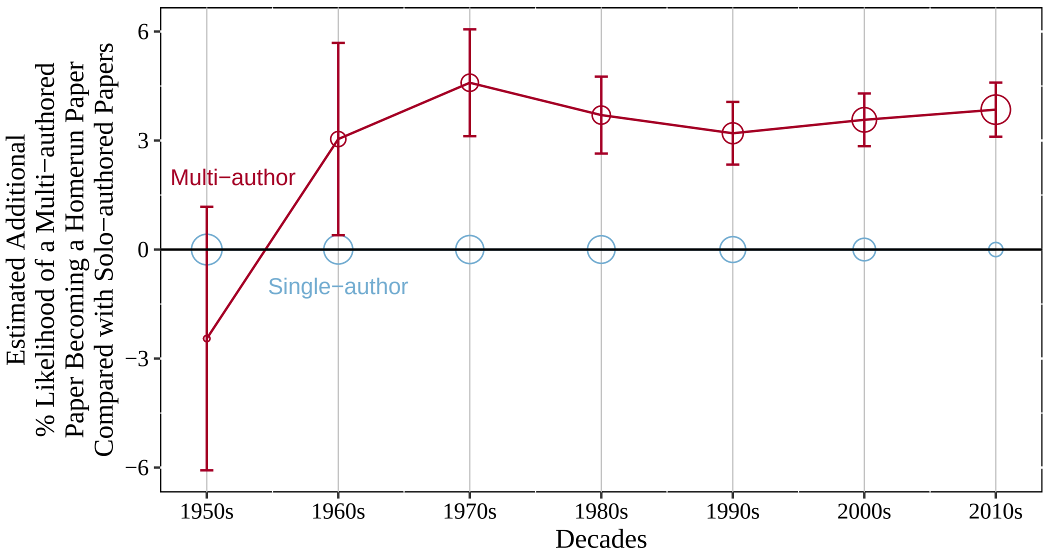
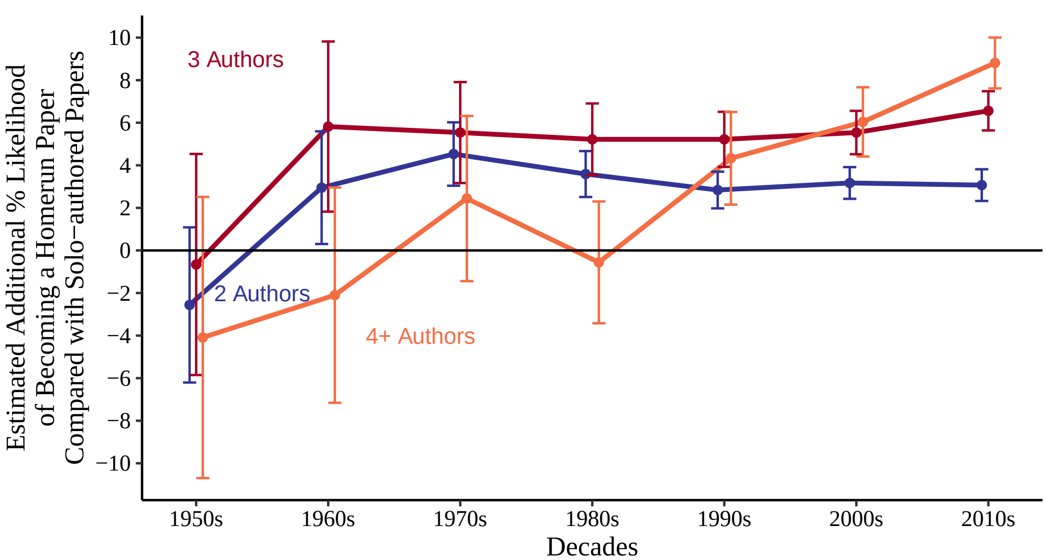


Figure 8: Evolution of Estimated Returns to Collaboration, 10-Year Periods



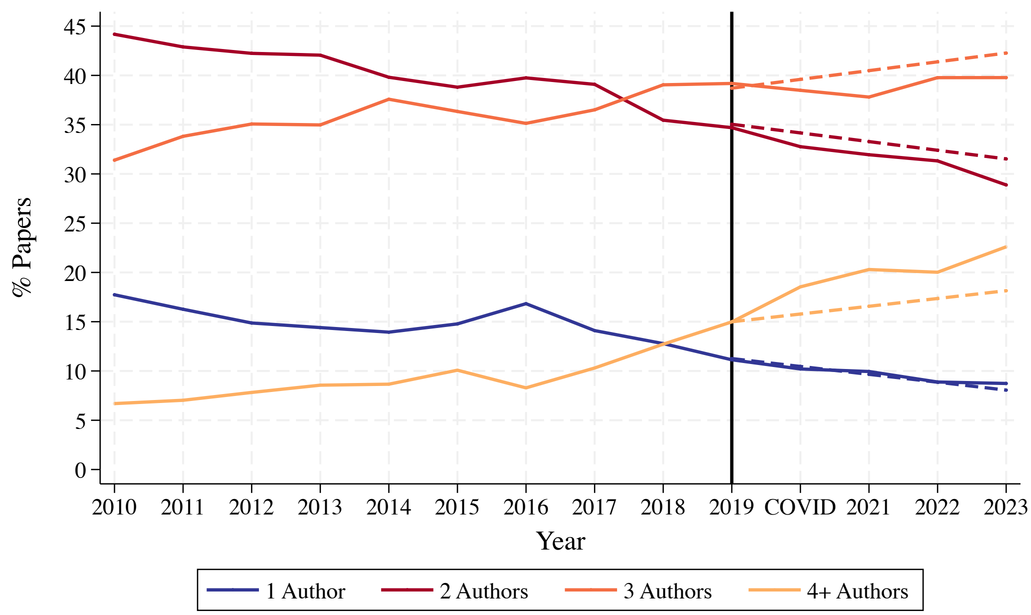
Note: We estimate Equation (6) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation in the top decile among EC64 papers published in the same year. Sizes of the circles correspond to the shares of N-Author papers that year.

Figure 9: Evolution of Estimated Returns to Number of Authors, 10-Year Periods



Note: We estimate Equation (6) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation in the top decile among EC64 papers published in the same year.

Figure 10: Deviation from Linear Trend, Number of Authors, 2010-2023 SSRN Working Papers



Note: Dashed lines are linear predictions using the yearly trends before 2019. The COVID period includes 2020-2023, with 2020 treated as a transition year.

Appendix A Additional Tables

Table A1: Predictors of Homerun Papers, Excluding T5 Papers, 1891-2020

	(1)	(2)	(3)	(4)
	% Likelihood of Becoming a Homerun Paper			
Number of Authors				
2	4.44***	4.62***	3.20***	3.44***
	(0.19)	(0.19)	(0.19)	(0.19)
3	7.19***	7.60***	5.25***	5.71***
	(0.27)	(0.27)	(0.27)	(0.27)
4	7.37***	7.84***	5.80***	6.12***
	(0.39)	(0.40)	(0.39)	(0.38)
$\mathbb{1}${Inter-Institutional}	0.72***	0.64***	-0.06	-0.30*
	(0.18)	(0.18)	(0.18)	(0.18)
$\mathbb{1}${Has Senior Author}	-0.23	-0.10	0.35**	0.01
	(0.17)	(0.17)	(0.17)	(0.16)
$\mathbb{1}${Has Top 10 Author}	9.05***	8.93***	7.65***	6.36***
	(0.27)	(0.28)	(0.27)	(0.27)
$\mathbb{1}${Has Top 10 Senior}	1.05***	1.07***	1.04***	0.46
	(0.38)	(0.38)	(0.37)	(0.36)
$\mathbb{1}${Has 11-30 Author}	4.49***	4.39***	3.07***	2.41***
	(0.26)	(0.26)	(0.26)	(0.26)
$\mathbb{1}${Has 11-30 Senior}	-0.14	-0.10	0.21	0.27
	(0.36)	(0.36)	(0.35)	(0.35)
$\mathbb{1}${US Institution}	1.43***	1.44***	1.94***	1.29***
	(0.15)	(0.15)	(0.15)	(0.16)
$\mathbb{1}${International Collab.}	-3.06***	-2.56***	-1.53***	-1.42***
	(0.21)	(0.22)	(0.22)	(0.21)
Number of Papers	155,392	155,391	155,391	155,391
Year FE		×	×	×
Field FE			×	
Journal FE				×

Note: A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year. Top 10 schools are Harvard, MIT, Yale, Stanford, Columbia, Princeton, UChicago, UPenn, Northwestern, and UCBerkeley. Top 11-30 schools are NYU, UCLA, UMich, Cal Tech, Cornell, UCSD, UW Madison, Duke, UMinn, Brown, CMU, BU, Johns Hopkins, UMD, UT Austin, UCDavis, Penn State, Rochester, UNC, UVA, Vanderbilt, and WUSTL. Fields are categorized by journal according to Table 1. A paper is inter-institutional if at least one author does not share an affiliation with another author. An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Predictors of Homerun Papers, 1960-2020

	(1)	(2)	(3)	(4)
	% Likelihood of Becoming a Homerun Paper			
Number of Authors				
2	4.57***	4.83***	3.22***	3.73***
	(0.20)	(0.20)	(0.20)	(0.20)
3	7.68***	8.20***	5.82***	6.54***
	(0.28)	(0.28)	(0.28)	(0.27)
4	8.25***	8.79***	6.79***	7.54***
	(0.41)	(0.41)	(0.40)	(0.40)
$\mathbb{1}\{$Inter-Institutional$\}$	0.50***	0.41**	-0.32*	-0.32*
	(0.19)	(0.19)	(0.18)	(0.18)
$\mathbb{1}\{$Has Senior Author$\}$	-0.52***	-0.34*	-0.19	-0.36**
	(0.18)	(0.18)	(0.18)	(0.17)
$\mathbb{1}\{$Has Top 10 Author$\}$	13.05***	12.90***	10.21***	7.89***
	(0.27)	(0.27)	(0.26)	(0.26)
$\mathbb{1}\{$Has Top 10 Senior$\}$	0.02	0.06	-0.13	-0.12
	(0.37)	(0.37)	(0.36)	(0.35)
$\mathbb{1}\{$Has 11-30 Author$\}$	5.54***	5.43***	3.75***	2.56***
	(0.27)	(0.27)	(0.26)	(0.26)
$\mathbb{1}\{$Has 11-30 Senior$\}$	-0.68*	-0.63*	-0.44	-0.22
	(0.37)	(0.37)	(0.36)	(0.35)
$\mathbb{1}\{$US Institution$\}$	1.07***	1.17***	2.23***	1.48***
	(0.16)	(0.16)	(0.16)	(0.16)
$\mathbb{1}\{$International Collab.$\}$	-2.91***	-2.36***	-1.31***	-1.30***
	(0.22)	(0.23)	(0.22)	(0.22)
Number of Papers	167,369	167,369	167,369	167,369
Year FE		×	×	×
Field FE			×	
Journal FE				×

Note: A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year. Top 10 schools are Harvard, MIT, Yale, Stanford, Columbia, Princeton, UChicago, UPenn, Northwestern, and UCBerkeley. Top 11-30 schools are NYU, UCLA, UMich, Cal Tech, Cornell, UCSD, UW Madison, Duke, UMinn, Brown, CMU, BU, Johns Hopkins, UMD, UT Austin, UCDavis, Penn State, Rochester, UNC, UVA, Vanderbilt, and WUSTL. Fields are categorized by journal according to Table 1. A paper is inter-institutional if at least one author does not share an affiliation with another author. An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Raw Citation Count by Paper Characteristics, 1886-2020

	(1)	(2)	(3)	(4)
	Number of Citations			
Number of Authors				
2	6.89***	4.04***	3.52***	4.48***
	(0.21)	(0.21)	(0.21)	(0.21)
3	16.15***	10.00***	8.37***	9.20***
	(0.30)	(0.31)	(0.30)	(0.31)
4	20.48***	14.08***	12.67***	13.50***
	(0.48)	(0.47)	(0.47)	(0.47)
$\mathbb{1}\{$Inter-Institutional$\}$	-1.53***	1.81***	0.49**	-0.32
	(0.19)	(0.19)	(0.19)	(0.20)
$\mathbb{1}\{$Has Senior Author$\}$	1.52***	-0.31*	-0.29	-0.44**
	(0.18)	(0.18)	(0.17)	(0.17)
Majority Author Top 10	12.70***	13.40***	11.30***	9.08***
	(0.26)	(0.25)	(0.25)	(0.25)
Majority Author 11-30	5.37***	5.46***	4.24***	3.12***
	(0.25)	(0.25)	(0.25)	(0.25)
$\mathbb{1}\{$US Institution$\}$	5.82***	3.87***	4.55***	3.73***
	(0.19)	(0.19)	(0.19)	(0.20)
$\mathbb{1}\{$International Collab.$\}$	5.19***	-1.88***	-0.45	-0.16
	(0.28)	(0.29)	(0.28)	(0.28)
Mean Citation	2.7	2.7	2.7	2.7
Number of Papers	224,598	224,597	224,597	224,597
Year FE		×	×	×
Field FE			×	
Journal FE				×

Note: Top 10 schools are Harvard, MIT, Yale, Stanford, Columbia, Princeton, UChicago, UPenn, Northwestern, and UCBerkeley. Top 11-30 schools are NYU, UCLA, UMich, Cal Tech, Cornell, UCSD, UW Madison, Duke, UMinn, Brown, CMU, BU, Johns Hopkins, UMD, UT Austin, UCDavis, Penn State, Rochester, UNC, UVA, Vanderbilt, and WUSTL. Fields are categorized by journal according to Table 1. A paper is inter-institutional if at least one author does not share an affiliation with another author. An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Estimated Correlations Between Returns and Popularity of Multi-Author Papers, 1950-2018

		$\Delta LRS_{2,t}$		
$LRR_{2,t-5}$	0.0010	-0.0221	-0.0272	-0.0294
	(0.0343)	(0.0466)	(0.0546)	(0.0557)
$LRS_{2,t-5}$		0.0254		-0.0438
		(0.0376)		(0.0747)
Year			0.0008	0.0016
			(0.0008)	(0.0017)
		$\Delta LRS_{3,t}$		
$LRR_{3,t-5}$	0.0017	-0.1077*	-0.0882*	-0.1206*
	(0.0206)	(0.0618)	(0.0462)	(0.0624)
$LRS_{3,t-5}$		0.1133*		0.0352
		(0.0606)		(0.0759)
Year			0.0042**	0.0041*
			(0.0019)	(0.0024)
		$\Delta LRS_{4,t}$		
$LRR_{4,t-5}$	0.0782**	0.1660***	0.0838**	0.1669***
	(0.0313)	(0.0603)	(0.0416)	(0.0598)
$LRS_{4,t-5}$		-0.1184		-0.1716**
		(0.0746)		(0.0875)
Year			-0.0001	0.0023
			(0.0019)	(0.0022)
Number of Years	64	64	64	64

Note: A homerun paper is a paper that has a 5-year EC64 citation count in the top decile among EC64 papers published in that year. $LRS_{n,t}$ is the natural log of the ratio between the share of n-author papers and the share of single-authored papers in year t. $LRR_{n,t}$ is the year t natural log of the relative n-author return, which is the ratio of the share of all homerun papers that are n-authored to the share of homerun papers that are single-authored. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Estimated Correlations Between Returns and Popularity of Multi-Authored Papers, 1950-2018

		$\Delta LRS_{2,t}$		
$\Delta LRR_{2,t-5}$	-0.0538	-0.0692*	-0.0543	-0.0715*
	(0.0376)	(0.0386)	(0.0375)	(0.0385)
$\Delta LR2S_{t-5}$		0.1171		0.1180
		(0.1054)		(0.1057)
Year			0.0002	0.0001
			(0.0006)	(0.0006)
		$\Delta LRS_{3,t}$		
$\Delta LRR_{3,t-5}$	-0.0393	-0.0137	-0.0421	-0.0112
	(0.0402)	(0.0480)	(0.0402)	(0.0479)
$\Delta LRS_{3,t-5}$		-0.0970		-0.1314
		(0.1253)		(0.1287)
Year			0.0010	0.0013
			(0.0009)	(0.0009)
		$\Delta LRS_{4,t}$		
$\Delta LRR_{4,t-5}$	0.1780***	0.1686***	0.1755***	0.1706***
	(0.0457)	(0.0494)	(0.0452)	(0.0490)
$\Delta LRS_{4,t-5}$		0.0439		0.0103
		(0.1064)		(0.1072)
Year			0.0022	0.0021
			(0.0014)	(0.0015)
Number of Years	61	61	61	61

Note: $LRS_{n,t}$ is the natural log of the ratio of the share of n-author papers to the share of single-author papers in year t. $LRR_{n,t}$ is the year-t natural log of the relative n-author return, which is the ratio of the share of all homerun papers that are n-authored to the share of homerun papers that are single-authored. A homerun paper is a paper that has a trailing 5-year citation in the top decile among EC64 papers published in the same year. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Top 50 Educational Institutions by Number of EC64 Publications

Order	Institution	Number of Papers							
	Time Period	1880-99	1900-19	1920-39	1940-59	1960-79	1980-99	2000-19	2020-23
1	University of London	1	4	67	375	889	1935	4229	1643
2	Harvard University	11	204	321	539	802	1898	2939	714
3	University of Chicago	6	17	118	204	628	1338	2437	843
4	University of California, Berkeley	0	1	7	154	497	1352	2061	662
5	Stanford University	1	12	40	71	536	1271	2021	680
6	London School of Economics and Political Science	0	3	66	330	604	951	1937	708
7	Massachusetts Institute of Technology	0	6	0	176	593	1247	1685	451
8	New York University	1	10	26	183	281	1014	1786	634
9	Yale University	2	22	16	70	473	1029	1495	603
10	Columbia University	4	45	66	238	291	891	1585	539
11	Princeton University	0	4	39	134	420	1024	1423	488
12	University of Pennsylvania	0	9	9	20	202	1150	1469	422
13	Northwestern University	3	5	4	61	218	1134	1451	397
14	Cornell University	3	33	42	91	256	893	1293	426
15	University of Michigan	1	5	43	116	268	723	1213	358
16	Duke University	0	0	25	112	152	577	1191	391
17	Institut Polytechnique de Paris	0	0	0	0	45	229	1469	595
18	University of Wisconsin–Madison	0	15	5	42	362	704	870	335
19	University of Toronto	2	3	3	45	208	600	1032	400
20	University of California, Los Angeles	0	0	2	97	243	791	910	240
21	University of California, Davis	0	0	0	7	176	740	811	241
22	University of British Columbia	0	0	0	12	206	718	797	240
23	University of Illinois Urbana-Champaign	0	2	4	54	234	682	755	238
24	University of Oxford	0	0	2	27	59	229	1179	472
25	University of Cambridge	0	0	26	109	188	561	807	270
26	University of Maryland, College Park	0	0	0	37	141	645	898	214
27	University of Minnesota	0	6	35	45	203	659	740	191
28	University of California San Diego	0	0	0	1	115	490	940	327

29	Université Paris 1 Panthéon-Sorbonne	0	0	0	0	6	197	1107	459
30	University College London	0	0	1	28	79	261	1013	377
31	The Ohio State University	0	9	20	29	160	620	724	191
32	Université Paris Sciences et Lettres	0	0	0	3	11	141	1085	488
33	University of Southern California	0	0	0	26	61	475	834	308
34	University of Warwick	0	0	0	0	113	411	847	327
35	Indiana University	0	0	0	27	187	568	659	247
36	University of Rochester	0	0	3	22	239	716	533	161
37	Michigan State University	0	0	0	40	264	455	615	197
38	Boston University	0	1	2	4	63	473	709	290
39	California University of Pennsylvania	9	10	19	120	301	289	572	162
40	Tel Aviv University	0	0	0	0	150	617	547	148
41	Carnegie Mellon University	0	0	6	2	173	532	590	146
42	The University of Texas at Austin	0	0	0	11	63	424	671	264
43	Tilburg University	0	0	0	0	1	366	838	210
44	Pennsylvania State University	0	0	0	12	123	381	608	253
45	Johns Hopkins University	12	27	8	114	176	307	458	244
46	École nationale des ponts et chaussées	0	0	0	0	1	67	902	376
47	Hebrew University of Jerusalem	0	0	0	11	292	462	453	127
48	Purdue University West Lafayette	0	1	1	20	312	408	422	168
49	University of Virginia	0	0	10	50	130	340	584	198
50	Vanderbilt University	1	0	0	20	95	313	680	196

Table A7: Top 50 Economists by Number of EC64 Publications

Name	Number of Papers								
Time Period	All	1880-99	1900-19	1920-39	1940-59	1960-79	1980-99	2000-19	2020-23
Peter C.B. Phillips	273	0	0	0	0	3	90	145	35
John J. Siegfried	229	0	0	0	0	23	58	142	6
Daron Acemoğlu	183	0	0	0	0	0	21	140	22
Joseph E. Stiglitz	182	0	0	0	0	55	89	30	8
F. Y. Edgeworth	181	70	89	22	0	0	0	0	0
Paul A. Samuelson	169	0	0	7	45	78	29	10	0
Stephen J. Turnovsky	164	0	0	0	0	37	74	48	5
Andrei Shleifer	164	0	0	0	0	0	69	83	12
Jean Tirole	162	0	0	0	0	0	77	80	5
James J. Heckman	152	0	0	0	0	5	53	86	8
M. Hashem Pesaran	151	0	0	0	0	6	63	68	14
Thomas J. Sargent	150	0	0	0	0	27	41	69	13
John A. List	149	0	0	0	0	0	2	129	18
Harry G. Johnson	143	0	0	0	40	103	0	0	0
William J. Baumöl	134	0	0	0	32	50	42	10	0
Drew Fudenberg	133	0	0	0	0	0	60	57	16
Martin Feldstein	130	0	0	0	0	58	53	19	0
René M. Stulz	130	0	0	0	0	0	64	56	10
Richard Blundell	126	0	0	0	0	0	46	67	13
Jeffrey G. Williamson	123	0	0	0	0	46	51	26	0
C. W. Guillebaud	121	0	6	36	41	38	0	0	0
Charles P. Kindleberger	117	0	0	2	27	45	40	3	0
Allan H. Meltzer	116	0	0	0	2	56	39	16	3
Stanley L. Engerman	115	0	0	0	0	50	40	25	0
Badi H. Baltagi	111	0	0	0	0	0	70	38	3
George J. Stigler	111	0	0	3	39	53	15	1	0
Sidney Pollard	110	0	0	0	10	41	59	0	0
Larry Samuelson	109	0	0	0	0	0	50	51	8
W. Kip Viscusi	109	0	0	0	0	3	63	39	4
David K. Levine	108	0	0	0	0	0	46	47	15
David Card	108	0	0	0	0	0	22	67	19
Edwin Cannan	107	21	46	40	0	0	0	0	0
Nicholas Crafts	106	0	0	0	0	16	64	24	2
Robert J. Barro	106	0	0	0	0	36	44	19	7
Peter Temin	106	0	0	0	0	40	44	21	1
Philippe Aghion	106	0	0	0	0	0	31	67	8
Éric Ghysels	105	0	0	0	0	0	38	57	10
Jean-Jacques Laffont	104	0	0	0	0	20	63	21	0
Randall Wright	104	0	0	0	0	0	36	58	10
David E. M. Sappington	104	0	0	0	0	0	48	49	7
Richard Zeckhauser	104	0	0	0	0	23	42	39	0
Elhanan Helpman	101	0	0	0	0	16	49	28	8

Matthew O. Jackson	100	0	0	0	0	0	25	66	9
William B. Walstad	100	0	0	0	0	2	49	48	1
Joel Mokyr	100	0	0	0	0	19	52	26	3
V. Kerry Smith	99	0	0	0	0	32	41	25	1
Jonathan Gruber	98	0	0	0	0	0	21	65	12
L. L. Price	97	42	44	11	0	0	0	0	0
Aldo Rustichini	97	0	0	0	0	0	34	56	7
A. C. Pigou	96	0	41	34	21	0	0	0	0

Table A8: Top 50 Economists by Number of Top-5 Publications

Name	Number of Papers								
Time Period	All	1880-99	1900-19	1920-39	1940-59	1960-79	1980-99	2000-19	2020-23
John J. Siegfried	115	0	0	0	0	3	11	101	0
Daron Acemoğlu	89	0	0	0	0	0	8	72	9
Frank H. Knight	89	0	4	49	36	0	0	0	0
Jean Tirole	81	0	0	0	0	0	38	38	5
Joseph E. Stiglitz	77	0	0	0	0	33	35	8	1
George J. Stigler	69	0	0	3	32	29	4	1	0
William J. Baumöl	69	0	0	0	20	32	14	3	0
James J. Heckman	67	0	0	0	0	5	25	35	2
Paul A. Samuelson	65	0	0	6	25	29	5	0	0
F. W. Taussig	62	13	35	14	0	0	0	0	0
Martin Feldstein	61	0	0	0	0	34	17	10	0
Franklin M. Fisher	59	0	0	0	5	42	10	2	0
Andrei Shleifer	58	0	0	0	0	0	16	35	7
James Laughlin	55	26	25	4	0	0	0	0	0
H. Parker Willis	53	23	28	2	0	0	0	0	0
Elhanan Helpman	52	0	0	0	0	8	21	19	4
Martin Bronfenbrenner	51	0	0	2	32	17	0	0	0
Harry G. Johnson	48	0	0	0	9	39	0	0	0
John A. List	48	0	0	0	0	0	0	44	4
H. J. Davenport	48	6	41	1	0	0	0	0	0
Drew Fudenberg	46	0	0	0	0	0	27	14	5
Thomas J. Sargent	45	0	0	0	0	11	16	16	2
Jacob Viner	44	0	1	37	5	1	0	0	0
David Card	44	0	0	0	0	0	12	26	6
Gene M. Grossman	44	0	0	0	0	0	20	19	5
Robert M. Solow	44	0	0	0	15	17	11	1	0
Kenneth J. Arrow	44	0	0	0	19	20	3	2	0
Alvin E. Roth	43	0	0	0	0	4	18	20	1
Robert J. Barro	42	0	0	0	0	16	16	10	0
Mark R. Rosenzweig	41	0	0	0	0	2	22	15	2
Chester W. Wright	40	0	21	15	4	0	0	0	0
Arthur W. Marget	40	0	0	37	3	0	0	0	0
Eric S. Maskin	40	0	0	0	0	2	30	7	1
Richard Blundell	39	0	0	0	0	0	10	26	3
Dale W. Jorgenson	39	0	0	0	0	26	10	3	0
Milton Friedman	39	0	0	3	16	14	6	0	0
Robert E. Hall	38	0	0	0	0	9	12	16	1
Alberto Alesina	38	0	0	0	0	0	11	24	3
Lawrence R. Klein	36	0	0	0	24	10	2	0	0
Donald W. K. Andrews	36	0	0	0	0	0	22	14	0
Emmanuel Farhi	36	0	0	0	0	0	0	29	7
William Fellner	35	0	0	0	22	12	1	0	0
Debraj Ray	35	0	0	0	0	0	8	25	2
Ernst Fehr	35	0	0	0	0	0	4	28	3
B. Douglas Bernheim	35	0	0	0	0	0	14	16	5
Gerhard Tintner	35	0	0	10	21	4	0	0	0
George A. Akerlof	35	0	0	0	0	9	18	8	0
Philippe Aghion	34	0	0	0	0	0	10	22	2
Raj Chetty	34	0	0	0	0	0	0	31	3
Eberhard Fels	34	0	0	0	6	28	0	0	0

Table A9: Top 25 Countries by Number of EC64 Publications

Country	Number of Papers							
Time Period	1880-99	1900-19	1920-39	1940-59	1960-79	1980-99	2000-19	2020-23
United States	84	598	1,228	4,642	14,850	36,369	47,887	15,593
Great Britain	5	19	179	1,230	3,457	7,121	14,733	5,417
Canada	4	7	14	98	1,165	4,238	5,452	1,828
Germany	2	3	6	2	132	956	5,323	2,614
France	0	2	2	29	147	1,180	4,333	1,812
Italy	3	1	9	3	105	748	3,624	1,765
Australia	0	0	23	25	422	1,190	2,902	1,464
Netherlands	0	0	3	39	150	1,190	3,369	1,274
China	0	0	3	2	10	71	2,052	2,686
Spain	0	0	0	4	17	527	2,845	1,004
Israel	0	0	0	11	479	1,431	1,511	428
Switzerland	0	0	1	2	37	374	2,084	1,009
Belgium	0	0	0	2	112	643	1,676	617
Japan	0	8	9	41	219	601	1,358	615
Hong Kong	0	0	0	2	2	266	1,421	851
Sweden	0	0	2	8	38	333	1,245	581
Denmark	0	0	2	5	18	226	1,137	603
Singapore	0	0	0	6	0	93	1,186	640
Austria	0	0	7	0	4	173	816	497
South Korea	0	0	0	0	2	138	785	358
Norway	0	0	0	1	48	150	702	347
Ireland	33	14	32	111	189	298	329	115
New Zealand	0	0	0	4	71	181	545	140
Brazil	0	0	0	0	29	127	492	239
Philippines	5	3	1	28	96	181	353	181
Rest of World	1,721	3,963	6,110	9,590	23,705	31,278	44,355	19,989

Appendix B Additional Figures

Figure B1: Multi-Author Papers Increased over Time

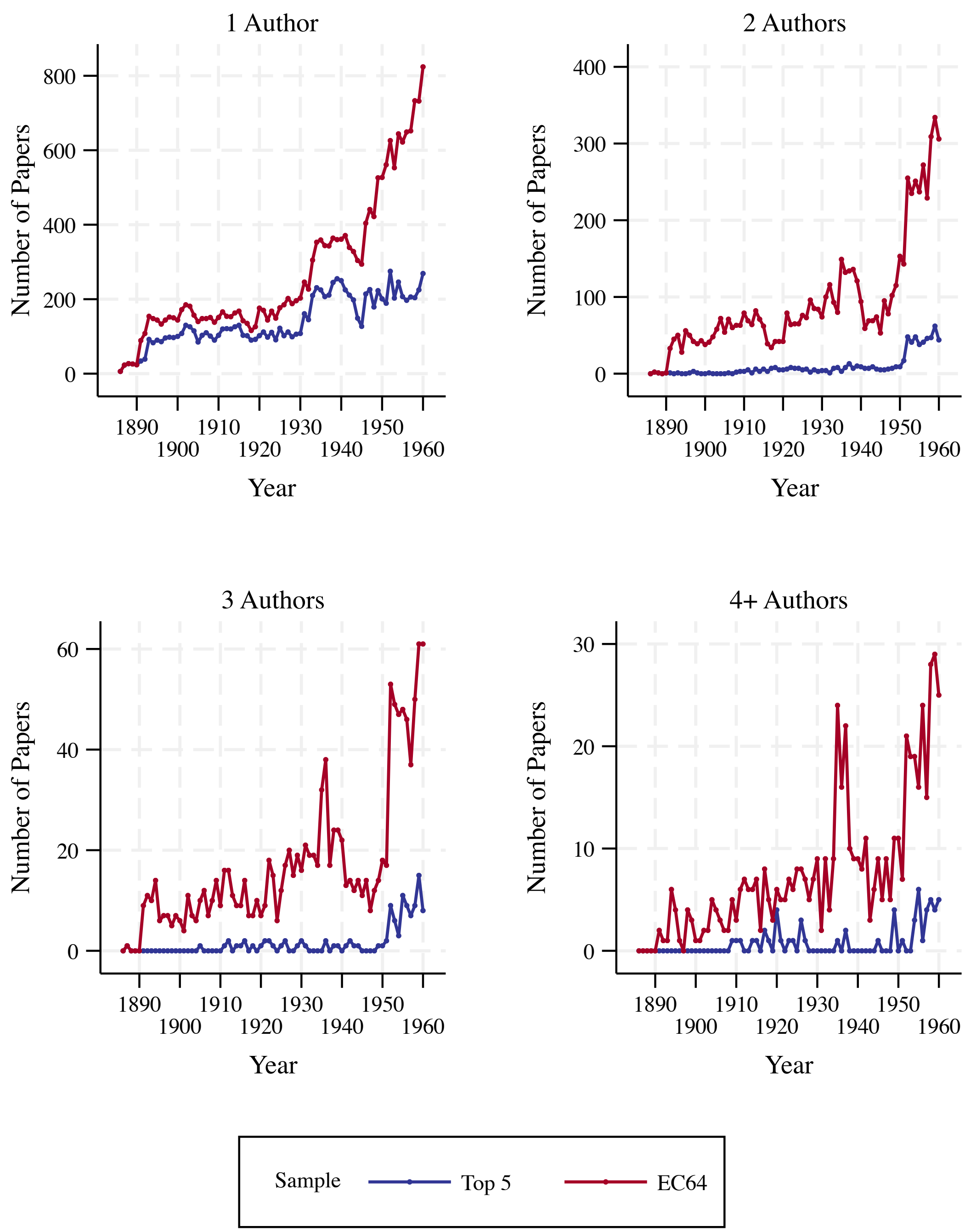
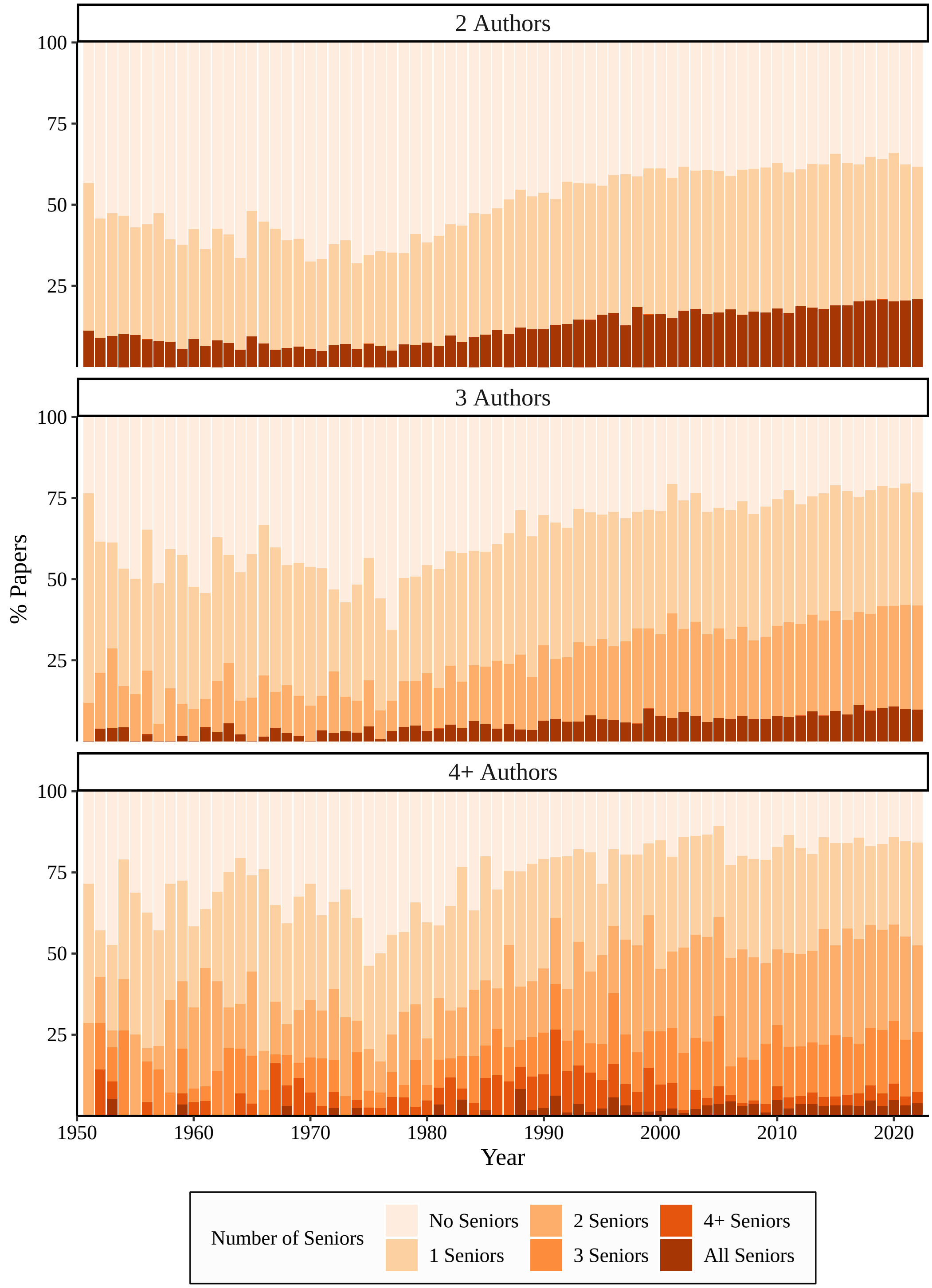


Figure B2: Experience Assortativity in EC64 Papers Conditional on Number of Authors



Note: An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior.

Figure B3: Number of Authors on a Paper in EC64 Journals, 1886-2023

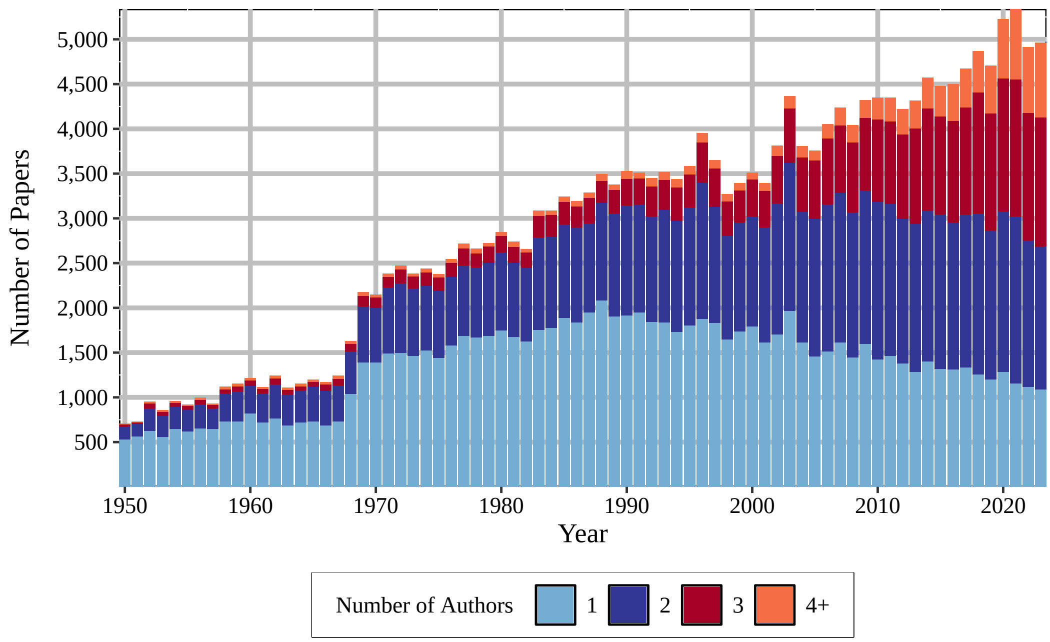


Figure B4: Multi-Author Papers Increased over Time

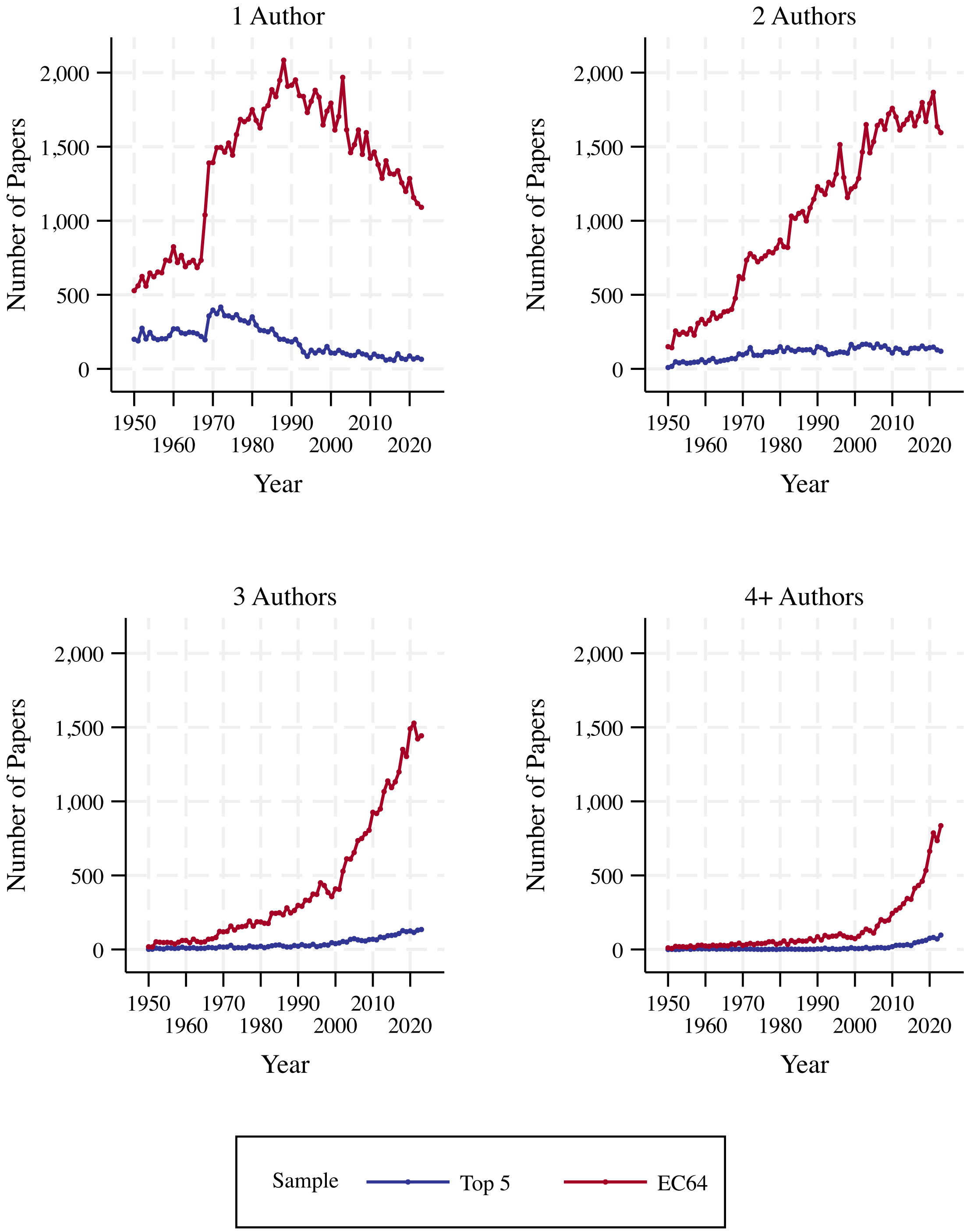


Figure B5: The Proportion of Multi-Author Papers Increased over Time

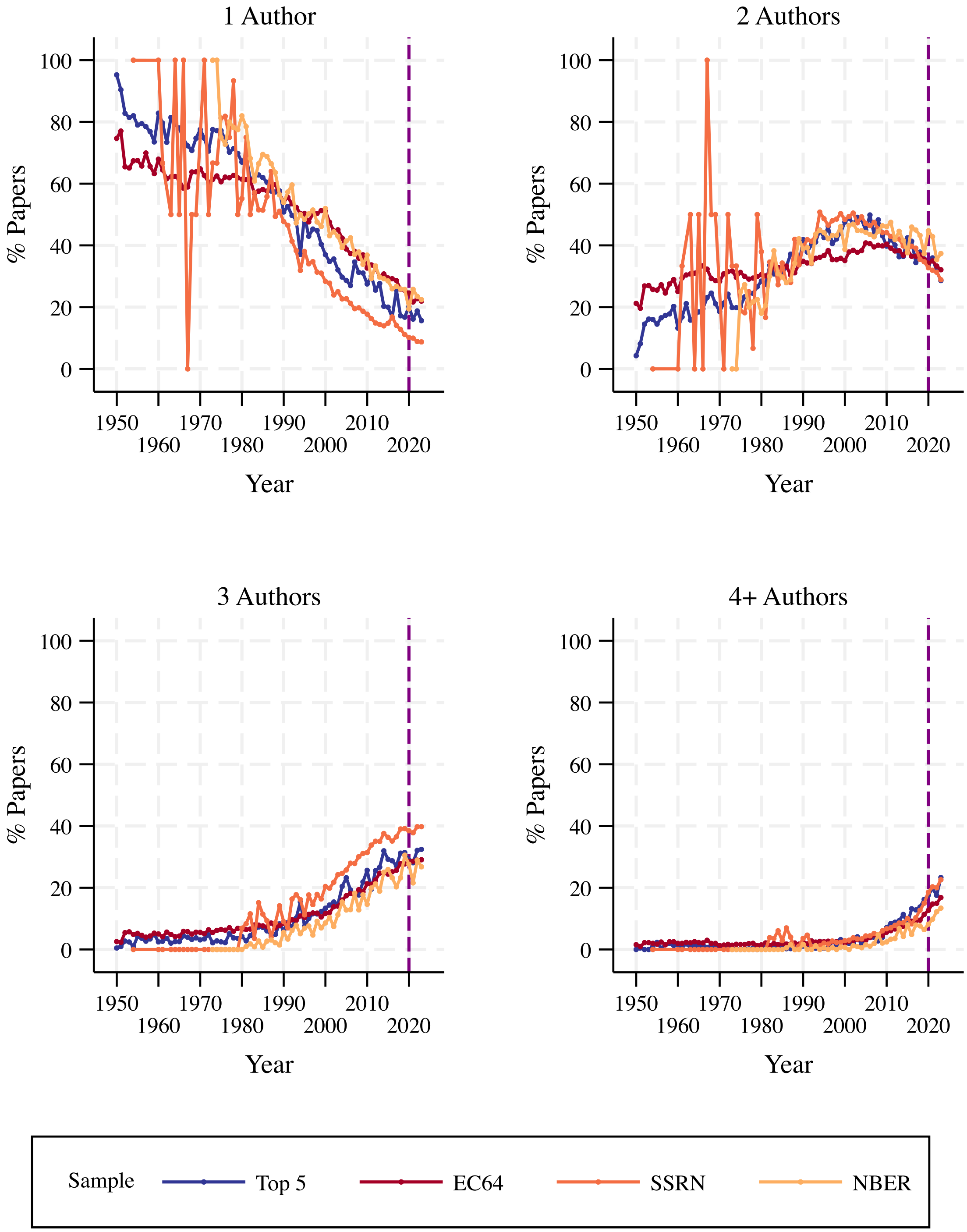


Figure B6: Number of Papers in Top-5 Journals, 1950-2023

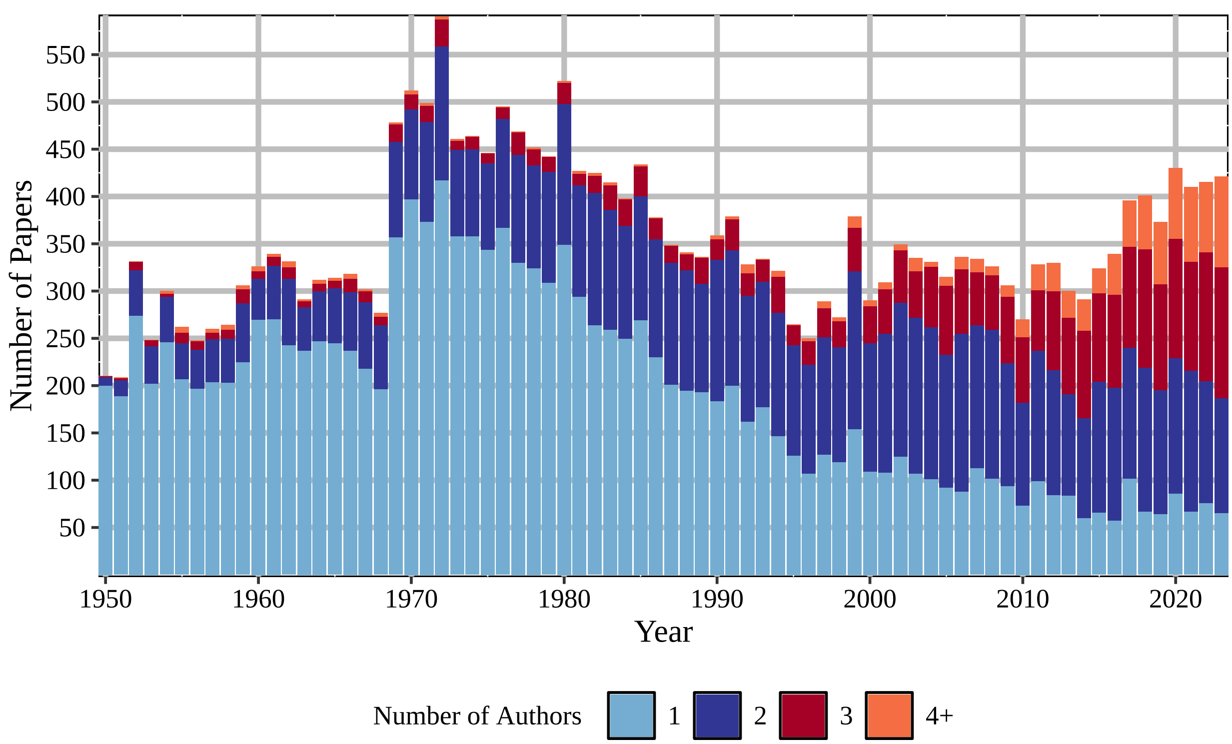
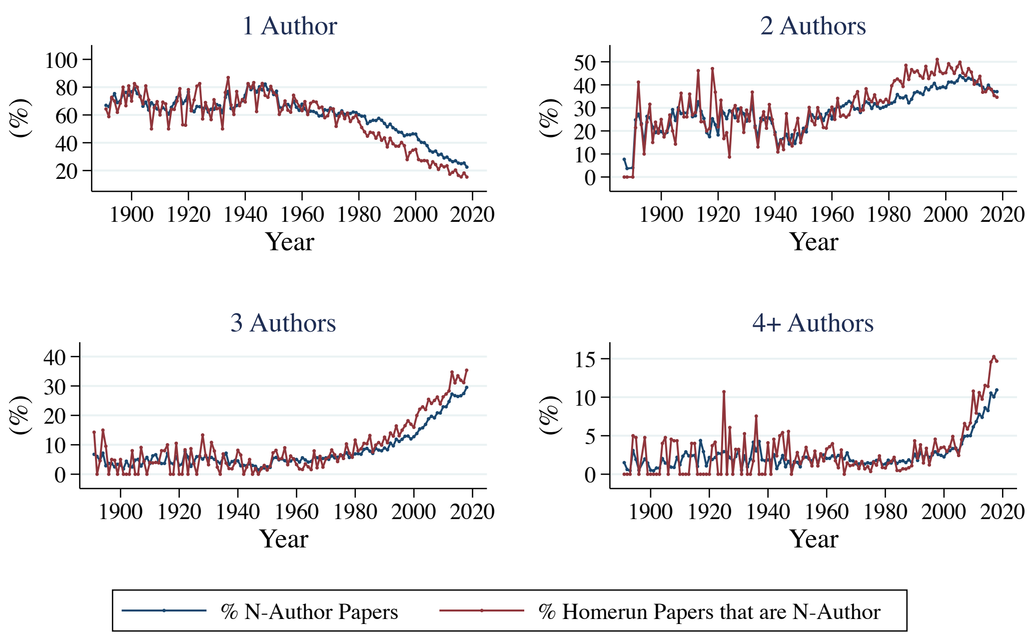
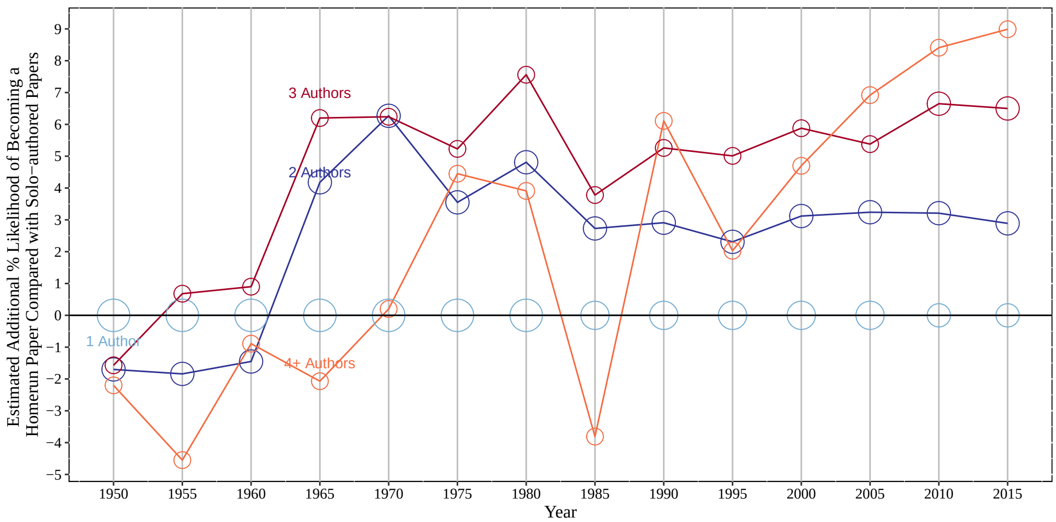


Figure B7: Evolution of the Fraction and Success of N-Author Papers



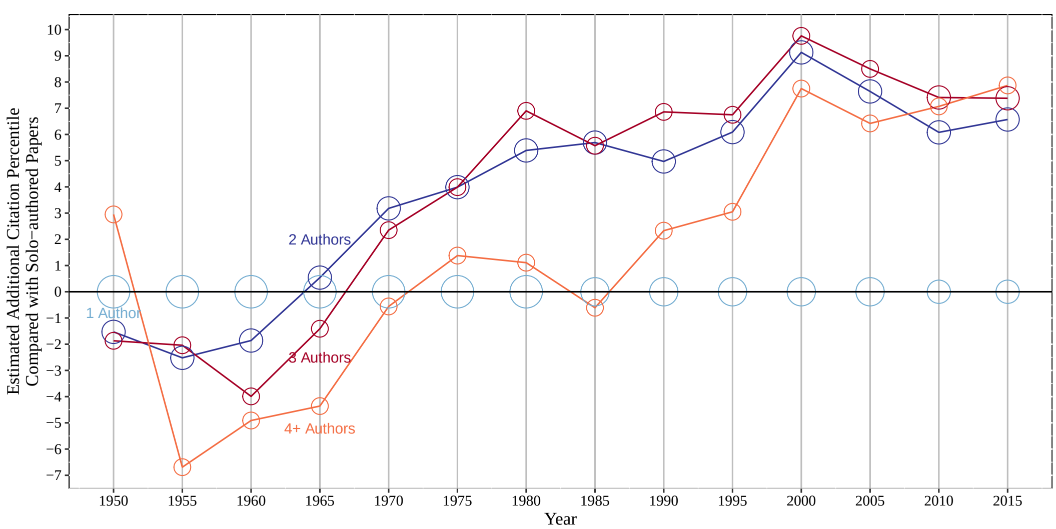
Note: A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year.

Figure B8: Evolution of Estimated Returns to Number of Authors, 5-Year Periods



Note: We estimate Equation (6) for each quinquennial. Each tick on the x-axis represents the 5-year period starting that year. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year.

Figure B9: Evolution of Estimated Returns to Number of Authors, Citation Percentile, 5-Year Periods

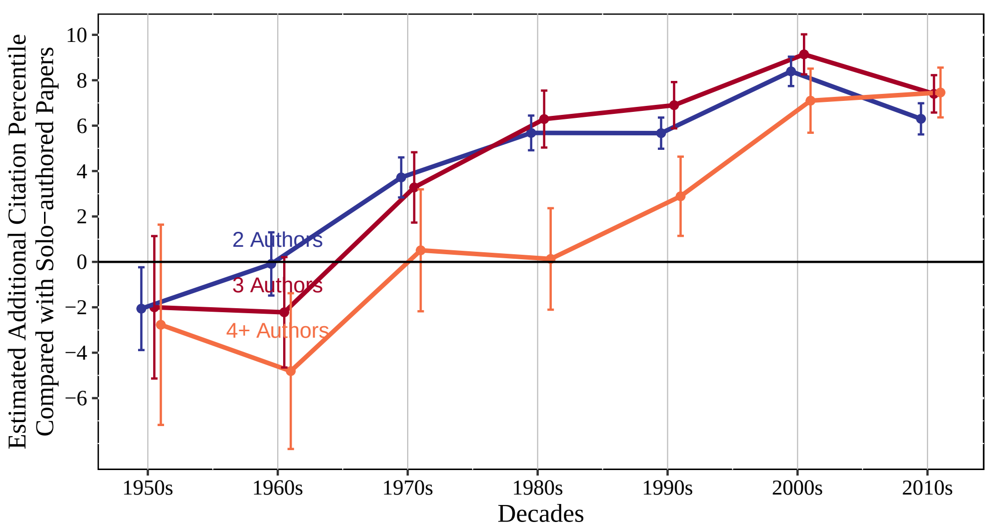


Note: We estimate Equation (6) for each quinquennial. Each tick on the x-axis represents the 5-year period starting that year. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year.

Figure B10: Evolution of Estimated Returns to Multi-Author Papers, Citation Percentile, 10-Year Periods

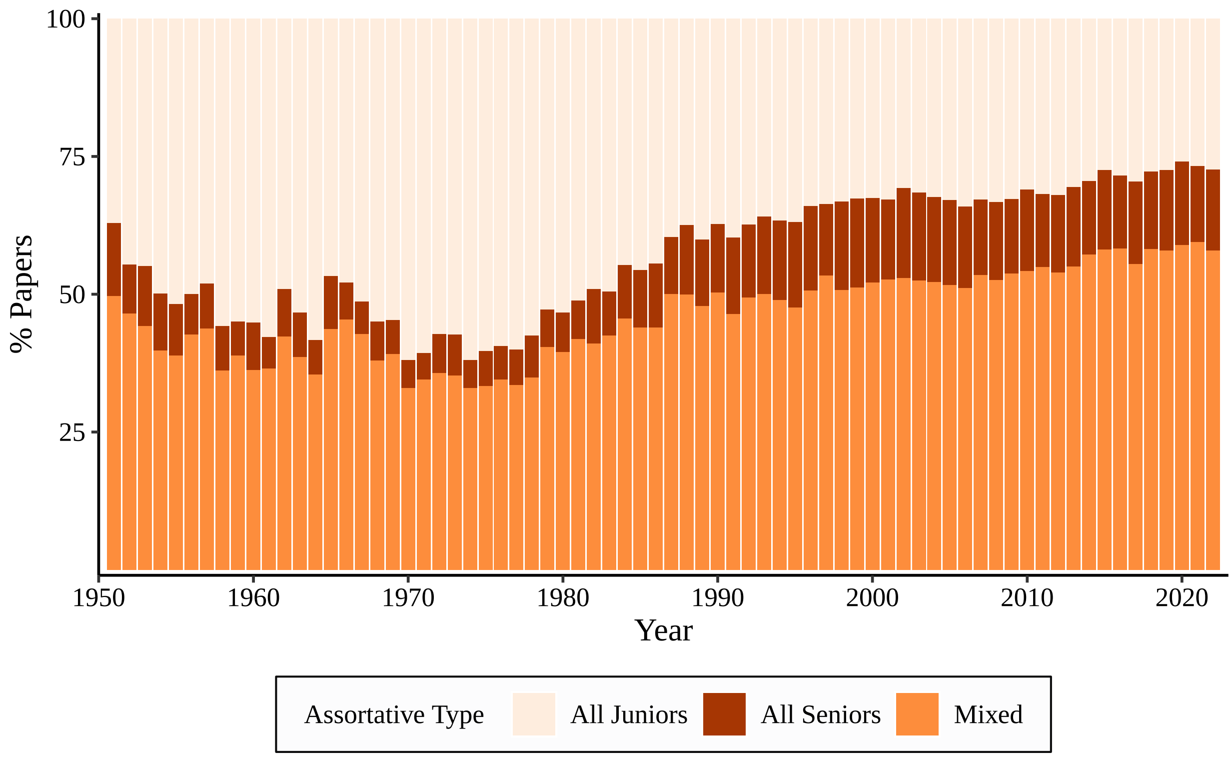
Note: We estimate Equation (6) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year. Sizes of the circles correspond to the shares of n-author papers that year.

Figure B11: Evolution of Estimated Returns to Number of Authors, Citation Percentile, 10-Year Periods



Note: We estimate Equation (6) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year.

Figure B12: Overall Decrease in Experience Assortativity in EC64 Papers



Note: An economist is a junior at the year of publication if it had been 9 or fewer years since their first EC64 publication.

Figure B13: Distribution of Authors by Number of EC64 Papers

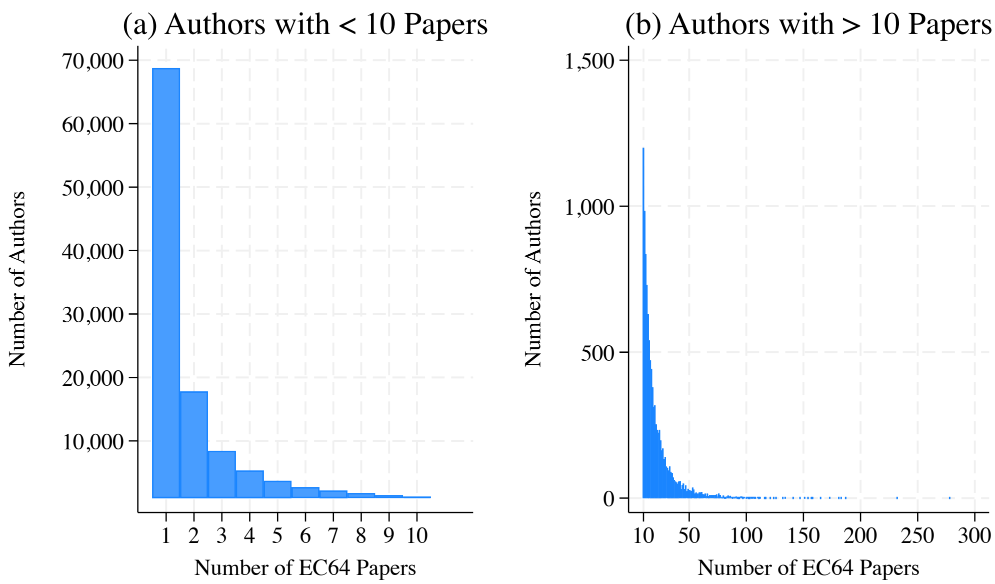


Figure B14: Distribution of Institutions by Number of EC64 Papers

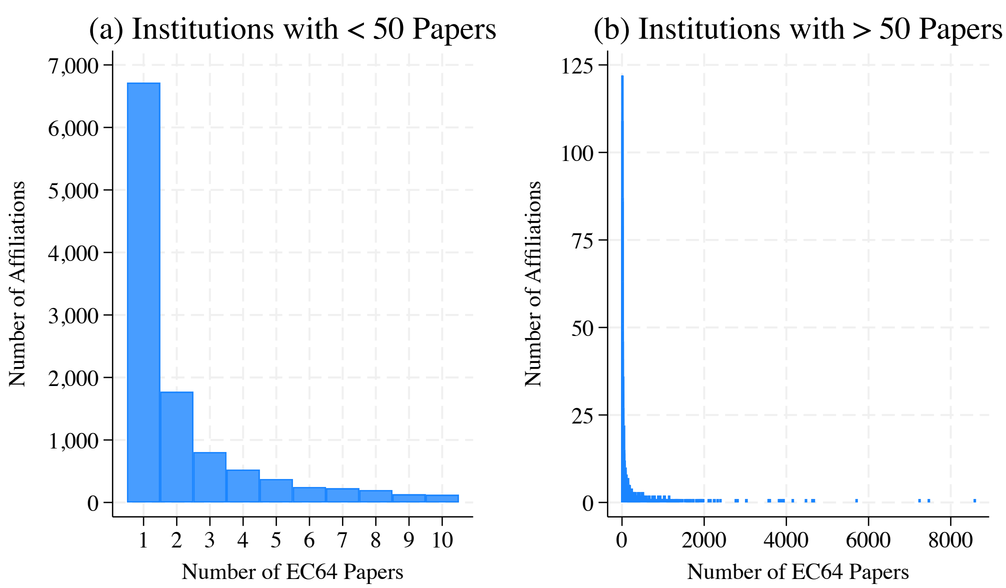


Figure B15: Evolution of Number of EC64 Publications from Top Countries

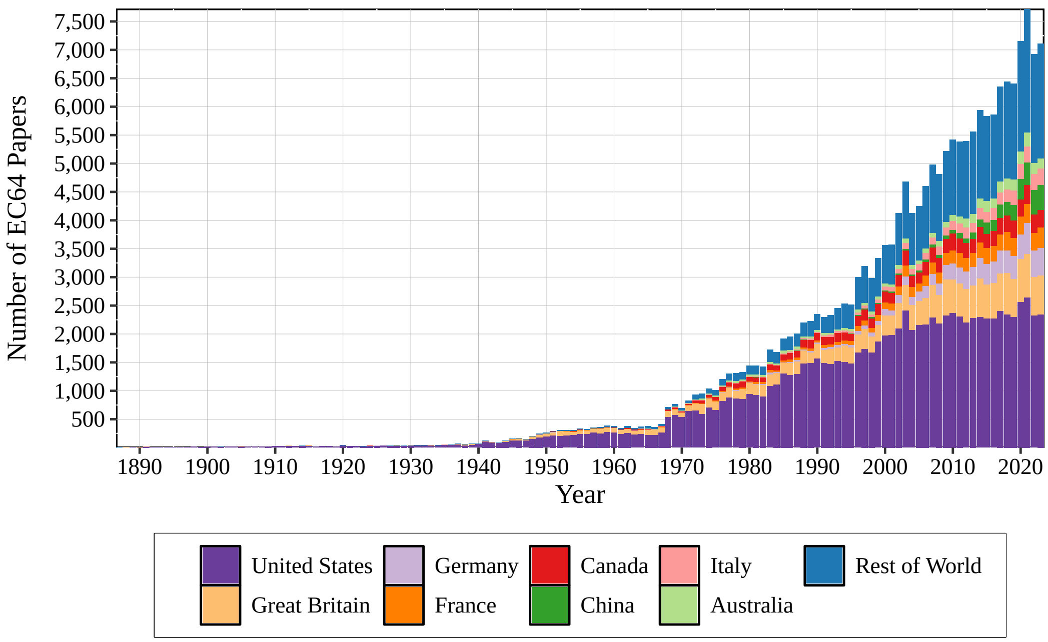


Figure B16: Evolution of Share of EC64 Publications from Top Countries

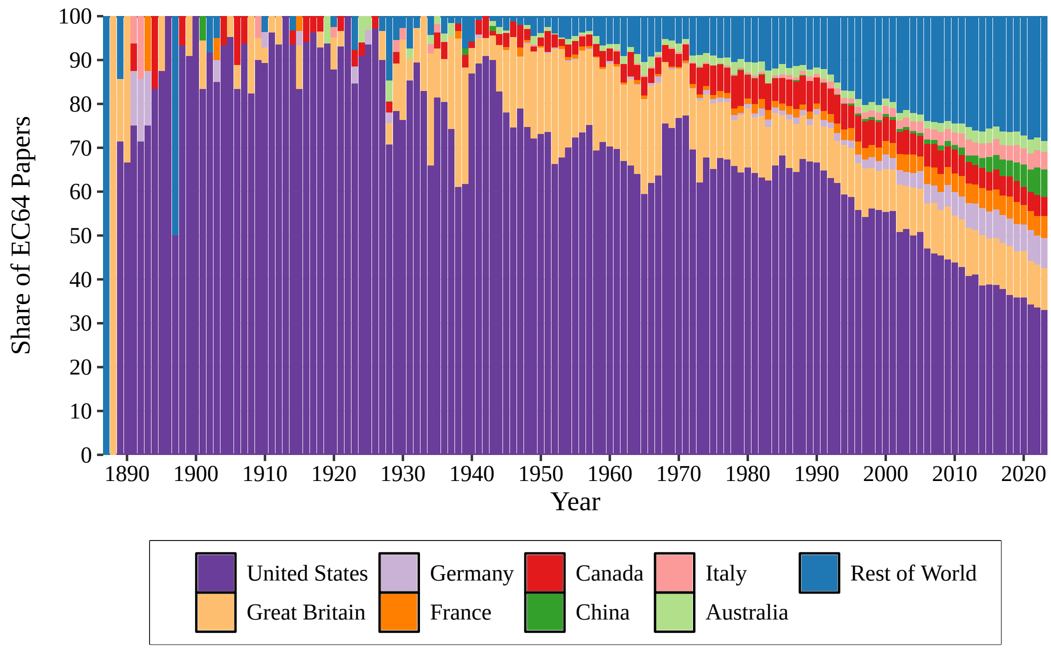


Figure B17: Evolution of the Share of T5 Publications from Top Countries

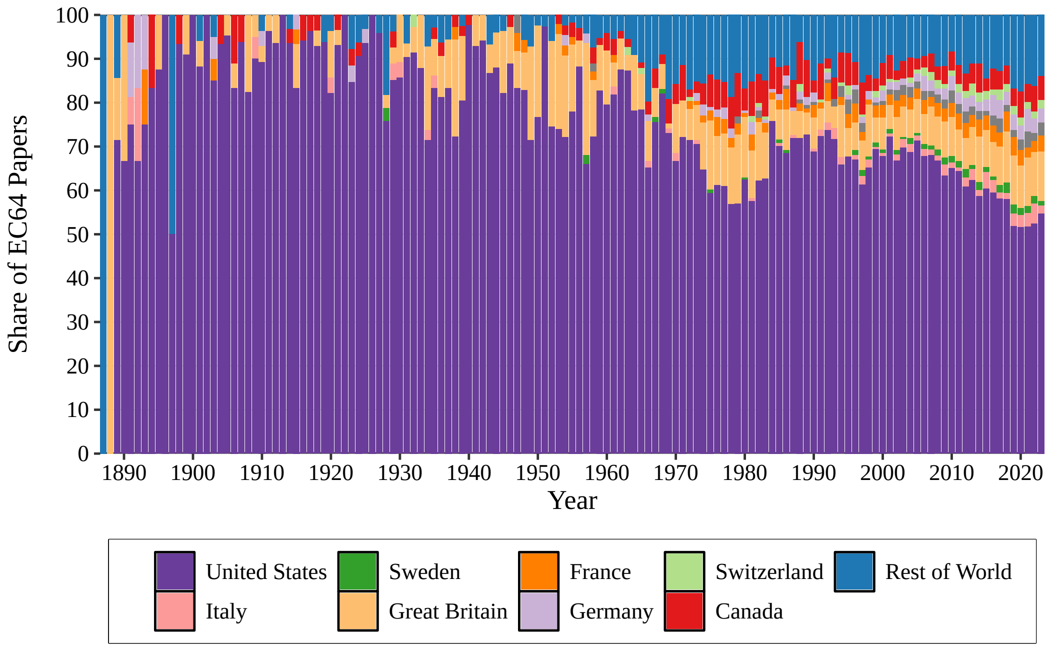


Figure B18: Distribution of Countries by Total Number of EC64 Papers

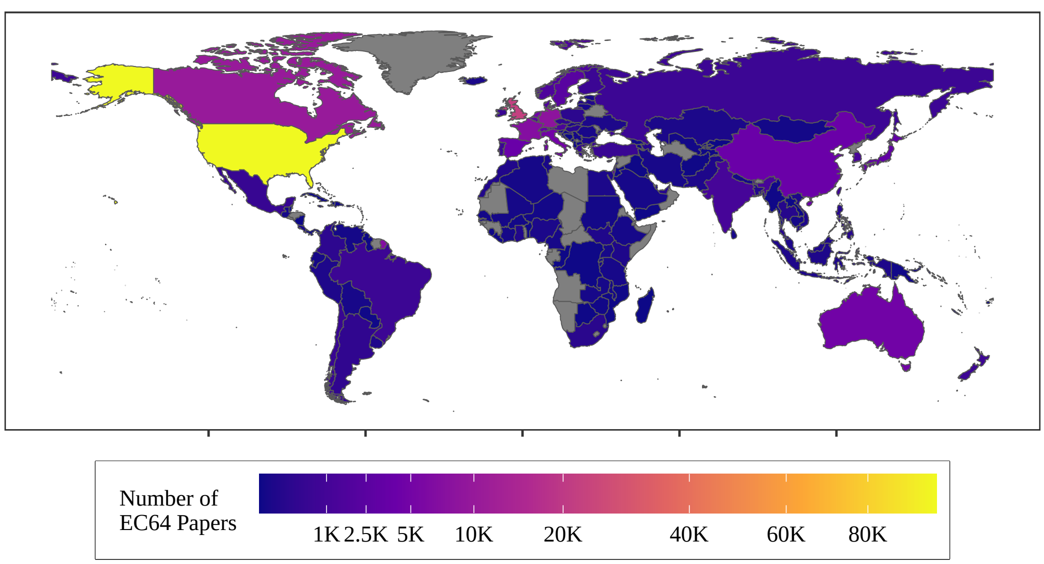
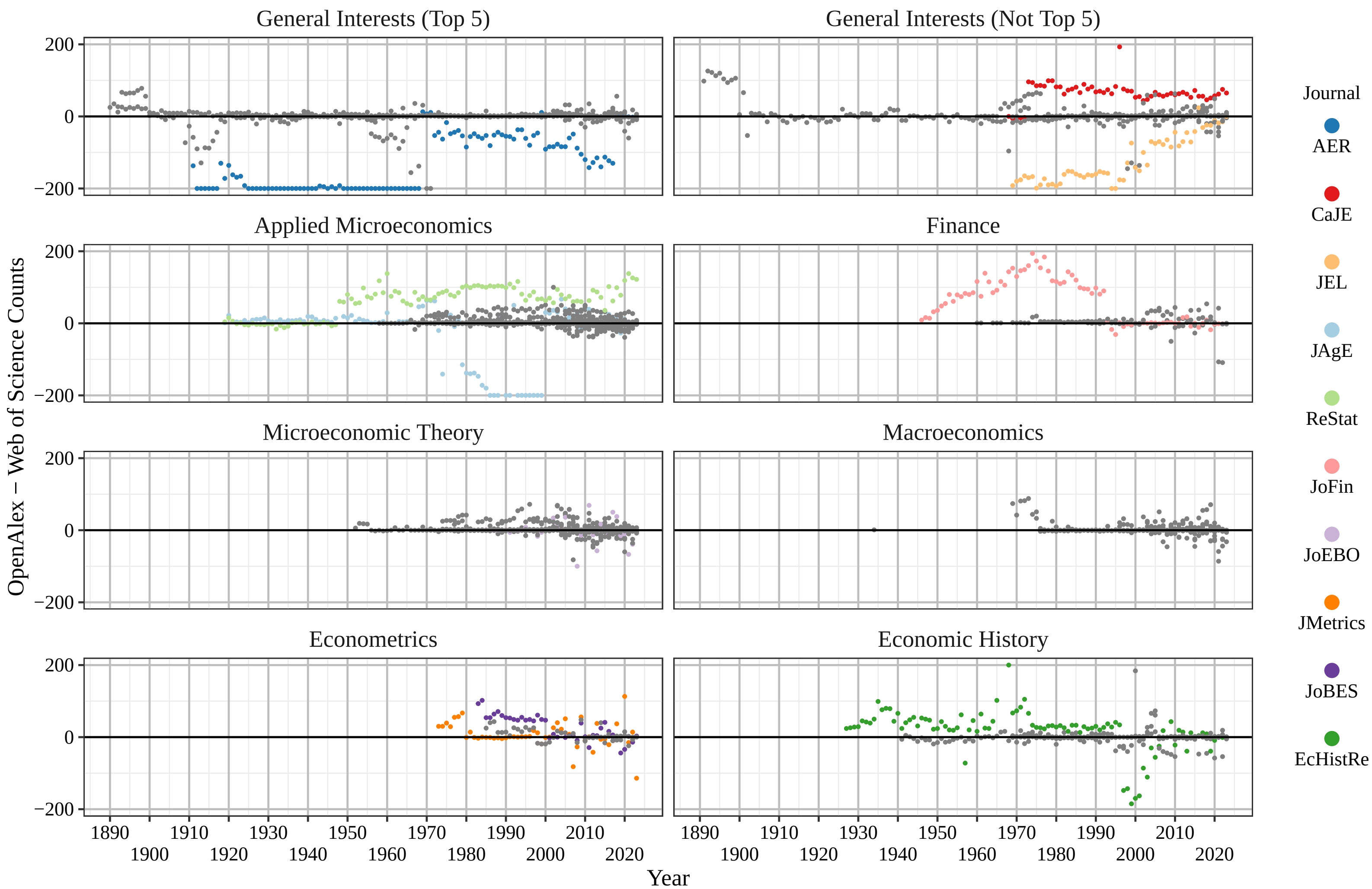
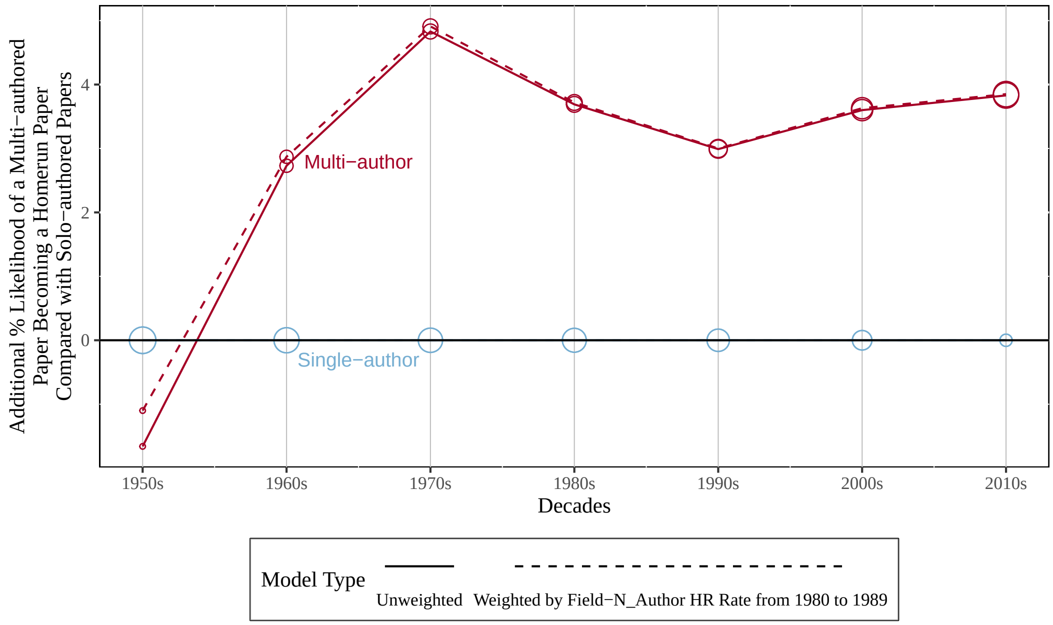


Figure B19: Differences Between OpenAlex and Web of Science Records by Field and Journal



Note: The journals shown are those with an average absolute difference greater than 25.

Figure B20: Evolution of Estimated Returns to Collaboration, 10-Year Periods

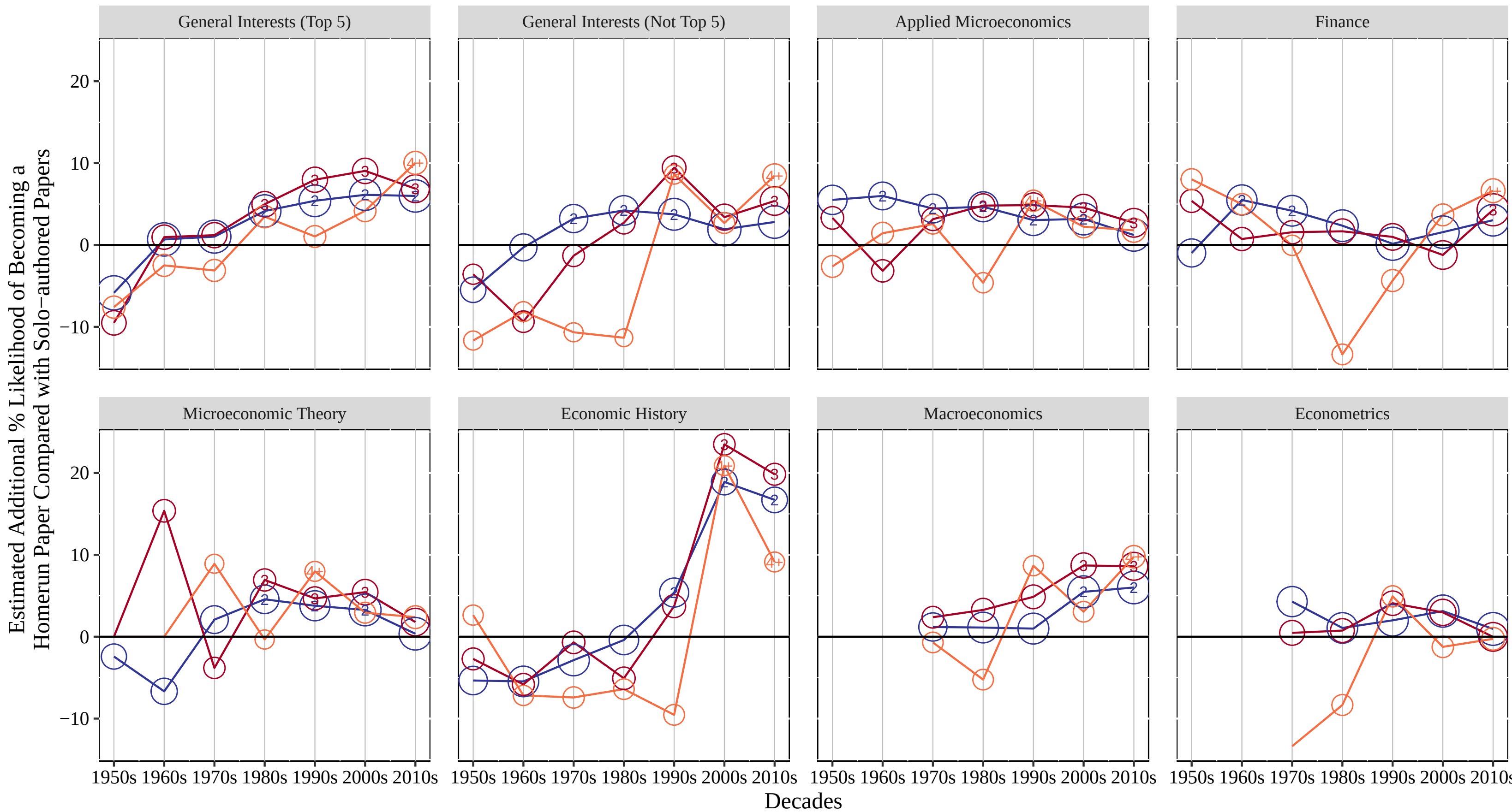


Note: We estimate Equation (6) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation in the top decile among EC64 papers published in the same year. Sizes of the circles correspond to the shares of N-Author papers that year.

Figure B21: Evolution of Estimated Returns to Multi-Author Papers by Field, 10-Year Periods

Note: We estimate Equation (6) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in that field in the same year. Sizes of the circles correspond to the shares of N-Author papers that year. The number of authors is noted in the center of the markers if the estimates are positive and statistically significant at the 5% level.

Figure B22: Evolution of Estimated Returns to Number of Authors by Field, 10-Year Periods

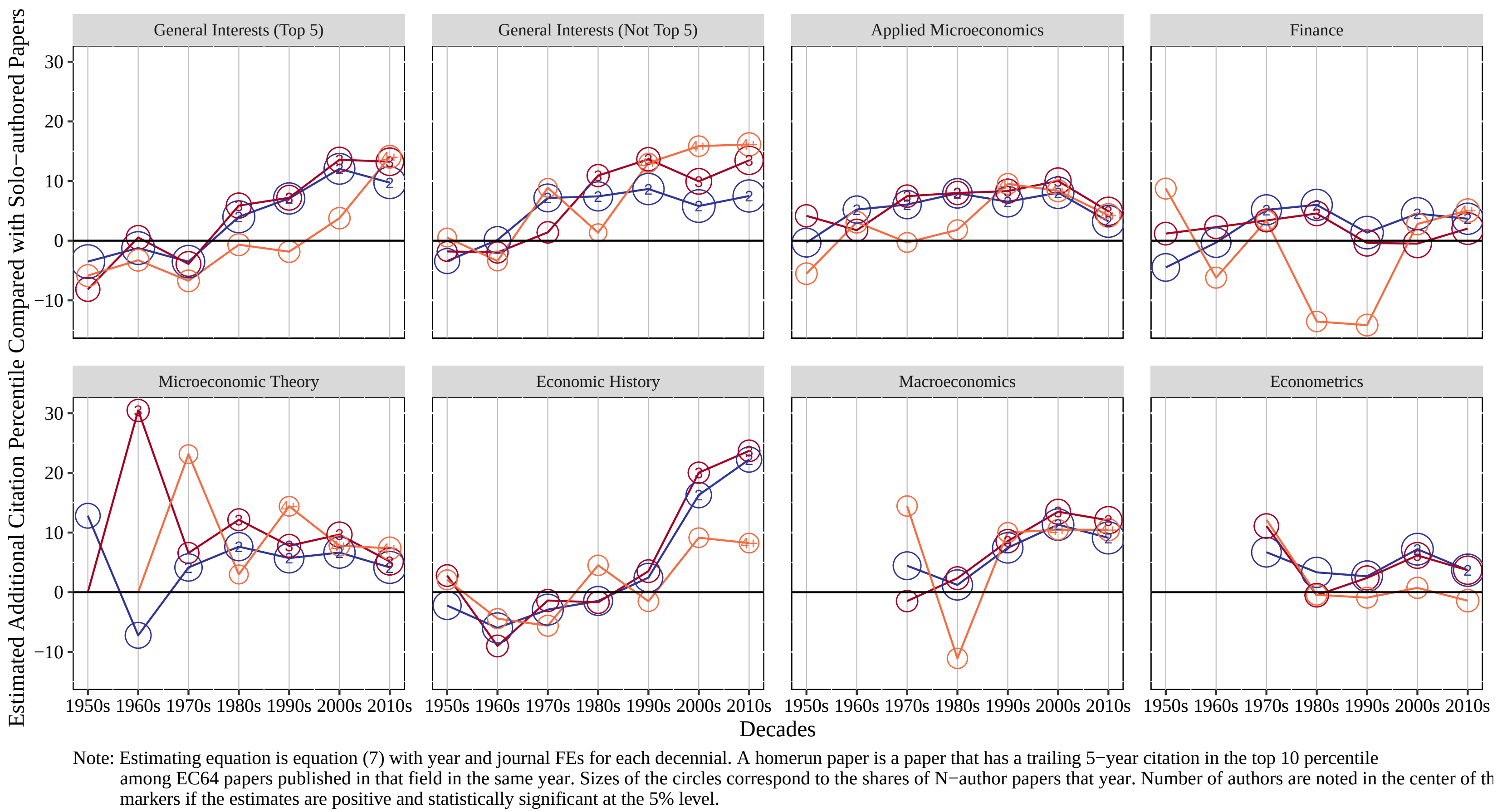


Note: We estimate Equation (6) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation in the top 10 percentile among EC64 papers published in that field in the same year. Sizes of the circles correspond to the shares of N-Author papers that year. Number of authors are noted in the center of the markers if the estimates are positive and statistically significant at the 5% level.

Figure B23: Evolution of Estimated Returns to Multi-Author by Field, 10-Year Periods

Note: We estimate Equation (6) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in that field in the same year. Sizes of the circles correspond to the shares of N-Author papers that year. The number of authors is noted in the center of the markers if the estimates are positive and statistically significant at the 5% level.

Figure B24: Evolution of Estimated Returns to Number of Authors by Field, 10-Year Periods



Note: We estimate Equation (6) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in that field in the same year. Sizes of the circles correspond to the shares of N-Author papers that year. The number of authors is noted in the center of the markers if the estimates are positive and statistically significant at the 5% level.